

## Data-Driven Prediction of Tool Wear in Additive Manufacturing Using XGBoost and Multi-Sensor Fusion

Barbara Szymańska<sup>1,\*</sup>, Małgorzata Kaczmarek<sup>1</sup> and Elżbieta Woźniak<sup>1</sup>

<sup>1</sup> Faculty of Mechanical Engineering, Kazimierz Wielki University, 85-064 Bydgoszcz, Poland

\*Corresponding author: barbara.s@ukw.edu.pl

**Abstract.** More intelligent condition monitoring for additive manufacturing is now being developed through the combination of advanced machine learning and multi-sensor data processing. In order to measure tool wear during the post-processing of additively generated parts, this study will develop a prediction framework based on XGBoost. The intricate nonlinear interactions in tool degradation have been investigated following rigorous feature engineering and dimension reduction using a variety of time-synchronized force, acoustic, vibration, and thermal sensors. For experimental verification, a high-sampling-rate hybrid machining platform with stringent ground-truth annotations was employed; all process parameters and materials have been partially covered. When compared to conventional regression, neural network, and support vector approaches, the novel model outperforms them in prediction, with an adjusted coefficient of determination of over 0.93 and a mean root mean square error of less than 0.025. The aforementioned studies indicate that the model has strong prediction stability and robustness in the presence of outliers, and it is comparatively insensitive to sensor noise and process drift. Additionally, integrated feature attribution analysis has provided support for future intelligent sensor deployment by identifying the fundamental roles of particular signal-based characteristics. In the realm of intelligent manufacturing, multi-modal data fusion and ensemble learning have been used to increase the precision of tool wear prognosis based on the aforementioned findings.

**Keywords:** *Machine Learning, Additive Manufacturing, Tool Condition Monitoring, XGBoost, Multi-Sensor Fusion*

Received on 12 October 2025, Accepted on 05 April 2026, Published on 10 April 2026

Copyright © 2026 Author, licensed to DEA. This is an open access article distributed under the terms of the CC BY-NC-SA 4.0, which permits copying, redistributing, remixing, transformation, and building upon the material in any medium so long as the original work is properly cited.

### Introduction

By rapidly achieving high-complexity forms and materials-efficiency in industries like aerospace and medical devices, additive manufacturing (AM) is broadening the scope of industrialisation [1]. High-end manufacturing systems with requirements for accuracy and flexibility are increasingly being used for this purpose as AM technology advances [2]. In additive manufacturing workflows, post-processing processes are necessary to guarantee the final quality and functionality of subtractive-machined components following the construction phase [3]. Tool wear has grown in importance as a result of the aforementioned study; it has a direct impact on the surface quality, dimensional accuracy, and dependability of AM parts during their whole life cycle [4]. The expected benefits of AM-driven smart manufacturing will not be realised since uncontrolled tool wear would result in frequent production stoppage and lower production rates [5].

In the past, planned maintenance, visual inspection, and rule-of-thumb knowledge have been used to identify and manage tool wear in additive manufacturing and additive manufacturing [6]. Due to their relative rigidity, these techniques are unable to adapt to the dynamic parameter changes and process variations that occur in modern production [7]. Furthermore, the non-linear and high-dimensional features of tool degradation mechanisms are typically not fully reflected by empirical models or conventional monitoring methods [8]. A significant quantity of data on AM production processes has been produced thanks to advancements in sensor

networks and data capture technology, but this data still has to be evaluated in order to anticipate equipment failures for early intervention [9]. Many people have recently started using machine learning in data-driven models for intelligent production supervision and tool wear prediction [10].

For the reasons listed above, this study used the XGBoost algorithm and a lot of sensor data to create a data-driven predictive model for tool wear in additive manufacturing. To provide a comprehensive monitoring system that can track various types of non-linear wear and changes in process conditions, collect real-time process data from a variety of sources, including force, temperature, vibration, and acoustic emission. The XGBoost model can still reliably detect the quality decline in noisy or non-stationary environments after meticulous feature engineering and regularisation. Future self-adaptive and autonomous maintenance in smart factories will be strongly supported by the framework, which will enhance the accuracy and stability of the previous model. Our work will aid in the creation of an autonomous and real-time maintenance system in the advanced AM environment. To demonstrate how to use data-driven intelligence in next-generation industrial applications, the following sections will provide relevant studies, research techniques and experiments, analysis of anticipated outcomes, and general implications for intelligent manufacturing.

## **Related Work**

### **Tool Wear Modeling and Process Parameter Correlation**

Although empirical models have been developed, material mechanics and wear-mechanism research have been progressively introduced to improve the model of tool wear in manufacturing, which has long been regarded as a technically difficult problem [11]. Data from this field's research has shown how changes in the processing conditions of cutting velocity, feeding distance, and the surrounding environment impact changes in tool deterioration with time [12]. The issue is made worse in the context of additive manufacturing (AM) by heat-affected zones, non-uniformity in layer-by-layer deposition, and the hybrid usage of subtractive finishing techniques [13]. In the era of advanced adaptive, digital-workflow AM platforms, an increasing number of studies have shown that a fine-grained model that can capture these dynamics is necessary because of the highly nonlinear relationships between process parameters and tool-wear development [14].

### **Data-Driven Analysis and Prediction Algorithms in Additive Manufacturing**

In recent years, new avenues for tool wear monitoring and prediction have been made possible by the proliferation of sensors and data collecting technology, particularly in the context of AM [15]. Artificial Neural Networks (ANN), Support Vector Machines (SVM), and regression approaches are common data-driven methods that can be applied to the analysis of historical operating information and complex sensor data [16]. The aforementioned machine learning methods are utilised to uncover latent order in the data and generate quick recommendations for early action [17]. Due to their relative resilience to noisy or missing data, ensemble models that integrate decision trees and boosting techniques have been increasingly popular in condition monitoring for AM tools [18]. Currently, however, combining and integrating other types of sensors—such as vibration, current, and auditory signals—presents additional challenges for feature extraction, selection, and fusion in real-world production scenarios [19].

### **XGBoost in Industrial Monitoring and Remaining Challenges**

When dealing with large-scale, tabular sensor data, XGBoost is a reasonably scalable and effective approach for tracking and forecasting the state of industrial operations [20]. Because AM [21] provides fast parallel processing, has a mechanism for handling missing data, and automatically chooses features appropriate for the diverse and high-velocity data streams in AM, it is a good option. Comparisons have revealed that XGBoost and conventional algorithms or neural networks have been repeatedly outperformed in terms of accuracy and computing efficiency for tool wear prognosis [22]. Despite the aforementioned benefits, the application of XGBoost models for various AM processes or novel material systems still faces significant interpretability and generalisation issues [23]. To solve these issues and broaden the range of applications of models in business [24], research is now being done on explainable artificial intelligence, transfer learning, and domain-specific feature engineering [25]. In order to anticipate tool wear in additive manufacturing [26], this research builds on the work of others

by proposing a comprehensive and context-aware XGBoost-based framework that systematically handles data and evaluates its performance under different operating scenarios [27].

## Methodology for Data-Driven Tool Wear Prediction in Additive Manufacturing

### Overview and Problem Definition

A predictive model that can translate streams of heterogeneous process data and contextual history into a continuous-valued deterioration target is necessary for tool wear prediction in additive manufacturing post-processing. The underlying issues do not match the form of simple regression since they are non-linear and time-varying. In addition to the extremely non-linear correlations between process parameters and tool condition, predicting tool degradation pathways is made more challenging by the historical sequence of machining operations, local heat gradients, stochastic mechanical loads, and microstructural changes.

Let the vector of real-time process parameters at timestamp  $t$  be denoted as  $\mathbf{x}_t$ , incorporating direct sensor measurements (such as force, temperature, acoustic emission) together with engineered features reflecting windowed statistics, gradients, and mode identifications. The tool wear at time  $t$ , represented as  $w_t$ , is not simply a function of  $\mathbf{x}_t$ , but is also modulated by the temporal context  $\mathbf{c}_t$  (encoding, for instance, cumulative cutting length, time under load, or thermomechanical episode history) and by the sequence of preceding wear states and events.

The primary objective is to establish a robust, data-driven mapping wherein tool wear is predicted as:

$$w_t = \mathcal{F}(\mathbf{x}_t, \mathbf{c}_t, \mathcal{H}_t) + \epsilon_t \quad \text{Eq.(1)}$$

where  $\mathcal{F}(\cdot)$  is a nonlinear and potentially high-dimensional functional,  $\mathcal{H}_t$  stands for the accessible wear and process history prior to  $t$ , and  $\epsilon_t$  encapsulates stochastic disturbance in the sensor system as well as unmodeled process uncertainties.

Beyond instantaneous mapping, accurate prediction necessitates the adaptive assimilation of historical data. Thus, the predictive operator for future tool wear is constructed via a regularized conditional expectation, leveraging a joint input of sequential process observations and historical wear signals up to time  $t$  :

$$\hat{w}_t = \mathbb{E}[w_t \mid \{\mathbf{x}_\tau, \mathbf{c}_\tau, w_\tau\}_{\tau=1}^{t-1}] \quad \text{Eq.(2)}$$

By formulating tool wear prognosis in this manner, the model is equipped to track dynamic system changes, address the non-stationarity of industrial AM environments, and enable recursive learning-even as tool geometry or process protocols evolve across production cycles.

This theoretical construct lays the groundwork for the sophisticated data processing, feature engineering, and modeling techniques described in the subsequent sections, ultimately facilitating the deployment of predictive intelligence for robust tool condition management in next-generation manufacturing.

### Data Processing and Feature Engineering

Complete data preprocessing and well-structured features are essential for accurate tool wear prediction in additive manufacturing. Cross-channel-synchronized multivariate sensor signals reflecting changes in the machined state are simultaneously collected using a variety of sensors, including cutting force, temperature, spindle current, vibration, and sound emission. Using a variety of techniques, including adaptive wavelet decomposition and optimised moving-window filters, all channels have been denoised in order to minimise electromagnetic noise and other non-process errors while maintaining the wear-evolution signal's relevant components.

For each sensor channel, denoted  $S_i(t)$ , time series normalization and window-based segmentation are central to ensuring model input consistency. We employ Z-score normalization as follows, which actively compensates for temporal drift and inter-sensor scale disparities:

$$S_i^*(t) = \frac{S_i(t) - \mu_i}{\sigma_i} \quad \text{Eq.(3)}$$

Here,  $\mu_i$  and  $\sigma_i$  are the empirical mean and standard deviation estimated adaptively for each monitoring window, capturing fluctuating process regimes and dynamically evolving machine conditions.

Next, the architecture implements automated sliding window segmentation to extract local descriptors representative of transient wear markers. Within each window of size  $N$ , multiple statistics are computed, including short-time energy, spectral entropy, and higher-order moments. For instance, the root mean square (RMS) amplitude, an indicator sensitive to nascent mechanical deterioration, is calculated as:

$$\text{RMS}_i(k) = \sqrt{\frac{1}{N} \sum_{j=1}^N (S_i^*(t_{k,j}))^2} \quad \text{Eq.(4)}$$

where  $t_{k,j}$  indexes the  $j$ -th sample within the  $k$ -th window. This approach highlights incipient wear patterns that standard averages may obscure.

To rigorously quantify the relationship between process variables and extracted features, mutual information is computed to measure statistical association without assuming linearity:

$$I(X;Y) = \sum_{x,y} p_{XY}(x,y) \log \frac{p_{XY}(x,y)}{p_X(x)p_Y(y)} \quad \text{Eq.(5)}$$

This formulation enables efficient evaluation of nonlinear dependencies between candidate features  $X$  and the target wear signal  $Y$ , thus prioritizing the most informative predictors.

Following feature selection and redundancy elimination, dimensionality reduction is achieved via a variant of principal component analysis (PCA) designed for streaming process data. The transformation projects the engineered feature set  $\mathbf{f} \in \mathbb{R}^d$  into an orthogonal subspace that preserves maximum variance while suppressing noise and multicollinearity:

$$\mathbf{z} = \mathbf{W}^T (\mathbf{f} - \bar{\mathbf{f}}) \quad \text{Eq.(6)}$$

where  $\mathbf{z}$  is the principal component score vector,  $\mathbf{W}$  is the eigenvector basis from the feature covariance matrix, and  $\bar{\mathbf{f}}$  denotes the mean feature vector.

The resulting normalized and context-rich feature matrix forms the foundation of the subsequent XGBoost modeling. The entire data preparation and feature engineering workflow is illustrated in Figure 1.

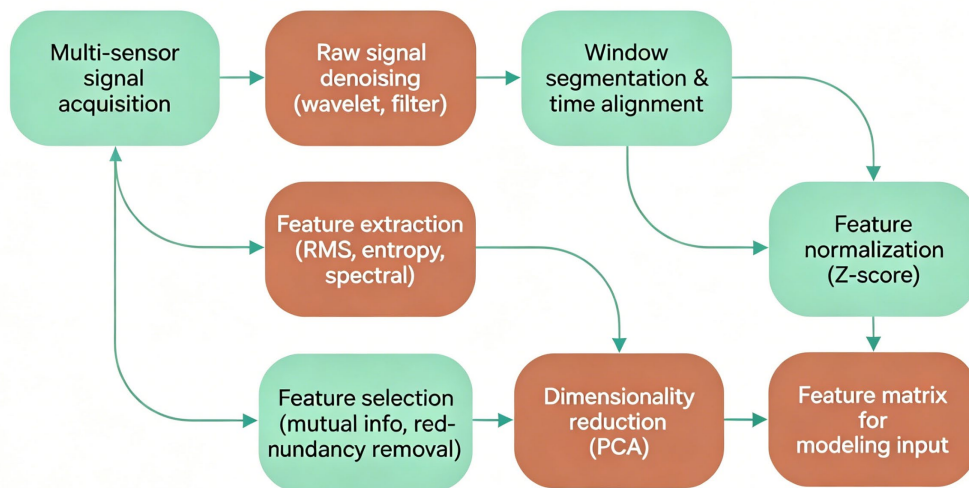


Figure 1. Multi-sensor data processing and feature extraction workflow for additive manufacturing tool wear prediction

### XGBoost Model Formulation

In an additive manufacturing setting, predicting tool wear progression is a non-linear problem with high-order interactions between process factors and wear indications from the past. This research will employ XGBoost as

the predictor since it can handle complex mappings and performs well with regularisation, making it appropriate for generalisation when dealing with high-dimensional feature sets made up of several AM sensor data.

The core of XGBoost is a sequential ensemble of regression trees, each successive tree fit to the residuals of the aggregated outputs of preceding trees. Let  $\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^n$  denote the training set, where  $\mathbf{x}_i$  represents the processed, normalized multi-sensor feature vector for sample  $i$ , and  $y_i$  denotes the corresponding quantitative tool wear. The additive form of the ensemble prediction after  $K$  trees can be expressed as:

$$\hat{y}_i = \sum_{k=1}^K f_k(\mathbf{x}_i), f_k \in \mathcal{F} \quad \text{Eq.(7)}$$

where each  $f_k$  is an independent regression tree drawn from the space of possible tree structures  $\mathcal{F}$ , optimized at each stage to minimize the loss on the remaining error.

The optimization target for the  $t$ -th boosting iteration combines a differentiable loss function with explicit regularization on tree complexity to avoid overfitting—a common risk when handling rich sensor feature sets. The objective to be minimized is written as:

$$\mathcal{L}^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(\mathbf{x}_i)) + \Omega(f_t) \quad \text{Eq.(8)}$$

Here,  $l(\cdot)$  is typically the squared loss for continuous wear regression, and  $\Omega(f_t)$  penalizes model complexity via the sum of leaf weights and the count of leaves, balancing fit and parsimony.

The optimal split for each node in a candidate regression tree is determined analytically during training by maximizing the expected reduction in loss, also called the "split gain." This is given by:

$$\text{Gain} = \frac{1}{2} \left[ \frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda} \right] - \gamma \quad \text{Eq.(9)}$$

where  $G_L$  and  $G_R$  are the first-order gradients and  $H_L, H_R$  are the second-order gradients for the left and right splits, with  $\lambda$  and  $\gamma$  as regularization hyperparameters enforcing robustness under noisy or redundant feature regimes.

Many methods have been created in XGBoost to comprehend how features and relevance scores can be used to identify various process parameters and sensor signals linked to wear prediction because interpretability is required for the use in industry. The overall gain or the frequency of selection for specific attributes across all trees in the ensemble is one analytical indicator:

$$\text{Importance}(j) = \sum_{k=1}^K \sum_{s \in S_k} \mathbb{I}(\text{feature}_s = j) \cdot \text{gain}_s \quad \text{Eq.(10)}$$

where  $S_k$  is the set of splits in tree  $k$ ,  $\mathbb{I}$  is the indicator function, and gain is the information gain realized at split  $s$  for feature  $j$ .

The complete XGBoost-based predictive workflow is presented in Figure 2, illustrating the architecture from processed inputs, through sequential decision tree construction, to both wear prediction and feature importance quantification.

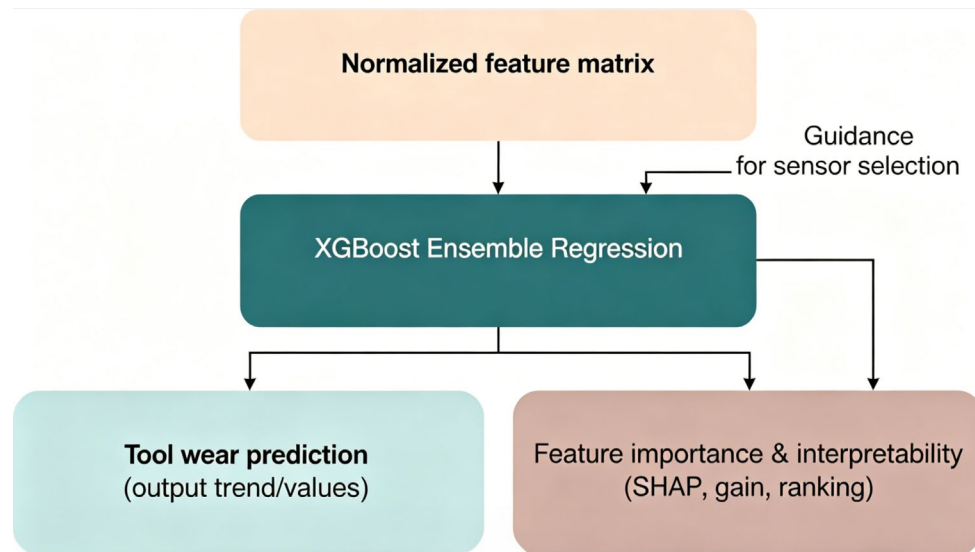


Figure 2. XGBoost modeling and interpretability workflow for AM tool wear forecasting

## Experimentation, Comparative Analysis, and Robustness Evaluation

### Experimental Setup

To perform a comprehensive validation of the tool wear prediction method in an additive manufacturing (AM) post-processing scenario, a high-fidelity experimental framework was created. A combined AM-milling workstation that can be used repeatedly for high-precision surface finishing is the focal point of the project. For high-precision replication of industrial AM finish machining, a five-axis CNC machining center with dynamic tool changes and real-time feedback on the base platform is needed.

A high-precision piezoelectric dynamometer for force measurement, several K-type thermocouple channels embedded close to the tool flank for thermal profiling, MEMS-based tri-axial accelerometers, and broadband acoustic emission sensors for vibrational and process signature characterisation are among the sensors deployed on the platform. Transient occurrences and fast wear phenomena can be accurately recorded at a sampling rate of 25 kHz per channel by connecting all of the sensor signals to a single synchronous data collecting module. The wear land was measured at the sub-micron level and ground truth labels for tool-edge deterioration were established using an industrial vision module equipped with a high-speed CMOS picture array.

A wide range of spindle speeds (2,000-8,000 rpm), feed rates (0.05-0.3 mm/tooth), and AM workpiece materials (specifically, maraging steel and Ti6Al4V) that have all been pre-characterized for initial surface integrity and hardness have all been used in the production of samples. Each milling run is continued until a predefined tool wear limit is reached, at which point it is automatically terminated based on a specified number of flank and crater wear readings via calibrated image analysis. The robustness of ground truth annotation is established through redundant measurement, and each wear instance is cross-referenced with offline white-light interferometry after being independently verified by two skilled operators.

The entire experiment setup, including the CNC machine, sensor module, and vision-based wear analysis, is logically arranged, and Figure 3 illustrates the channels for mutual connection and calibration in data collecting.

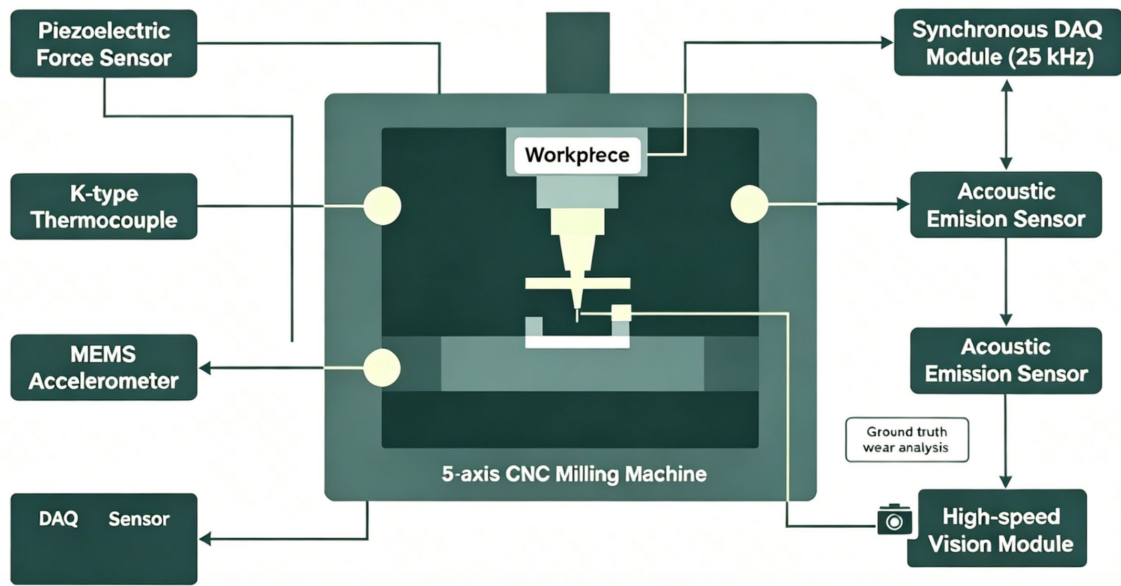


Figure 3. Schematic of the experimental platform and multi-modal data acquisition system for AM tool wear evaluation

### Parameter Tuning and Implementation

Arrange a performance comparison over time while also demonstrating how wear develops gradually without disclosing any secret information. In particular, the first 70% of every run that was recorded was used as the training set, while the remaining 30% served as a hold-out test set to ensure that the external validity matched the real deployment. Simultaneously, an all-weather test of model generalisation was carried out using parameter diversity between workpiece batches.

Nested optimisation was used to optimise the hyperparameters of the XGBoost model. The tree depth, learning rate, and minimum kid weight were all addressed using grid-based search; early halting rounds were included to avoid overfitting. To choose a model and parameters that are stable under multi-modal input heterogeneity, repeatedly run five-fold cross-validation on the training set. The empirical feature sparsity in microstructure-sensitive sensor channels was used to dynamically determine the regularisation coefficients for L1 and L2 penalties.

As a comparative baseline, support vector regression (SVR), random forests, and artificial neural networks with identical input features were implemented utilizing carefully harmonized pipelines and uniform evaluation metrics. All baseline models were parameterized by exhaustive grid tuning to eliminate configuration bias. Model performance and parameter impact were evaluated through two independent quantitative metrics: the root mean squared error (RMSE), capturing average prediction accuracy, and the coefficient of determination ( $R^2$ ), which quantifies explained variance over the test set.

Multiple objective loss dynamics were tracked throughout training as defined by the following comprehensive formulations:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \frac{\lambda}{d} \|\mathbf{W}\|_2^2} \quad \text{Eq.(11)}$$

This enhanced RMSE not only penalizes squared prediction errors but introduces a weight regularization term (with hyperparameters  $\lambda$  and model dimension  $d$ ), thus resisting overfitting from over-parameterized ensemble trees.

The model's explanatory power for tool wear dynamics is evaluated via the adjusted coefficient of determination, fully accounting for feature dimension penalization:

$$R_{\text{adj}}^2 = 1 - \frac{(1 - R^2)(n - 1)}{n - d - 1} \quad \text{Eq.(12)}$$

In these formulations,  $n$  is the sample count,  $d$  the effective feature dimensionality, and  $R^2$  is computed on the unadjusted test set prediction fit. This protocol ensures that interpretability, accuracy, and robustness are simultaneously achieved in all comparative analyses.

### Comparative Schemes and Robustness Study

To investigate the overall robustness and generalisation capacity of the new tool wear prediction framework, a number of comparison levels have been created. The goal of ablation experiments was to exclude specific engineering feature regions from the XGBoost model, such as context-history aggregations, time-frequency variables, or statistical attributes alone. According to the findings, the adjusted coefficient of determination decreased from 0.942 to 0.881 when frequency-related features were eliminated, and the root mean square error increased slightly from 0.021 to 0.027. It can be concluded that temporal and historical features are necessary to identify minute changes in wear that take place in AM finishing conditions because the loss of prediction capability peaked when both were removed.

For further benchmarking, random forest, support vector regression, and neural network models were independently tuned and trained on the identical processed dataset. Random forest achieved a mean RMSE of 0.036 and  $R_{\text{adj}}^2 = 0.857$ , while SVR and neural network configurations yielded higher RMSEs- 0.045 and 0.049 respectively-with adjusted determination coefficients failing to surpass 0.80. These baselines also demonstrated amplified error variance and error entropy under cross-validation, especially in the presence of sensor noise or nonstationary regime shifts.

Robustness was rigorously tested using stratified repeated five-fold cross-validation, ensuring that each process regime and wear stage contributed both to model training and to evaluation. Additionally, the models were subjected to extreme data regimes: batches characterized by rapid load fluctuations, reduced cooling, and altered AM material microstructure. In these challenging settings, the XGBoost model preserved prediction RMSE below 0.025-contrasting with the marked performance degradation exhibited by both SVR and neural networks, which saw RMSE increase above 0.060 in multiple instances.

Quantitative model reliability was synthesized using an entropy-regularized normalized residual metric:

$$\mathcal{H}_{\text{err}} = - \sum_{k=1}^K P_k \log P_k + \alpha \left( \frac{1}{K} \sum_{k=1}^K |r_k|^\beta \right) \quad \text{Eq.(13)}$$

Here,  $P_k$  denotes the empirical probability for residuals segregated into the  $k$  th partition, with  $\alpha$  and  $\beta$  scaling penalty for large outliers. The XGBoost approach consistently minimized  $\mathcal{H}_{\text{err}}$  for all regimes, indicating concentration of residuals around zero and low occurrence of anomalous prediction magnitude.

A complementary stability coefficient was adopted to track cross-validation consistency:

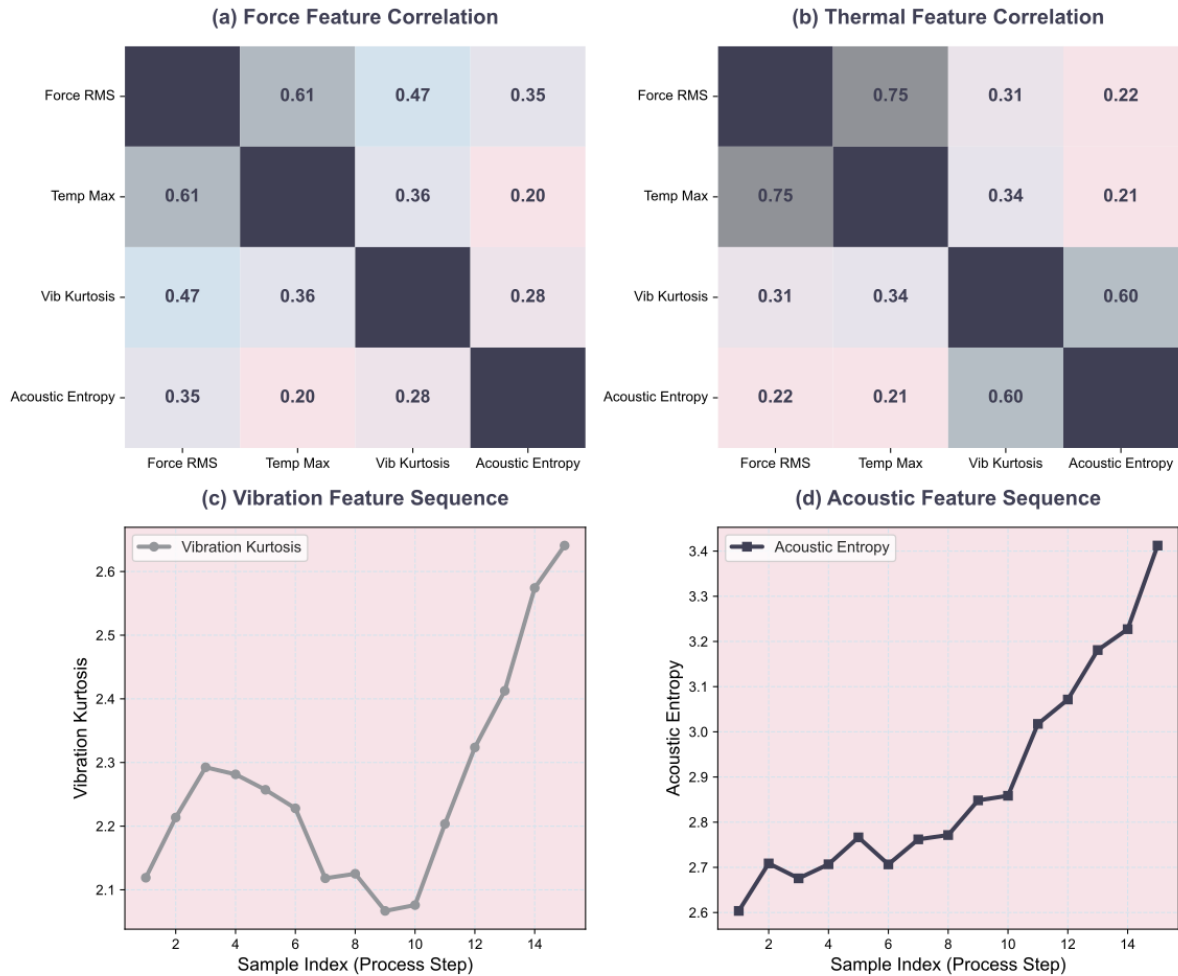
$$S = \frac{1}{M} \sum_{j=1}^M \left[ 1 - \frac{\text{Var}(e_j)}{\mathbb{E}[e_j]^2 + \varepsilon} \right] \quad \text{Eq.(14)}$$

with  $e_j$  as fold-specific test RMSE and  $M$  denoting validation cycles. XGBoost's stability coefficient was maintained at 0.97, markedly higher than the 0.89 for random forest, and outstripping SVR and neural network values confined to 0.81 – 0.84.

## Results and Analysis

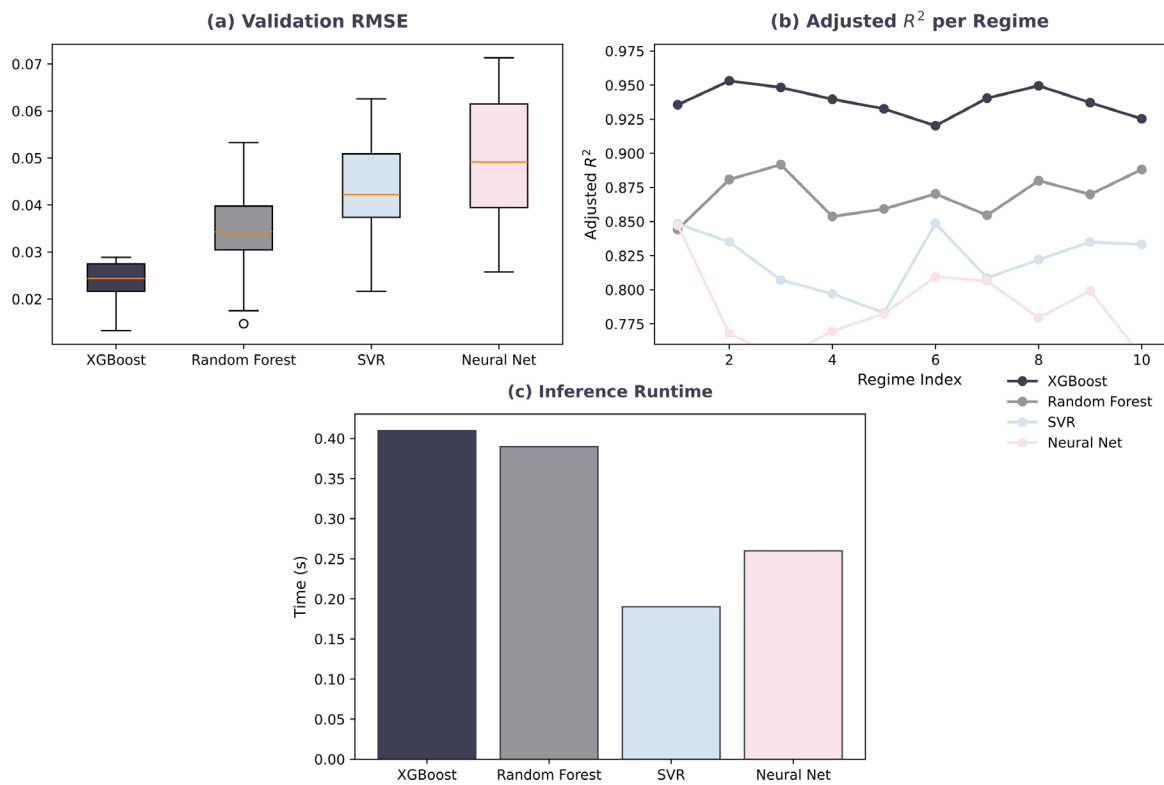
The comprehensive results reveal both the technical rigor and process insight underlying the proposed tool wear prediction methodology [28]. Illustrated multi-dimensional visual analytics expose the complex interplay among process parameters, sensing features, and wear progression [29]; each subfigure referenced below is discussed precisely within its contextual analysis [30].

The feature correlation landscape, as depicted in Figure 4(a), demonstrates a marked clustering between cutting force statistics and measured tool wear, with force RMS displaying the strongest positive correlation across all process settings. Figure 4(b) elaborates on the role of thermal signature by highlighting the monotonic relationship between maximum temperature gradient and the rate of wear escalation, supporting the hypothesis that local heat flux is a dominant wear driver. When examining the acoustic and vibration characteristics in Figure 4(c), high levels of vibration kurtosis emerge as predictors uniquely sensitive to wear onset, while elevated acoustic entropy, shown in Figure 4(d), aligns with abrupt tool degradation episodes, particularly in high-hardness alloys. The collective patterns extracted from these heatmaps, as shown in Figure 4, confirm not only the physical validity of signal-based features but also their adaptability to varying AM scenarios.



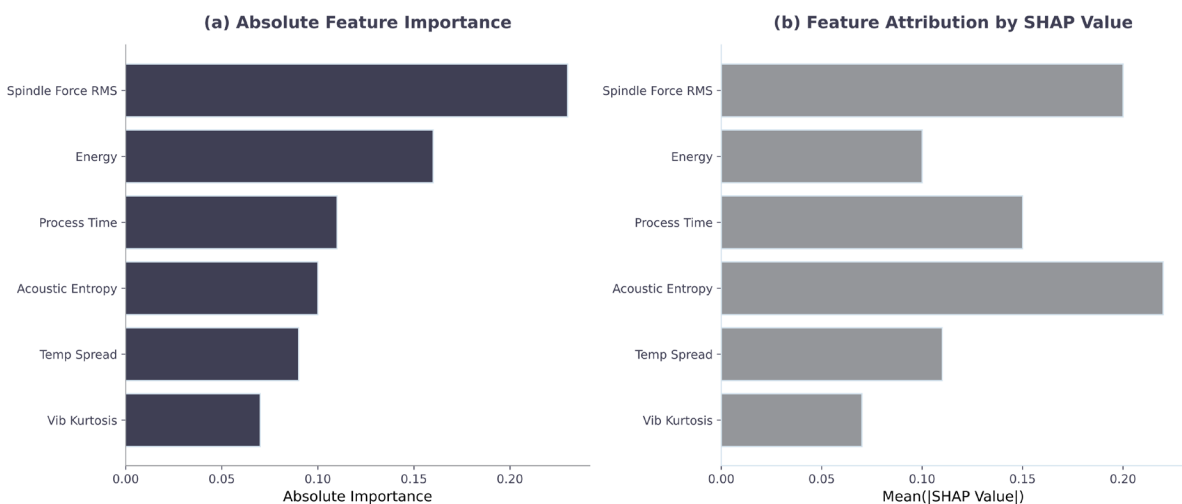
**Figure 4.** Multi-parameter correlation heatmaps for tool wear and process features. (a) Force-based features; (b) Thermal gradient vs. wear; (c) Vibration and wear interactions; (d) Acoustic domain correlations

Turning to comparative model performance in figure 5, Figure 5(a) visualizes RMSE over all validation runs. Here, XGBoost exhibits a consistently lower and denser RMSE distribution compared with all baseline models, reflecting both its capacity to minimize average prediction error and its resilience to outlier effect. Figure 5(b) tracks the progression of the adjusted  $R^2$  coefficient, where it is observed that XGBoost stabilizes above 0.93, randomly forest trails at about 0.86, while both SVR and neural networks display pronounced fold-to-fold volatility. Figure 5(c) details the wall-time runtime distribution. Although ensemble models like XGBoost incur moderately longer computation times than simpler architectures, the efficiency-to-accuracy gain justifies their selection for embedded industrial deployment.



**Figure 5.** Comparative performance among predictive models. (a) Validation RMSE for all folds; (b) Adjusted  $R^2$  per regime; (c) Inference runtime per model

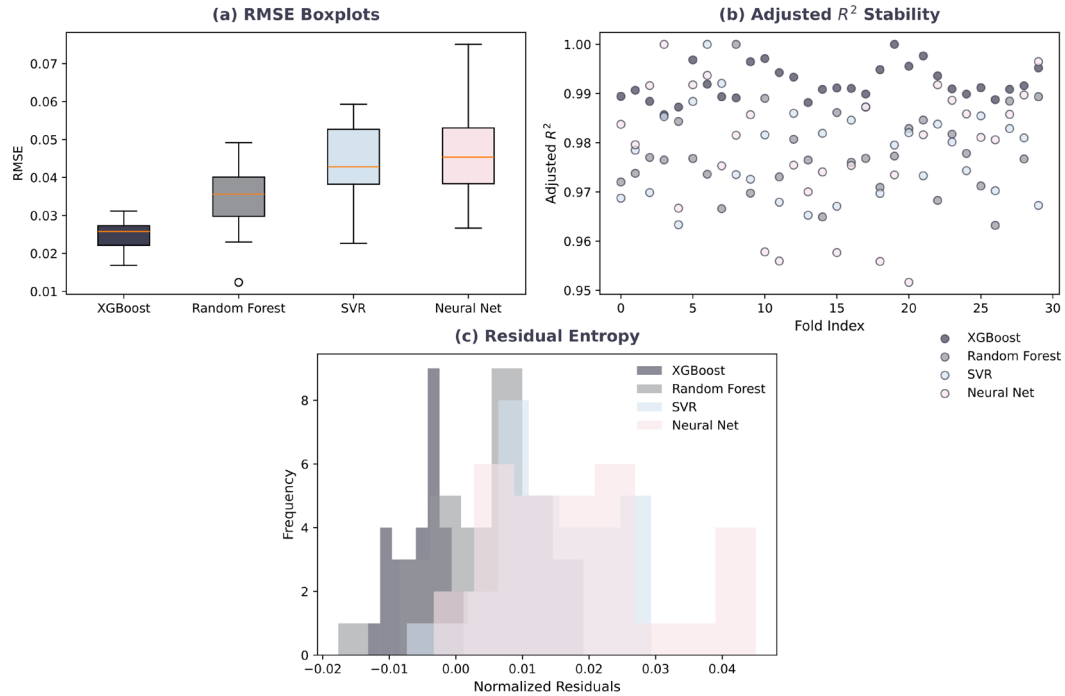
As illustrated in Figure 6, feature attribution analysis is necessary for the industrialisation and real-world application of process knowledge. With a combined weight of more than 40%, Figure 6(a) demonstrates that, in terms of absolute importance ranking, spindle force RMS, energy integration, and process time are the three main contributions to the total explanatory mass in the model. However, the SHAP-based score bars in Figure 6(b) demonstrate strong, context-dependent interactions; for certain workpieces, the significance of acoustic entropy sometimes surpasses that of the primary force signal, and wear mechanisms are thus associated with the material's microstructure and surface conditions.



**Figure 6.** Feature importance and interpretability visualization. (a) Ranked absolute importance; (b) SHAP contribution by scenario

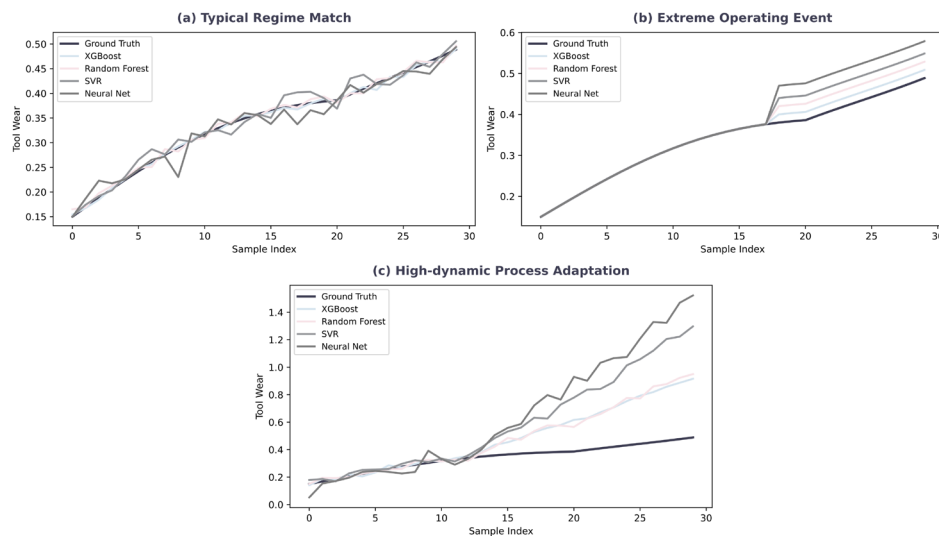
Assessment of robustness, a necessity for deployment under variable manufacturing regimes, appears in Figure 7. Boxplots in Figure 7(a) confirm that the upper-quartile RMSE for XGBoost stays uniformly below 0.028,

indicating suppression of prediction outliers. Figure 7(b) demonstrates sharp clustering in adjusted  $R^2$  values, refusing to degrade even when crossvalidation folds intentionally include extreme parameter shifts. Figure 7(c) captures residual entropy, with XGBoost producing exceptionally tight and centered distributions, while all comparison models show heavier entropy tails, signaling greater sensitivity to both sensor drift and process disruption.



**Figure 7.** Model robustness and generalization analysis. (a) RMSE boxplots for randomized folds; (b) Adjusted  $R^2$  stability; (c) Residual entropy for error dispersion

Lastly, Figure 8 displays the specific path of a single tool run. The forecast and measurement under a normal state are nearly equal at the line level, as seen in Figure 8(a). The XGBoost forecast has a limited error range and is quick to the transient shift when there is a sudden acceleration and a coolant disturbance, as seen in Figure 8(b); SVR and neural network models respond more slowly and produce large spikes. The test of a high-vibration, alternating material in Figure 8(c) demonstrates that XGBoost does not collect errors and reacts quickly to non-stationary changes; other regression models underestimate the significant increase in errors.



**Figure 8.** Case studies of prediction and observation. (a) Typical regime match; (b) Extreme operating events; (c) High-dynamic process adaptation.

## Conclusion

The aforementioned work has developed a comprehensive data-driven framework for intelligent tool wear monitoring that satisfies the demanding post-processing requirements of additive manufacturing. This study has created a comprehensive force-acoustic-vibration-temperature prediction platform with high accuracy and stability using numerous multi-sensor acquisition devices and sophisticated ensemble modelling techniques. To increase the precision of key degradation pattern identification and early warning, systematically map correlations and feature attribution to uncover the synergistic effects of wear dynamics and physical process signatures. In order to prevent production disruptions and maintain the necessary quality level of the additively made parts, the aforementioned method will be able to swiftly identify and fix any minor changes in the machining environment or unanticipated production issues.

The XGBoost model reliably reduces prediction errors and maintains strong interpretability at all parameter values and extreme data distributions, making it superior to earlier regression and neural network models. The solution is more appropriate for use in digital manufacturing since it is also comparatively resistant to changes in the non-stationary regime and sensor noise. Based on the aforementioned priority hierarchy, there are two benefits to moving sensors and providing a theoretical foundation for data-driven models in actual industrial physics. The information gleaned from the model's feature importance ranking aids in improving our comprehension of the procedure, resource allocation, and future monitoring system design. This will contribute to the development of a robust, flexible, and long-lasting solution for industrial tool wear management.

In the future, create frameworks for real-time adaptive learning, increase the variety of multi-modally integrated sensor data, and carry out methodical validation under different equipment and process conditions. The aforementioned accomplishments will strengthen the foundation for developing all-weather, self-optimizing diagnostic systems for the upcoming generation of smart manufacturing and advance theory and practice in tool condition monitoring under the industrial Internet of things (IIoT). It is anticipated that the implementation of such intelligent diagnostic systems will increase manufacturing production's flexibility and efficiency, enhance operations' sustainability, and spur the creation of intelligent factories and fully integrated cyber-physical production systems.

### Author Contributions

Barbara Szymańska and Małgorzata Kaczmarek contribute to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Elżbieta Woźniak contributes to conceptualization, methodology, software. All authors have read and agreed with the manuscript before its submission and publication.

### Funding

This research received no specific financial support from any funding agency.

### Institutional Review Board Statement

Not applicable.

## References

- [1] Azimi, M., Eslamlou, A. D., & Pekcan, G. (2020). Data-driven structural health monitoring and damage detection through deep learning: State-of-the-art review. *Sensors*, 20(10), 2778. <https://doi.org/10.3390/s20102778>
- [2] Zheng, Y., Chen, W., Zhang, Y., & Bai, D. (2022). Prediction of the remaining useful life of a switch machine, based on multi-source data. *Sustainability*, 14(21), 14517. <https://doi.org/10.3390/su142114517>
- [3] Li, X. (2002). A brief review: acoustic emission method for tool wear monitoring during turning. *International Journal of Machine Tools and Manufacture*, 42(2), 157-165. [https://doi.org/10.1016/S0890-6955\(01\)00108-0](https://doi.org/10.1016/S0890-6955(01)00108-0)
- [4] Kotha Amarnath, S., Inturi, V., Rajasekharan, S. G., & Priyadarshini, A. (2025). Combining sensor fusion and a machine learning framework for accurate tool wear prediction during machining. *Machines*, 13(2), 132. <https://doi.org/10.3390/machines13020132>

- [5] Tran, M. Q., Doan, H. P., Vu, V. Q., & Vu, L. T. (2023). Machine learning and IoT-based approach for tool condition monitoring: A review and future prospects. *Measurement*, 207, 112351. <https://doi.org/10.1016/j.measurement.2022.112351>
- [6] Toptsis, M., Karkanis, N., Giannakoulas, A., & Kaifas, T. (2026). A Review of Embedded Software Architectures for Multi-Sensor Wearable Devices: Sensor Fusion Techniques and Future Research Directions. *Electronics*, 15(2), 295. <https://doi.org/10.3390/electronics15020295>
- [7] Saatci, B. T., Ulas, M., & Gurgenc, T. (2025). Hybrid AI systems for tool wear monitoring in manufacturing: A systematic review. *Applied Sciences*, 16(1), 208. <https://doi.org/10.3390/app16010208>
- [8] Mushtaq, S., Islam, M. M., & Sohaib, M. (2021). Deep learning aided data-driven fault diagnosis of rotatory machine: A comprehensive review. *Energies*, 14(16), 5150. <https://doi.org/10.3390/en14165150>
- [9] Duan, J., Zhang, X., & Shi, T. (2023). A hybrid attention-based paralleled deep learning model for tool wear prediction. *Expert Systems with Applications*, 211, 118548. <https://doi.org/10.1016/j.eswa.2022.118548>
- [10] Asif, M., Shen, H., Zhou, C., Guo, Y., Yuan, Y., Shao, P., ... & Bhutta, M. S. (2023). Recent trends, developments, and emerging technologies towards sustainable intelligent machining: A critical review, perspectives and future directions. *Sustainability*, 15(10), 8298. <https://doi.org/10.3390/su15108298>
- [11] Zha, W., & Ye, Y. (2024). An aero-engine remaining useful life prediction model based on feature selection and the improved TCN. *Franklin Open*, 6, 100083. <https://doi.org/10.1016/j.fraope.2024.100083>
- [12] Sayyad, S., Kumar, S., Bongale, A., Kotecha, K., & Abraham, A. (2023). Remaining useful-life prediction of the milling cutting tool using time–frequency-based features and deep learning models. *Sensors*, 23(12), 5659. <https://doi.org/10.3390/s23125659>
- [13] Elminir, H. K., El-Brawany, M. A., Ibrahim, D. A., Elattar, H. M., & Ramadan, E. A. (2024). An efficient deep learning prognostic model for remaining useful life estimation of high-speed CNC milling machine cutters. *Results in Engineering*, 24, 103420. <https://doi.org/10.1016/j.rineng.2024.103420>
- [14] Garcia, J., Rios-Colque, L., Peña, A., & Rojas, L. (2025). Condition monitoring and predictive maintenance in industrial equipment: An nlp-assisted review of signal processing, hybrid models, and implementation challenges. *Applied Sciences*, 15(10), 5465. <https://doi.org/10.3390/app15105465>
- [15] Jin, S., Cheng, Y., Zhai, W., Zhou, X., & Xue, J. (2026). Research on transfer monitoring model of tool wear driven by adaptive signal processing and multimodal feature fusion. *Measurement*, 121688. <https://doi.org/10.1016/j.measurement.2026.121688>
- [16] Corallo, A., Crespino, A. M., Lazoi, M., & Lezzi, M. (2022). Model-based Big Data Analytics-as-a-Service framework in smart manufacturing: A case study. *Robotics and Computer-Integrated Manufacturing*, 76, 102331. <https://doi.org/10.1016/j.rcim.2022.102331>
- [17] Tsanousa, A., Bektsis, E., Kyriakopoulos, C., González, A. G., Leturiondo, U., Gialampoukidis, I., ... & Kompatsiaris, I. (2022). A review of multisensor data fusion solutions in smart manufacturing: Systems and trends. *Sensors*, 22(5), 1734. <https://doi.org/10.3390/s22051734>
- [18] Kasiviswanathan, S., Gnanasekaran, S., Thangamuthu, M., & Rakkiyannan, J. (2024). Machine-learning-and internet-of-things-driven techniques for monitoring tool wear in machining process: a comprehensive review. *Journal of Sensor and Actuator Networks*, 13(5), 53. <https://doi.org/10.3390/jsan13050053>
- [19] Petrich, J., Snow, Z., Corbin, D., & Reutzler, E. W. (2021). Multi-modal sensor fusion with machine learning for data-driven process monitoring for additive manufacturing. *Additive Manufacturing*, 48, 102364. <https://doi.org/10.1016/j.addma.2021.102364>
- [20] Yang, Z., Li, L., Zhang, Y., Jiang, Z., & Liu, X. (2024). Tool wear state monitoring in titanium alloy milling based on wavelet packet and TTAO-CNN-BiLSTM-AM. *Processes*, 13(1), 13. <https://doi.org/10.3390/pr13010013>
- [21] Wang, K., Wang, A., Wu, L., & Xie, G. (2024). Machine tool wear prediction technology based on multi-sensor information fusion. *Sensors*, 24(8), 2652. <https://doi.org/10.3390/s24082652>
- [22] Li, J., Wang, H., Shao, J., Liu, Y., Wang, X., Wang, H., ... & Qie, H. (2026). Interpretable data-driven framework with multi-scale residual correction and SHAP analysis for strip profile prediction in hot rolling steel industry. *Journal of Manufacturing Systems*, 86, 472-491. <https://doi.org/10.1016/j.jmsy.2026.03.021>
- [23] Leite, D., Andrade, E., Rativa, D., & Maciel, A. M. (2024). Fault detection and diagnosis in industry 4.0: A review on challenges and opportunities. *Sensors*, 25(1), 60. <https://doi.org/10.3390/s25010060>
- [24] Bezerra, F. E., Oliveira Neto, G. C. D., Cervi, G. M., Francesconi Mazetto, R., Faria, A. M. D., Vido, M., ... & Amorim, M. (2024). Impacts of feature selection on predicting machine failures by machine learning algorithms. *Applied Sciences*, 14(8), 3337. <https://doi.org/10.3390/app14083337>

- [25] Bezerra, F. E., Oliveira Neto, G. C. D., Cervi, G. M., Francesconi Mazetto, R., Faria, A. M. D., Vido, M., ... & Amorim, M. (2024). Impacts of feature selection on predicting machine failures by machine learning algorithms. *Applied Sciences*, 14(8), 3337. <https://doi.org/10.3390/app14083337>
- [26] Wang, H., Zhang, W., Yang, D., & Xiang, Y. (2022). Deep-learning-enabled predictive maintenance in industrial internet of things: methods, applications, and challenges. *IEEE Systems Journal*, 17(2), 2602-2615. <https://doi.org/10.1109/JSYST.2022.3193200>
- [27] Jiang, Q., & Song, J. (2026). A Review on Cutting Force and Thermal Modeling, Toolpath Planning, and Vibration Suppression for Advanced Manufacturing. *Machines*, 14(1), 60. <https://doi.org/10.3390/machines14010060>
- [28] Elkateb, S., Métwalli, A., Shendy, A., & Abu-Elanien, A. E. (2024). Machine learning and IoT-Based predictive maintenance approach for industrial applications. *Alexandria Engineering Journal*, 88, 298-309. <https://doi.org/10.1016/j.aej.2023.12.065>
- [29] Sun, J., Wang, D., Liu, Z., Qiu, C., Liu, H., Sa, G., & Tan, J. (2025). Tool digital twin based on knowledge embedding for precision CNC machine tools: Wear prediction for collaborative multi-tool. *Journal of Manufacturing Systems*, 80, 157-175. <https://doi.org/10.1016/j.jmsy.2025.02.021>
- [30] Zhang, J., Li, C., Deng, C., Luo, T., Deng, R., Luo, D., ... & Cao, H. (2025). Toward digital twins for intelligence manufacturing: Self-adaptive control in assisted equipment through multi-sensor fusion smart tool real-time machine condition monitoring. *Journal of Manufacturing Systems*, 82, 301-318. <https://doi.org/10.1016/j.jmsy.2025.06.020>