Journal of Artificial Intelligence Practice (2025)
Clausius Scientific Press, Canada
DOI: 10.23977/jaip.2025.080315
ISSN 2371-8412 Vol. 8 Num. 3

Case Analysis in AI Practice Courses: A Comparative Study of Tool Wear Prediction Methods

Chunhua Feng[1,a,*], Hui Ye[1,b]

[1]*School of Mechanical Engineering, University of Shanghai for Science and Technology, Shanghai, 200093, China*

[a]*fengchunhua333@163.com*, [b]*13764729736@163.com*

[*]*Corresponding author*

Keywords: AI, Tool Wear Prediction, CNN-LSTM

Abstract: Artificial intelligence is anticipated to play a crucial role in shaping the future of education and academic research. Using a mechanical testing course as a case study, this paper illustrates how AI can be effectively integrated into engineering education by examining various AI methodologies through the application of tool wear prediction. In predictive modelling, commonly used intelligent algorithms mainly come from traditional machine learning techniques, such as support vector machines (SVM) and random forests, as well as deep learning methods like long short-term memory (LSTM) and gated recurrent units (GRU). Traditional models generally rely on manual feature extraction, which provides a degree of interpretability but often falls short in capturing the dynamic characteristics of time-series data. This study assesses the performance of several deep learning algorithms in predicting tool wear. The CNN-LSTM hybrid model consistently outperformed other models across all evaluation metrics. Specifically, compared to the GRU model, it reduced RMSE by 42.07% and MAE by 52.06%, while improving R^2 by 4.43%. When compared to the standalone LSTM model, the CNN-LSTM model achieved a 17.72% reduction in RMSE and a 42.25% decrease in MAE, along with a 2.97% increase in R^2. These results indicate that the CNN-LSTM architecture successfully combines CNN's proficiency in automatic local feature extraction with LSTM's capacity to model long-term temporal dependencies, thereby providing a highly effective and accurate method for tool wear prediction.

1. Introduction

At present, AI technology has been extensively integrated into higher education teaching. However, effectively enabling students to grasp the industrial applications of AI technology remains an urgent challenge. This paper addresses this issue by using the cutting tool—a key component that is highly susceptible to wear during machining—as a case study to illustrate the integration of AI into both production and education. The condition of the cutting tool directly influences machining quality, efficiency, and cost. Particularly when machining difficult-to-cut materials, tool wear accelerates significantly. Severe wear can lead to a sharp increase in cutting forces, vibration, and temperature, which compromises machining accuracy and surface quality, and may even result in part rejection or equipment damage [1]. A conservative tool change strategy typically leads to a relatively low utilization rate of tool life, ranging from 50% to 80% [2], and increase the downtime (accounting for more than 20%) [3]. Implementing tool condition monitoring and wear prediction enables timely tool replacement, thereby enhancing processing efficiency and maintaining product quality. Research indicates that the adoption of a tool condition monitoring system can reduce production costs by 10% to 40% [4]. Consequently, achieving accurate prediction of tool wear is of considerable engineering significance for improving both production efficiency and product quality.

Traditionally, tool wear prediction has mainly relied on manual evaluation by experienced personnel, which often falls short in ensuring high precision. With recent technological advancements, data-driven approaches have gained increasing prominence. However, two major challenges persist in real-world applications. First, feature extraction is typically based on manually designed features and domain expertise, making the process time-consuming and susceptible to subjectivity. These manually derived features are often generic indicators that fail to effectively capture the underlying dynamic patterns of tool wear progression, thereby limiting the model's generalization capability. Second, tool wear is inherently a temporal process influenced by historical operational conditions. Many conventional shallow machine learning methods or feedforward neural networks struggle to model long-term temporal dependencies, which compromises the accuracy and reliability of wear prediction.

To address the aforementioned challenges, this paper proposes an intelligent tool wear monitoring method based on the CNN-LSTM algorithm. This method directly acquires the original time-series signals generated during machining through multiple sensors. A one-dimensional convolutional neural network (CNN) is then employed to automatically extract deep features from these signals, eliminating the need for the labor-intensive process of traditional manual feature extraction. The resulting feature sequences are subsequently fed into a long short-term memory network (LSTM), which captures the temporal dependencies inherent in the tool wear process. Finally, a fully connected layer is utilized to achieve precise prediction of the tool wear amount. By integrating the feature extraction capability of CNN with the temporal modeling strength of LSTM, the proposed method constructs an end-to-end intelligent monitoring framework that significantly enhances both prediction accuracy and model robustness.

2. Intelligent Algorithm for Predicting Tool Wear

2.1 Comparison of the Advantages and Disadvantages of Prediction Algorithms

In research on tool wear prediction, the intelligent algorithms employed can generally be categorized into two main types: traditional machine learning methods and deep learning approaches. These categories differ significantly in terms of feature processing, model capabilities, and the scenarios in which they are most effectively applied.

Conventional machine learning approaches, including Support Vector Machines (SVM), Random Forests, and Gradient Boosting Trees (such as XGBoost and LightGBM), are largely dependent on the precision of manually engineered features. These methods offer several benefits, such as a straightforward model architecture, efficient training processes, strong generalization capabilities even when data samples are scarce, and a high degree of interpretability. For instance, decision tree-based models can generate rankings of feature importance, offering insights into how various sensor features influence the assessment of wear conditions. Nevertheless, these techniques often fall short in capturing complex temporal dynamics and long-term dependencies inherent in the cutting process, and their effectiveness is closely tied to the quality of selected features.

In contrast, deep learning approaches can automatically extract distinguishing features directly from raw sensor data, thereby significantly reducing the need for manual feature engineering. Notably, the LSTM network and the Gated Recurrent Unit (GRU) have become widely used for tool wear prediction due to their strong capability in modeling temporal dependencies. These architectures are particularly effective in processing long sequential data, such as vibration and cutting force signals. However, deep learning models generally require a large amount of labeled training data, involve high computational costs, demand extensive training time, and pose challenges in hyperparameter tuning.

In summary, traditional machine learning approaches are more appropriate for scenarios characterized by limited data availability, low feature dimensionality, and a high demand for model interpretability. In contrast, deep learning techniques demonstrate superior performance in processing large-volume, high-dimensional time series data. With sufficient computational resources, these methods can achieve more accurate forecasting results.

2.2 The Algorithm Execution Process

This paper proposes a tool wear monitoring method based on a CNN-LSTM architecture. Flowchart of intelligent tool wear monitoring based on CNN-LSTM is shown in Fig. 1. Original processing signals are collected through multiple sensors, and CNN is utilized to automatically extract relevant features. Subsequently, LSTM is applied to model the temporal dependencies within the extracted features, thereby enabling accurate prediction of the tool wear amount. By integrating the feature extraction capability of CNN with the temporal modeling strength of LSTM, this end-to-end framework significantly enhances both prediction accuracy and robustness.

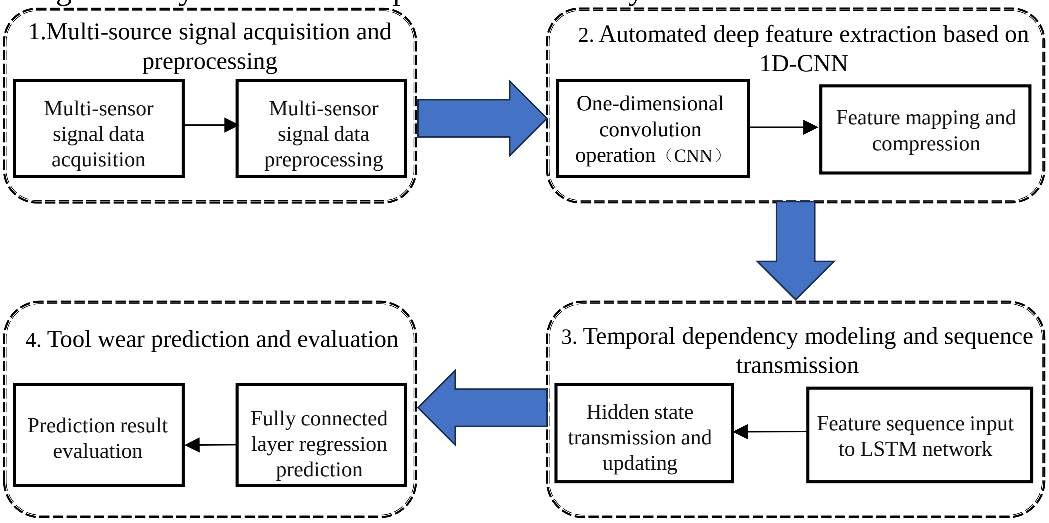

Fig.1 Flowchart of Intelligent Tool Wear Monitoring Method Based on CNN-LSTM.

2.3 CNN-LSTM Methodology

In this study, the data was obtained from a dataset provided during a data competition hosted by the PHM Society in 2010. The dataset was collected using a multi-sensor system that captured high-frequency raw signals throughout the milling process, with an initial sampling rate of up to 50 kHz. To improve the accuracy and reliability of the subsequent analysis, a systematic preprocessing procedure was implemented. First, unstable signal segments at the beginning and end of the cutting process were identified and removed using the upper quartile (Q3) threshold, ensuring that only high-quality signal segments under stable cutting conditions were retained, as shown in Fig. 2. Subsequently, to strike a balance between data volume and signal fidelity, the dataset was downsampled at a ratio of 1:10, reducing the sampling rate to 5 kHz. This downsampling step significantly reduced storage and computational requirements while preserving the essential characteristics of the original signals.

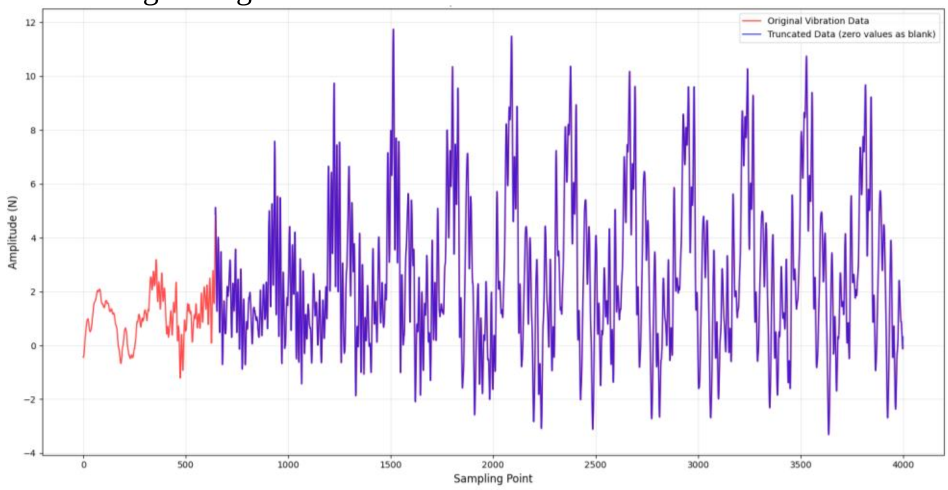

Fig.2 Before and after eliminating invalid data

To further enhance data quality, this study employed the Hampel filter to handle signal outliers. Any data point exceeding a threshold defined as three times the standard deviation was replaced with the mean value computed from a sliding window containing 1,000 adjacent points. This method effectively eliminated impulse noise and anomalous disturbances in the cutting signal, as shown in Fig. 3. Furthermore, wavelet packet decomposition was applied for additional noise reduction. The signal was decomposed into eight levels using the "db8" wavelet basis function, and the soft threshold was adaptively determined based on the median absolute deviation (MAD) criterion. This facilitated the precise identification and suppression of noise components. The denoised signal was subsequently reconstructed, as depicted in Fig. 4. This multi-stage preprocessing approach significantly improved signal quality, thereby establishing a robust foundation for subsequent tool wear monitoring and predictive modeling.

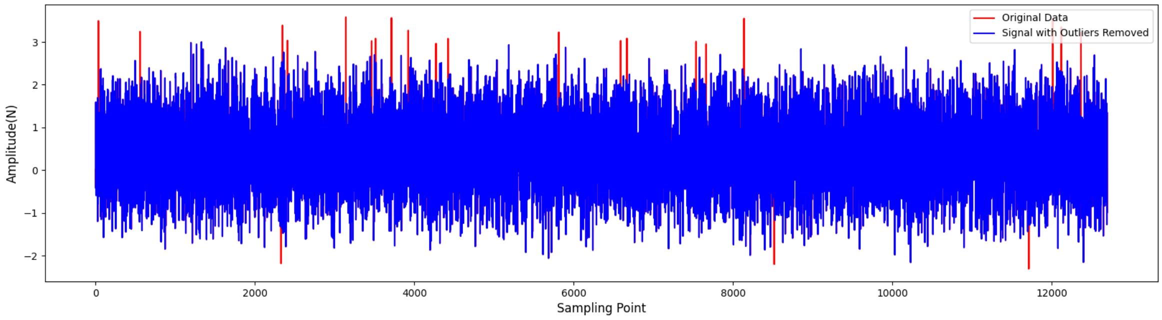

Fig.3 The comparison before and after removing the intermediate abnormal data

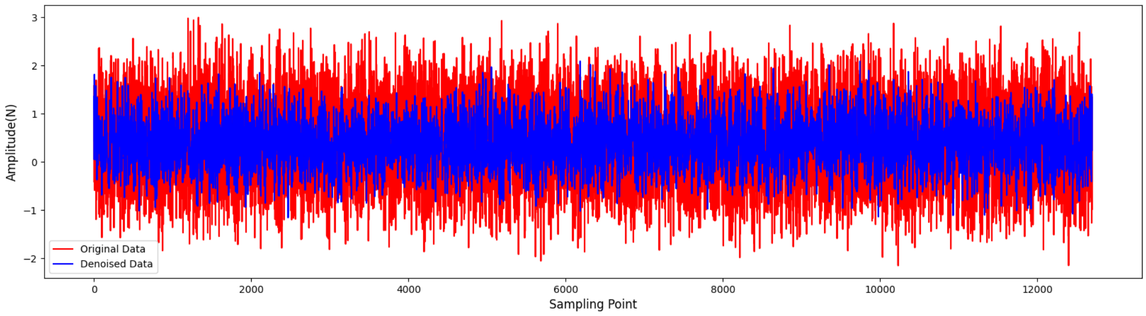

Fig.4 Schematic diagrams of raw data and denoised data

The preprocessed high-quality sensing signals are fed into a deeply integrated CNN–LSTM network architecture to enable end-to-end accurate prediction of tool wear. This process primarily involves two core stages:

Initially, a one-dimensional convolutional neural network (1D-CNN) is employed to automatically extract in-depth features. The preprocessed time series signal is fed into the convolutional layer, where multiple one-dimensional convolutional kernels slide across the signal, detecting and identifying salient features and underlying patterns within the local waveform. This process effectively replaces traditional, expert-driven manual feature engineering. Subsequently, the pooling layer is applied to reduce the dimensionality of the feature maps generated by the convolution. While preserving the most critical feature information, this step also reduces the data size and enhances the spatial invariance of the extracted features.

Subsequently, the feature sequence extracted by the Convolutional Neural Network (CNN) is fed into the LSTM to model its temporal dependencies. Leveraging its unique gating mechanism, the LSTM unit effectively captures long-term dependencies in the feature sequence over time and retains key state transitions during the tool wear process. The network processes the input sequentially through time steps, continuously updating and propagating the hidden state, ultimately producing an output that encapsulates the temporal dynamic information of the entire sequence. This output is then mapped to the predicted tool wear value via a fully connected layer. By integrating CNN's capability in automatic feature extraction with LSTM's strength in modeling long-term sequential dependencies, the hybrid CNN-LSTM model significantly enhances the accuracy and robustness of tool wear prediction. As illustrated in Figure 5, the CNN-LSTM model's predictions closely follow the true values, demonstrating strong tracking performance.

To comprehensively verify the actual performance of the proposed model, this paper systematically conducts comparative experiments between the CNN-LSTM model, the GRU model, and the LSTM model. To more objectively evaluate the prediction capabilities of each model, this paper selects the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as the main evaluation indicators, which are used to quantify the deviation between the model prediction results and the actual wear values. From the quantitative analysis results shown in Table 1, it can be seen that the CNN-LSTM model outperforms other comparison models in the three key indicators of MAE, RMSE, and R^2 The coincidence degree between its prediction results and the true measured values is higher, which fully indicates that the model performs outstandingly in the tool wear prediction task and has significant performance advantages.

Fig.5 The prediction results of the CNN-LSTM model

Table 1 Comparison of prediction results of different data-driven models

Schemes	RMSE	MAE	R^2
GRU	8.0954	5.0882	0.9128
LSTM	5.7010	4.2232	0.9257
CNN-LSTM	4.6909	2.4390	0.9532

3. Conclusion

This study employs the CNN-LSTM algorithm for intelligent monitoring of tool wear states. By collecting raw time series data from various sensors—including vibration, cutting force, and acoustic emission—a one-dimensional CNN is utilized to automatically extract key features, thereby eliminating the complex and time-consuming manual feature extraction process typical of traditional methods. The proposed model first leverages CNN to capture spatial features within the sensor signals, followed by the application of a LSTM to model temporal dependencies in the time series, enabling accurate characterization of tool wear trends. Experimental results demonstrate that the method significantly outperforms traditional machine learning models in tool wear prediction, with a maximum reduction in MAE of nearly 80%. These findings further validate the feasibility and superiority of end-to-end deep learning approaches in tool condition monitoring, offering robust technical support for predictive maintenance in intelligent manufacturing systems.

The application of AI technology in future tool wear prediction offers several key advantages. First, in terms of model lightweighting and structural optimization, improvements in network architecture and the adoption of more efficient convolutional and recurrent units can enhance generalization ability and computational efficiency under complex working conditions. Second, regarding multi-modal sensing fusion, a deep fusion framework can be developed to integrate various signals—such as vibration and acoustic emission—for end-to-end joint feature extraction and wear state prediction. Finally, in terms of system integration and application promotion, combining embedded deployment with transfer learning techniques enables the extension of this method to diverse processing scenarios and equipment health management systems, thereby promoting the integrated innovation of perception and decision-making systems in intelligent manufacturing.

Acknowledgements

This research is funded by the Ministry of Education industry-university cooperative education project No. 231104429231321.

References

[1] Li B. (2012). A review of tool wear estimation using theoretical analysis and numerical simulation technologies. International Journal of Refractory Metals and Hard Materials, 35, 143-151.

[2] Li Y, Liu C, Hua J, Gao J, Maropoulos P. (2019). A novel method for accurately monitoring and predicting tool wear under varying cutting conditions based on meta-learning. CIRP Annals, 68(1), 487-490.

[3] Ghosh S, Naskar SK, Mandal NK. (2018). Estimation of residual life of a cutting tool used in a machining process. MATEC Web of Conferences (Vol. 192, p. 01017). EDP Sciences.

[4] Karandikar J, McLeay T, Turner S, Schmitz T. (2015). Tool wear monitoring using naive Bayes classifiers. The International Journal of Advanced Manufacturing Technology, 77, 1613-1626.