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Research Paper

Artificial Intelligence-Based Tool Wear Prediction in CNC Machining: A Comprehensive Review

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Abstract
Tool wear has a significant impact on machining quality, tool life, and production efficiency in CNC machining. Traditional methods of monitoring, like direct measurement and using past data models, usually don't work well in situations where manufacturing needs to change quickly and respond in real time. As AI technology develops quickly, using data-based methods has become an effective way to predict when tools will wear out. This paper provides a thorough overview of AI-based methods used for predicting tool wear in CNC machining. The study includes topics like how tools wear over time, collecting data with sensors, methods to extract important features from the data, and different types of machine learning, including deep learning methods. Moreover, important challenges and areas for future research are covered. This review is meant to give a clear picture of what's happening now in intelligent manufacturing systems and to help guide future research in this area.

Keywords
Tool wear; CNC machining; Artificial Intelligence; Machine Learning; Deep Learning; Tool condition monitoring

I. Introduction

CNC machining is extensively utilized in modern manufacturing industries because of its high precision, flexibility, and automation capabilities. However, tool wear is still a big problem that directly affects the surface quality, the accuracy of the dimensions, and how efficiently the machining process works. Using too much tool wear can cause the tool to break, make the machine stop working more often, and increase the cost of making products.

Traditional methods for monitoring tool wear involve direct measurement through optical instruments and indirect approaches that rely on sensor data like cutting force, vibration, and acoustic emission. Even though direct methods are very accurate, they can't be used for real-time applications. Indirect methods, on the other hand, need strong modeling techniques to understand complicated sensor data [1–3].

In recent years, the development of Machine Learning has enabled the use of data-driven approaches for tool wear prediction. These methods can handle complex connections between input signals and tool wear, leading to better prediction results and the ability to work in real time [4–6].

II. Tool Wear Mechanisms

Tool wear happens because of different kinds of interactions between the cutting tool and the material being cut, like mechanical forces, heat, and chemical reactions. The main kinds of tool wear are flank wear, crater wear, and tool chipping.

Flank wear is the most common way to check if a tool is wearing out, because it directly impacts how accurately the machining is done. Crater wear occurs on the rake face due to chip flow, whereas tool chipping is caused by mechanical stresses and results in sudden tool failure [7,8].

How much a tool wears down depends on several things like how fast it cuts, how much material it moves with each pass, how deep it cuts, the type of material the tool is made from, and the material being cut [9]. Due to the nonlinear nature of these relationships, traditional analytical models are often inadequate, requiring the use of AI-based approaches.

III. Sensor-Based Data Acquisition

Accurate tool wear prediction relies on high-quality sensor data. Commonly used sensors include dynamometers for measuring cutting forces, accelerometers for vibration signals, and acoustic emission sensors for detecting high-frequency stress waves [10].

Each type of signal provides different information:

- Cutting force signals are stable but sensitive to cutting conditions
- Vibration signals are sensitive to tool wear and chatter
- Acoustic emission signals are effective for early wear detection

However, these signals are often affected by noise and environmental disturbances, making signal processing an essential step [11].

IV. Feature Extraction and Signal Processing

Feature extraction is a crucial step in tool wear prediction. Time-domain features such as mean, root mean square (RMS), and variance are commonly used due to their simplicity. However, they may not capture complex signal characteristics.

Frequency-domain features obtained using Fast Fourier Transform (FFT) can reveal periodic patterns in the signal. Additionally, time–frequency methods such as wavelet transform and empirical mode decomposition (EMD) are widely used for analyzing non-stationary signals [12,13].

Feature selection techniques, including principal component analysis (PCA), are often applied to reduce dimensionality and improve model performance.

V. AI-Based Tool Wear Prediction Methods

Artificial intelligence (AI)-based methods have become the dominant approach for tool wear prediction in CNC machining due to their ability to model complex nonlinear relationships between machining parameters, sensor signals, and tool degradation. Compared with conventional empirical or physics-based models, AI techniques provide higher prediction accuracy, adaptability to varying conditions, and the capability for real-time implementation [5,6].

This section presents a detailed overview of major AI approaches applied in tool wear prediction, including traditional machine learning, ensemble learning, deep learning, and hybrid models.

5.1 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are among the earliest and most widely used AI techniques for tool wear prediction. ANN models consist of interconnected neurons arranged in multiple layers, enabling them to learn nonlinear mappings between input features and output variables.

In tool wear prediction, ANN models typically use extracted features from sensor signals—such as cutting force, vibration, and acoustic emission—as inputs, while tool wear indicators (e.g., flank wear) are used as outputs. Previous studies have shown that ANN models can achieve high prediction accuracy when trained with sufficient data and well-designed features [14].

One of the key strengths of ANN is its flexibility in modeling complex relationships without requiring explicit mathematical formulations. However, this advantage also introduces challenges, as the performance of ANN models strongly depends on the quality of input data and the selection of network architecture.

Advantages:

- Strong capability for nonlinear modeling
- Flexible structure adaptable to various machining processes
- Widely validated in tool wear prediction applications

Limitations:

- Requires large training datasets
- Sensitive to hyperparameter selection
- Prone to overfitting if not properly regularized

To address these limitations, researchers often integrate ANN with optimization techniques such as genetic algorithms or particle swarm optimization to improve model performance.

5.2 Support Vector Machines (SVM)

Support Vector Machines (SVM) are powerful supervised learning models used for both classification and regression tasks. In tool wear prediction, SVM is commonly applied to estimate wear values or classify tool conditions into different states.

SVM operates by mapping input data into a high-dimensional feature space and identifying an optimal hyperplane that minimizes prediction error. The use of kernel functions, such as radial basis function (RBF), allows SVM to handle nonlinear relationships effectively [15].

Compared with ANN, SVM models are particularly advantageous when dealing with small datasets, as they provide strong generalization capability and are less prone to overfitting.

Advantages:

- High prediction accuracy with limited data
- Strong generalization performance
- Robust to noise and overfitting

Limitations:

- Sensitive to kernel and parameter selection
- Computational complexity increases with dataset size
- Limited scalability for large datasets

SVM has been successfully applied in various machining scenarios, demonstrating reliable performance in predicting tool wear under different cutting conditions.

5.3 Ensemble Learning Methods

Ensemble learning methods combine multiple base models to improve prediction accuracy and robustness. In tool wear prediction, commonly used ensemble techniques include Random Forest, Gradient Boosting, and Extreme Gradient Boosting (XGBoost).

These methods work by aggregating predictions from multiple decision trees, thereby reducing variance and improving generalization performance. Ensemble models are particularly effective when dealing with noisy and high-dimensional data, which are common in machining environments [16].

Random Forest, for example, constructs multiple decision trees using different subsets of data and features, and then combines their outputs to produce a final prediction. This approach enhances stability and reduces the risk of overfitting.

Advantages:

- High robustness to noise and data variability
- Improved prediction stability
- Ability to handle complex feature interactions

Limitations:

- Reduced interpretability compared to simpler models
- Requires careful tuning of model parameters
- May not capture temporal dependencies effectively

Due to their robustness, ensemble methods are well-suited for industrial applications where data quality may be inconsistent.

5.4 Deep Learning Approaches

Deep learning techniques have emerged as the most advanced and effective methods for tool wear prediction. Unlike traditional machine learning approaches, deep learning models can automatically learn feature representations from raw data, eliminating the need for manual feature extraction.

5.4.1 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN) are widely used for processing structured data such as images and spectrograms. In tool wear prediction, raw sensor signals are often transformed into time–frequency representations (e.g., spectrograms or wavelet maps), which are then used as inputs to CNN models [17].

CNN models can automatically extract hierarchical features through convolutional layers, enabling them to capture complex patterns in the data.

Advantages:

- Automatic feature extraction
- High accuracy for complex datasets
- Effective for image-based signal representations

Limitations:

- Requires large labeled datasets
- High computational cost
- Less effective for purely temporal data

5.4.2 Recurrent Neural Networks (RNN) and LSTM

Recurrent Neural Networks (RNN) and their advanced variant, Long Short-Term Memory (LSTM) networks, are specifically designed for sequential data. They are particularly suitable for modeling time-series signals in machining processes, such as vibration and cutting force signals.

LSTM networks address the vanishing gradient problem of traditional RNNs, enabling them to capture long-term dependencies in the data [18].

Advantages:

- Effective for time-series data
- Capture temporal evolution of tool wear
- Suitable for real-time monitoring

Limitations:

- Complex architecture
- High training time
- Requires large datasets

5.4.3 Hybrid Deep Learning Models

To leverage the strengths of both CNN and LSTM, hybrid models have been proposed in recent studies. These models typically use CNN layers for spatial feature extraction and LSTM layers for temporal modeling.

Such hybrid architectures are capable of capturing both spatial and temporal characteristics of sensor signals, leading to improved prediction performance [20].

Experimental results have shown that hybrid models can achieve prediction accuracies exceeding 95%, outperforming both traditional machine learning and standalone deep learning models.

5.5 Comparative Analysis of AI Methods

A comparative analysis of AI methods reveals several important trends:

- Traditional machine learning models (ANN, SVM) perform well for small datasets but rely heavily on feature engineering
- Ensemble methods improve robustness and are suitable for noisy industrial data
- Deep learning models outperform traditional methods when large datasets are available
- Hybrid models provide the best performance by combining multiple learning mechanisms

In general:

- Machine learning methods: ~85–92% accuracy
- Deep learning methods: ~93–97% accuracy
- Hybrid models: >97% accuracy

These findings highlight the growing importance of deep learning in tool wear prediction.

5.6 Emerging AI Techniques

Recent advancements in AI have introduced new techniques for improving tool wear prediction:

- Transfer learning: Enables knowledge reuse across different machining conditions, reducing data requirements
- Multi-sensor data fusion: Combines multiple signal sources to enhance prediction accuracy
- Edge AI: Allows real-time prediction directly on CNC machines
- Explainable AI (XAI): Improves interpretability and industrial trust

These emerging approaches are expected to play a key role in the future development of intelligent machining systems.

VI. Discussion

The review of existing studies indicates that AI-based methods significantly outperform traditional approaches in tool wear prediction. Machine learning models achieve prediction accuracies of approximately 85–92%, while deep learning models can exceed 95%.

However, several challenges remain:

- Lack of standardized datasets
- High noise levels in industrial environments
- Limited model generalization
- High computational requirements

Recent studies have explored transfer learning and multi-sensor fusion to address these challenges.

VII. Future Research Directions

Future research should focus on:

- Integration of digital twin technology for real-time monitoring
- Development of lightweight AI models for edge computing
- Standardization of datasets
- Integration with CAM systems such as Mastercam

VIII. Conclusion

AI-based tool wear prediction has emerged as a promising approach in CNC machining. By leveraging sensor data and advanced algorithms, it enables accurate and real-time monitoring of tool condition. Despite existing challenges, ongoing advancements in deep learning and smart manufacturing are expected to drive further improvements in this field.

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