Automated Tool Wear Detection for Aircraft Industry Applications

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Abstract

The growing demand for precision and reliability in aerospace manufacturing requires intelligent, automated solutions for tool condition monitoring. This project introduces a deep learning–based system for real-time detection and prediction of tool wear during high-speed drilling of Carbon Fiber Reinforced Polymer (CFRP) components. At its core is a hybrid CNN-LSTM model that captures both spatial and temporal patterns from multi-sensor data streams, including vibration, acoustic emission, and spindle current. The system operates non-intrusively, continuously analyzing drilling signals without disrupting production workflows. By mapping sensor signatures to tool wear stages, it enables predictive insights that support optimized tool replacement schedules, extended tool life, and improved safety standards. The proposed framework enhances production efficiency through automated, scalable, and intelligent wear monitoring, tailored for aerospace industry applications.

Keywords: Tool Wear Detection, Deep Learning, CNN-LSTM, CFRP Drilling, Predictive Maintenance, Non-Intrusive Monitoring, Aerospace Manufacturing.

Introduction

In modern aerospace manufacturing, the integration of advanced materials such as Carbon Fiber Reinforced Polymer (CFRP) has become essential due to its superior strength-to-weight ratio, durability, and corrosion resistance. While CFRP greatly enhances aircraft performance, it also poses significant machining challenges. High-speed drilling, a critical operation for component assembly, accelerates tool wear because of the abrasive nature of carbon fibers. This not only reduces tool life but also risks hole quality degradation, production delays, and increased costs, making efficient tool wear monitoring vital for ensuring both productivity and safety.

Conventional approaches to tool wear detection, including manual inspections, offline measurements, and rule-based monitoring systems, are often intrusive, time-consuming, and impractical for high-throughput production environments. Moreover, tool degradation progresses through multiple stages—initial wear, steady wear, and catastrophic failure—that subtly influence machining dynamics. These changes manifest in vibration, acoustic emission, and spindle current signals, which contain valuable information but are often nonlinear, noisy, and difficult to interpret using traditional signal processing or threshold-based methods.

To overcome these limitations, deep learning offers a transformative approach by automatically extracting complex patterns from multi-sensor data streams. Convolutional Neural Networks (CNNs) are well-suited for identifying spatial features in signal representations, while Long Short-Term Memory (LSTM) networks excel at capturing temporal dependencies across sequences. By combining these architectures, a hybrid CNN-LSTM model can effectively learn both spatial and temporal characteristics of drilling signals, enabling accurate detection and prediction of tool wear progression under real-world operating conditions.

This project proposes a deep learning–based, non-intrusive monitoring framework for automated tool wear detection in aerospace drilling applications. By continuously analyzing vibration, acoustic emission, and spindle current signals during CFRP drilling, the system enables real-time assessment of tool wear without interrupting production. The proposed approach supports predictive maintenance, optimizes tool replacement schedules, and extends tool life, ultimately enhancing manufacturing efficiency, safety, and scalability in next-generation aerospace production environments.

I. Literature Survey

[1] Early research in tool wear monitoring primarily focused on direct measurement and rule-based approaches. Techniques such as optical inspection, toolmakers' microscopes, and force sensors were employed to assess wear during or after machining. While effective in controlled laboratory environments, these methods were intrusive, time-consuming, and unsuitable for large-scale industrial applications. As a result, researchers explored indirect measurements based on cutting forces, vibration, and acoustic emission signals. Classical machine learning algorithms, such as Decision Trees, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), were applied to extract statistical features from these signals and classify tool wear conditions. However, these models were heavily dependent on handcrafted features and lacked generalization under varying cutting parameters.

[2] With the advent of advanced sensing technologies, non-intrusive approaches gained prominence. Acoustic emission sensors, vibration sensors, and spindle current monitoring provided rich streams of process data without interrupting operations. Studies demonstrated correlations between tool wear progression and signal variations in the time, frequency, and time-frequency domains. Traditional feature engineering techniques, such as Fast Fourier Transform (FFT) and Wavelet Packet Decomposition (WPD), were widely applied to extract meaningful patterns from noisy signals. Nevertheless, the reliance on manual feature selection limited scalability, as optimal features often varied across tools, materials, and cutting conditions.

[3] The rise of deep learning enabled more robust and automated feature extraction for tool condition monitoring. Convolutional Neural Networks (CNNs) have been widely adopted to analyze sensor signals by capturing spatial patterns from raw or transformed data, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been employed to model temporal dependencies in sequential data. Hybrid CNN-LSTM architectures have shown particular promise by integrating spatial and temporal learning, achieving higher accuracy in detecting tool wear progression. Applications in machining of alloys, composites, and CFRP have demonstrated the potential of these models to outperform traditional methods by learning hierarchical representations directly from sensor data.

[4] Despite these advances, several challenges remain. Many existing studies are limited to laboratory conditions and fail to address the variability of industrial aerospace drilling environments, such as high spindle speeds, heterogeneous CFRP material properties, and tool wear dynamics under real production cycles. Furthermore, most frameworks lack real-time processing capabilities, restricting their applicability in automated, continuous monitoring. There is also limited integration of multi-sensor fusion strategies, where combining vibration, acoustic emission, and spindle current could significantly enhance robustness and predictive power.

[5] To address these limitations, this project proposes a deep learning–based, non-intrusive monitoring framework using a CNN-LSTM hybrid model. By fusing heterogeneous sensor data streams collected during high-speed CFRP drilling, the system can automatically extract both spatial and temporal features to assess and predict tool wear in real time. Unlike traditional approaches, the proposed method minimizes manual feature engineering, operates continuously without halting production, and provides predictive insights for proactive tool replacement. This contributes to improved production efficiency, extended tool life, and enhanced safety in aerospace manufacturing applications.

II. Proposed Solution

Our project introduces a deep learning–based, non-intrusive framework for automated tool wear detection in high-speed CFRP drilling. The system integrates multi-sensor inputs, advanced signal processing, and a CNN-LSTM hybrid architecture to provide real-time assessment and prediction of tool wear stages.

A. System Overview and Core Architecture

The system is structured into four primary layers: a Sensor Input Layer, a Data Preprocessing Layer, a CNN-LSTM Hybrid Model, and an Output and Visualization Layer. This modular architecture enables continuous monitoring of drilling operations, seamless feature extraction, and accurate wear classification without interrupting production. The hybrid deep learning approach ensures both spatial and temporal patterns in sensor signals are captured, supporting robust wear detection and prediction.

B. Sensor Input and Labeling Phase

During drilling operations, the system collects data from three primary sensors: vibration sensors, acoustic emission (AE) sensors, and spindle motor current monitors. These signals provide complementary information about tool–material interaction. To establish ground truth, each drilling operation is labeled based on offline tool wear measurement, classifying tool condition into three stages: Fresh, Moderate, and Worn. This labeled dataset forms the foundation for supervised learning.

C. Data Preprocessing

Raw sensor signals often contain noise and variability caused by machine dynamics and environmental factors. To address this, preprocessing is performed in three steps:

Signal Denoising: Filtering techniques are applied to reduce noise while preserving key wear-related features.

Spectrogram Generation: Short-Time Fourier Transform (STFT) or Fast Fourier Transform (FFT) converts time-domain signals into spectrograms, enabling CNNs to capture frequency-based wear patterns.

Normalization: Scaling ensures consistent input ranges, improving training stability and generalization.

D. CNN-LSTM Hybrid Model

The core of the framework is a CNN-LSTM hybrid network designed to learn both spatial and temporal features:

CNN Layers extract spatial representations from spectrograms, highlighting localized wear patterns.

LSTM Layers capture temporal dependencies by modeling the progression of tool wear across multiple drilled holes.

Dense Output Layer performs classification of wear stages (Fresh, Moderate, Worn) or regression for predicting remaining tool life.

E. Model Training and Optimization

The model is trained using the Adam optimizer with loss functions tailored to task type:

Categorical Cross-Entropy for wear stage classification.

Mean Squared Error (MSE) for tool life prediction.

Performance is evaluated using key metrics such as Accuracy and F1-score, ensuring both precision and robustness in real-world applications.

F. Real-Time Prediction and Alerts

Once deployed, the system provides real-time wear predictions during ongoing drilling operations. Predictions are continuously updated as new sensor data streams in. When the model detects a transition into the “Worn” stage, the system issues an alert for tool replacement, preventing potential damage or part rejection.

G. Visualization and Decision Support

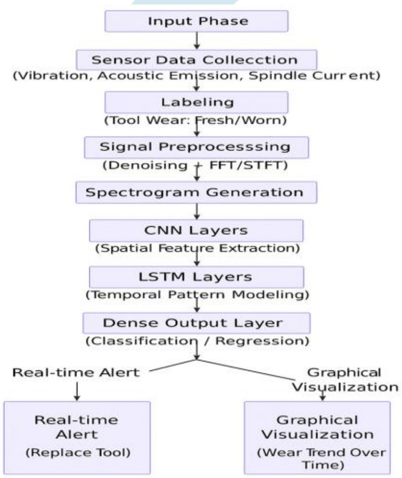
A dedicated visualization module generates dynamic graphs of wear progression, allowing operators to track tool condition over time. This feature not only enhances situational awareness but also supports predictive maintenance planning by highlighting trends in tool degradation.

H. Modularity and Extensibility

The modular design ensures adaptability across different machining conditions and materials. Additional sensors or alternative preprocessing techniques can be integrated without redesigning the entire framework. Similarly, the CNN-LSTM model can be extended with attention mechanisms or transformer-based architectures to further enhance predictive accuracy, making the system scalable for broader aerospace manufacturing applications.

III. System Architecture

The proposed system architecture for automated tool wear detection in CFRP drilling operations is illustrated. It is designed to process multi-sensor inputs, perform advanced signal preprocessing, and leverage a CNN-LSTM hybrid deep learning model for real-time tool wear assessment. The workflow begins with raw signal acquisition and proceeds through multiple computational layers, culminating in real-time wear alerts and visual analytics for decision support.



Sensor signals—including vibration, acoustic emission (AE), and spindle motor current—are continuously collected during drilling. These signals are labeled offline into Fresh, Moderate, and Worn tool wear categories to build the ground truth dataset. Preprocessing operations such as denoising and spectrogram generation (via FFT/STFT) convert raw signals into structured inputs for the CNN-LSTM model. The CNN layers capture spatial wear patterns from spectrograms, while the LSTM layers model the temporal evolution of tool degradation across drilling cycles. The dense output layer then performs classification (wear stage prediction) or regression (remaining tool life estimation).

Outputs are integrated into a dual monitoring interface:

Real-Time Alerts for tool replacement to prevent catastrophic failures.

Graphical Visualization of wear progression, allowing operators to monitor tool health trends and schedule predictive maintenance.

This modular architecture ensures scalability, adaptability to different sensor setups, and the potential integration of more advanced deep learning models (e.g., attention mechanisms) for future improvements.

A. Dataset Distribution of Sensor Inputs

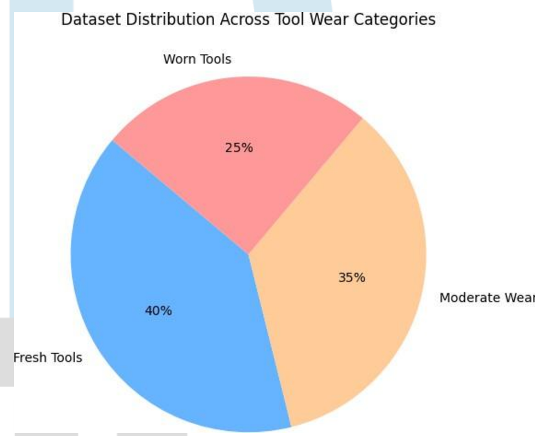
From initial experimental drilling trials, the dataset is distributed across three tool wear categories:

Fresh Tools → 40%

Moderate Wear → 35%

Worn Tools → 25%

This distribution highlights that most data is generated in the early and mid-stages of tool life, while catastrophic wear is less frequently observed. Such imbalance necessitates data augmentation and weighted loss functions to ensure reliable model performance across all wear stages.



B. Module Completion Status

The system development is divided into six major modules:

Sensor Data Acquisition → 100% completed

Data Labeling and Ground Truth Generation → 100% completed

Signal Preprocessing (FFT/STFT + Denoising) → 80% completed

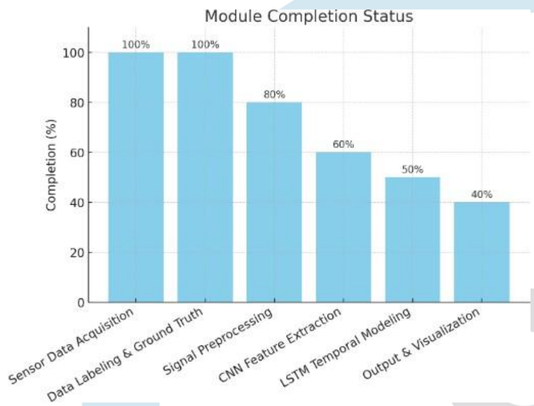
CNN Feature Extraction Module → 60% completed

LSTM Temporal Modeling Module → 50% completed

Output & Visualization (Alerts + Graphs) → 40% completed

Currently, the focus is on optimizing the

CNN-LSTM integration and completing the visualization layer. Once finalized, the system will be ready for real-time deployment in aerospace drilling setups.



C. Response Adaptation and Security

The system is designed with two levels of adaptation:

Operator Mode: Simplified alerts (e.g., “Tool nearing worn stage – replace soon”) and intuitive wear progression graphs.

Engineer Mode: Detailed analytics including raw signal overlays, spectrogram comparisons, and predicted Remaining Useful Life (RUL).

For security, the system ensures role-based access control, encrypted sensor data storage, and audit trails for monitoring tool condition records. This is particularly critical in aerospace manufacturing, where compliance and traceability are essential.

IV. Conclusion

In conclusion, the proposed deep learning–based monitoring system provides an effective and non-intrusive solution for automated tool wear detection in high-speed CFRP drilling operations. By integrating vibration, acoustic emission, and spindle current signals with advanced preprocessing and a CNN-LSTM hybrid architecture, the framework is capable of capturing both spatial wear patterns and temporal degradation trends. This enables accurate classification of tool wear stages and prediction of remaining tool life under real-world aerospace manufacturing conditions.

The system outputs—real-time alerts for tool replacement and graphical visualization of wear progression—support proactive maintenance strategies, reducing the risk of catastrophic tool failures while improving production quality and efficiency. Its modular design ensures adaptability, allowing for the integration of additional sensors, advanced deep learning modules, or industrial APIs for seamless deployment.

Overall, this project demonstrates the feasibility and benefits of applying deep learning to aerospace tool condition monitoring. The proposed approach not only extends tool life and reduces operational costs but also enhances safety and scalability in next-generation automated drilling systems.

VI. References

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