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Research Paper

Deep Learning-Based Prediction of Cutting Temperature in CNC Hard Turning: A Comprehensive Review

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Abstract
Cutting temperature is one of the most critical factors influencing tool wear, surface integrity, and machining performance in CNC hard turning. Traditional analytical and empirical approaches are limited in capturing nonlinear thermo-mechanical interactions. Recent advances in Deep Learning enable accurate prediction using multi-sensor data. This paper presents a comprehensive review of cutting temperature prediction methods, focusing on deep learning approaches. Mechanisms of heat generation, measurement techniques, and AI-based models are discussed. Future directions for intelligent machining are also identified.

Keywords: *CNC hard turning, Deep Learning, Cutting temperature*

I. Introduction

CNC hard turning has emerged as an alternative to grinding for machining hardened steels due to its flexibility and efficiency. However, the process generates extremely high temperatures, often exceeding 800°C [1].

Cutting temperature strongly affects tool wear, residual stress, and surface integrity [2,7]. High temperatures accelerate diffusion and oxidation wear mechanisms, reducing tool life [5].

Traditional prediction approaches include analytical models, empirical models, and numerical simulations such as finite element analysis [3,4]. However, these approaches often fail to capture nonlinear interactions among machining variables.

Recent developments in Artificial Intelligence have enabled data-driven modeling. In particular, deep learning models demonstrate superior capability in predicting cutting temperature [15,17].

II. Fundamentals of Cutting Temperature

2.1 Heat Generation Mechanisms

Heat is generated in three zones: primary shear zone, secondary deformation zone, and tertiary zone [5].
Studies show that 60–80% of heat is carried away by the chip, while the rest is absorbed by the tool and workpiece [1].

2.2 Factors Affecting Cutting Temperature

Cutting temperature is influenced by:

- Cutting speed (dominant factor) [8]
- Feed rate and depth of cut [9]
- Tool material and coating [7]
- Workpiece hardness [6]

Higher cutting speed leads to increased friction and plastic deformation, resulting in higher temperature [8].

III. Temperature Measurement Techniques

3.1 Direct Methods

Thermocouples and infrared thermography are widely used for temperature measurement [4]. Infrared methods provide non-contact measurement but require calibration.

3.2 Indirect Methods

Indirect estimation uses sensor signals such as force, vibration, and acoustic emission [23]. These signals correlate with cutting temperature and are suitable for predictive modeling.

IV. Signal Processing and Feature Engineering

Signal processing is essential for extracting meaningful features from raw sensor data.

4.1 Time-Domain Features

Common features include RMS, mean, and variance [23].

4.2 Frequency-Domain Features

FFT-based features help identify dominant frequencies related to machining dynamics [24].

4.3 Time–Frequency Analysis

Wavelet transform and EMD are widely used for non-stationary signals [25].

V. AI-Based Prediction Methods

5.1 Machine Learning Methods

ANN models are widely used for predicting cutting temperature [11,12]. SVM models provide good generalization performance for small datasets [14].
Ensemble methods such as Random Forest improve prediction accuracy [13].

5.2 Deep Learning Methods

5.2.1 CNN

CNN models extract spatial features from signal representations such as spectrograms [16].

5.2.2 LSTM

LSTM models capture temporal dependencies in machining signals [17].

5.2.3 Hybrid CNN–LSTM

Hybrid models combine spatial and temporal learning, achieving the highest accuracy [18,30].

5.2.4 Advanced Models

Transformer-based models have recently been applied for machining prediction tasks [27,28].

5.3 Multi-Sensor Data Fusion

Combining multiple sensor signals significantly improves prediction accuracy [20,21].

VI. Comparative Analysis

Deep learning models outperform traditional approaches in most cases.

- ANN: medium accuracy [11]
- SVM: robust performance [14]
- CNN/LSTM: high accuracy [16,17]
- CNN-LSTM: highest accuracy (>97%) [18]

VII. Discussion

Deep learning methods show strong potential for predicting cutting temperature. However, challenges remain:

- Data scarcity
- Noise in industrial environments
- High computational cost
- Limited generalization [21,29]

VIII. Future Research Directions

Future research should focus on:

- Digital twin integration [29]
- Edge AI for real-time prediction [19]

- Transfer learning [13]
- Explainable AI

IX. Conclusion

Deep learning-based methods significantly improve cutting temperature prediction in CNC hard turning. Hybrid models provide the best performance. Further research is needed to enhance robustness and industrial applicability.

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