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Correspondence to:
Jiawen Tian
571226090@qq.com

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Tool wear prediction based on xLSTM combined with the ECA attention mechanism model

Jiawen Tian and Shuqiang Wang

School of Mechanical and Power Engineering, Shenyang University of Chemical Technology, Shenyang 110000, China

Abstract Tool wear is a crucial factor in the milling process, directly impacting machining accuracy, part quality, and production costs. Accurate prediction of tool wear enables timely tool replacement, reducing downtime and enhancing product quality. However, traditional methods fall short of the high demands of smart manufacturing. To address this, a tool wear prediction method based on an extended long short-term memory (xLSTM) network with an efficient channel attention mechanism has been proposed. Time-frequency domain features are extracted using variational mode decomposition. Multi-domain features are derived from multi-sensor data, and Pearson decomposition is utilized to decrease the dimensionality in feature engineering. The xLSTM is used to improve the inherent defects of the original LSTM model in terms of extracting the stored signal, expanding the memory capacity, and allowing parallel operation, to achieve the model's precision in predicting the extent of tool wear. The performance of the model was improved by introducing an efficient channel attention mechanism (ECA) to consider the weights of different feature mappings. In this research, the model was evaluated against the other four models (LSTM, transformer, LSTM-ECA, and xLSTM) in three sets of crossover experiments using four regression indexes, RMSE, MSE, MAE, and R^2, and the results were all optimal, which verified the superiority and generalization of the method.

1. Introduction

Automated production is a crucial component of Industry 4.0. Machining automation is an important part of production and processing automation. As an end-effector tool in the machining process, the tool is highly susceptible to damage and consumption due to its direct contact with the machined workpiece [1, 2], which consequently impacts the machining quality of the workpiece [3-5]. Studies have shown [6, 7] that tool wear and collapse are the most important causes of machining quality, process failure, and increased production costs. The resulting downtime constitutes 7 %-20 % of the overall machining process downtime [8], while the expense of tools and tool replacements makes up 20 %-30 % of the total machining cost [9], and the consumption of tool status monitoring, tool regrinding, and management is more than 3 times higher than the cost of the tool itself and even has a 25 % impact on productivity [10]. Therefore, online tool wear monitoring (TCM) holds great importance for automating the production process and remains a popular topic in both academic and industrial research circles.

Tool condition monitoring techniques are categorized into direct and indirect monitoring methods. Direct TCM methods typically use optical instruments or machine vision algorithms to directly measure or calculate tool wear [11, 12]. However, environmental factors such as light, material debris, and cutting fluid during machining can have a significant impact on the direct method [13, 14]. With the advancement of sensor technology, indirect TCM methods have received increasing attention, which use one or more sensors to gather digital signals, including cutting force [15], vibration [16], acoustic emission (AE) [17], motor current [18], and sound [10], from which to extract features related to the amount of tool wear variation [19, 20], and then use