



# Tool wear prediction in turning using workpiece surface profile images and deep learning neural networks

Meng Lip Lim<sup>1</sup> · Mohd Naqib Derani<sup>1</sup> · Mani Maran Ratnam<sup>1</sup> · Ahmad Razlan Yusoff<sup>2</sup>

Received: 10 September 2021 / Accepted: 23 April 2022 / Published online: 6 May 2022  
© The Author(s), under exclusive licence to Springer-Verlag London Ltd., part of Springer Nature 2022

## Abstract

Accurate prediction of tool flank wear during turning is important so that the cutting tool can be replaced before excessive damage occurs to the workpiece surface. Existing online methods of tool wear prediction using sensor signals can be affected by noise, thus resulting in false alarms. The aim of this work is to develop deep learning regression models to predict tool wear state using features extracted from 2-D images of surface profile of the workpiece. Two models, namely convolutional neural network (CNN) and deep neural network (DNN), were compared in terms of prediction accuracy. Images of the workpiece surface profile were captured using high-resolution camera with the aid of backlighting after each machining pass. Workpiece surface profile images along a distance of two wavelengths were cropped and fed into the CNN network for wear prediction. For the DNN model, the surface height data were extracted to subpixel accuracy from each cropped image and used to train the model. Based on the results, the CNN model was able to predict the wear state with an accuracy of 98.9%, with an average testing RMSE of 2.0969, while the DNN model can predict wear state at an accuracy of 89.1%, with average testing RMSE of 2.5881. The study shows that cropped images of the machined surface profile can be more reliably used to predict the amount of tool flank wear during turning by using the CNN model compared to the height data used in the DNN model.

**Keywords** Tool wear · Deep learning · Neural network · Surface profile · Image

## 1 Introduction

Monitoring of the tool state has been an important area of research over the last three decades, and the dominant type of wear monitored is the tool flank wear [1–4]. Wear monitoring methods can be classified broadly into direct and indirect methods. In the direct method, the tool flank wear is measured directly, such as using a microscope, while in the indirect method, the wear is quantified indirectly from signals related to the cutting process. The signals include motor current, cutting force, acoustic emission, temperature, and vibration. Unlike the direct methods, the advantage of the indirect method is that tool wear can be monitored without

interrupting the machining process. Thus, the use of sensor signals for tool wear monitoring is used until today [5, 6].

Recently, many researchers are exploiting the benefits of deep learning neural network and data-driven intelligent methods for tool condition monitoring. Li et al. [7] proposed a novel method for monitoring and predicting tool wear under varying cutting conditions based on meta-learning. The meta-learning method can learn how the fully connected neural network model learns the correlation between tool wear and the monitoring signals. The authors acquired cutting force, power and current, and processed them to obtain features sensitive to tool wear. They utilized the entropy weight-grey correlation analysis method to calculate the ranks of the signal features due to the stochastic nature of the acquired signals. Xu et al. [8] used deep learning to predict tool wear by implementing multi-scale feature fusion. They used multiple sensors, such as accelerometer, acoustic emission (AE) sensor, and force sensor to acquire the signals, which were processed and fed into parallel convolution neural networks. The vibration and AE signals used in the networks, however, could be easily influenced by

✉ Mani Maran Ratnam  
mmaran@usm.my; mmmr5417@yahoo.com

<sup>1</sup> School of Mechanical Engineering, Universiti Sains Malaysia, Engineering Campus, 14300 Nibong Tebal, Penang, Malaysia

<sup>2</sup> College Engineering, Universiti Malaysia Pahang, 26300 Kuantan, Pahang, Malaysia