國立中興大學機械工程學系

碩士學位論文

以複合 AI 模型為主之適多工況刀具磨耗智慧監控方法與系統研究

Study on intelligent monitoring methods and systems for tool wear under multiple working conditions based on hybrid AI models

指導教授：王世明 Dr. Shih-Ming Wang

研究生：曾畦菖 Ci-Chang Zeng

中華民國一一三年十二月

摘要

本研究針對刀具狀態對加工品質、成本及製程穩定性的影響，進行實驗規劃與大數據分析，並基於複合 AI 模型使用 C# 開發一套智慧監控系統，用於多工況下刀具剩餘壽命預測，系統能即時監控加工過程，並準確的預測刀具剩餘壽命，確保製程連續性和穩定性。本研究比較多種資料排序方式與不同優化器（SGD、RMSprop、Adam、RAdam）的性能，並進行權重設定實驗，以確定最適模型權重，通過 L18 直交表進行參數優化，並引入生成對抗網絡（GAN）技術增加資料量，顯著提升模型準確性及數據多元性。結果顯示，LSTM、GRU 混合模型提升預測精度，並為遷移學習奠定基礎，本研究採用原始資料量的一半結合遷移學習技術，模型預測 RMSE 為 0.0615，訓練時間縮短至 130 秒，大幅提高多工況模型的訓練效率。此外，在遷移學習過程中加入生成對抗網絡（GAN），模擬更接近真實情況的數據環境，進一步增強模型對數據的學習能力和泛化性能。在實際應用中，該系統經過粗加工、精加工和新工況驗證能準確監測刀具磨耗並預測剩餘壽命。在粗加工中，於 887 秒時模型預測刀具磨耗量為 0.146 mm 與實際值僅相差 0.006 mm，刀具剩餘壽命尚有 1923.5 秒；在 1873 秒時系統預測刀具剩餘壽命僅剩 480 秒，低於下一製程所需的 887 秒，即時發出預警避免加工異常。在精加工情境中，261 秒時系統預測工件表面粗糙度達臨界門檻值 Ra 1.4 μm，刀具剩餘壽命為 64 秒，無法接下來的製程系統發出警告。在遷移式學習方法驗證中，新工況情境一於 957 秒時預測刀具磨耗量為 0.063 mm 與真實值僅相差 0.001 mm；新工況情境二於 2351 秒時預測刀具磨耗量為 0.156 mm 與真實值相差 0.02 mm，預測刀具剩餘壽命為 1080 秒。在 2415 秒時，因振動相對增加倍率超過門檻，系統預測刀具剩餘壽命為 0 秒，無法滿足後續製程 970 秒需求，並發出更換刀具的提醒，以確保加工穩定性。

關鍵詞：刀具剩餘壽命、機器學習、生成對抗網絡、遷移式學習、智慧監測

Abstract

This study focuses on the impact of tool conditions on machining quality, cost, and process stability through experimental planning and big data analysis. An intelligent monitoring system was developed using C# and a hybrid artificial intelligence model to predict the residual lifetime of tools under various operating conditions. The system enables real-time monitoring of the machining process and accurately predicts the residual lifetime of tools, ensuring process continuity and stability. The study compares multiple data sequencing methods and evaluates the performance of different optimizers, including Stochastic Gradient Descent, Root Mean Square Propagation, Adaptive Moment Estimation, and Rectified Adaptive Moment Estimation. Weight initialization experiments were conducted to determine the optimal model weights. Parameter optimization was performed using an L18 orthogonal array, and Generative Adversarial Networks were introduced to augment data volume and diversity, significantly enhancing model accuracy and data variability. Results show that the hybrid Long Short-Term Memory and Gated Recurrent Unit model improves prediction accuracy and establishes a foundation for transfer learning. By combining 50% of the original data with transfer learning techniques, the model achieved a root mean square error of 0.0615, and training time was reduced to 130 seconds, significantly improving training efficiency under multi-condition scenarios. Additionally, Generative Adversarial Networks were incorporated during the transfer learning process to simulate a data environment closer to real-world conditions, further enhancing the model's learning capacity and generalization performance. In practical applications, the system was validated in rough machining, fine machining, and new operating conditions, demonstrating its ability to accurately monitor tool wear and predict residual lifetime. In the rough machining scenario, the model predicted a tool wear of

0.146 millimeters at 887 seconds, with a deviation of only 0.006 millimeters from the actual value, and estimated the residual lifetime to be 1923.5 seconds. At 1873 seconds, the system predicted only 480 seconds of residual lifetime remaining, which was insufficient for the next process requiring 887 seconds. The system issued an immediate warning to prevent machining anomalies. In the fine machining scenario, at 261 seconds, the system predicted the workpiece surface roughness would reach the critical threshold of Ra 1.4 micrometers, with a residual lifetime of 64 seconds. As the tool could not support subsequent processes, the system issued a warning. For validation of the transfer learning method, in New Operating Condition Scenario 1, at 957 seconds, the system predicted a tool wear of 0.063 millimeters, deviating by only 0.001 millimeters from the actual value. In New Operating Condition Scenario 2, at 2351 seconds, the system predicted a tool wear of 0.156 millimeters, with a deviation of 0.02 millimeters, and estimated the residual lifetime to be 1080 seconds. At 2415 seconds, due to the relative increase in vibration exceeding the threshold, the system predicted a residual lifetime of 0 seconds, which could not meet the subsequent process requirement of 970 seconds. The system issued a tool replacement alert to ensure machining stability.

Keywords: Tool Residual Lifetime, Machine Learning, Generative Adversarial Network, Transfer Learning, Intelligent Monitoring