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ORIGINAL ARTICLE

Machine learning models for enhanced cutting temperature prediction in hard milling process

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Abstract

Cutting temperature is the most crucial quality character in the machining process. By prudently controlling this factor, high precision workpiece can be produced. Determination of cutting temperature in milling operation is challenging, time consuming and expensive process. These cost and time losses can be eliminated by predicted cutting temperature with machine learning models. The present study deals with the prediction of the cutting temperature on end milling of H11 steel with coated cemented carbide tool under three cooling environments, such as dry Machining, Minimum Quantity Lubrication (MQL) and Nano Fluid Minimum Quantity Lubrication (NMQL). In this study, various machine learning models such as Regularized Linear Regression Model (RLRM), Decision Tree (DT), XGB Regression (XGBR), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Gaussian Process Regression (GPR) were developed. These models use speed, feed, and lubrication conditions as input parameters. Among all the models, GPR yielded the best performance, achieving the highest evaluation metric scores of mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE), determination coefficient (R^2) and accuracy as of 14.04, 18.79, 14%, 0.9 and 85% respectively.

Keywords Machine learning model · Temperature prediction · MQL · End milling

1 Introduction

Cutting temperature is a critical factor in machining operations that affects many aspects of manufacturing. The life and wear of tools is one of its key effects. Elevated cutting temperatures may hasten tool deterioration, necessitating regular tool replacements. Consequently, there may be a rise in production expenses and tool change downtime [1]. Effective temperature management is essential for prolonging the life of cutting tools, which can result in substantial cost savings. The integrity of the workpiece material is intimately related to the cutting temperature. The structural integrity and material qualities of the machined parts may be impacted by thermal damage brought on by extreme temperatures. Preserving the quality and integrity of the final components requires maintaining ideal cutting temperatures [2].

Predicting cutting temperature values is paramount for several reasons. It empowers manufacturers to optimize their machining processes by adjusting critical parameters like cutting speed, feed rate, and tool material. By staying within desired temperature limits, manufacturers can enhance efficiency, reduce tool wear, and minimize the likelihood of thermal damage to the workpiece [3]. Furthermore, predictive models for cutting temperature are invaluable for tool selection. By knowing the expected temperature levels, manufacturers can select cutting tools that can withstand the anticipated thermal loads and conditions, ensuring tool longevity and optimal performance throughout machining processes [4]. Recognizing the paramount importance of predicting cutting temperature with precision, it is imperative to devise an efficient predictive model

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tailored specifically for this task. Hence, the adoption of machine learning techniques has been identified as the optimal approach to develop the model [5].

Machine Learning (ML) models are complex algorithms that use data to identify underlying patterns and relationships. They can learn from past data without requiring explicit programming for every task, allowing them to make predictions or decision on their own when presented with new, unknown data [6]. Machine learning predictive models offer distinct advantages over traditional analytical models, owing to their heightened flexibility, adaptability, scalability, and proficiency in handling imbalanced dataset and non-numerical data. These merits have garnered significant attention from researchers and practitioners alike [7]. ML models are primarily categorized into supervised learning, employing labeled data for prediction, unsupervised learning, identifying patterns from unlabeled data, and reinforcement learning, achieving optimal performance through interaction with an environment and rewards [8].

The cutting temperature predictive ML model, devised by Mia et al. during turning experiments on AISI 1060 under dry and high cooling conditions, utilized the Artificial Neural Network (ANN) algorithm. The input variables integrated into this model include spindle speed and feed rate. Comparative analysis with the Response Surface Model (RSM) showed that the ANN model outperformed in terms of mean absolute error (MAE) values [9]. Furthermore, a comparative study by Gupta et al. involved the utilization of RSM and the Adaptive Neuro-Fuzzy Inference System (ANFIS) model for predicting cutting force, cutting temperature, and surface roughness in Nano Fluid Minimum Quantity Lubrication (NMQL)-assisted turning. The findings revealed that the ANFIS model surpassed RSM in terms of predictive accuracy [10]. The highly stable and accurate Gaussian Process Regression (GPR) model was developed by Zhang et al. to anticipate the cutting force, surface roughness, and tool life during the turning process. The model's input variables were feed rate, cutting speed, and depth of cut [11].

Bustillo et al. introduced several ML algorithms, including Decision Trees (DT), k-Nearest Neighbors (KNN), Random Forest (RF), and ANN, to forecast HSS tool life during the turning of AISI 1045. Their study revealed that the RF model exhibited impressive result [12]. Likewise, Drouillet et al. employed spindle speed and spindle power data, along with the curve fitting method of ANN, to predict tool life in milling operations. Their results demonstrated minimal variation between the predicted and actual remaining useful tool life, highlighting the model's accuracy [13]. The three ML models such as linear regression, RF and Support Vector Machine (SVM) were formulated by Dubey et al. for predicting surface roughness value in NMQL assisted turning of AISI304 steel, and the models were compared with experimental value. Among the three, the RF model gave better result than others, achieving determination coefficient (R^2) value of 0.8176 when utilizing nano-particles of 40 nm in size [14]. Furthermore, the study by Gupta et al. confirmed the exceptional predictive capabilities of the RF algorithm in comparison to SVM, Ada Boost, and Multilayer Perceptron for predicting cutting energy consumption during turning operation [15].

In another comparative study, Mahfouz et al. delved into the performance of ML models such as SVM, KNN, and DT. Their investigation centered on the end milling of aluminum dataset, yielding noteworthy findings. Notably, SVM emerged as the frontrunner, displaying superior performance across various metrics, including an impressive 81.25% accuracy, 0.83 precision, 0.812 recall, and an F-measure of 0.808 [16]. Moreover, the support vector concept was utilized in the machine learning model developed by Mäkiaho, T.; Vainio, H. et al. for predicting blade wear during milling operations. In their study, they conducted a comparative analysis of different kernel functions; including the Gaussian radial function (RBF), linear kernel, and polynomial kernel. The evaluation was based on metrics such as the root mean square (RMS) value, where the RBF kernel exhibited the highest performance metrics [17]. Akbari et al. employed a physics-based substructure framework within a Bayesian learning algorithm to predict the stability of a set of milling machine tools within a production plant. Through the validation process, it was observed that the effectiveness of predictions was enhanced, even when using suboptimal training data [18]. Additionally, Kim et al. noted an enhancement in predictive effectiveness concerning tool wear during the end milling by implementing a Bayesian learning approach within the Deep Multiscale Convolutional Neural Network (DMSCNN) model [19].

Examining the existing literature, it is apparent that numerous researchers have dedicated their efforts to constructing ML models geared towards predicting various parameters in machining processes, such as cutting force, power, surface roughness, and tool wear. However, a notable gap exists in research that specifically focuses on the application of ML algorithms for predicting cutting temperature, particularly within MQL and NMQL cooling conditions. Furthermore, there is a scarcity of studies that conduct comparative analyses involving more than four ML models and three or more evaluation metrics. Consequently, this study is determined to develop a customized ML model capable of forecasting temperature variations within the intricate domain of end milling operations, encompassing scenarios from dry machining to MQL and NMQL cooling setups. Additionally, the research aims to provide a thorough comparative evaluation of eight ML algorithms—Regularized