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Predicting tool life in turning operations using neural networks and image processing

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ABSTRACT

A two-step method is presented for the automatic prediction of tool life in turning operations. First, experimental data are collected for three cutting edges under the same constant processing conditions. In these experiments, the parameter of tool wear, V_B, is measured with conventional methods and the same parameter is estimated using *Neural Wear*, a customized software package that combines flank wear image recognition and Artificial Neural Networks (ANNs). Second, an ANN model of tool life is trained with the data collected from the first two cutting edges and the subsequent model is evaluated on two different subsets for the third cutting edge: the first subset is obtained from the direct measurement of tool wear and the second is obtained from the *Neural Wear* software that estimates tool wear using edge images. Although the complete-automated solution, *Neural Wear* software for tool wear recognition plus the ANN model of tool life prediction, presented a slightly higher error than the direct measurements, it was within the same range and can meet all industrial requirements. These results confirm that the combination of image recognition software and ANN modelling could potentially be developed into a useful industrial tool for low-cost estimation of tool life in turning operations.

1. Introduction

Increasing the scope of automated turning processes will at all times have to respond to the highest requirements in terms of reliable predictions of tool life. Tool-life assessment usually requires significant time and material resources and is therefore a relatively expensive procedure. Hence, the importance of accurately predicting tool life and the cutting- edge replacement schedule, before defects or catastrophic wear stop the process, even more so as accurate tool life is crucial for optimizing cutting productivity and the cost of turning processes. Tool life depends directly on the level of tool cutting edge wear. If we are to control the surface conditions of the cutting edge and the prediction of machining time, then the level of cutting-edge wear must be very carefully established. There is a considerable body of research on cutting-edge wear that report prediction methods for tool-life and cutting-condition with the aim of preventing catastrophic wear.

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Recent publications on the subject include reports on studies of wear resistance and turning tool wear [1–5]. Soliman et al. [1] studied the parameters of cutting-edge wear for work-pieces with and without TiN with respect to the cutting time coating in various modes of dry turning. The cutting edge durability of coated tools has been found to be 4.5–5 times greater than that of uncoated tools. Jawaid et al. [2] studied the parameters of cutting-edge wear in the turning of Ti-6246 titanium alloy at various cutting speeds and feed rates. An optical microscope was used to measure tool wear and to determine tool life, both of which varied significantly at different feed rates and cutting speeds. Mrkvica et al. [3] discussed the tool life of Pramet Tools Ltd., studying varied intensities of tool wear at various feed rates and cutting speeds in the turning of an Inconel 718 alloy. Sadílek et al. [4] performed real-time monitoring of cutting tool wear on an XCSRNR2525M-1207SEN turning tool, by measuring impedance layers applied to Silicon Nitride Ceramic KS6000 inserts. Kupczyk and Komolka [5] studied the high durability of cutting insert edges made of WC-5 nanocrystalline cemented carbides in the turning of EN-ISO 42CrMo4 toughening steel. However, no real-time monitoring of these parameters may be found in the studies of tool wear and cutting edge durability described in [1–3,5]. The real-time electrical resistance measurement used in [4] requires the use of special tools, which significantly limits its use.

There are various papers that have described the monitoring of tool wear and the life of turning tools [6–12]. Rehorn et al. [6] offered a review of sensors and signal processing methodologies used for tool condition monitoring in turning, drilling and milling. Cakir and Isik [7] used the tool life and condition monitoring system to study variations in the cutting forces when turning AISI 1050 steel with coated and uncoated tungsten carbide ISO P25 tools. Sahin [8] compared the tool life of ceramic and cubic boron nitride (CBN) cutting tools when machining hardened bearing steels using the Taguchi method. Gadelmawla et al. [9] determined the correlation between the texture of machined surfaces and machining time. Krolczyk et al. [10] carried out a study to determine the life of carbide-coated tools and the tool point surface topography. Antonialli et al. [11] monitored tool life and tool wear of Inconel 625, and the resulting surface roughness following taper turning in comparison with straight turning was evaluated. Kundrák et al. [12] offered a mathematical model for tool life and its experimental assessment in the turning of 100Cr6 bearing steel with CBN tools at various cutting speeds.

Today, a whole range of neural network and Artificial Intelligence (AI)-based methodologies [13–38] have been developed that model the correlation between the input (process data) and the output (tool life or tool wear) parameters of the turning process. Ezugwu et al. [13] predicted tool life and failure modes in turning grey cast iron (grade G-14) with a mixed-oxide ceramic cutting tool (type K090). Tool life and failure mode for each experiment and the corresponding data were used to train an Artificial Neural Network (ANN), in this case a Multi-Layer Perceptron (MLP), using the back-propagation algorithm. Sick [14] assessed on-line and indirect tool-wear monitoring in turning with ANNs, comparing the methods applied in the publications and the methodologies used to select certain methods for the performance of simulation experiments, to evaluate the results and for their presentation. Abu-Zahra and Yu [15] used discrete wavelet transformations of ultrasound waves to measure the gradual wear of carbide inserts during turning. A three-layer MLP architecture was developed that yielded the best correlation (95.9%) of the ultrasound measurements with the level of tool wear. Scheffer et al. [16] conducted a comparative evaluation using ANNs and hidden Markov models (HMMs) for modeling complex correlations between the input set of sensor signal functions and tool life during turning. Ojha and Dixit [17] assessed tool wear by fitting a best-fit line on the data in the steady wear zone and establishing the time until tool failure by extrapolation. ANNs are often used to predict lower, upper, and most likely estimates of tool life. Silva et al. [18] used an artificial intelligence system for condition monitoring that is able to detect when a tool wears out. Natarajan et al. [19] expanded the use of the back-propagation feed from ANN to predict tool life in turning. Özel et al. [20] developed a multiple linear regression model and ANN models for predicting surface roughness and tool flank wear when finishing the turning of AISI D2 steels (60 HRC) using ceramic wiper (multi-radii) design inserts. Sarma and Dixit [21] compared the performance of a mixed oxide ceramic tool in dry and air-cooled turning of grey cast iron, taking into account tool wear, surface roughness of the machined piece, forces and cutting vibration. Pal et al. [22] offered an ANN-based sensor fusion model for a tool-wear monitoring system in turning processes. A wavelet packet tree approach was used for the analysis of the acquired signals, namely cutting strains in tool holder and motor current, and the extraction of wear-sensitive features. D'Addona et al. [23] used cognitive modelling of tool-wear progress based on ANN supervised training derived from investigational tool-wear measurements during industrial turning of Inconel 718 aircraft engines. They obtained a dependable trend of tool-wear curves for optimal utilization of tool life and stepped increases in productivity, while preserving the surface integrity of the machined parts. Attanasio et al. [24,25] compared Response Surface Methodology (RSM) with ANN fitting techniques for tool-wear prediction in longitudinal turning of AISI 1045 steel rods. These papers have all shown that the ANN models provide better approximations than RSM in the prediction of the amount of the tool-wear parameters. Finally, although ANN is the most common AI technique used for tool-wear prediction in turning [26], other AI techniques have been tested for this industrial task: Gajate et al. [27] presented a two model-based approach for tool-wear monitoring on the basis of neuro-fuzzy techniques. A four-input (i.e., time, cutting forces, vibrations and acoustic emissions signals) single-output (tool wear rate) model was designed and implemented on the basis of three neuro-fuzzy approaches (inductive, transductive and evolving neuro-fuzzy systems). Yiqiu et al. [28] tested Support Vector Machines (SVM) to predict tool wear, considering texture features of the surface as inputs with better generalization capabilities compared with ANN models.

Tool images as a source of data for assessing tool wear or tool life are usually used in the direct approach [29–38]. Jammu et al. [29] covered the use of unsupervised neural networks for tool breakage detection in turning assisted by a number of sensors. Pfeifer and Wiegers [30] discussed the advantages of machine vision as a direct measurement technique. Kerr et al. [31] described the use of digital image-processing techniques in the analysis of worn cutting-tool images for assessing their