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Surface roughness modeling and optimization of tungsten–copper alloys in micro-milling processes

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ABSTRACT

Nowadays, the micrometric and nanometric dimensional precision of industrial components is a common feature of micro-milling manufacturing processes. Hence, great importance is given to such aspects as online metrology and real-time monitoring systems for accurate control of surface roughness and dimensional quality. A real-time monitoring system is proposed here to predict surface roughness with an estimation error of 9.5%, by using the vibration signal that is emitted during the milling process. In the experimental setup, the *z*-axis component vibration is measured using two different diameters under several cutting conditions. Then, an adaptive neuro-fuzzy inference system model is implemented for modeling surface roughness, yielding a high goodness of fit indices and a good generalization capability. Finally, the optimization process is carried out by considering two contradictory objectives: unit machining time and surface roughness. A multi-objective genetic algorithm is used to solve the optimization problem, obtaining a set of non-dominated solutions. Pareto front representation is a useful decision-making tool for operators and technicians in the micro-milling process. An example of the Pareto front utility-based approach that selects two points close to both extreme ends of the frontier is described in the paper. In the first case (point 1), machine time is of greater importance, and in the second case (point 2), importance is attached to surface roughness. In general terms, users can select different combinations, at all times moving along the Pareto front.

1. Introduction

The manufacturing industry is in a process of continuous change. Every day, smaller components are needed and quality control in manufacturing is more difficult, due to the demand for micro/nano-scale parts in such sectors as electronics, medicine, and aerospace industry. However, high-quality products depend on the proper operation of machine-tool, cutting tool, control, and cooling systems, which must be guaranteed. Consequently, tool condition monitoring is becoming a key issue that requires the development of efficient model-based systems, to estimate not only clear tool-wear patterns, but also the values of surface roughness, by using information from forces, vibrations [1], acoustic emissions, temperature and voltage acquired during the cutting process [2,3]. Average surface roughness (R_a) measures the arithmetic average of absolute profile height deviations from the mean line, recorded along the evaluation length. R_a is a key metric in the metal finishing industry [4].

In particular, such phenomena as chatter [5] and run-out [6] have a strong influence on surface roughness and burr formation during the milling and micro-milling process [7]. Shen et al. [8] investigated the effects of assisted ultrasonic vibration on the operation of micro-end milling, applying a numerical analysis to the trajectory of a tool tip

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attached to a two-flute end mill. They reported a negative effect of assisted ultrasonic vibration in the feed direction on surface roughness at the slot bottom, but a positive effect on the dimensional accuracy of the slot width. In a similar analysis [9], but on a micro-milling scale in this case, they proposed Ultrasonic Vibration-Assisted Micro (UVAM) milling with longitudinal vibration of the work piece to simulate the trajectory of the cutter tooth. The influence of different ultrasonic vibration amplitudes on surface roughness was processed with UVAM, setting optimum vibration amplitude for the aluminum alloy AL6061.

In general, monitoring systems have three basic levels: feature extraction, modeling and decision level [10]. In the past, another two levels were used: analog and digital filtering [10], but with the use of techniques such as wavelet transform, the filtering process is actually included in the feature extraction step. Fast-Fourier transform (FFT) [11], wavelet transform (WT) [12], Hilbert–Huang transform (HHT) [3], and time series are the most frequently reported techniques for feature extraction [2]. Likewise, artificial neural networks [13], neuro-fuzzy and fuzzy systems [14–16] and hidden Markov models [17] were the most frequently reported for the modeling step. Several monitoring systems were proposed in the literature, for estimating tool wear and for detecting tool breakage [18].

Surface roughness is also predicted by using monitoring systems [19,20]. Dong and Wang [21] proposed a method for modeling surface roughness with an Adaptive Network-based Fuzzy Inference System (ANFIS) and a leave-one-out cross-validation approach, in an end milling process. Zeroudi and Fontaine [22] presented a surface reconstruction model based on a methodology developed for predicting cutting forces and surface roughness directly from CAM data, in a freeform milling process.

Another interesting issue is to establish the optimal cutting parameters. Evolutionary algorithms, especially, genetic algorithms [23], are one of most widely used techniques for obtaining the optimal cutting parameters [24]. In particular, multi-objective approaches [25] have been used to find the so-called Pareto front [26], providing an optimal solution set which can be used for an *a posteriori* decision-making process, performed to increase product quality and process productivity [27]. Decision-making algorithms are gaining ground in the manufacturing industry every day [28]. One example is the risk–value decision-making tool for performance assessment of manufacturing scenarios proposed by Shah et al. [29]. These measures are therefore consolidated to obtain a global performance indicator of value and a global indicator of risk, while keeping inter-criteria influences on mind to facilitate decision-making, by clarifying the performance under various scenarios. Bhavsar et al. [30] developed a multi-objective optimization method based on genetic algorithms, to obtain the best combination between the material removal rate and surface roughness for focused ion beam micro-milling of cemented carbide.

The study reported in this paper proposes a real-time monitoring system for predicting surface roughness in a micro-milling process of tungsten–copper alloys, by using vibration signals that are measured during the micro-milling process on-line. The main contributions of this paper are twofold: firstly, it develops two surface roughness estimation models (i.e., a regression model and neuro-fuzzy model); secondly, this model-based cutting-parameter optimization sets the best operating conditions for the micro-milling process. Economies related to the Pareto front at an industrial level are based on an increase in production levels, at all times guaranteeing the technical constraints, with clear improvements in the efficiency of modern manufacturing techniques.

The paper consists of five sections. After this introduction, the experimental setup is explained. In the third section, the proposed monitoring system is described, while the fourth section shows the optimization of the cutting parameters. Finally, the conclusions are drawn in the fifth section and future work is outlined.

2. Experimental setup

A Kern Evo high-precision machining center, with a maximum spindle speed of 50 000 rpm and Blum laser system, was used to run experimental tests. A micro-milling process with 0.5 mm and 1 mm-diameter mills was performed on a sintered tungsten–copper alloy (W78Cu22), having a 78% of tungsten and a 22% of copper. The WCu alloy, with more than 75% of tungsten, is widely used in chip carriers, substrates, flanges and frames for power semiconductor devices. The high thermal conductivity of copper together with the low thermal expansion of tungsten allows thermal expansion matching to silicon, gallium arsenide, and some ceramics. WCu can also be used as a contact material in a vacuum. When the contact is very fine grained (VFG) the electrical conductivity is much higher than a normal piece of Copper Tungsten. Nowadays, the mechanical, thermal and electrical properties of this alloy are opening new niches for aviation and aerospace components [31], which mainly focus on large mechanical vibration absorption, high absorption of ionizing radiation (gamma or X-rays), and high thermal and electrical conductivity. Some emerging applications include components for radio-frequency (RF) equipment and antenna, electrodes for electro-discharge machines, and high density counterbalances [3,32]. In this investigation, the high conductivity was the fundamental criterion to choose this material, being very useful in the development of small devices applied to the electronic and robotic fields. Three cutting parameters were considered in the processes: cutting speed, v; feed rate, f; and axial depth of cut, a_P. The radial depth of cut, a_e; was equal to the mill radius in all of the slots.

Fig. 1 depicts the real-time monitoring system platform; this is equipped with a Deltatron 4519-003 Brüel & Kjaer monoaxial accelerometer on the z-axis, with a sensitivity of 10.58 mV/g and bandwidth of 20 kHz. The sensor was connected to a PCB PZT 482A22 amplifier to supply power, in order to obtain an acceptable voltage measurement, easily processed by most data acquisition systems.

The vibration signals (V_z) were fed into an NI 6251 National Instruments data-acquisition card, with a sampling frequency of 50 kHz, processed in a National Instruments high-performance PXI-8187 embedded controller.