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Editorial

Special Issue on "Machining Dynamics and Parameters Process Optimization"

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1. Introduction and Scope

In 1907, F.W Taylor—the father of production engineering—exposed the fundamentals of modern machining and defined chatter as the most obscure and delicate of all problems facing the machinist. However, a century later, chatter is still a hot topic at the forefront of machining problems. New casted materials with higher properties lead to challenging designs with even thinner walls and floors. Despite nowadays new processes emerge, parts still need to be finished with metal removal processes as ever if aiming for good quality and close tolerances. Specifically, this book, *Machining Dynamics and Parameters Process Optimization*, includes a series of ten studies with some new advances regarding machining dynamics in metal cutting. The topics include the dynamic characterization of machine tools, experimental dampening techniques, or optimization algorithms combined with signal monitoring.

2. Contributions

All the contributions were divided into three different sub-topics.

2.1. Dynamic Characterization of Machine Tools and Stability Analysis

Unstable vibrations in machining processes arise due to the regenerative effect of the uncut chip thickness. Stability analysis enables the prevention of these undesirable vibrations, improving tool life, surface roughness and, in general, productivity. For instance, Alvarez et al. [1] present an innovative method for calculating stability maps in cylindrical and centerless infeed grinding process. The method is based on the application of the Floquet theorem by repeated time integrations. Additionally, Sosa et al. [2], discussed an updated method of the enhanced multistage homotopy perturbation method for the solution of delay differential equations (DDE) with multiple delays. The authors demonstrated better convergence rates and less computation time for the calculation of the stability lobes for multivariable cutters in the milling process. This method is also a very promising tool that could be extended to other machining processes.

The dynamic characterization of machine tools also plays an important role in understanding and increasing performance. This task demands accurate dynamic models and sophisticated approaches to characterize new machine tools. In the industrial scenario, the machining performance with robots is highly dependent on their dynamics; Sun et al. [3] introduced a method to predict natural frequencies of industrial robots that brings new knowledge for improving a 6R Robot's dynamics.

2.2. Devices and Experimental Techniques

The productivity during the machining of thin-floor and thin-walled components is limited due to unstable vibrations that are likely to occur when increasing depth of cut. Puma-Araujo et al. [4] designed a custom-built semi-active magnetorheological damper device that increases the damping ratio and modal stiffness of a thin-floor workpiece, significantly expanding the stable areas when milling with a bull-nose cutter. A path is given for extending this practice towards industrial use.

Another source of vibration in five-axis machining is the discontinuities of the linear-segment toolpath inducing fluctuation in the programmed feed rate. Gao et al. [5] proposed a double B-spline curve-fitting and synchronization-integrated feed rate scheduling method. They experimentally concluded that this method generates a smooth toolpath with an allowable fitting error. The optimal setting of the computer numerical control (CNC) plays an important role in the machining performance; specifically, Yu et al. [6] developed a practical methodology to tune the CNC parameters effectively for easy implementation in a commercial CNC controller. They studied three turning machining modes: high-speed, high-accuracy and high-surface quality in terms of dynamics errors. Similarly, the accuracy determined by the CNC in a flute-grind of an end-mill, has an impact on the performance of the cuter. Fang et al. [7] proposed a new projection model intending to optimize the wheel's location and orientation for the flute-grinding to achieve higher accuracy and efficiency.

2.3. Monitoring Systems and Machining Optimization

Contemporary additive manufacturing (AM) has demonstrated the potential to manufacture lightweight, complex parts of which subtracting manufacturing was incapable. However, most of these parts still require a machining stage to achieve the required dimensions and surface roughness. Accordingly, Grossi et al. [8], presented an approach to predict the dynamics of a thin-walled component produced using wire–arc–additive manufacturing. The knowledge of the workpiece dynamics evolution throughout the machining process is necessary for cutting parameter optimization.

Furthermore, innovative machining monitoring systems based on artificial intelligence (AI) can minimize machining errors and yield high productivity by predicting and avoiding adverse conditions that cause a lack of dimensional accuracy and tool breakage. Mamledesai et al. [9] proposed a tool condition monitoring framework that included different quality requirements and monitors if the tool produces conforming parts. They used computer vision, a convolution neural network (CNN), and transfer learning (TL) to detect changes in quality indicators. However, because Industry 4.0 is becoming a reality in all the manufacturing sectors, deep learning (DL) for big data has emerged as a key tool. Zhang et al. [10] presented a tool-wear monitoring method for complex part milling based on deep learning. The features were pre-selected based on the cutting force model and wavelet packet decomposition. The pre-selected cutting forces, vibration and condition features were introduced into a deep autoencoder for dimension reduction, and then a deep multi-layer perceptron was developed to estimate tool wear.

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