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Prediction of dressing in grinding operation via neural networks

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Abstract

In order to obtain a modelling and prediction of tool wear in grinding operations, a Cognitive System has been employed to observe the dressing need and its trend. This paper aims to find a methodology to characterize the condition of the wheel during grinding operations and, by the use of cognitive paradigms, to understand the need of dressing. The Acoustic Emission signal from the grinding operation has been employed to characterize the wheel condition and, by the feature extraction of such signal, a cognitive system, based on Artificial Neural Networks, has been implemented.

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Keywords: Dressing; grinding; Acoustic emission signal; Artificial neural networks

1. Introduction

Grinding operations are abrasive processes which involve material removal. The material removal is carried out by the action of abrasive particles, positioned on a grinding wheel [1]. The grinding operation is one of the most common of all metalworking operations; even if abrasive processes are capable of high material removal rates, they are generally employed as a finishing operation.

Grinding processes are directly influenced by many factors, such as the workpiece, machine, grinding wheel and process settings. The monitoring and control of the process, not only allows to keep under control the process itself, but allows to improve the process performance and to avoid scraps and to reduce defects to a minimum possible to ensure high accuracy and quality [2].

The grinding wheel plays an important role in both the surface roughness and the material removal. The classification of the grinding wheel as "sharp" (with cutting capacity) or "dull" (with loss of cutting capacity) is fundamental to achieve the best performance of any abrasive operation [3, 4]. In order to understand the wheel conditions and to estimate and approximate the wheel life cycle time, as accurate as possible, before the regeneration of the wheel through a dressing operation, the grinding operation itself was monitored. Through a sensor monitoring system, the Acoustic Emission (AE) signal was acquired and statistics derived from this signal. The combination of these statistics with the working parameters of the grinding operation will be employed to feed a cognitive decision making support system, such as an Artificial Neural Network (ANN) system, to determine the wheel condition at each grinding pass and to predict and estimate the dressing need.

Understanding and estimating the wheel life cycle before a dressing pass is fundamental to reduce the time and cost of the grinding operation itself, by minimizing the number of grinding passes without material removal and, furthermore, to avoid defects and to optimize the whole operation time.

Cognitive systems, such as Genetic Algorithms (GAs) and Artificial Neural Networks, are increasingly employed to optimize any kind of process and in the planning of any kind of engineering system [5 – 14]. ANNs are widely used in supporting the decision-making system of various manufacturing processes, such as lost wax casting processes,

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to predict the tool-wear in milling and turning operations and to predict the dressing wear of grinding operations [8].

This research work focuses on a methodology for the prediction of the wheel wear and dressing need in cylindrical internal grinding operations. The aim of this study is, therefore, to supply a robust tool for the detection and prediction of the best time for the dressing operation, in order to minimize time for stops and to optimize the whole grinding operation.

2. Description of the grinding and dressing operation

The grinding operation were carried out at the Ar.Ter. SrL factory plant. The worked material was an AISI316; the performed operation was a cylindrical internal grinding, executed with the parameters indicated in Table 1, cooled with a water based coolant mixed to oil (4% oil, 96% water):

Table 1. Working parameters for each Test.

Parameters	Test 1	Test 2	Test 3
Material	AISI316	AISI316	AISI316
Feed rate [m/s]	0.00875	0.00875	0.00875
Speed of the spindle [rpm]	440	440	440
Speed of the piece [rpm]	40	40	40
Depth of cut per pass [mm[	0.03	0.03	0.05
Initial piece diameter [mm]	245.11	324.60	326.55
Required diameter	245.40	324.90	326.90
# of Passes	18	16	9

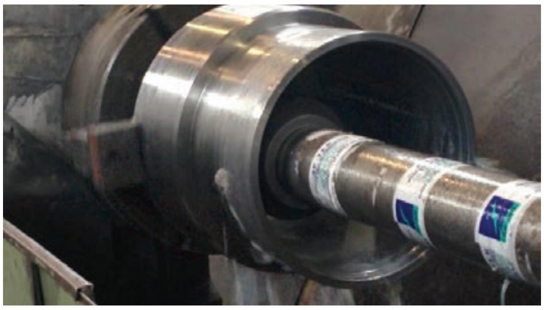

Fig. 1. Internal grinding operation at Ar.Ter. SrL.

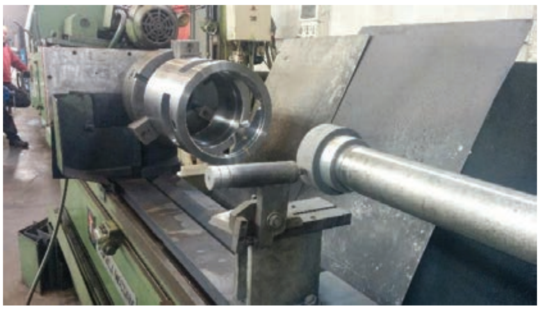

Fig. 2. Dressing operation at Ar.Ter. SrL.

A parameter, which has been monitored and kept under control during the dressing operation of the wheel, was the overlap ratio [15]. The overlap ratio, Eq. 1, is a parameter which correlate the width of action of the dresser, b_d, which was assumed as a constant in each Test, and the dressing feed rate per wheel revolution, S_d, which was constant during each Test. From all of this, it comes that the overlap ratio, U_d, is constant for assumption

$$U_d = \frac{b_d}{S_d} \approx const. \quad (1)$$

The working piece was a CAGE16 component for Gas and Oil distribution pipes. Each piece was worked with the same conditions. The signal acquisition was performed on three test acquisition. The tests were carried out on a real production piece and, because of this, they had to be set with real production parameters, to avoid any scrap or defect. Basically, the test number three differs for the lowest number of passes, due to the deepest depth of cut set. The diameter of the working piece may also change, according to the production at Ar.Ter. SrL (Fig. 1). Starting from an initial diameter as the piece reached the working station for grinding, a material removal operation at the internal diameter was needed to set the piece at the data sheet specification. The abrasive grinding wheel, which was used for the material removal, was a Norton Silicon Carbide (SiC) 38A60LVS. The dressing passes (Fig. 2) were carried out by mean of a DIAVIK natural diamond at 1.5 carat weight; the diamond was mounted on a turned CM1 steel tool and the depth of cut was set at 0.03 mm. The feed rate of the wheel at 0.00875 m/s, turning at 440 rpm, without coolant. The wheel dimension was d_{1-3}x50x65 mm, where d_{1-3} was the diameter of the wheel measured for each of the three tests that varied from a maximum of 176 mm to a minimum value of 126 mm. The peripheral speed varied according to the wheel diameter used of each test and it oscillated from 4.05 m/s to 2.90 m/s.

3. Signal acquisition

The acoustic emission signal was acquired using the Montronix BV100™ broadband vibration sensor, provided with two channels to measure both the vibrations and the high frequency acoustic emission (AE) signals. The acoustic emission signal was acquired at 10 kHz. The analogue acoustic emission and sensor signals was then amplified by a Montronix TSVA4G amplifier. The specifications of the AE amplifier are reported in Table 2. The use of AE sensor signals has been widely employed to detect many phenomena in manufacturing processes, due to the working wide sensor bandwidth from 100 to 900 kHz [16, 17]. The AE sensor signals have as input a preamplifier with a high input impedance and low output impedance. Furthermore, a root mean square (RMS) converter, a gain selection unit, and filters are embedded in the preamplifier. In order to pass by this acquisition problem, the Montronix BV100™ was set to acquire RMS signals. The gain set for the acoustic emission RMS (AE_{RMS}) signals is equal to 10 to properly visualize the signals without exceeding the maximum threshold of 10 V imposed by the data acquisition (DAQ) board.