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PREDICTIVE ASSESSMENT OF THE TURNING TOOL WEAR USING ARTIFICIAL INTELLIGENCE

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Abstract. *Growing developments have been designed in terms of models and algorithms, which involve Artificial Intelligence, and they aim to contribute in the process and machine variables monitoring, by applying Industry 4.0 principles. In this aspect, one of the main challenges consists of monitoring and identifying the point of tool change, which often depends on 100% of the humans. The goal of this work was to determine the wear occurrence of carbide inserts in a machining center, applying turning operations of AISI P20 steel. To reach this purpose, a MTConnect open-source communication protocol was used. Also, a design of experiments based on a composite central design was applied, considering a total of 80 tests, with variation of follow cutting parameters defined based on usual values found in industrial environments: cutting speed; feed rate; cutting depth; and selection of cutting fluid activation. As process outputs, data sets were collected related to the motor powers and loads concerning the spindle, X-axis and Z-axis as a function of the motor use percentages. Moreover, new inserts and artificially worn inserts (corresponding to 0.3 mm of flank tool wear) were utilized in experimental procedure. To analyze the data sets, a model using the OLAM (Optimal Linear Associative Memory) neural network was established without previous treatments of these data. From this initial contribution, the results indicated a range between 65 and 90% of correct answers to predict the tool wear according to different conditions. Finally, 3/4 of the data set was designated for training the neural network, whereas 1/4 was directed at its validation. This work can be seen as an important and useful resource to help identify the tool change time during machining processes.*

Keywords: *Industry 4.0, Tool wear, OLAM Neural Network, Turning Processes*

1. INTRODUCTION

Strategies focused on the growing technologies applied to the more flexible and collaborative production systems are examples of approaches incorporated into the Industry 4.0 terminology. Moreover, these resources make it possible to develop environments and settings destined to industrial smart manufacturing with integration of the Artificial Intelligence (AI), Big Data, Industrial Internet of Things (IIoT), real-time monitoring, and predictive assessment using computing techniques with high performance, resulting in the time and cost reductions, and customized and tailored product creations. Therefore, there is a trend to promote the modifications related to the conventional methods and models, especially in manufacturing processes, based on the employment and development of new and innovative technologies of information allied with the knowledge of industrial processes (Lindström *et al.*, 2019; Wu *et al.*, 2017).

Different technologies can be used to identify patterns in view of data that include specified features or event prognosis and, then, they utilized the software outputs with a determined role. The traditional computational systems may be distinguished from AI as a function of: (i) in the first case, the standards are designed by experts and, introduced in computers as simplified algorithms; and (ii) in turn, for the AI, data are collected, supported by the computers, applied in complex algorithms occurring their processing, with the creation and determination of the set of rules. In the last case, computational machines continuously analyze the rules and recalibrate them according to necessity, consisting of a feedback of information traffic into the system (Núñez Reiz *et al.*, 2019).

Concerning the manufacturing processes, the Data Science based on the knowledges and analytical techniques, studies with monitoring of input variables, models and efficient procedures allow the definition and refining of methodologies arising from Machine Learning. In this sense, Data Science and Big Data can be applied to analyses in order to predict precisely the tool lifetime, machinery responses and output parameters of industrial processes, anticipating unusual events and avoiding damages that result in human risks, security problems, and economic losses. Thus, the importance of predictive work oriented by data collection and monitoring can be justified in industrial environments (Diez-Olivan *et al.*, 2019).

In particular, Machine Learning can lead to a more intelligent use and management of products and services, with decreases due to the costs, spending and wastes; also, with disposal reduction related to the excessive amount of time, allowing the enhancement of the quality in final workpieces (Preez; Oosthuizen, 2019). At the same time, it tends to provide systems established with the purpose of ensuring the human security (Shang; You, 2019).

Regarding manufacturing, Moreira, *et al.* (2019) pointed out studies utilizing new methods of data analysis in order to obtain improvements during computer numerical control (CNC) machining operations. Analytical models were implemented to evaluate the correlations between the surface roughness and machining parameters. In view of empirical approaches, these authors carried out contributions to the optimization in the control of process variables, applying Big Data and Artificial Intelligence. In the literature (Oraby; Hayhurst, 2004), researches driven to the analyses of nonlinear regression have also been utilized to establish models, aiming of determining the wear and lifetime of cutting tools in terms of the variation of the force components which act on the cutting edge of the tool.

Throughout the machining, the thermomechanical conditions, mechanical properties and surface characteristics of the tool and workpiece, parameters of the contact between these body and counter body of the tribological system, and the chip formation along the operations tend to affect the mechanical and thermal stress and strain fields resulting in the cutting tool. This fact promotes modifications regarding the tool geometry and dimensions, which can entail gradual or abrupt modifications of its morphology due to wear mechanisms, occurring loss of functionality of the cutting tool during the machining processes. Based on a definition of the behavior pattern of the tool wear and models, a recommendation of an ideal time of tool change can be found, with resource economy and avoiding damages related to its performance in service or its final breaking. For instance, to help in this designation about the change time of the single-point turning tools, the ISO 3685 standard indicated a limit corresponding to 0.3 mm for the average flank wear (VB_B) (Azmi, 2015; Yang et al., 2019).

According to Li, *et al.* (2019), data-driven methods can be used in addition to predictive approaches to assess the wear of machining tools, using training with artificial neural networks to recognize patterns and/or algorithms involving machining learning concepts. Currently, there are efforts to establish relations between the sensor signals and the tool wear responses. Furthermore, the monitoring methodologies due to the tool lifetime can be differentiated into direct or indirect. Direct methods are related to the experimental / field measurements using, for example, laser and optical technologies and ultrasonic sensors (García-Ordás et al., 2017). On the other hand, indirect methods are destined to define indirectly tool conditions based on the physical parameters of processes and machines, e.g. behaviors of vibrations, force or sounds/noises (Li et al., 2000).

The main goal of the present study was to investigate and develop an initial evaluation, focused on identifying and recognizing the time in which the carbide inserts should be changed during the turning operations in a CNC lathe machine. To reach this objective, the production of a database was necessary, by means of the information collecting and storage in two steps - before and throughout the manufacturing process -, as well as the application of AI resources and MTConnect communication protocol.

2. MATERIALS AND METHODS

Experimental tests of turning were conducted in the Mazak Quick Turn 200MA Machining Center (Figure 1b), which has the following specifications: maximum main axis spindle speed - 5,000 rpm; longitudinal path (X-axis) – 225 mm; vertical path (Z-axis) – 605 mm; and motor output (30 min) – 15 kW

The carbide inserts applied to the machining operations consisted of the CNMG 120408 PM model, from Sandvik Coromant, presenting a cutting edge effective length of 12.096 mm; a corner radius with 0.794 mm; an insert thickness corresponding to 4.763 mm; a total mass of 0.01 kg; and an inscribed circle diameter with 12.7 mm (Sandvik Coromant, 2020a). Furthermore, these inserts were coated with cemented carbides, composed of a tungsten carbide HC substrate with CVD $TiCN+Al_2O_3+TiN$ coating. In turn, the insert holder was constituted by the Coroturn® 107 model (ISO C4-DCLNL-27050-12), from Sandvik Coromant, providing features as follows: the tool cutting edge angle of 95°; the tool lead angle of -5°; the coolant pressure corresponding to 40 bar; the connection diameter with 40 mm; functional length and width of 50 and 27 mm, respectively; the maximum torque of 3.9 N.m; and a total mass of 0.44 kg (Sandvik Coromant, 2020b).

The database was assembled using experimental tests incorporating a set with new inserts ($VB_B = 0$), whereas the other set with worn inserts which was exposed a tool wear corresponding to the $VB_B = 0.30 \pm 0.05$mm. Regarding wear evaluation, the Olympus BX50 optical microscope was applied, which presented a camera connected to a computer that

allowed monitoring and characterization of the process. In addition, the 500X magnifying lens with a 0.01 mm scale division was considered in this study. Figure 1a shows the schemes for the two cutting edges settings described here.

Figure 1. (a) Conditions assigned to the insert studies, which were considered for the wear assessments of the machining tool. In (b), the Mazak Machining Center, located at the Advanced Manufacturing Laboratory of the Mauá Institute of Technology, can be seen.

The machined specimens were composed of AISI P20 tool steel, in which dimensions were standardized as 50 mm in diameter and 100 mm in length. The chemical composition of this steel (% wt.) consisted of: 0.37% C; 2.0% Cr; 1.4% Mn; 0.20% Mo; 1.0% Ni; 0.30% Si; 0.010% S; and Fe in balance. The initial condition related to these samples resulted in a Vickers hardness of 291 ± 6 HV_{30}.

A design of experiments (DOE) was carried out on the basis of the methodology of central composite design (CCD), considering the distance between the axial points and the center (α) equal to 1.682, promoting the participation of extreme values of experimental tests estimated from the necessary increase in power. Moreover, 20 tests were delineated to be repeated for the respective conditions: (a) use of cutting fluid and new tool; (b) use of cutting fluid and worn tool; (c) dry machining and new tool; and, finally, (d) dry machining and worn tool. Therefore, 80 experimental tests appear to arise from the established process conditions. Regarding the cutting parameters, Table 1 denotes the high and low levels assigned to the produced DOE.

Table 1. The cutting parameters and respective levels defined for the experimental procedure refer to the turning tests.

Parameter / Input Variable	Low Level	High Level
Cutting Speed - v_c [m/min]	150	250
Feed Rate - f [mm/rot]	0.2	0.3
Depth of Cutting - a_p [mm]	1.0	2.0
Cutting Fluid	Yes	No
Insert	New	Worn

A Phyton-connected MTConnect protocol was utilized in terms of machine response monitoring and data collection. As stated by Lynn, et al. (2018), the MTConnect is a well-established open protocol of communication, which provides integrations between devices and machines during processes, allowing the acquisition of multiple sensor signals, real-time monitoring and minimized time of information exchanges in manufacturing systems. Its structure is based on the Extensible Markup Language (XML) and internet technology by the Hypertext Transfer Protocol (HTTP) to share data and information, and to conduct the interface between the machine panels and the sensors, reducing losses and optimizing processes.

In this work, the update frequency of the MTConnect protocol for the network has been labeled as 1 Hz (1 s), in which a script in MATLAB was coded to collect data files 3 times per second (3 Hz), avoiding losses of important information about the turning tool characterization throughout the machining tests.

Furthermore, the programming of the Optimal Linear Associative Memory (OLAM) neural network was conducted in view of the results obtained from the turning tests, and the data were acquired and analyzed without prior treatments. The OLAM model is a linear classifier and the learning process cannot reach a convergence point if the data are not linearly separated, limiting the suitable classification.

Input variables of the process inserted into the OLAM network were listed as: the spindle load as a function of usage percentage (CC); the tool X-axis load as a function of the usage percentage (CCX); the tool Z-axis load as a function of the usage percentage (CCZ); the spindle power and speed (P_m and RPM, respectively). These variables in addition to cutting parameters displayed in Table 1 provided the assessments via neural network with employment of AI algorithms. The beginning of data collect was synchronized with machining, causing the coincident and adequate times of the database creation and the manufacturing process.

The OLAM neural network was programmed and trained based on the results extracted from the machining, since the objective consisted of applying this methodology to define whether tool wear was or was not present throughout the manufacturing system. Consequently, the neural network was built using 3/4 of the input data destined to its training (60 lines of the database), whilst 1/4 of the input data (20 lines of the database) has been projected to verify the model effectiveness, by means of the validation conducting the evaluation of the OLAM response compared to the current tool wear condition (VB_B).

3. RESULTS AND DISCUSSION

Some data are supplied in order to exemplify the variables monitored and worked in the research: (i) Table 2 shows a parcel of the data collected during the machining with the cutting fluid and new tool settings; (ii) nevertheless, it can be noted in Table 3 the data resulted of the dry machining and new tool conditions. In some trials, normalized values for -1 were introduced with respect to the no-applied situation or inconsistent factor, while the normalized value of 1 was destined when there is a use or existent factor. It can be observed that, in accordance with a combination of predefined values of cutting speed, feed and cutting depth, the monitored data pointed out the maximized value for the spindle speed of about 4520 rpm (line 10 - Table 3), and its minimized value corresponding to 758 rpm (line 9 - Table 2).

Table 2. Mean values for the tests, considering the use of fluid during the machining of the AISI P20 steel and $VB_B = 0$ (new inserts).

Test	*PtType*	*Blocks*	v_c [m/min]	f [mm/rot]	a_p [mm]	CC [%]	CCX [%]	CCZ [%]	P_m [kW]	RPM
1	1	1	150	0.20	1.0	19.62	26.37	11.00	2.16	2512
2	1	1	250	0.20	1.0	21.00	27.95	12.00	2.31	1768
3	1	1	150	0.30	1.0	19.00	25.00	11.00	2.09	1836
4	1	1	250	0.30	1.0	33.37	35.69	15.48	3.67	2899
5	1	1	150	0.20	2.0	26.94	26.00	15.00	2.93	1338
6	1	1	250	0.20	2.0	42.00	26.00	15.00	4.62	2411
7	1	1	150	0.30	2.0	52.87	26.20	17.02	4.97	1183
8	1	1	250	0.30	2.0	41.37	32.24	13.06	4.52	1683
9	-1	1	116	0.25	1.5	32.94	23.00	16.00	2.47	758
10	-1	1	116	0.25	1.5	45.13	27.61	11.26	4.96	3930
11	-1	1	200	0.17	1.5	25.60	26.36	14.00	2.82	2357
12	-1	1	200	0.33	1.5	38.00	23.00	15.00	4.18	1354
13	-1	1	200	0.25	0.7	15.00	30.00	9.00	1.65	1457
14	-1	1	200	0.25	2.3	42.31	29.00	18.00	4.65	2053
15	0	1	200	0.25	1.5	31.29	29.97	34.22	3.37	2096
16	0	1	200	0.25	1.5	32.61	26.39	12.61	3.59	3031
17	0	1	200	0.25	1.5	35.00	27.25	14.25	3.85	2664
18	0	1	200	0.25	1.5	32.67	29.52	17.67	3.51	1428
19	0	1	200	0.25	1.5	34.56	27.06	13.75	3.80	2110
20	0	1	200	0.25	1.5	30.33	32.70	20.65	3.32	1344

Table 3. Mean values for the tests, considering dry machining of AISI P20 steel and $VB_B = 0$ (new inserts).

Test	*PtType*	*Blocks*	v_c [m/min]	f [mm/rot]	a_p [mm]	CC [%]	CCX [%]	CCZ [%]	P_m [kW]	RPM
1	1	1	150	0.20	1.0	26.00	22.00	15.00	1.96	994
2	1	1	250	0.20	1.0	27.00	22.00	13.00	2.97	1768
3	1	1	150	0.30	1.0	24.27	23.53	34.93	2.50	1847
4	1	1	250	0.30	1.0	45.06	23.24	11.00	4.48	4420
5	1	1	150	0.20	2.0	30.08	21.00	18.00	3.31	1460
6	1	1	250	0.20	2.0	47.33	24.83	22.00	5.21	2391
7	1	1	150	0.30	2.0	61.53	20.04	20.66	5.79	1190
8	1	1	250	0.30	2.0	65.28	20.00	17.57	6.79	1967
9	-1	1	116	0.25	1.5	24.05	27.37	32.00	2.45	1872
10	-1	1	116	0.25	1.5	68.00	23.00	18.00	6.62	4520
11	-1	1	200	0.17	1.5	30.00	24.00	19.00	3.30	2122
12	-1	1	200	0.33	1.5	39.94	21.03	16.47	4.39	1507
13	-1	1	200	0.25	0.6	17.45	24.18	11.82	1.92	1563
14	-1	1	200	0.25	2.3	52.56	21.00	21.00	5.78	2273
15	0	1	200	0.25	1.5	39.35	20.00	16.00	4.33	2546
16	0	1	200	0.25	1.5	42.00	23.00	20.00	4.62	3031
17	0	1	200	0.25	1.5	38.00	21.00	19.00	4.18	2652
18	0	1	200	0.25	1.5	34.00	19.00	17.00	3.74	1446
19	0	1	200	0.25	1.5	33.48	24.48	21.65	3.68	1697
20	0	1	200	0.25	1.5	33.62	18.94	17.90	3.70	1354

Figure 2 denotes exemplified data, that were obtained from the process monitoring, for the fourth set of experimental tests, considering the conditions of new (a) and worn (b) inserts. In this figure, the loads in each axis and the surface temperature of the turning tool can be noticed. There was a significant variation in loads, especially on the x and z axes (CCX and CCZ).

(a) (b)

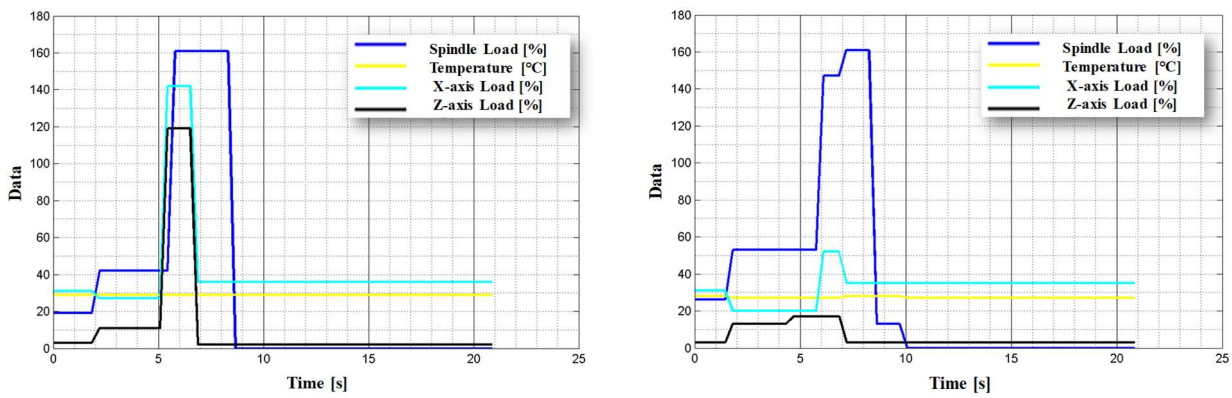

Figure 2. Data outputs exemplified for the process with the presence of cutting fluid during the machining of P20 steel, whose data collected were implemented in the OLAM neural network: (a) graph of the fourth test, taking $VB_B = 0$ for the tool condition; and (b) graph of the fourth test, taking $VB_B = 0.3$ mm for the tool wear condition.

Figure 3 shows the results derived from the algorithm as a function of the correct answers of the OLAM neural network, which indicated a suitable success rate in general. The highest index corresponded to 90% for the condition with the cutting fluid and the new insert. On the other hand, the worst case was designed by an index of 65%, which occurred for the dry turning and worn insert use. In particular, the lowest result of correct answers (65%) issue can be explained in view of the considerable scattering measurements found for the loads and powers, seen in Figure 3, allied with the most critical and severe condition of the tests that occurred there (without cutting fluid and tool previously worn). Thus, the results obtained can be taken as consistent. Also, they can be considered as a relevant initial contribution concerning the improvements and better understanding related to the variables acting in the industrial manufacturing process, since the assessment of the tool wear is not a simple task to be executed by the operators on the shop floor.

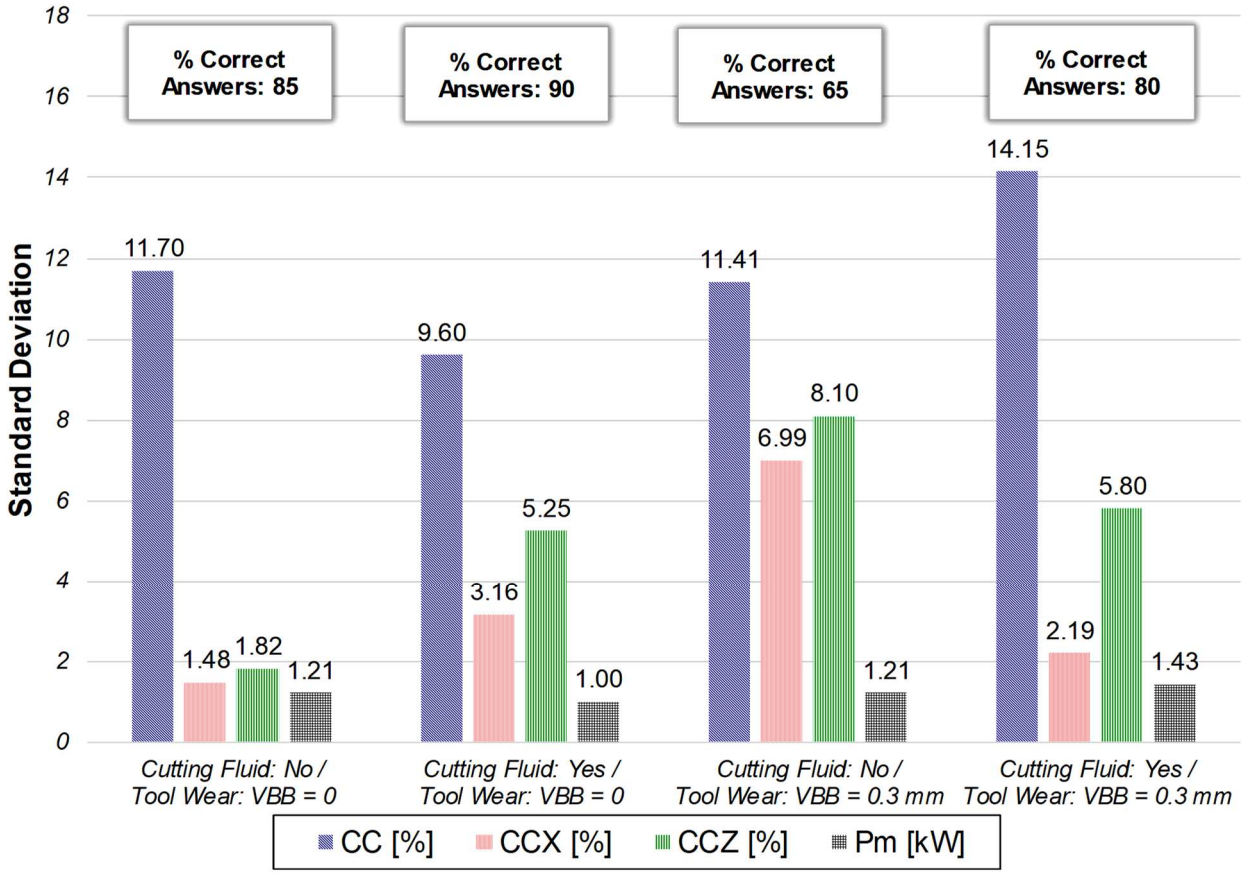

Figure 3. The standard deviation of the loads and power associated with each axis of the machine and the percentage of correct answers provided by the OLAM neural network.

It is important to highlight that no data overlap has been observed; however, the model developed with the OLAM neural network was unable to provide correct answers for all the machining conditions studied. In practical terms, one of the main difficulties consisted of preparation for the artificial wear of tools, which generated slight differences in terms of VB_B, which may have consequences in the dispersed data monitored and collected as inputs. Moreover, the network weights associated with the load parameters can make it difficult to identify their standard deviations, which may result in a reduction in the efficiency of the input data sets. Another aspect that tends to affect the outcomes is the linear classifier implied by the OLAM network.

Apart from the limitations pointed out, the task of identifying the tool wear cannot be seen as easy. The definitions of the time for changing the tool during the process depends on, very often, the knowledge and visual observation by the machine operators, which can intensify its complexity when a low value as 0.3 mm is stipulated. To corroborate this definition, it is worth mentioning that operators often act according to conservative practical aspects in the industries, in order to avoid the tool failure and damages, as well as their consequences in the manufacturing processes: cutting tools are replaced very early of reaching their lifetime; or machining conditions are attenuated, applying input parameters with the least 20-50% than the recommendation, arising extra costs in the production systems (Salonitis e Kolios, 2014).

Finally, the wear of the presence of the cutting tool consists of a natural source of process variation, which promotes modifications in terms of geometry and tool-workpiece contact requirements, leading to consequences referring to the power consumption of the machine tool.

4. CONCLUSIONS AND FINAL REMARKS

The use of the MTConnect protocol applied to the monitoring of input parameters in a CNC machining center has been shown to be valid and applicable, despite the low frequency of data acquisition of the system (1 Hz).

Indeed, the OLAM linear neural network was able to predict the results with a minimum of 65% corresponding to the correct answers, which was considered appropriate based on the aspects as follows: (i) the number of the experimental tests carried out; (ii) the dispersive index of the input values collected during the process related to the loads and powers in the distinct axes; and (iii) the critical conditions considered intrinsic and assigned to the manufacture, e.g. reduced effective results found for the dry machining and flank tool wear minimum as 0.3 mm. In spite of some simplifications, these results are seen as promising to be implemented in future studies in order to incorporate supervision systems, alerting

the operator about the turning insert change moment in machine tools. Based on this initial contribution, it was intended to obtain a time economy, since there is a significant decrease in the intermediary machinery breakdowns to assess the insert by the humans; at the same time, there is a pronounced trend to reduction of the losses addressed to the workpiece and tool, with the discard of inserts being conducted in a more assertive and controlled mode.

Therefore, the AI model developed in this work integrated some concepts and technologies regarding the Industry 4.0 fields, focusing on the definition of the optimal point of the turning tool change throughout the machining process.

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6. RESPONSIBILITY NOTICE

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