International Journal of Advanced Engineering Research and Science (IJAERS)
Peer-Reviewed Journal
ISSN: 2349-6495(P) | 2456-1908(O)
Vol-8, Issue-5; May, 2021
Journal Home Page Available: https://ijaers.com/
Article DOI: https://dx.doi.org/10.22161/ijaers.85.25

Industry 4.0 Machine Learning to Monitor the Life Span of Cutting Tools in an Automotive Production Line

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Received: 11 Feb 2021;
Received in revised form:
09 Apr 2021;
Accepted: 03 May 2021;
Available online: 17 May 2021

***Keywords*— Industry 4.0, machine learning, machining tooling automotive, smart factory.**

Abstract *— The evolution of manufacturing processes in the global industrial scenario is correlated with the growing integration of information technologies, storage capacity and data processing, effective communication between sectors and the development of intelligent and autonomous lines that seek zero waste and quick take-up. decision. In the productive sphere, the use of these resources characterizes intelligent factories, where the manufacture of physical objects is integrated into the information network. Industry 4.0 provides a more flexible, sustainable and agile production chain prioritizing autonomous decision-making integrating hundreds of thousands of generated data and machine learning for problem solving, process improvement and agile and absolute productive monitoring. The present study seeks to prove how decision making through supervised machine learning programming models contributes to cost reduction, increased productivity, waste elimination and process improvement in monitoring tool life in cutting tools used in machining lines process for the manufacture cylinder blocks and cylinder heads of combustion engines in the automotive sector. The knowledge generated from this study reinforces the need and relevance of the concept's dissemination of the fourth industrial revolution in the country, an industrial trend adopted globally in recent years.*

I. INTRODUCTION

Since the beginning of the industrial age, three industrial revolutions have been witnessed. Until in 2011 in Hannover Germany, industry 4.0 or fourth industrial revolution, began to gain prominence on the world stage [1].

The fourth industrial revolution model proposes the integration of man-machine-data analytics [2]. Faster and smarter decisions from integrated concepts of Internet of Things IoT, Cyber-physical systems, data analytics and machine learning [2]. Countries with strategic plans for implementing Industry 4.0: Industry 4.0 program in Germany, Industrial Internet plan in the US, and the Internet+ or Made in China 2025 plan [3]. The benefits that the implementation of Industry 4.0 concepts can provide for the machining industry: increased productivity, preventive maintenance and diagnostics, fault detection, monitoring of process cutting tools, vibration detection among others [4].

Among the objectives of this article are to prove how the application of machine learning and remote data analysis for decision making in optimizing the life of cutting tools used in the machining process in the automotive sector aiming at the implementation of Industry 4.0 in manufacturing.

Investigate the theoretical concepts and tools needed to evaluate the relevance of machine learning and remote data analysis for efficient decision making in the process.

Present the results obtained in productivity and cost reduction with the use of Industry 4.0 for monitoring the life of cutting tools in the machining process for parts in the automotive sector.

Score the difficulties and barriers to implementing the concepts of industry 4.0 in the machining processes of the automotive sector.

According to data from [5], Brazil currently ranks 69th in the global innovation index showing a 7% decline in positions in the ranking of innovation efficiency and productivity of industries between the period from 2006 to 2016. The benefits for the academic and industrial area point out that the use of Industry 4.0 concepts should offer production engineering sectors an integrated chain, agile, without waste and able to make faster and more effective decisions.

II. THEORECTICAL BACKGROUND

Industry 4.0 seeks to deal with global challenges, to generate competitive strength for organizations, considering the globalization between markets [6].

The integration that industry 4.0 provides, using real-time information to generate new business models, to individualize products and services allows the organization to control the value chain by connecting human capital with objects and system [7].

Internet of things (IoT) is an integration of emerging technologies that establishes a new path for industrial production systems [1].

IoT enables physical devices (sensors, actuators, meters, etc.) to connect into a network to exchange information and supply data. These technologies are the foundation of IoT as a network of connected devices that generates the supply data for the enterprise using big data [8].

Cyber-physical system (CPS), or cyber-physical systems are characterized as computer (cyber) systems that act within a mechanical or electrical (physical) system, intended to perform specific dedicated functions with real-time computing constraints. According to this conception, in CPS, multiple devices are networked to detect, monitor, and act on physical elements [9].

Artificial intelligence is the field that seeks to study the creation of agents with intelligence, which have the goal of approaching human intelligence, providing autonomy for a machine or system to be able to make decision based on training of hypothetical models dispensing human interaction [10].

- Enable self-organized production system;
- Intelligent monitoring and diagnostics;
- Agile and accurate decision making;
- Failure prediction.

Artificial neural network (ANN) is a mathematical computational model inspired by the structure and/or functional aspects of biological neural networks. In most cases, an ANN is an adaptive system capable of changing its structure based on external or internal information flowing through the network during the learning phase [11].

Machine learning, machine learning (ML), is a methodology that uses an algorithm capable of recognizing data patterns and making predictions. It is a tool of great potential in various areas of the production system. Machine learning categories are divided into: supervised learning: the machine is trained with data and its respective correct answers; unsupervised learning: it develops the algorithm to predict an outcome not known and reinforced learning: the algorithm is penalized for its actions through trial and error [12].

Phyton™ is an open source software development platform, which makes it freely usable and distributable, even for commercial purposes. Python's license is administered by the Python Software Foundation. The language was developed by Guido Van Rossum in 1990 and the adoption of the language is constantly expanding in the areas of data science, machine learning, big data and web development. Currently the language is expanding in technology companies such as Google, Yahoo, Microsoft, Disney, Air Canada, BitTorrent and others [13].

Cutting tools - Machining is a manufacturing process that generates shape, dimensions and surface finish to a formed part by the removal of material in the form of chips. The interference between the cutting tool and the workpiece during the machining process is responsible for the removal of material called chips. A cutting tool is made of a material with good thermal conductivity, specific heat and thermal expansion, mechanical strength, abrasion resistance and hardness higher than the material to be processed [14].

Machining operations are widely used in the manufacturing industry on components that require precision and quality surface finish. As it is a widespread operation in the industry with its processes established years ago, machining can provide low operating costs when ensured the best condition of process, machine, tool, cooling, cutting parameters, among others [15].

The lifetime of a cutting tool is by definition the time it works until it loses cutting ability according to an established specification. After this time, which can be determined by means of the number of pieces, the number of operations performed or converted into linear meters, the tool must be replaced or sent to the re-sharpening process [16].

For cutting tools, the end of useful life occurs due to wear on the cutting edge due to contact with the workpiece during machining. The wear can be accentuated due to incorrect cutting parameters that contribute to the formation of a false cutting edge that accelerates the edge wear process. The dimensional accuracy and surface quality of the final part may be affected, since the roughness will be higher due to the use of a worn tool. This continuous use of a cutting tool, which has already reached its established useful life, can generate not only problems related to the quality of the part, but also tool breakage making its re-sharpening unfeasible in certain cases [17].

A wear occurs from the continuous and microscopic loss of particles from the tool edge as a result of cutting in the machining process. Wear is classified as flank or frontal wear: which occurs on the clearance surface of the tool as a result of contact with the workpiece, this being the most common occurrence; notch wear: where the wear occurs at both ends of the tip changing the shape of the tool tip and influencing the finish of the machined surface and crater wear or cratering: which can occur on the exit surface of the edge due to friction between tool and chip, the growth of this type of wear can lead to tool breakage [16].

Besides the classified wear, there are also the failure mechanisms that are processes that fatigue the cutting edges, consequently leading the edge to wear and have its continuity of cutting unfeasible. Among the most frequent malfunctions we can cite the false cutting edge, where the chips detached from the cutting process are welded by pressure on the edge and change the geometry of the edge, preventing the correct cut. Thermal cracks that arise due to temperature variation during machining and chipping on edges that is the result of overloading by mechanical tensile stresses during the process are also considered malfunctions [18].

Tool life is directly dependent on the level of tool wear. To control the tip surface conditions and the prediction of machining time the level needs to be carefully established. There is a body of research on tip wear that reports prediction methods for tool life and cutting conditions in order to prevent catastrophic wear [19].

III. METHOD AND MATERIAL

The data used for this research were collected by the team responsible for managing the machining processes and cutting tools of the automotive company located in Vale do Paraíba – São Paulo - Brazil. We considered the life cycle data obtained through the global tool setting variset (GTSv) cutting tool management system used in the plant from the machining operations of blocks and cylinder heads used in the assembly of three-cylinder engines, where the information of life cycle, the causes of tool change, machine, operation, shift, date and time of change correspond to a production of approximately ninety thousand blocks and cylinder heads manufactured from January to December of 2020.

The raw parts of the cylinder blocks and cylinder heads are cast in aluminum with some specific areas according to the product design reinforced in sintered steel, such as the cylinder housings and crankshaft bearing supports in the cylinder blocks and the combustion valve guides and seats in the cylinder heads. The raw parts are forwarded to the machining processes on their respective lines.

The cutting tools involved in the machining processes of engine blocks and cylinder heads are bars with interchangeable cubic boron nitride (CBN) and carbide (tungsten carbide and sintered cobalt) inserts for machining internal diameters with the need for high abrasion resistance, carbide drills and reamers for precision hole making, carbide taps for threading processes, endmills and reamers made of polycrystalline diamond (PCD) material highly used in aluminum machining processes as it offers higher productivity due to the high cutting parameters employed.

The cutting tools, before being sent to the machining operations, are prepared in the presetting room according to process specifications. That is, tool heights are adjusted to avoid collisions, cutting knife diameters and when necessary according to the type of tool, the number of inserts required for each machining sequence.

After the physical adjustment and correction of the tool dimensions in the presetting machine, the tool identification information, expected tool life, coolant pressure to be used, machining operation and line, and preset data are recorded. This information is recorded according to a standard map established in the recording tag.

This recording is performed by the presetting machine, which has in its database the preset programs with all the necessary information for each tool in the process. After adjusting the tool, the recording is done on its tag, a Balluff chip of the low frequency - radio frequency identification (RFID BIS C) type that uses two frequency bands: 455 kilohertz (kHz) for recording and seventy kHz for reading. Recording is essential to the process, because when replacing the tool, the machine must recognize the information recorded to continue the operation. Once the recording is done the machine will print a tag with the basic information that is confronted in the machine after reading the tag at the moment of tool replacement.

After the tool reaches its end of life or if its premature replacement is necessary, the machine will re-record the last information in the tag's internal map so that this data can be returned and stored in the tool change history, helping in the management. The output information is: the reason for the tool change, the achieved tool life, the expected tool life, the machine, the operation, the time and the shift of the tool removal. All other original preset and tool identification information initially saved before machine entry is retained.

The tool life accounting system used in the plant is called GTSv. It is a multitasking resource used by the tool managers that allows monitoring and storing the tool life history, by means of occurrence information and reports of unscheduled changes and their several reasons, tool breakage and tool life alteration by engineering request. The tool life management occurs from the information supplied and stored, after each tool change in the process. In addition to the tool life monitoring features of the operations the system allows:

Inventory control:

- Define and view stock locations in the plant;
- Check quantity assigned to a location;
- Check total plant quantity;
- Check maximum and minimum stock quantities;
- Generate inventory control reports;
- Monitor quantities of components available;
- Generate inventory automatically;
- Extract stock from various locations;
- Integration with the supply chain to schedule tool purchases.

Multi-Action Set:

- Creation of dynamic product trees;
- Reporting of cutting tools that have not reached useful life;
- Reporting of tools with high consumption per operation;
- Feature to monitor tool life online;
- Monitor total and unit tool costs according to consumption and tool life.

The feature to monitor tool life online through live view, integrates the control system of parts produced by the factory information system (FIS) that has connectivity on the machines with the GTSv. This allows anyone with access to the GTSv to view in real time the tool life of any tool in the process. This feature facilitates the availability of the tool on the machine for its replacement at the correct time, avoiding unscheduled changes before the end of the tool life and the correct programming of the tool preset time.

The FIS system is responsible for monitoring the plant's production equipment, and its main function is to follow up bottleneck operations, the daily production volume to be reached, the verification of production and maintenance indicators. The production line machines communicate with the FIS by means of sensors connected to a wireless network, transmitting to the system the machine availability for each machined part. The GTSv in its live view feature uses this information in real time to check how many parts a particular tool has produced.

The computer numerical control (CNC) machining centers used in the enginee block and head lines are the G500 type from the manufacturer Grob. The machines have a modular horizontal machining pattern and articulated table suitable for flexible mass production of automotive components such as cylinder blocks and cylinder heads. The machines have gantry-type automation part loading, where automated robots travel down the line through portals supplying the machines with parts operation after operation.

Through the cyber-physical system (CPS) the electronic sensors of the machines send the tracking signals to the cloud. This data is interpreted by the FIS. Thus the engineers responsible for the line keep track of the bottleneck operation, the machines in shutdown, the failures that occur throughout the process and that need maintenance intervention, and the volume produced.

The integration between machines and systems is the first step required to use IoT resources and store data that will serve as the basis for machine learning.

Tool life is the average time the tool will work until it reaches the maximum allowable edge wear without presenting irreversible damage to the tool such as breakage or affecting product quality. However, in addition to the wear and quality factor there is another important point to be considered in tool life: the cost.

The tool cost per unit produced, called tool CPU, is summarized as the number of parts that the tool is capable of producing (tool life) divided by the unit cost of this tool. Therefore, the more parts a tool is capable of producing, the lower its cost per unit produced and the higher its productivity, since the tool will remain in operation for longer, reducing the machine stoppage for replacement, which impacts the cycle time of the process.

Through the history stored in the GTSv it is possible to analyze the behavior of the useful life of each process tool. For the cases in which the tool does not reach or there is a great variation of useful life, the stored information will be the base to start the study to verify the cause of the problem and correct it. For the cases in which the tool behaves according to the expected useful life, not generating occurrences of breakage or early replacement, it is possible to start a study to increase its useful life with the objective of reducing its tool CPU and increasing its productivity.

This study is conducted by analyzing the tool life achieved over a certain period of time and monitoring the wear of the cutting edge, to ensure that the initially proposed tool life will not present a critical wear that will prevent the extension of the cutting condition of the edge. After this initial analysis, a longer life is proposed and the edge wear is monitored during the test, if the wear remains stable the new life will be approved and changed throughout the process.

However, this test period can take months to complete. There are tools that have an initial useful life with high values and the test will depend on the volume to be produced over the months. In periods where the scheduled production is lower, more time will be needed to validate the new life under test.

The literature reinforces that cutting edge wear varies as a function of the cutting parameters used and as a function of the time the tool remains cutting. The stages of wear as a function of time can be predicted by considering the use of correct cutting parameters. Initially the wear tends to grow rapidly for a short period once the tool starts machining, after this period the wear stabilizes presenting a steady and controlled increase until it reaches its maximum breaking point where it will not be recommended to extend the tool life without offering risks to product quality and tool breakage.

For cases where the cutting parameters are already consistent with the process needs and the initial tool life is constantly reached, it is possible to start the gradual increase of tool life and then validate the wear without offering risks to production.

The assessment of tool life generally requires significant time and material resources, and is therefore considered a relatively expensive procedure. Hence, the importance of accurately predicting tool life and preparing replacement schedules before defects or catastrophic wear brings the process to a halt. Furthermore, accurate tool life is crucial for optimizing the cutting productivity and cost of machining processes.

Increasing the scope of automated transformation processes will, at all times, have to meet the highest requirements in terms of reliable tool life predictions. That is, from the connectivity features between machine, FIS and GTSv commented in this chapter it is possible to teach the machine to analyze the cases in which a given tool will complete the tool life constantly and make the decision of the gradual increase according to the stored database.

3.1 Development of the PYTHON™ model

The Python™ development platform that has its license administered by the Python Software Foundation (PSF) has a relatively simple language, an extensive library that allows to elaborate new applications using open source code. In addition to having a language that facilitates programming, Python is a distributable software, available for download and installation of its libraries directly from the PSF website.

Through its simple language it is possible to elaborate simple classification algorithms such as for example the detection of spam and non-spam e-mail, or to predict a sale from the user's profile. The possibilities when it comes to classification are unlimited.

In the manufacturing context, classification within supervised learning is one of the most used methods of machine learning, because it allows to identify to which category a certain information belongs and "train" the machine to be able to differentiate the received information according to a database previously analyzed.

This method was chosen to validate the idea of increasing the life of cutting tools used in the manufacturing processes of blocks and cylinder heads of three-cylinder engines. For this, data was collected from ninety cutting tools that were removed from the machining machines for reaching or not the previously established useful life throughout the year 2020 and directly linked to the volume of ninety thousand blocks and cylinder heads produced.

IV. RESULTS AND DISCUSSION

This Initially, the database was made up of the date and time of the change, a descriptive summary of the tool identification (line identification - operation - tool code), the reason for the tool change, the expected useful life, the useful life accomplished, the type of change, the operation and the machine located.

Table 1 exemplifies the information surveyed between January 06 and 13, 2020 for the test tool DB-050-01-

T5012, the tool identification reference follows the following order of information:

- DB - Refers to the machining line, where DB indicates block machining line and DH head machining line;

- 050 - Informs the machining operation, in this case operation 50;

- 01 - Informs the position in the tool magazine, in this case analyzed refers to the first position of tool storage in the magazine;

- T5012 - Informs the tool identification number.

The data management software, GTSv, establishes a tolerance of up to -10 pieces to consider that the tool life is completed, in this example of Table 1 the expected tool life is 200 pieces, but in the cases where the tool reached up to 190 pieces it is considered completed tool life. This tolerance exists to prevent the machine from being idle waiting for a tool, with this tolerance the operator will have enough time to inform about the need to change the tool without the need to leave the machine in shutdown waiting for a tool.

Table 1: Collected data to build the Big Data

Change Date	ID	Reason	Expected Count	End Count	Op	Mac	End Life
1/6/20 15:42	DB-050-01-T5012	Scheduled	200	200	050	050.1	Complete
1/8/20 21:31	DB-050-01-T5012	Scheduled	200	200	050	050.3	Complete
1/8/20 21:32	DB-050-01-T5012	Scheduled	200	200	050	050.1	Complete
1/9/20 8:36	DB-050-01-T5012	Scheduled	200	108	050	050.2	Incomplete
1/9/20 16:38	DB-050-01-T5012	Scheduled	200	195	050	050.4	Complete
1/9/20 19:55	DB-050-01-T5012	Scheduled	200	194	050	050.1	Complete
1/9/20 23:49	DB-050-01-T5012	Scheduled	200	194	050	050.3	Complete
1/10/20 17:11	DB-050-01-T5012	Scheduled	200	196	050	050.2	Complete
1/13/20 7:33	DB-050-01-T5012	Scheduled	200	135	050	050.1	Incomplete
1/13/20 13:18	DB-050-01-T5012	Scheduled	200	146	050	050.2	Incomplete

After the survey and filtering of the initial data, excluding inaccurate information from the collected data, the classification step of tools that reached the programmed useful life and the tools that did not reach it was performed to assign in binary language a value that we will use in the programming to identify the two cases.

Next, the binary classification was performed through Microsoft Excel using a condition function, of type "IF" establishing "1" for complete useful life and "0" for incomplete useful life. Table 2 illustrates the addition of the binarization information in the example in Table 1 for the DB-050-01-T5012 tool.

Table 2: Classification of the tool life in binary numbers and the tool change time

Change Date	ID	Reason	Expected Count	End Count	Op	Mac	End Life	Binary
1/6/20 15:42	DB-050-01-T5012	Scheduled	200	200	050	050.1	Complete	1
1/8/20 21:31	DB-050-01-T5012	Scheduled	200	200	050	050.3	Complete	1
1/8/20 21:32	DB-050-01-T5012	Scheduled	200	200	050	050.1	Complete	1
1/9/20 8:36	DB-050-01-T5012	Scheduled	200	108	050	050.2	Incomplete	0
1/9/20 16:38	DB-050-01-T5012	Scheduled	200	195	050	050.4	Complete	1
1/9/20 19:55	DB-050-01-T5012	Scheduled	200	194	050	050.1	Complete	1
1/9/20 23:49	DB-050-01-T5012	Scheduled	200	194	050	050.3	Complete	1
1/10/20 17:11	DB-050-01-T5012	Scheduled	200	196	050	050.2	Complete	1
1/13/20 7:33	DB-050-01-T5012	Scheduled	200	135	050	050.1	Incomplete	0
1/13/20 13:18	DB-050-01-T5012	Scheduled	200	146	050	050.2	Incomplete	0

From the binary classification data, the process of data interpretation was started through conditional structures in Python language. These routines will show that the program can interpret and differentiate the cases in which the automatic lifetime increase should occur.

The conditional routine will receive the information of anticipated tool change, before completing the useful life represented by 0, or tool change by completed useful life, represented by 1. Table 3 presents the accounting of tool changes DB-170-04-T17004 of the block machining line in operation 170, which occurred throughout the year 2020, all changes were according to the completed useful life.

Table 3: Tool changes DB-170-04-T17004

Change Date	ID	Reason	Expected Count	End Count	Op	Mac	End Life	Binary
1/9/20 17:20	DB-170-04-T17004	Scheduled	2000	1995	170	170.1	Complete	1
1/10/20 19:32	DB-170-04-T17004	Scheduled	2000	1991	170	170.2	Complete	1
1/10/20 19:33	DB-170-04-T17004	Scheduled	2000	1998	170	170.3	Complete	1
1/13/20 20:22	DB-170-04-T17004	Scheduled	2000	1995	170	170.4	Complete	1
1/30/20 07:46	DB-170-04-T17004	Scheduled	2000	1999	170	170.2	Complete	1
2/20/20 20:28	DB-170-04-T17004	Scheduled	2000	1997	170	170.1	Complete	1
2/20/20 21:34	DB-170-04-T17004	Scheduled	2000	1998	170	170.2	Complete	1
2/20/20 22:23	DB-170-04-T17004	Scheduled	2000	1998	170	170.3	Complete	1
7/16/20 21:32	DB-170-04-T17004	Scheduled	2000	2493	170	170.2	Complete	1
8/3/20 21:04	DB-170-04-T17004	Scheduled	2000	2675	170	170.4	Complete	1
10/6/20 17:00	DB-170-04-T17004	Scheduled	2000	2993	170	170.2	Complete	1
11/9/20 13:53	DB-170-04-T17004	Scheduled	2000	2628	170	170.3	Complete	1
11/17/20 19:07	DB-170-04-T17004	Scheduled	2000	1995	170	170.4	Complete	1
12/7/20 19:12	DB-170-04-T17004	Scheduled	2000	1993	170	170.1	Complete	1

Fig. 1 illustrates the automatic tool life increase condition for tool DB-170-04-T17004 suggesting the tool life increase by 10%, as all changes were according to the completed life.

```
In [6]: # changes from DB-170-04-T17004
        # current tool life 2000 parts

        toolchange = [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]
        if toolchange == [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1
            toollife = 2000*1.1 #10% improvement
        else:
            toollife = 2000
        print(toollife)

        2200.0
```

Fig. 1: Conditional Code in Python for tool DB-170-04-T17004.

The next case analyzed does not present several tool changes due to the fact that the reported tool life is higher than the case presented in Fig. 1, however the conditional routine works the same way. It is known that in specific cases, such as PCD tools, it is possible to reach, in certain cases, about 50% of increase in the tool life due to the wear resistance presented by the tool in stable processes.

Table 4 presents the analyzed information of the DH-120-11-T12010 tool of the head machining line in operation120, occurred throughout the year 2020, all four changes were according to the completed service life.

Table 4: Tool changes DB-120-11-T12010

Change Date	*ID*	*Reason*	*Expected Count*	*End Count*	*Op*	*Mac*	*End Life*	*Binary*
10/8/20 14:17	DH-120-11-T12010	*Scheduled*	25000	24092	120	120.2	*Complete*	1
2/19/20 12:49	DH-120-11-T12010	*Scheduled*	25000	25000	120	120.1	*Complete*	1
12/7/20 20:35	DH-120-11-T12010	*Scheduled*	25000	25000	120	120.4	*Complete*	1
10/8/20 14:16	DH-120-11-T12010	*Scheduled*	25000	24092	120	120.3	*Complete*	1

Fig. 2 illustrates the automatic tool life increase condition for the DB-120-11-T12010 tool suggesting the life increase by 10% due to the changes occurring according to the completed life.

```
In [5]: # changes from DH-120-11-T12010
        # current tool life 25000 parts

        toolchange = [1, 1, 1, 1]
        if toolchange == [1, 1, 1, ]:# changes from DH-120-11-T12010
        # current tool life 25000 parts
            toollife = 25000*1.1 #10% improvement
        else:
            toollife = 25000
        print(toollife)

        27500.0
```

Fig. 2: Conditional Code in Python for tool DH-120-11-T12010.

The cases in which the tool presents variation in changes due to completed service life and early changes, the condition of the routine indicates the permanence of the service life at the current value. Table 5 presents the information analyzed for tool DB-050-04-T5004 of the block machining line in operation 50, where the changes occurred throughout the year 2020.

The reason for the six changes ranged from end of life to early tool change, which may indicate a quality or process problem involving the tool where a decision was made to replace it with a new one.

Table 5: Tool changes DB-050-04-T5004

Change Date	*ID*	*Reason*	*Expected Count*	*End Count*	*Op*	*Mac*	*End Life*	*Binary*
1/16/20 21:12	DB-050-04-T5004	*Scheduled*	7000	6998	050	050.1	*Complete*	1
3/16/20 20:15	DB-050-04-T5004	*Scheduled*	7000	9998	050	050.3	*Complete*	1
8/14/20 07:42	DB-050-04-T5004	*Scheduled*	7000	4192	050	050.4	*Incomplete*	0
10/6/20 17:02	DB-050-04-T5004	*Scheduled*	7000	6657	050	050.3	*Incomplete*	0

Fig. 3 illustrates the veto of the automatic tool life increase condition for tool DB-050-04-T5004 maintaining the current life value as a function of unscheduled changes.

```
In [7]: # changes from DB-050-04-T5004
        # current tool life 7000 parts

        toolchange = [1, 1, 0, 0]
        if toolchange == [1, 1, 1, 1]:
            toollife = 7000*1.1 #10% improvement
        else:
            toollife = 7000
        print(toollife)

        7000
```

Fig. 3: Conditional Code in Python for tool DB-050-04-T5004.

Condition routines associated with repetitions, which are used to execute the same part of a program, is an alternative to prove through Python that it is possible to make decisions of a certain automatic lifetime increase when a tool analyzed for a period always completes its lifetime without generating quality or process problems.

However, when it comes to machine learning, the ideal is to develop a model by means of an algorithm that will train the machine to make these decisions automatically.

From the same information presented it is possible to create a Bayesian type algorithm, called naive_bayes, which will perform the machine training from the classification data. This multinomialNB, NB (naive bayes) algorithm is available in sklearn's Python library.

Once the model is trained to fit the data and markers, it is necessary to implement the prediction method to the model to predict which element we want to be discovered or which decision to make. This is done using the predict method.

Fig. 4 presents the idea of the model to train the program to classify between two tools which one will fit the increased lifetime automatically. This is the starting point for the implementation of machine learning. In the example between tools T12009 and T12010, tool T12010 has all four end-of-life replacements, and tool T12009 among its four replacements there was an early replacement indicating some problem associated with the tool. Therefore, the model should choose tool T12010.

```
In [*]: # Predict test to implement tool increase

        T12009 = [1, 1, 0, 1]
        T12010 = [1, 1, 1, 1]


        dados = [T12009, T12010]

        marcacoes = [1, -1]

        Toolincrease = [1, 1, 1, 1]

        from sklearn.naive_bayes import MultinomialNB

        modelo = MultinomialNB()
        modelo.fit(dados, marcacoes)
        print(modelo.predict(toolincrese))

        T12010
```

Fig. 4: Classification modeling within tools classes for the life time increasing.

The model for predicting the automatic tool life increase is the first step in the implementation of the supervised learning classification concepts. For the complete implementation of the presented theory it is necessary to perform a systemic work integrating the cyber-physical systems of the CNC machining centers, the sensors used during the machining execution and the network interpreting the data. So that besides learning the classification differentiation, the machine also executes the decision made and provides new data for monitoring the process closing the ideal industry 4.0 chain.

Analyzing the achieved data of increased lifetime of cutting tools in an automatic way by means of a model to simulate machine learning, the results of cost reduction and productivity increase of the involved cutting tools and that supplied the exchange data to the database were verified.

From the implementation of the decision making model of the tool life increase involved in the research through machine learning, it is possible to estimate that after the developed and implemented project there will be a reduction in the tool unit cost (tool CPU) of the machining lines and an increase in productivity due to the larger quantity of parts produced by each tool.

The estimated saving of the tool CPU is presented in Table 6, where the increase in the useful life of the tools involved in the process was considered to be about 10%. These data reinforce the economic feasibility for the company from the implementation of the proposed model, where the cost reduction as a function of the annual volume of ninety thousand engines can reach R$170,000.00.

Table 6: Cost saving expectation by the modeling implementation

Machining Line	Tool CPU		Tool CPU Less 10%		Saving		Saving 90k Engines	
Cylinder Head	R$	8,67	R$	7,80	R$	0,87	R$	78.300,00
Cylinder Block	R$	9,60	R$	8,58	R$	1,02	R$	91.800,00
					Total Saving		R$	170.100,00

It is worth pointing out that the values presented are estimates from the proof of the model. It is necessary to implement and develop the model so that it converses with the cyber-physical system of the machines and machine learning occurs automatically. In addition to the economic results suggested through this research, it is important to note that the theoretical concepts and the use of Industry 4.0 concepts were fundamental to the application of machine learning and remote data analysis for efficient decision making in the process. Which reinforces the relevance and trend of the subject in the industrial and academic scenario of the production engineering field.

V. CONCLUSION

This research sought, based on the knowledge generated, to present satisfactory data to answer the fundamental questions that permeated the study. It was proven that from the development of a supervised machine learning model with routines for verification of tool life increase it is possible to reduce process costs by guaranteeing the extension of tool life and making it possible to increase productivity. Through the study developed and the results obtained, it was possible to validate and prove the importance of data analysis and machine learning for efficient decision making in manufacturing processes in the automotive sector. The use of the concepts of Industry 4.0, machine learning, and modeling were essential to establish considerable gains in productivity and the reduction of cutting tool costs in the machining processes.

The practical implications of this study contribute to the dissemination of fundamental knowledge of research sectors in increasing rise in the world industrial scenario, such as industry 4.0, the use of artificial intelligence in production chains through machine learning, and the search for efficiency of machining processes highly used in the automotive sector, aiming at continuous cost reduction and increased productivity.

The limitations are centered on the need to continue the development of the model presented, so that the machines in the process are able to classify the cases liable to increase the tool life and execute the decision made without the need for human interference. For this it is important to seek ways to integrate the cyber-physical systems of the CNC machining centers, the sensors used during the machining execution, and the data network.

It is suggested for the development of further research from this generated knowledge, the development of the classification algorithm for machine learning through the creation of a cloud-based neural network for intelligent online diagnosis that allows the monitoring of the cutting tool during machining.

ACKNOWLEDGEMENTS

Authors wish to acknowledge the University of the State of São Paulo, Faculty of Engineering of Guaratinguetá – São Paulo - Brazil, for its assistance during the research period.

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