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ORIGINAL ARTICLE

Simple machine learning allied with data-driven methods for monitoring tool wear in machining processes

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Abstract

The aim of this work was to identify the occurrence of machine tool wear in carbide inserts applied in a machine turning center with two steel materials. Through the data collected with an open-source communication protocol during machining, eighty trials of twenty runs each were performed using central composite design experiments, resulting in a data set of eighty lines for each tested material. The data set consisted of forty lines with the tool wear condition and forty lines without. Machining parameters were set to be in the range of the usual industrial values. The cutting parameters in the machining process were cutting speed, feed rate, cutting depth, and cutting fluid applied in the abundance condition and without cutting fluid (dry machining). The collected data were the spindle motor load, *X*-axis motor load, and *Z*-axis motor load in terms of the percentage used. AISI P20 and AISI 1045 steels workpieces were tested with both new and worn inserts, and a flank tool wear of 0.3 mm was artificially induced by machining with the same material before the data collecting experiment. Two approaches were used in order to analyze the data and create the machine learning process (MLP), in a prior analysis. The collected data set was tested without any previous treatment, with an optimal linear associative memory (OLAM) neural network, and the results showed 65% correct answers in predicting tool wear, considering 3/4 of the data set for training and 1/4 for validating. For the second approach, statistical data mining methods (DMM) and data-driven methods (DDM), known as a self-organizing deep learning method, were employed in order to increase the success ratio of the model. Both DMM and DDM applied along with the MLP OLAM neural network showed an increase in hitting the right answers to 93.8%. This model can be useful in machine monitoring using Industry 4.0 concepts, where one of the key challenges in machining components is finding the appropriate moment for a tool change.

Keywords Machine learning · Deep learning · Data-driven · Tool wear · Machining

1 Introduction

Industry 4.0 is one of the terms used to describe the high-technology strategy that was promoted by the German government and has been implemented by the industry in the past decade. It covers a set of leading-edge internet technologies to make production systems more flexible and collaborative. In this approach, it is possible to create smart manufacturing environments which integrate big data, advanced analytics, high-performance computing, the Industrial Internet of Things (IIoT), and artificial intelligence to produce highly customizable goods with higher quality at lower costs [1]. Manufacturing has been a fundamental aspect of national development and prosperity. It contributes greatly to an individual's quality of life, a nation's growth, and the power and position of a country. Machine learning and networking of cyber-physical technologies are on the rise [2]. The direct contact between the cutting tool and workpiece material, and the chips during the machining operation, imposes extreme thermal and mechanical stresses on the cutting tool. As a result, changes to the geometry, volume loss, and

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the sharpness of the cutting tool can occur either gradually or abruptly. These changes, which are known as tool wear, normally take place at rates that are dependent upon the machining conditions, workpiece material, and the cutting tool material or geometry [3]. The tool condition and life span are critical components of cost optimization. There is a real need to devise means of detecting tool wear as well as to predict the remaining life for effective management of the manufacturing lead time. In this context, several methods are being investigated to effectively monitor the wear condition of cutting tools in automated cutting processes and then detect the correct time to perform the exchange. This is important because, by being aware of the wear pattern behavior, engineers can determine the most economical time for exchange, avoiding reaching the stage of tool breakdown [4]. The ISO standard 3685 establishes a limit of 0.3 mm for average flank wear (VB_B).

These tool life monitoring methods can be categorized basically into two main groups: direct and indirect methods [5]. Direct methods (DM) measure the actual value, which could be the flank wear, of faults using laser, optical, and ultrasonic sensors. The most common procedure uses computational vision [6, 7]. Another approach used is indirect methods, where the physical parameters of the process or machine are employed to represent the tool condition indirectly. These parameters could be vibration, force, or sound [8]. The indirect methods (IM) in turn can be categorized by two approaches: continuous tool wear estimation and tool wear classification. The basic difference is how the tool wear is handled: as a continuous variable and treated using data-driven techniques, or as a discrete variable, belonging to specific classes defined by the authors. Although the continuous estimation is more precise, the majority of current research considers tool wear detection based on tool wear classification to be more suitable, mainly for practical reasons, since the change is performed by the operator based on a pattern or range previously established [9].

Tool condition monitoring has been gaining more consideration in the automated manufacturing process in recent times [10] and the current tool wear level directly affects the surface quality of workpieces and even the performance of machine tools. Tool breakage may lead to more serious consequences such as scratching and scrapping of the workpieces, paralysis of the manufacturing system, and even operator casualties [11]. The propagation of tool wear is affected by the complex material–process interactions and process conditions (e.g., feed rate, cutting speed, dry vs. cutting fluid), which together make tool condition prognosis a major challenge in terms of (1) relating sensing data with the tool condition and (2) revealing the tool wear progression pattern based on variations in the sensing data. Compared with a new tool, a worn tool has a different cutting edge geometry and, accordingly, the associated sensing signals [12].

In a review of the literature, it is possible to observe different achievements in IM. [9] proposed a tool monitoring system using a convolutional neural network (CNN) as a deep learning method. Based on the results, CNN consistently responded better to other machine learning algorithms between all three signals (support vector machine, Bayesian rigid network, and K nearest neighbor method) from two accredited data sets, which proved its robustness and high performance in a milling process. [13] proposed a new drill wear condition monitoring method based on a fuzzy neural network. Spectral analysis of the vibration signal was used to generate a set of indices for monitoring. The relationship between the tool wear condition and these indices was described by a fuzzy neural network and led to feasible results [7]. [14] had developed a new tool wear class detection method based on a supervised learning data mining technique (LAD—Logical Analysis of Data), which has the property of finding interpretable patterns that were embedded in the data. Through an analysis of the generated patterns, class identifiers were found and the machining variables that have a clear and apparent influence on the tool wear were determined. The accuracy of LAD was evaluated and validated by comparison with an ANN technique and led to better classification accuracy [14].

[1] implemented an algorithm for the prediction of flank tool wear in high-speed machining in milling processes. It was conducted with RF (Random Forest) and MapReduce-based PRF algorithms. The MapReduce-based PRF (Parallel Random Forest) algorithm was implemented on the Amazon EC2 cloud. The condition monitoring data, including cutting force, vibration, and acoustic emission, collected from 315 milling tests were used to evaluate the performance of the algorithms. By implementing RF in parallel on the cloud, a significant increase in the processing speed (14.7 times in terms of increase in training time) was achieved, with a high prediction accuracy of tool wear (8 times better) in terms of the reduction in mean squared error.

[15] explored the effect of tool wear and surface roughness during the CNC turning of D2 steel by using acoustic emission and force sensors by monitoring the flank wear until the critical value of 0.3 mm. It was concluded that the methods for sensing cutting tool wear are crucial in view of the optimum use of cutting tools with an effective monitoring system, and both the radial forces and the surface roughness increased considerably as the wear progressed. The acoustic emission was also analyzed, and parameters were found to increase proportionally with tool wear.

In this paper, we propose a novel method to identify the exchange point of a carbide insert in a lathe machine, through data collected during machining using the MTConnect® communication protocol. MTConnect® is a data and information exchange standard that is based on a data dictionary of terms describing information associated with manufacturing operations. This free and open protocol enables devices and systems from different suppliers to capture and share information in a common format [16, 17]. The great advantage of this work is that no expensive sensor or dynamometers were used, as in a great number of the cited works. The signals were collected by the common sensor from a machine installed during production by the manufacturer and can be easily adopted in industrial applications.

This paper is organized as follows: The next sections present the background and formulation of the machine learning algorithm which is used in this paper. Section 3 introduces the materials and experimental methods which are used in this study. The results and discussion are presented in Section 4 and we outline the main conclusions in Section 5.

1.1 IoT

The IoT dates back to 1998, described by a British researcher and an MIT co-founder. Nowadays, it is essential to monitor and control many applications [18]. According to [19], the IoT, cloud computing, and CPS (cyber-physical systems) are essential in Machine Tool 4.0, which defines a new generation of machines that are smarter, connected, accessible, and adaptive. IoT and intelligent sensing have been applied to the remote servicing, condition monitoring, fault diagnosis, maintenance, and management of the machine tool [20]. [21] talk about Cloud manufacturing (CMfg), which is supported by IoT and cloud computing and converts typical services in smart manufacturing. IoT can help in many manufacturing aspects. [22], for example, presents a study to analyze the energy monitoring of a die casting machine, where the feasibility of the method was demonstrated. Another example is described by [23], who use the IoT to develop a machine model for CNC machine-tools through OPC-UA, and by [24] in a study of digital twin communication for smart manufacturing.

MTConnect® is an open, royalty-free manufacturing communication protocol that enables communication between manufacturing devices and other software [25]. It has been adapted for manufacturing factories to minimize the delay time in communication and provide multiple sensor data [26]. According to [27], MTConnect® has a great capability for real monitoring and data exchange in manufacturing systems.

The MTConnect® standard provides connectivity and the ability to monitor and collect data across the entire production line: machines, cells, devices, and processes. Its standard is based on XML and HTTP Internet technology for real-time data sharing directly from the machine panel or its sensors [28]. Easy to implement, this network platform can help companies monitor equipment or manufacturing cells, reducing losses and optimizing production.

Figure 1 shows Mazak machines' [29] general scheme of the communication pattern application, where the adapter consists of a communication card connected to the machine panel that collects, through the application programing interface (API), the CNC (computer numeric control) information and sends it by the transmission control protocol (TCP) to the MTConnect® agent, who organizes and maintains the data for later transfer in the network (HTTP).

Once available on the network and knowing the access address, it is possible to collect the information from the XML (Extensible Markup Language) file using any software programming language. In this work, Python software was used to read XML directly from the network where the machine was connected.

1.2 Machine learning

Machine learning is becoming very popular nowadays, and is used in a lot of industries and activities, since its major goal is to optimize systems and bring intelligence to them [2]. According to [30], data-driven methods can be used to predict tool wear using predictive models trained by machine learning or pattern recognition algorithms. Some researchers attempted to establish the relationships between sensor signals and tool wear in their methods based on machine learning, such as artificial neural network and support vector machine [10, 30]. [2] also cites evolutionary and swarm intelligence-based algorithms and response surface methodology as a machine learning technique. [31], for example, presents a prediction model development of machining force, cutting energy, and cutting pressure in turning using three regression-based machine learning techniques (polynomial regression, support vector machine, and Gaussian process regression) as well as artificial neural networks. [32] used a hybrid approach, also using machine learning to predict cutting forces with a deep neural network and finite element analysis [2]. [33] used a machine learning classification for modeling tool life using a "true life curve" using shop floor production data.

The optimal linear associative memory (OLAM) model, as proposed by [34] in 1972, is a well-known computational paradigm of associative memory. As such, information in OLAM is stored distributed in a matrix operator, so that it can recall stored data by specifying all or a portion of a key (degraded key). OLAM has the property of providing rapid recall of information, and it can tolerate local damage without a great degradation in performance.

OLAM is a linear classifier and if the cases are not linearly separable, the learning process will never reach a point where all the cases are classified properly; in this case, there will be fewer correct classifications than expected. Figure 2 shows a schematic operation.

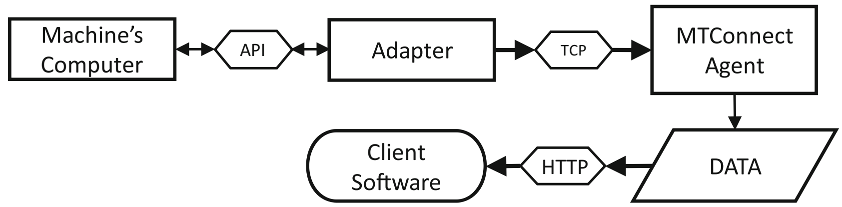


Fig. 1 MTConnect® general scheme [29]

2 Methods and materials

2.1 Experiment

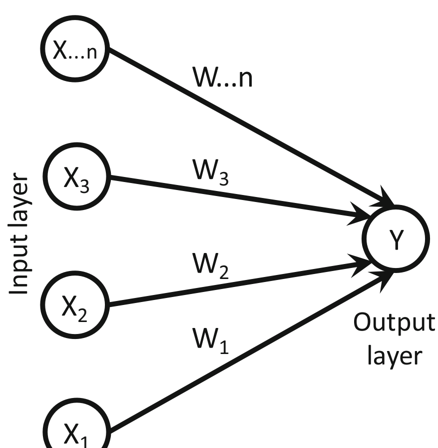
A design of experiments "Response Surface Design" with 6 center points was used to establish 20 experiments with the parameters indicated in Table 1. Each set of 20 experiments was then replicated with:

- usage of cutting fluid with new insert;
- usage of cutting fluid with worn insert;
- dry machining with new insert;
- dry machining with worn insert.

The machining experiments were conducted with two kinds of steel workpieces, AISI 1045 and AISI P20, resulting in a data set of 160 runs.

For the central composite design (CCD), the alpha value applied was 1.682, creating the most extreme values of the experiment, which combined and increased the spindle power demand.

To ensure that the conditions tested were adequate, the cutting parameters were selected based on the tool insert manufacturer's catalog. For AISI 1045 steel, values are quite comfortable; however, when higher mechanical property materials are machined, the case of AISI P20 steel, it is noticed that the upper parameters are at the limit of the operation, but can still be used without great implications.



$$X_1W_1 + X_2W_2 + X_3W_3 + \cdots X_nW_n += +Y \quad yields \rightarrow \quad +1$$
$$X_1W_1 + X_2W_2 + X_3W_3 + \cdots X_nW_n += -Y \quad yields \rightarrow \quad -1$$

Fig. 2 Schematic operation of an OLAM [34]

For the main machining experiments, two types of insert, new and worn, were used. Insert average flank wear value (VB_B) was considered and set up as fixed for the tests, with wear $VB_B = 0$ meaning a new insert and $VB_B = 0.3$ mm a worn tool.

This variable certainly affected the net results on the runs. It was made in this way to guarantee real conditions, as a work condition in machining when the tool is new at the beginning and the wear will increase up to $VB_B = 0.3$ mm, when the tool can be considered unusable.

To ensure the worn tool condition ($VB_B = 0.3$ mm) constant, an "artificial wear set up" was applied before the main central composite design (CCD) experiments. The insert was worn by machining work parts (same material) with cutting parameters at the upper limit of their values for the CCD; the wear was monitored until it reached 0.3 mm ± 0.05 mm. A digital microscope was used for the tool wear control. Every tool edge was used for only two CCD runs, this way assuring less divergence from the original VB_B condition.

Also, the cutting fluid was taken to be fixed for each sequence (20 tests) made with cutting fluid (first set) and without (dry condition—second set).

The insert used was a standard CNMG 120408 PM from Sandvik Coromant and the insert holder was Coroturn® 107. A total of 80 runs was performed for each of the two materials tested (AISI P20 and AISI 1045) in order to create a data set to train a machine learning model.

The materials tested were:

- AISI P20 steel with the chemical composition: C 0.37%; Cr 2.0%; Fe 94.73%; Mn 1.4%; Mo 0.20%; Ni 1.0%; Si 0.30%; S < = 0.010% and hardness corresponding to 291 HV.

Table 1 Cutting parameters

Input	Low level	High level
Cutting speed "vc" (m/min)	150	250
Feed rate "*f*" (mm/r)	0.2	0.3
Cutting depth "ap" (mm)	1	2
Cutting fluid	Yes	No
Insert tool	New	Worn

- AISI 1045 with the chemical composition: C 0.46% Fe 98.5, Mn 0.70% P <= 0.040%, S <= 0.050% and hardness of about 170 HV.

An MTConnect linked with Python software was used for the monitoring of the machine. Figure 3 shows the machining turning center Mazak Quick Turn 200MA with the main characteristics: main spindle chuck size: 8 in.; maximum speed: 5000 rpm; motor output (30 min rating): 15 kW; travel (*X*-axis): 225 mm; travel (*Z*-axis): 605 mm. In Fig. 3, it is possible to observe the insert tool in the initial condition and the worn insert.

Figure 4 presents an excerpt of the XML code generated by the MTConnect® agent. As it is a standardized protocol, it is possible through a programming resource to access all XML instances that represent the data to be collected.

The collected data were as follows: CC—spindle load; CCX—tool *X*-axis load; CCZ—tool *Z*-axis load; Pm—spindle power, along with the parameters applied.

To access the instances and read the XML protocol data, a program was created in Python software with the aim of collecting the load values on the machine spindle motor, *X*-axis servomotor, and *Z*-axis servomotor. A computer connected to the same network as the machine accessed the XML protocol and acquired the information during the trial. The start of collection was synchronized with the beginning of machining, and the duration of the collection was estimated beforehand to coincide with the end of machining.

The collected values were then automatically stored in a spreadsheet for further data processing. In addition to the spreadsheet, an application chart was generated for experiment verification and validation.

3 Acquisition results and discussion

Figure 5 shows an example of the graph generated during one of the tests. The default MTconnect® XML protocol update frequency for the network is 1 s (1 Hz), and the MATLAB script was programmed to acquire the file three times per second (3 Hz), thus ensuring no loss of information during the trial runs. The data processing consisted of eliminating the initial and final values that represented the beginning and end of the machining process, for example, in Fig. 5 eliminating the first second of collection and the final 3 s. Once the values were filtered, the values were averaged to make the responses uniform.

Table 2 shows that some test input factor values have been normalized to −1 (not applied or non-existent factor) and 1 (used or existing), as is the case for the cutting fluid and for the existence of tool wear.

After all the machining experiments, a data set of 160 lines of runs was composed with their respective assigned values along the input parameters.

4 Machine learning models

4.1 OLAM

An OLAM (optimal linear associative memory) linear neural network was programmed from the results of the machining tests, and the collected data set was tested without any previous treatment. The ultimate goal was to predict whether or not tool wear was present during the machining process. OLAM network training was done with 3/4 of the entire data set, 90 runs or lines, and the model's effectiveness was tested/validated by comparing the network response versus the wear condition (VB_B) of the 1/4 tests (30 lines) not used for training.

The inputs for the OLAM model were the runs CC, CCX, CCZ, Pm, RPM plus the input parameters of the runs with cutting fluid, vc, *f*, and ap.

The OLAM neural network showed a rate of 65% correct answers, which is also a good result, as the assessment of tool

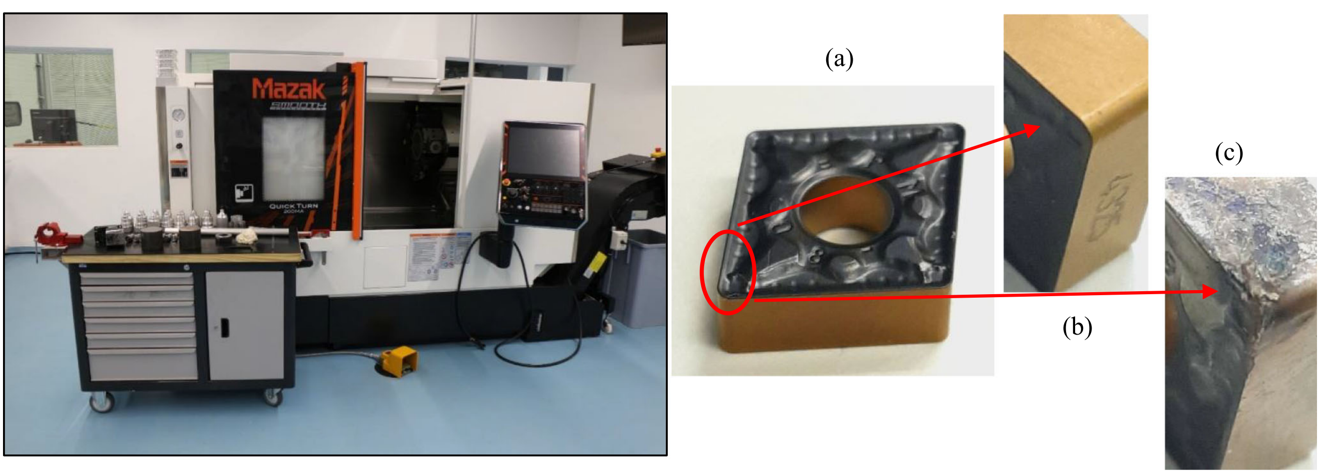
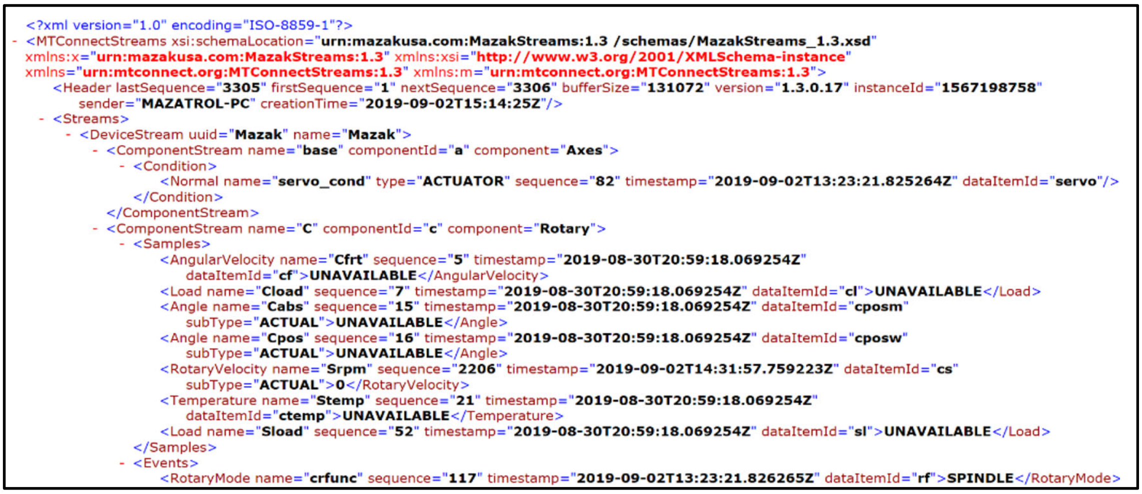


Fig. 3 Machining turning center (**a**), new insert (**b**), and worn insert (**c**)



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  xmlns:x="urn:mazakusa.com:MazakStreams:1.3" xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
  xmlns="urn:mtconnect.org:MTConnectStreams:1.3" xmlns:m="urn:mtconnect.org:MTConnectStreams:1.3">
    <Header lastSequence="3305" firstSequence="1" nextSequence="3306" bufferSize="131072" version="1.3.0.17" instanceId="1567198758"
      sender="MAZATROL-PC" creationTime="2019-09-02T15:14:25Z"/>
  - <Streams>
    - <DeviceStream uuid="Mazak" name="Mazak">
      - <ComponentStream name="base" componentId="a" component="Axes">
        - <Condition>
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          </Condition>
        </ComponentStream>
      - <ComponentStream name="C" componentId="c" component="Rotary">
        - <Samples>
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              dataItemId="cf">UNAVAILABLE</AngularVelocity>
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          </Samples>
        - <Events>
            <RotaryMode name="crfunc" sequence="117" timestamp="2019-09-02T13:23:21.826265Z" dataItemId="rf">SPINDLE</RotaryMode>
```


Fig. 4 Example from XML file generated in MTConnect®

wear on the shop floor is not always easy for the machine operator to perform. The exact setup time for changing the worn tool insert is always a challenge in manufacturing shops.

Overfitting issues were not observed, and the proposed OLAM model was not able to give correct values for all cases. The difficulty in preparing the main cutting edge and small differences between them usually causes variations in the results. These poor results can be partially attributed to the standard deviation observed in Table 3.

For the experimental run with no cutting fluid and wear $VB_B = 0.3$, the standard deviations observed in the CCX and CCZ values were higher compared with the other results. Probably, the OLAM weights associated with these parameters were not able to identify this variation, resulting in a loss of accuracy for this entire set of runs.

For real machining conditions, the presence of tool wear in the process is a natural source of variation. Tool wear changes the geometry associated with chip formation, which can in turn modify the machine's power consumption.

Identifying tool wear is a difficult task, and depends on the operator's expertise and knowledge as well as good vision, because the value of $VB_B = 0.3$ means that the operator has to search for a defect of 0.3 mm on the tool's side surface.

Another point is that OLAM is a linear classifier; if the overall condition is not linear and if the cases are not linearly separable, the learning process will never reach a point where all the cases are classified properly.

Fig. 5 Signal example of one test

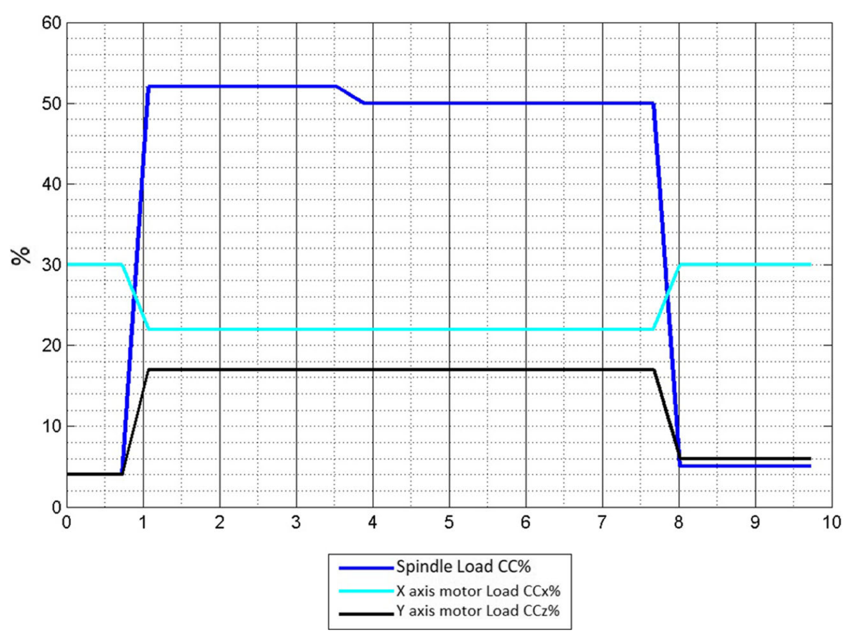

Table 2 Data collected for the tool without wear in material AISI P20

Cutting fluid: yes Wear: no										
Run	CC (%)	CCX (%)	CCZ (%)	Pm (kW)	RPM	Cutting fluid	vc (m/min)	*f* (mm/rot)	ap (mm)	VB_B (mm)
1	19.62	26.37	11.00	2.16	2512	1	150	0.20	1.000	0
2	21.00	27.95	12.00	2.31	1768	1	250	0.20	1.000	0
3	19.00	25.00	11.00	2.09	1836	1	150	0.30	1.000	0
4	33.37	35.69	15.48	3.67	2899	1	250	0.30	1.000	0
5	26.94	26.00	15.00	2.93	1338	1	150	0.20	2.000	0
6	42.00	26.00	15.00	4.62	2411	1	250	0.20	2.000	0
7	52.87	26.20	17.02	4.97	1183	1	150	0.30	2.000	0
8	41.37	32.24	13.06	4.52	1683	1	250	0.30	2.000	0
9	32.94	23.00	16.00	2.47	758	1	116	0.25	1.500	0
10	45.13	27.61	11.26	4.96	3930	1	284	0.25	1.500	0
11	25.60	26.36	14.00	2.82	2357	1	200	0.17	1.500	0
12	38.00	23.00	15.00	4.18	1354	1	200	0.33	1.500	0
13	15.00	30.00	9.00	1.65	1457	1	200	0.25	0.659	0
14	42.31	29.00	18.00	4.65	2053	1	200	0.25	2.341	0
15	31.29	29.97	34.22	3.37	2096	1	200	0.25	1.500	0
16	32.61	26.39	12.61	3.59	3031	1	200	0.25	1.500	0
17	35.00	27.25	14.25	3.85	2664	1	200	0.25	1.500	0
18	32.67	29.52	17.67	3.51	1428	1	200	0.25	1.500	0
19	34.56	27.06	13.75	3.80	2110	1	200	0.25	1.500	0
20	30.33	32.70	20.65	3.32	1344	1	200	0.25	1.500	0

4.2 Data-driven methods

In order to improve the OLAM-MLP results, statistical data mining methods (DMM) and data-driven methods (DDM), known as a self-organizing deep learning method, were employed in order to increase the success ratio of the model.

Aiming to assure the consistency of the data set values obtained during the experimental setup, the Student's *t* test was first employed to search for test situations that could be out of the normal distribution. This step was implemented as a data mining procedure over the entire data set. The standard deviation results associated with the worn tool condition (Table 3) showed higher overall values. A hypothesis was then raised in order to confirm the adherence of each test to the entire data set.

Table 3 Standard deviation of the results

Run	Standard deviation		
	CC	CCX	CCZ
Cutting fluid: no Wear: $VB_B = 0$	11.70	1.48	1.82
Cutting fluid: yes Wear: $VB_B = 0$	9.60	3.16	5.25
Cutting fluid: no Wear: $VB_B = 0.3$	11.41	6.99	8.10
Cutting fluid: yes Wear: $VB_B = 0.3$	14.15	2.19	5.80

After running the procedure, the data set was reduced from 160 runs (lines) to 123 runs (lines), showing that 37 lines of information acquired were out of the normal distribution of the experimental design. This new set was then clustered by the DDM self-organizing deep learning method through the CC, CCX, and CCZ parameters, resulting in two clusters (Figs. 7 and 8). The number of clusters was defined by the elbow method, where the number is chosen to be the value at which no significant changes are sensed by the model due to new values of clustering, the within clusters sum of squares method (WCSS) (Fig. 6).

The clustering result can be viewed in Figs. 7 and 8, where two red circles define the clusters points.

Figure 9a presents the flowchart for MLP OLAM single implementation, where the whole data set was directly used without any previous treatment. With this approach, the MLP-OLAM method was able to give 65% correct answers. Figure 9b presents the complete implemented procedure for

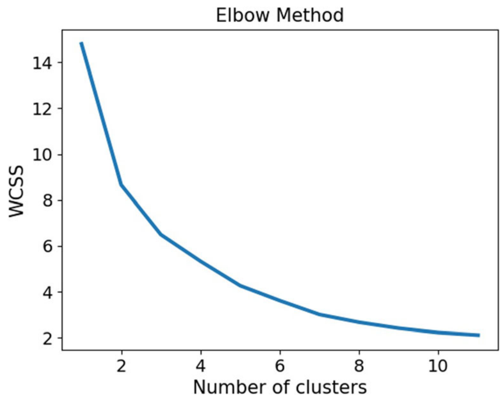

Fig. 6 WCSS versus number of clusters

the DMM-DDM-MLP OLAM method. First, the whole data set was tested with the Student's *t* test, then after separating non-normal experimental runs, the resulting data set was treated by a self-organizing deep learning method (*K*-means) that separated the two data sets.

After clustering, the two data sets were separately evaluated again with MLP OLAM. Data set A was found to have 59 lines from a total of 123 lines; for training, the MLP 3/4 of the data were used and 1/4 was used to validate. Data set B had 64 lines of which 3/4 were for training and 1/4 for validating. The MLP OLAM model increased its efficiency to 80% in data set A and 93.8% for data set B (Table 4).

5 Results discussion

Given the complexity of the machining process, even with a good accuracy of 93.8%, the algorithm results "*it must be substituted*", should be considered as a recommendation only, to serve as another support criterion in the decision of changing the tool.

According to [35], the optimal goal is that this information be finally incorporated into the machining policy design and process planning online through tool wear sensing methods.

Every day on the shop floor, many inserts are replaced before reaching the end of its service life. Often, the operator changes the insert because of the start of a new batch of parts, or because his shift has started; generally, a conservative industrial practice according to [36] states that to avoid failures and related consequences, tools are often replaced well before the end of their useful lifetime, or the machining data are set down to prevent tool wear leading an extra cost when data are about 20–50% lower than recommended for economical values [37].

Also [38], which implemented a naïve Bayes classifier, states that tool wear or breakages can result in unscheduled machine downtime in an industrial production environment, poor quality, or scrapping of the part resulting in a significant economic loss.

In industrial practice, the algorithms can serve as a support for the exchange decision, the operator may be required to make a visual inspection to confirm that the insert should be substituted, and, if the algorithm has made an incorrect indication, this information/condition can be added to the training database in order to improve subsequent results. In increasing algorithm amount data, fed with new validated conditions, its success rate tends to be better and more accurate.

The idea of the algorithm is to improve the use of the edges and notify the operator if the algorithm understands that the insert has reached the end of its life. Assuming a 6.2% error in a real case, the operator will still be able to validate the

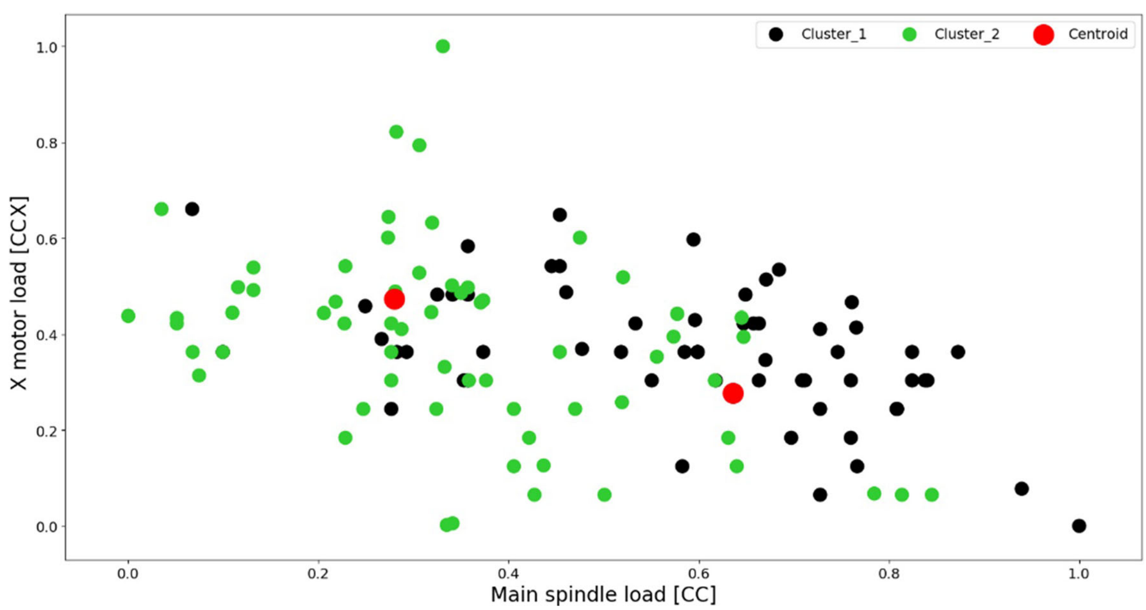

Fig. 7 Clusters centroids identified, 2D view for CC versus CCX

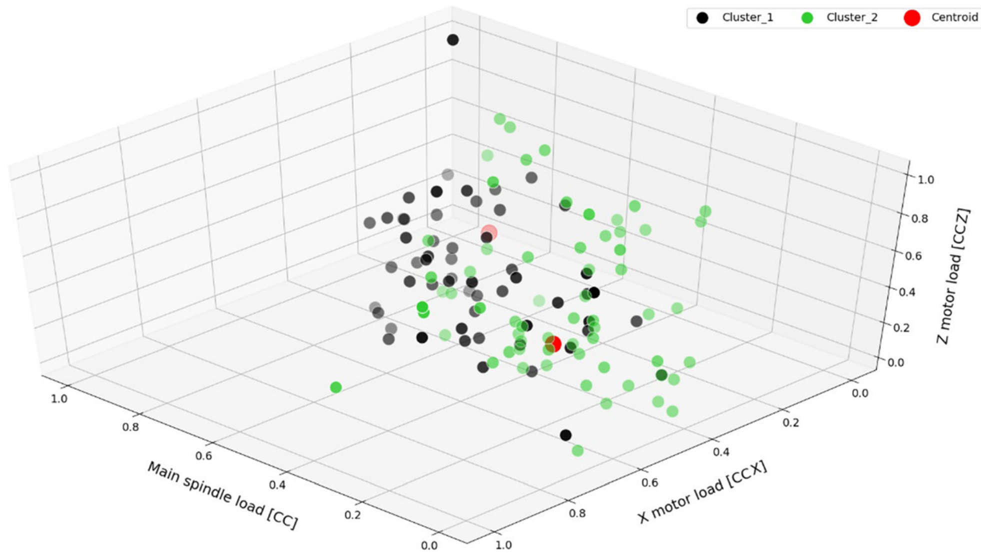

Fig. 8 Clusters centroids identified, 3D view of relationship

identification by discarding the insert or returning it to the machine, in the case of the 6.2% that possibly will have the wrong information.

Also, it is a reasonable practice that the operator supervises the processes to avoid the risk of having a tool breakage due to an incorrect algorithm, e.g., "*it can continue to work*" that may scrap the machined part or damage the machine.

6 Conclusions

A great advantage of this work is the fact that it does not use the expensive sensors or special dynamometers that are used widely in dedicated research. It was possible to work with the serial signals already made available by the machine through a standard and simple internet protocol.

For the present work, two approaches were adopted in order to analyze the data and create the machine learning process for predicting the end of life of a cutting tool in a machining process (tool wear).

Data were collected with the use of an MTConnect® monitoring system in the equipment. Despite its low acquisition frequency (1 Hz), this method proved to be reliable for the MLP application.

For a prior analysis, the collected data set was tested without any previous treatment, with an OLAM neural network.

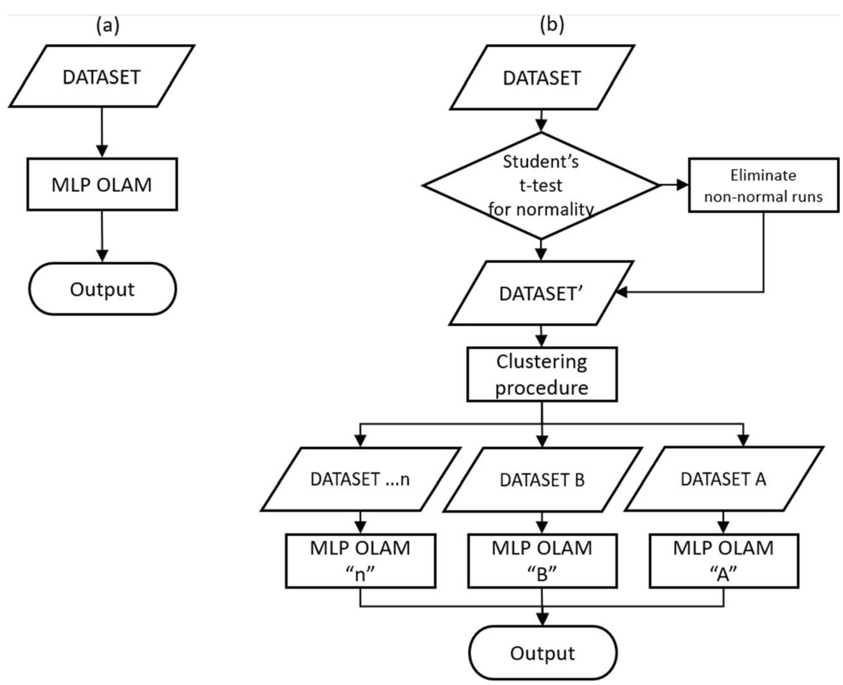

Fig. 9 (**a**) Flowchart for direct MLP OLAM neural network use. (**b**) Flowchart of complete implemented DMM-DDM-MLP OLAM procedure

Table 4 Results summary

Procedure	Cluster	Training runs	Validation runs	Correct answers
MLP OLAM	No	120	40	65%
DMM-DDM-MLP OLAM	A	44	15	80%
DMM-DDM-MLP OLAM	B	48	16	93,8%

The network was able to predict the results with a minimum of 65% reliability, which is adequate, given the number of tests used and the variation due to the results of the inserts with wear $VB_B = 0.3$. The MLP OLAM was programmed considering 3/4 of the data set for training and 1/4 for validation.

In the second approach, statistical data mining methods (DMM), Student's *t* test, and data-driven methods (DDM), known as a self-organizing deep learning method, were employed in order to increase the success ratio of the model. Both the DMM and DDM applied along with the MLP OLAM neural network showed an increase in hitting the right answers of between 80 and 93.8%.

This application can be adapted in a supervisory system to advise the moment for tool change in industrial applications, eliminating or reducing the need for the machine operator to intervene in the tool change process, and thus giving the equipment autonomy.

This model can be useful in machine monitoring using Industry 4.0 concepts, where one of the key challenges in machining components is to find the best moment for making a tool change.

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