MTconnect monitoring to predict tool wear in turning

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Abstract. The objective of this work was to identify the exchange point of a carbide insert in a turning center through data collected during machining using MTConnect® communication protocol. Eighty trials were performed through design of experiments using central composite design and varying the cutting parameters: cutting speed (150-200 m/min), feed rate (0.2-0.3 mm/v), cutting depth (1-2 mm), cutting fluid (in abundance and dry). The collected data were: spindle load, X axis load, Z axis load and spindle power during the turning of AISI P20 steel, with new and worn inserts on the main edge (Vb = 0.3 mm). To analyze the data was used the OLAM Neural Network. The results showed a hit percentage of 70%, showing the viable application for the identification of the exchange point. This model can be useful in machine monitoring using Industry 4.0 concepts, where one of the key challenges is finding the tool change point that most often depends on the operator.

Keywords: machining learning, MTConnect, wear.

1 Introduction

Manufacturing has been a fundamental aspect to national development and prosperity. It greatly contributes 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 (Preez; Oosthuizen, 2019).

The direct contact between cutting tool, workpiece material, and the chips during machining operation imposes extreme thermal and mechanical stresses on the cutting tool. As a result, changes to the geometry, volume loss, and sharpness of the cutting tool, can occur either gradually or abruptly. These changes, which are known as tool wear, normally take place at the rates dependent upon machining conditions, workpiece material, as well as the cutting tool material or geometry (Azmi, 2015). Experienced operators can determine if the tool has failed according to these changes. This way is easy to cause two problems: Firstly, it's too early to change the tool that the tool has not reached the service life, which causes tool waste and increases tool cost; Secondly, if the tool changes too late, it is easy to cause that the surface precision of the parts is not enough or the parts are damaged because the tool is working in a failure state (Yang et al, 2019).

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 remaining life for effective management of manufacturing lead time. Dimensional tolerances as well as the quality of the finished workpieces are dependent on this. Given high stresses, friction and temperature that tools must withstand, wear is inherent to any cutting process. A method for early detection and monitoring of wear evolution is a necessity within a ''just in time'' policy for tool change. Tool wear monitoring methods can be classified into two groups: I) direct methods in which wear is directly measured using optical, radioactive or electrical resistance sensors; II) indirect methods which perform wear evaluation on the basis of parameters measured during the cutting operation: cutting forces, acoustic emission or vibrations (Kilundu; Dehombreux; Chiementin, 2011).

Tool condition monitoring is gaining more consideration in automated manufacturing process in recent time (Gouarir et al., 2018) 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 casualty of the operators (Kong et al, 2019).

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 tool condition, and (2) revealing tool wear progression pattern based on variations in the sensing data. Compared to a new tool, a worn tool has a different cutting edge geometry, and accordingly, the associated sensing signals (Wang et al, 2019).

1.1 IOT

MTConnect® is an open, royalty-free manufacturing communication protocol that enables communication between manufacturing devices with others softwares.

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. Easy to implement this network platform can help companies monitor equipment or manufacturing cells, reducing losses and optimizing production.

Fig. 1 shows Mazak machines (Mazak, 2019) general scheme of the communication pattern application where the adapter consists of a communication card connected to the machine panel that collects the CNC information and sends it to the MTConnect agent who organizes and maintains the data for later transfer in the network. .

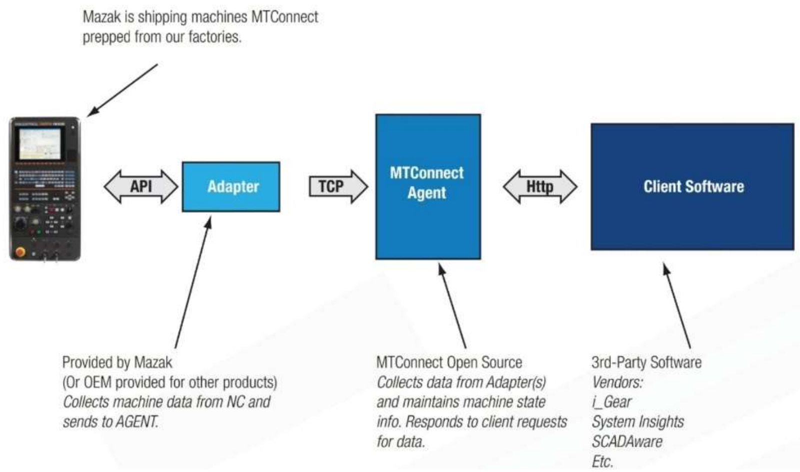


Fig. 1. MTConnect® general scheme. (Mazak, 2019)

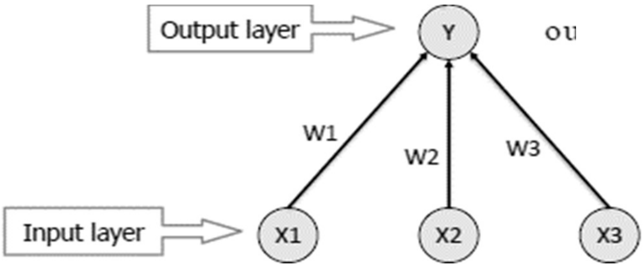
Once available on the network and knowing the access address, it is possible to collect the information from the XML file using any software programming language. In this work Matlab® software was to read XML directly from the network where the machine was connected.

1.2 Machine learning

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 (Li et al, 2019).

The optimal linear associative memory OLAM model, as proposed by Kohonen 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 a stored data by specifying all or portion of a key (degraded key). The 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, Fig 2 shows a schematic operation



$$X_1W_1 + X_2W_2 + X_3W_3 + \cdots X_nW_n += +Y \xrightarrow{yields} +1$$

$$X_1W_1 + X_2W_2 + X_3W_3 + \cdots X_nW_n += -Y \xrightarrow{yields} -1$$

Fig.2. Schematic operation of an OLAM

The objective of this work is to stablish the correct moment to change the worn tool using the machine signals monitored via MTConnect.

2 Methods and Materials

A Design of Experiments "Response Surface Design" with 6 center points was used to stablish the 20 experiments as indicated on the Table 1

Table 1. Table captions should be placed above the tables.

Input Parameter	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

Insert wear (VB) was considered a fixed condition for all runs with wear V_B=0 meaning new insert and V_B = 0,3 mm a worm tool. A digital microscope was used for the tool wear control. Also the cutting fluid was taken to be fixed each sequence (20 tests) was made with cutting fluid (first set) and without (dry condition-second set).

The insert used was the the Model CNMG 120408 PM from Sandvik Coromant and the Holder Coroturn 107. A total of 80 runs was performed in order to create a data set to train a machine learn model.

The material for all the tests was the AISI P20 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 Hv = 291.

A MTConnection linked with a Matlab Software were used to the monitoring of the machine. The Fig. 1 shows the machining turning center Mazak Quick Turn 200MA 500U used for all the tests. In the same Fig. 3 is possible to observe the insert in the initial condition and the worn insert.

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

The wear condition of the tool is very difficult to control, since it was obtained from machining tests and manual operator measurements by a digital microscope. This variable certainly will affect the net results on the runs.

The Fig. 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.


```
  <?xml version="1.0" encoding="ISO-8859-1"?>
- <MTConnectStreams xsi:schemaLocation="urn:mazakusa.com:MazakStreams:1.3 /schemas/MazakStreams_1.3.xsd"
  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>
             <Normal name="servo_cond" type="ACTUATOR" sequence="82" timestamp="2019-09-02T13:23:21.825264Z" dataItemId="servo"/>
           </Condition>
         </ComponentStream>
       - <ComponentStream name="C" componentId="c" component="Rotary">
         - <Samples>
             <AngularVelocity name="Cfrt" sequence="5" timestamp="2019-08-30T20:59:18.069254Z"
                dataItemId="cf">UNAVAILABLE</AngularVelocity>
             <Load name="Cload" sequence="7" timestamp="2019-08-30T20:59:18.069254Z" dataItemId="cl">UNAVAILABLE</Load>
             <Angle name="Cabs" sequence="15" timestamp="2019-08-30T20:59:18.069254Z" dataItemId="cposm"
                subType="ACTUAL">UNAVAILABLE</Angle>
             <Angle name="Cpos" sequence="16" timestamp="2019-08-30T20:59:18.069254Z" dataItemId="cposw"
                subType="ACTUAL">UNAVAILABLE</Angle>
             <RotaryVelocity name="Srpm" sequence="2206" timestamp="2019-09-02T14:31:57.759223Z" dataItemId="cs"
                subType="ACTUAL">0</RotaryVelocity>
             <Temperature name="Stemp" sequence="21" timestamp="2019-08-30T20:59:18.069254Z"
                dataItemId="ctemp">UNAVAILABLE</Temperature>
             <Load name="Sload" sequence="52" timestamp="2019-08-30T20:59:18.069254Z" dataItemId="sl">UNAVAILABLE</Load>
           </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®

The collect data were: CC – Spindle load; CCx – X axis load; CCz – Z axis load; Pm – Spindle power.

To access the instances and read the XML protocol data, a program was created in the Matlab® software that aimed to collect the load values on the machine spindle motor, X axis servomotor and Z axis servomotor. Fig. 5 presents the interface designed to be used at the time of collection. A computer connected to the same network as the machine accessed the XML protocol and acquired the information during the Matlab® application trial. The start of collection synchronized with the beginning of machining, the duration of the collection was previously estimated to coincide with the end of machining.

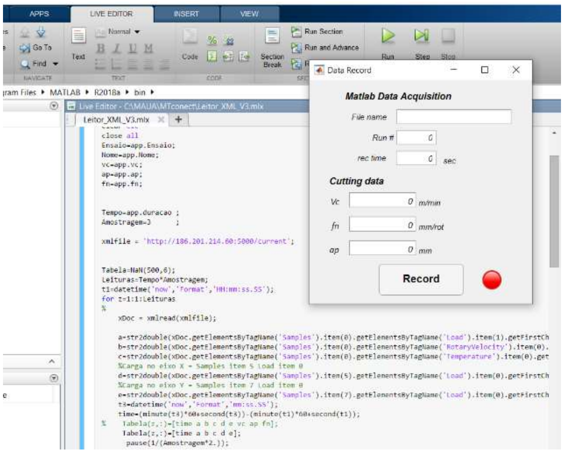


Fig. 5. Matlab application created for the online collect data

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

3 Results and discussions

The Fig. 6 shows an example of the graph generated during one of the tests. The default MTconnect® XML protocol update frequency for the network is one second (1 Hz), the Matlab script was programmed to acquire the file three times per second (3Hz) 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. 3 eliminating the first second of collection and the final three seconds. Once the values were filtered, the values were averaged to normalize the assay responses.

The Table 2 and Table 3 show some test input factor values have been normalized to -1 (not applied or non-existent factor) and 1 (used or existing), it is the case for the use or not of cutting fluid and for the existence or no wear.

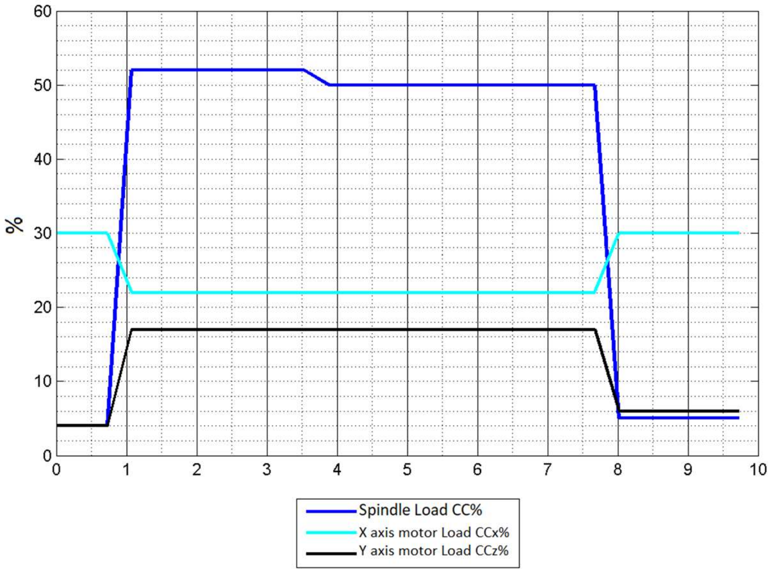


Fig. 6. Signal example of one test

An OLAM (optimal linear associative memory) linear neural network was programmed from the results of the machining tests. The ultimate goal was to predict whether or not tool wear was present during the machining process. The entire data set was used in the preparation of the model (network training), the model effectiveness was tested comparing the network response versus the wear condition (VB) of the tests.

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

The OLAM neural network showed reasonable hit rates overall. For the tests with cutting fluid condition and no wear the index was the highest of 90%. The worst case was without cutting fluid and worn tool insert the index was 65%, which is also an excellent result as the assessment of tool wear on the shop floor is not always easy for the machine operator to perform. The exact setup time for changing the worm tool insert is always a challenge in manufacturing shops.

Although the use of the entire data set could result in overfitting issues, the proposed OLAM model wasn't able to give correct values for all cases. The Table 2 represents the runs made with new tool insert (V_B=0) and use of cutting fluid, the model was able to give 90% of correct values.

The Table 3 presents the final results for the other runs. The results were: 85%, 65% e 80%. As mentioned before, the worn insert tool sets for both cases showed lower successful rate than compared to new insert tool. One reason is the difficult to prepare the main cutting edge and small differences between then. Another reason for this poor's results can be partially addressed to the standard deviation observed in Table 3.

For the experimental run with no cutting fluid and wear VB= 0,3, the standard deviation observed in c CCX and CCZ values were the higher compared to the others results. Probably the OLAM weights associated with these parameters were not able to identify this variation, resulting in loss of accuracy for this entire set runs.

				Cutting fluid: YES		Wear: NO					Network	
Run	CC	CCX	CCZ	Pm	RPM	Cutting fluid	vc	f	ap	VB	VB_OLAM	errors
1	19.62	26.37	11.00	2.16	2512	1	150	0.20	1.000	-1	**-1**	0
2	21.00	27.95	12.00	2.31	1768	1	250	0.20	1.000	-1	**-1**	0
3	19.00	25.00	11.00	2.09	1836	1	150	0.30	1.000	-1	**-1**	0
4	33.37	35.69	15.48	3.67	2899	1	250	0.30	1.000	-1	**-1**	0
5	26.94	26.00	15.00	2.93	1338	1	150	0.20	2.000	-1	**-1**	0
6	42.00	26.00	15.00	4.62	2411	1	250	0.20	2.000	-1	**1**	1
7	52.87	26.20	17.02	4.97	1183	1	150	0.30	2.000	-1	**-1**	0
8	41.37	32.24	13.06	4.52	1683	1	250	0.30	2.000	-1	**-1**	0
9	32.94	23.00	16.00	2.47	758	1	116	0.25	1.500	-1	**-1**	0
10	45.13	27.61	11.26	4.96	3930	1	116	0.25	1.500	-1	**-1**	0
11	25.60	26.36	14.00	2.82	2357	1	200	0.17	1.500	-1	**-1**	0
12	38.00	23.00	15.00	4.18	1354	1	200	0.33	1.500	-1	**-1**	0
13	15.00	30.00	9.00	1.65	1457	1	200	0.25	0.659	-1	**-1**	0
14	42.31	29.00	18.00	4.65	2053	1	200	0.25	2.341	-1	**-1**	0
15	31.29	29.97	34.22	3.37	2096	1	200	0.25	1.500	-1	**1**	1
16	32.61	26.39	12.61	3.59	3031	1	200	0.25	1.500	-1	**-1**	0
17	35.00	27.25	14.25	3.85	2664	1	200	0.25	1.500	-1	**-1**	0
18	32.67	29.52	17.67	3.51	1428	1	200	0.25	1.500	-1	**-1**	0
19	34.56	27.06	13.75	3.80	2110	1	200	0.25	1.500	-1	**-1**	0
20	30.33	32.70	20.65	3.32	1344	1	200	0.25	1.500	-1	**-1**	0
												2
											Successful	**90%**

Table 2 – Collect data for the tool without wear

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

Identify tool wear is a difficult task, it depends on the operator's expertise and knowledge and also a good vision because a V_B= 0.3 means that the operator has to search for a defect of 0. 3 mm on the tool side surface.

Run		Standard deviation				Successful
		CC	CCX	CCZ	Pm	
Cutting fluid: NO	Wear: VB=0	11,70	1,48	1,82	1,21	85%
Cutting fluid: YES	Wear: VB=0	9,60	3,16	5,25	1,00	90%
Cutting fluid: NO	Wear: VB=0,3	11,41	6,99	8,10	1,21	65%
Cutting fluid: YES	Wear: VB=0,3	14,15	2,19	5,80	1,43	80%

Table 3 – Standard deviation of the results

Another point is that OLAM is a linear classifier, perhaps 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.

Maybe the use of another machine learning that covers nonlinearity issues could result in better results.

4 Conclusions

The use of MTConnect monitoring system in the equipment, despite of its low acquisition frequency (1Hz), proved to be reliable for the application.

The network was able to predict the results with a minimum of 65% reliability, adequate, given the number of tests used and the variation due to the results of the inserts with wear VB=0.3.

The application can be adapted in a supervisor system to advise the moment of tool change in an industrial application.

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