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A New Architecture Paradigm for Tool Wear Prediction during AISI 9840 Drilling Operation

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Abstract

In conventional machining processes based on the chip removal mechanism, the progressive wear of the tool determines a change of the geometric characteristics of the cutting edge. Tool wear is a complex phenomenon and related tool life depends on several factors, such as cutting parameters, lubrication, and tool-workpiece relative trajectories. Tool wear progression affects the quality of the machined parts, making the tool replacement necessary even before its breakage. Moreover, in industrial practice, tool replacement cannot depend on the subjectivity of the operator, thus, the definition of an optimized strategy for cutting tool wear monitoring before tool failure is mandatory. This work compares Random Forest and Neural Network models for predicting tool wear in drilling. For the development of predictive models, tool life tests were performed by drilling through holes on AISI 9840 steel parts, with a coated tungsten carbide drill of 8 mm of diameter and by using constant cutting parameters. Flank wear of the tool was monitored. A set of statistical features computed from the vibration signals, the acoustic emission signals, the power signals and the torque signals constitute the input of the algorithms. The classification accuracy was 88% and 91% for Neural Network and Random Forest models respectively. In order to correctly define the tool replacement policy during production, the developed Random Forest model has been implemented in an industry, through production management software, achieving promising results.

Keywords: Drilling; Tool wear monitoring; Random Forest; Neural Networks.

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1. Introduction

Tool wear monitoring is one of the most important and urgent problems to solve in order to realize fully automated systems. Drilling is one of the processes commonly used in material removal operations. It represents one third of all material removal operations in industries [1] and consequently the studies about the monitoring of the drills wear are crucial to improve efficiency and sustainability of the metal cutting processes.

Regardless the type of machining process, the wear determines two main effects on the tool geometry, i.e. the flank wear and the crater wear on the rake surface [2,3]. These latter, due to their influence on tool life, replacement policy, manufacturing costs, surface integrity, and surface roughness [4,5], are assessed by two numerical parameters: the width of flank wear (VB), and the ratio K, defined as the ratio between the maximum depth of the crater on the rake surface (KT) and its distance from the unworn cutting edge (KM). In drilling, VB can be calculated in different positions of both cutting edges [6] or only the maximum value of VB can be considered [7,8].

Tool wear measurement methods are direct and indirect. The direct method is implemented using optical devices to measure the geometry of the tool wear. The indirect method is based on the acquisition of signals during machining, and on the identification of the relationship between tool wear and the signals, such as acoustic emission or spindle vibration. However, the direct method cannot continuously evaluate the tool wear because the geometry of the drill is not visible during a cutting operation, while the indirect method allows continuous estimation of tool wear [1]. In a production line, thanks to sensors and data acquisition systems (DAQ), the indirect method is able to automatically collect reliable data during processing and to monitor the trend of tool wear based on the collected data. Furthermore, the implementation of predictive models based on Random Forest (RF) and Neural Network (NN) methodologies can anticipate the wear evolution, allowing the correct estimation of the tool life.

During last years, the indirect monitoring of tool wear in industrial process has been subjected to a deep investigation. In [6], an evaluation of the real-time prediction of tool wear/break when drilling Inconel 625, through NN based on spindle power data was described. Oberlè et al. [9] examined the behaviour of the RF algorithm on the prediction of tool life in drilling, by acquiring the torque values of the spindle with a frequency of 1000 Hz, for each tool at regular intervals, until the predefined end of tool life is reached. Ravikumar and Ramachandran studied tool condition monitoring based on sound signals using a RF classifier [10]. In [8], the acoustic emission (AE) signal has been used for the drilling monitoring system. In [11], performance tool was monitored by acquiring the vibration signals developed during the drilling of stainless steel plates by means of HSS tools. A multisensory data fusion approach was adopted in [12] to monitor the tool wear and to develop an artificially intelligence (AI) based predictive model.

This document aims to describe in detail the steps and the architecture of a predictive maintenance system able to monitor and to predict flank wear in drilling. In order to collect the data necessary for the model development, experimental tests were performed by drilling AISI 9840 steel sample with a coated tungsten carbide drill. During the drilling operations, the VB parameter was measured both directly and indirectly. The direct method was carried out with the use of an optical microscope, while the indirect method exploited the use of sensors such as accelerometer and AE. In addition, the power and torque developed by the spindle during the process were acquired directly from the numerical control (CN) of the machine tool. In the first phase of the analysis, the NN and the RF were considered as models for predicting tool wear. A Standard Scaler was used to improve the precision of the models. For each model a grid search was performed with the application of different combinations of parameters. Each combination was evaluated using the K-Fold Cross Validation (KCV) [13] technique and using the accuracy as an optimization measurement.

2. Architecture of the tool wear predicting model

In this section, the architecture of the Machine Learning (ML) model suitable to predict tool wear in industrial applications is described. The model must be trained by providing both offline and online experimental measurements to be correlated to the tool wear. For doing this, the direct measurements are useful to calibrate the indirect measurements continuously acquired during machining. The online sensors produce signals that are first translated through the data acquisition system and then analyzed to create the correct dataset to insert into the AI model. The entire procedure is summarized in Fig. 1. The architecture can be divided in three main sections, i.e. the data source, the data acquisition and processing, the analysis and prediction of the tool wear.

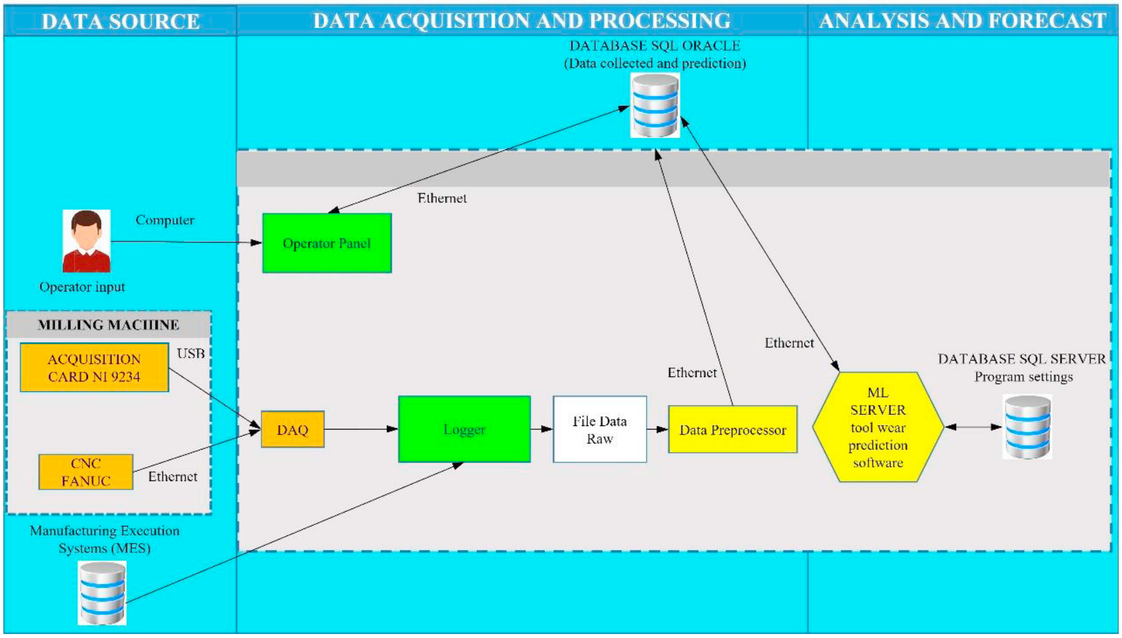


Fig. 1. Architecture of the tool wear predictive model.

The data source represents the data involved in the process. They can be classified by considering the three origins of the data: the logistics software for Manufacturing Execution Systems (MES); the machine tool and the sensors installed on it; and the operator. The MES software contains all the information regarding the machining process to be performed on a given machine tool, such as the tool diameter, the tool length, the number of tool flutes, the material of tool and workpiece. Moreover, it contains the technological process parameters for a specific operation, such as, the feed rate and the cutting speed. The physical and process signals measured during machining are acquired from the machinery using sensors and data supplied by the CN. More information about the monitored signals for the specific study case described in this work will be provided in the following section. Finally, the operator must enter the data which are not currently present in the MES software, such as the state of tool wear VB, the image of tool wear VB and an identification code of the employed tool.

The data acquisition and processing task is performed through some software that collect and subsequently elaborate the data in order to provide a suitable input to the machine learning algorithms. Four different software are employed:

- Data Acquisition (DAQ) Device Manager
- Operator Panel
- Logger
- Data Preprocessor

The DAQ Device Manager is responsible for interfacing with various data acquisition devices and providing a unified interface for one or more data consumers. The Operator Panel, visible in Fig. 2, has the task to authenticating the user who wants to access the system, reading the predictions made by the ML model and showing them to the user, allowing the operator to add notes on the wear of the tool, writing the inputs provided by the user in the database.

Logger has the task of collecting data from DAQ Device Manager and from the MES, identifying when the tool is working to record the machining data.

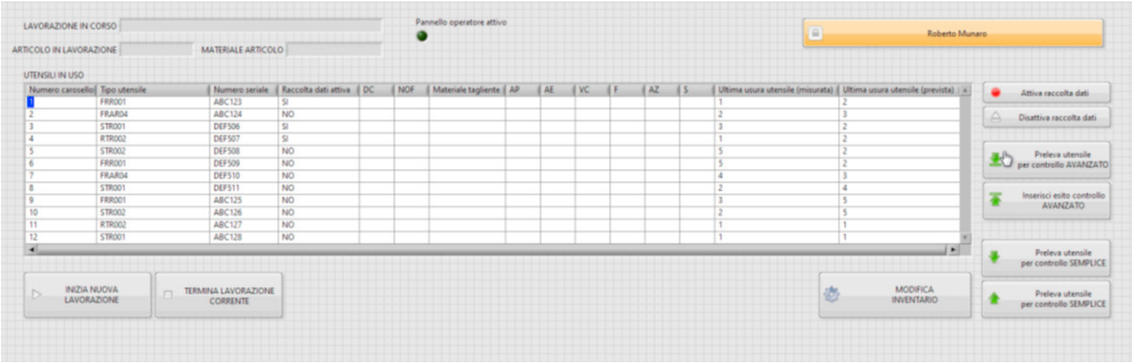


Fig. 2. Architecture of the tool wear predictive model.

Data Preprocessor has the task of processing the recorded data to compute and extrapolate summary features, e.g. the signal main frequency from Fast Fourier Transform (FFT). The Data Preprocessor saves the extracted features in the SQL database.

The analysis and prediction part of the algorithm is deputed to supervise the training phase of the ML model and the classification the states of wear of the tools. In fact, a Wear Level (WL) index is defined as an integer ranging on two levels. WL index is computed by assuming a starting value equal to 1, which corresponds to a VB value of 0 mm. A WL index of 2 correspond to the maximum acceptable value of VB, named as VBMAX. During the training phase, the WL index is computed by performing a linear interpolation between VB = 0 and VB = VBMAX and the calculated index is rounded to the nearest integer. When the model is in production, for each record entered in the database, the ML model must make a prediction about the state of wear of the tool used. The result is saved in SQL database.

The SQL database consists of:

- a Tool table, which represents the catalogue of tools used during machining. They can be added by the user. A record consists of a unique identifier, a serial number that identifies the tool;
- a Tool Type table, which represents the different types of tools and their characteristics, such as the diameter, and the process parameters;
- an Article table, which represents the catalogue of the articles produced during the manufacturing process;
- an Article Type table, which represents the various types of articles and their intrinsic characteristics (material, hardness of material, etc.);
- a Machine Setting table, which represents the configuration of the machinery during a certain process;
- a Quality Check table contains the result of the tool wear measurement. It is identified by the time the check was made, the ID of the user who made the check, the ID of the machine configuration on which the check was performed, the VB value or other quality indicator, and the level of wear (Wear Level) detected by the operator;
- a Feature table, which contains a row for each machining done with the selected tip. Each line contains the timestamp of when the machining was done, the features extracted from the Logger and the Label field, initially empty. Label is used during the training phase by the machine learning algorithm and is compiled afterwards using the quality checks provided by the operators;
- a Forecast table contains the predictions made by the machine learning model for each individual recording. They can be used from the operator panel to show the user the estimated wear status of the drill.

3. Experimental study case

In this section, the procedure described in Section 2 is applied to an industrial application, consisting of a through pass drilling. The drilling operations are performed on a 5-axis vertical machining centre, Robodrill Fanuc CNC Series 31i-B5 Plus.

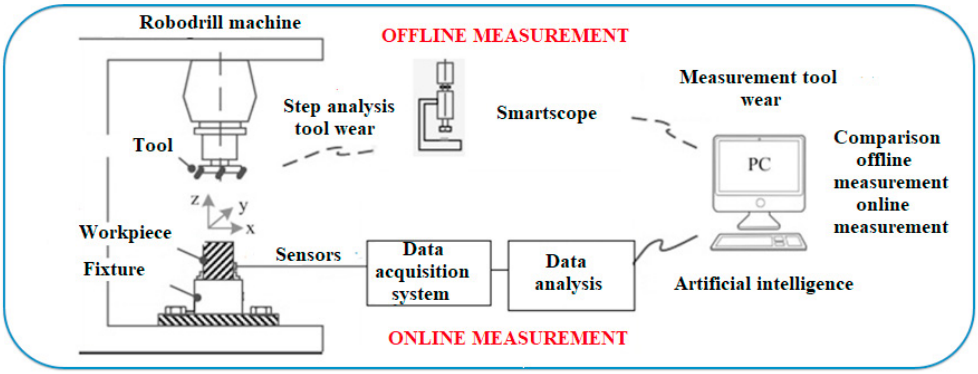
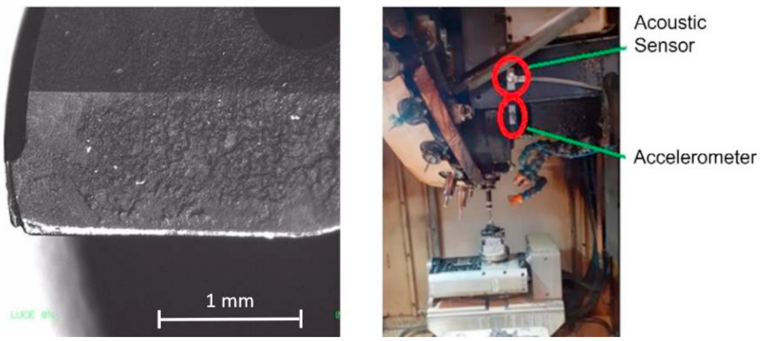


Fig. 3. Description of the experimental procedure to collect data for the training of the ML model of tool wear.

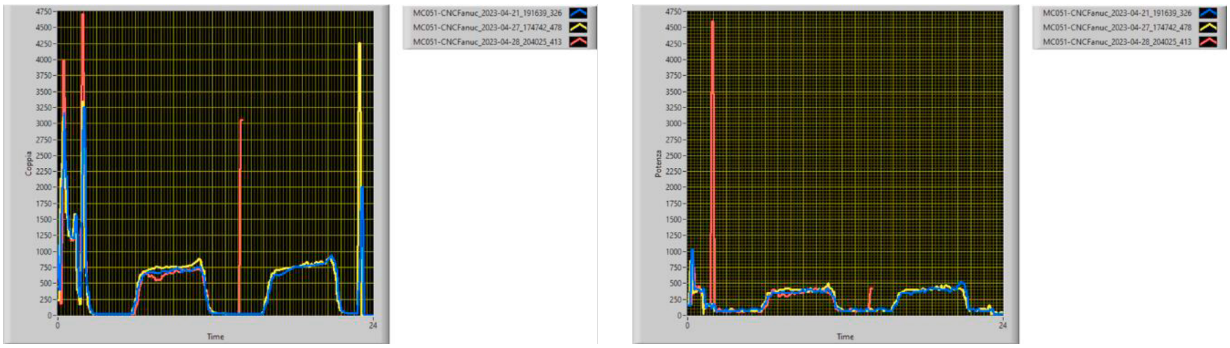
3.1. Drilling test on instrumented machine

An industrial product in AISI 9840 is drilled by using a solid carbide drill coated with nano Chrome and Nickel layer (OSG 8688908 ADO-PLT). The main geometrical features of the drill are parabolic flutes, a diameter 8.03 mm, a point angle 160°, drilling depth of 40 mm and a total length of 90 mm. Based on the drilling literature for AISI 9840, a spindle speed S = 1200 rpm and a feed rate F = 70 mm/min were selected to conduct the experiments and to obtain the best possible data sets for the ML model training. The experiments were performed with a water-soluble coolant at a concentration of 6%. The experimental procedure is schematized in Fig. 3. It consists in machining a specific number of parts before performing the offline measurements of the VB parameter by using the optical microscope OGP SmartScope LITE 300 with a high-magnification camera of x400. The procedure is iteratively repeated until the limit value of VBMAX equal to 0.185 mm is reached. Fig. 4a provides an example of the VB offline measurement. During the machining operations, the system continuously performs the online measurements. They consist in the spindle power signal and the spindle torque signal acquired from the library of numerical control (CNC FANUC Focas), the vibration in x, y and z directions acquired from three accelerometers (sensor Kistler 8763B500CBSP5) and the sound acquired from an acoustic emission sensor (sensor Kistler 8152C1050510). Fig. 4b shows the sensors installed on the machine, while Fig. 5 illustrates an example of the acquired signal.



(a) (b)

Fig. 4. An example of worn profile of drill (a) and the illustration of the sensors mounted on the machine structure (b).



(a) (b)

Fig. 5. An example of torque signal (a) and spindle power signal (b).

The data acquired through sensors are read through an acquisition card (NI 9234), which is mounted on a compact DAQ chassis (NI cDaq 9184). The 80% of the experimental data are employed to train the algorithm, while the remaining 20% are used to test the model: for a total number of 9 tools for the training phase and 3 tools for the testing.

3.2. Software architecture

A Logger (iDaqDTLogger) has the task to collect the data previously described only during machining and if the tool is one of those indicated by the Operator Panel as a selected tool for data acquisition.

The Data Preprocessor extracts some variables from the signals, in the time and frequency domains both, and it provides the data to ML algorithm. More specifically, power and torque are elaborated in time domain in order to compute the power plateau time, power plateau average value, power plateau standard deviation, torque plateau time, torque plateau average, torque plateau standard deviation. Vibration and acoustic emission are elaborated in frequency domain through FFT analysis. The computed variables are peak frequency, peak frequency power density, 2500-4000 Hz band power, 2500-4000 Hz band peak frequency, band power density 2500-4000 Hz, band power 5500-7000 Hz, band peak frequency 5500-7000 Hz, band power density 5500-7000 Hz, band power 8500-10000 Hz, band peak frequency 8500-10000 Hz, density power band 8500-10000 Hz.

Before computing the features, some manipulations are performed on the signal. More specifically, the first 3 seconds and the last 2 seconds of recording are cut, because they correspond to the tool change; the first plateau of the power and torque signal is identified (even when the drilling are more than one), approximating the square wave signal and extracting the part of the signal where it rises and then it falls again above a minimum threshold (double threshold). The head and tail are cut from the extracted part until the value exceeds the 25th percentile of the extracted values, to avoid taking transients into consideration as well.

Once the mathematical variables are computed, they are used to train the ML algorithm to predict the WL index. During a preliminary analysis, several classifiers were tested and compared. The two most promising classification models resulted the Random Forest and the Neural Network. Furthermore, the preliminary analysis demonstrated as the usage of a scaler is useful to improve the accuracy of the models, especially as regards the Neural Network. In this case a Standard Scaler was employed only on training data. A grid search was performed for both models, with the application of different combinations of the setting parameters of the ML models. Each combination was then evaluated using the K-fold Cross Validation (KCV) technique (with k = 5) and using the accuracy as an optimization measure. For each model and for each combination of parameters, the following outputs were calculated: the average value of the accuracy, calculated on the 5 folds of the training set; the standard deviation of the accuracy, calculated on the 5 folds of the training set; the accuracy obtained on the predictions made on the test set; the precision obtained on the predictions made on the test set; the sensitivity (recall) obtained on the predictions made on the test set; the combination of parameters used for that particular model training.

4. Results

The optimized setting parameters of NN and RF models, named as Neural Network 1 and Random Forest 1, are listed in Table 1 and Table2.

Table 1. Optimized parameters for NN model.

Model	Alpha	Beta 1	Beta 2	Hidden Layer Sizes	Learning rate	Learning rate init.	Max iter.	Random State
NN	1	0.9	0.9	100, 10	costant	0.001	10000	42

Table 2. Optimized parameters for RF model.

Model	Bootstrap	Max depth	Max features	Min impurity decrease	N estimators	Random State
RF	True	30	sqrt	0.0001	5000	42

The best results obtained from the two employed classifiers, are summarized in Table 3. The results show that both the Neural Network and the Random Forest ML models are capable of achieving very high percentage values of precision and accuracy. These latter are in fact always greater than 80%. The algorithm was initially trained on all the data computed from the Data Processor.

Table 3. Prediction of Neural Network and Random Forest ML algorithms.

Model	Mean accuracy	Std accuracy	Accuracy test	Precision test	Recall test
Neural Network 1	0.88	0.007	0.88	0.93	0.85
Random Forest 1	0.89	0.017	0.91	0.92	0.90

The same experiment was repeated, using only the features extracted from the numerical control. With this second approach, the number of mathematical variables extrapolated by the signals was reduced from the original dataset to 6, calculated only on the power and torque signals. The best results for the classifiers of this second methodology, named as Neural Network 2 and Random Forest 2, are listed in Table 3.

Table 4. Prediction of Neural Network and Random Forest ML algorithms using only the features extracted from the numerical control.

Model	Mean accuracy	Std accuracy	Accuracy test	Precision test	Recall test
Neural Network 2	0.82	0.019	0.81	0.85	0.80
Random Forest 2	0.81	0.027	0.82	0.85	0.80

As visible, with the second approach, which limits the number of the analyzed features by using only the power and torque as source, there is a loss of accuracy of about 5-10%; that, in an industrial application of the algorithm, can be considered acceptable as well. The most considerable advantage of the second approach is the meaningful time and cost saving because only the data acquired from the CNC are employed, avoiding additional sensors.

The highest accuracy of the Random Forest model applied on the entire data set (Random Forest 1), is clearly visible by comparing the results of Table 3 and Table 4. Concerning this, Random Forest 1 was individuated as the best solution and then used to predict the tool wear of the entire dataset, including the data collected to evaluate the ML model performance.

An example of the results of the tool wear prediction for three different drills, as a function of the number of the executed drilling operations, is visible in Fig. 6. The plots on the left report the comparison between the values of WL index computed by using the offline measurements, reported as red circles, and the predictions made by the ML model, indicated with blue crosses. The graphs on the right show the related confusion matrix where the offline measurements and the ML model predictions of WL index are named as True label and Predicted label respectively. A “True” value of the label indicates that the VB_{MAX} has been reached, while the contrary if the label value is “False”. When both the labels assume the same value, there is agreement between the offline measurements and predictions, whilst if the two labels have different values (i.e.: True-False) there is a contradiction amongst measurements and predictions. Moreover, the confusion matrix reports the number of the cases staying in the different areas, giving estimation of the reliability of the ML model.

The overlap of the main part of both measured (red circles) and predicted (blue crosses) results underlines the good capability of the proposed model to forecast the tool wear behavior during the drilling operations. This is enforced as well by the high values of the number in the correspondence of the "True-True" or "False-False" combinations in the confusion matrix. Related to the not overlapped values, the more critical situation is when the tool has physically reached VB_{MAX}, while the failure has not been assessed by the prediction model. This is the case, in particular, for the first and the second tool shown in Fig. 6, where an edge crack was experimentally observed (Fig. 7).

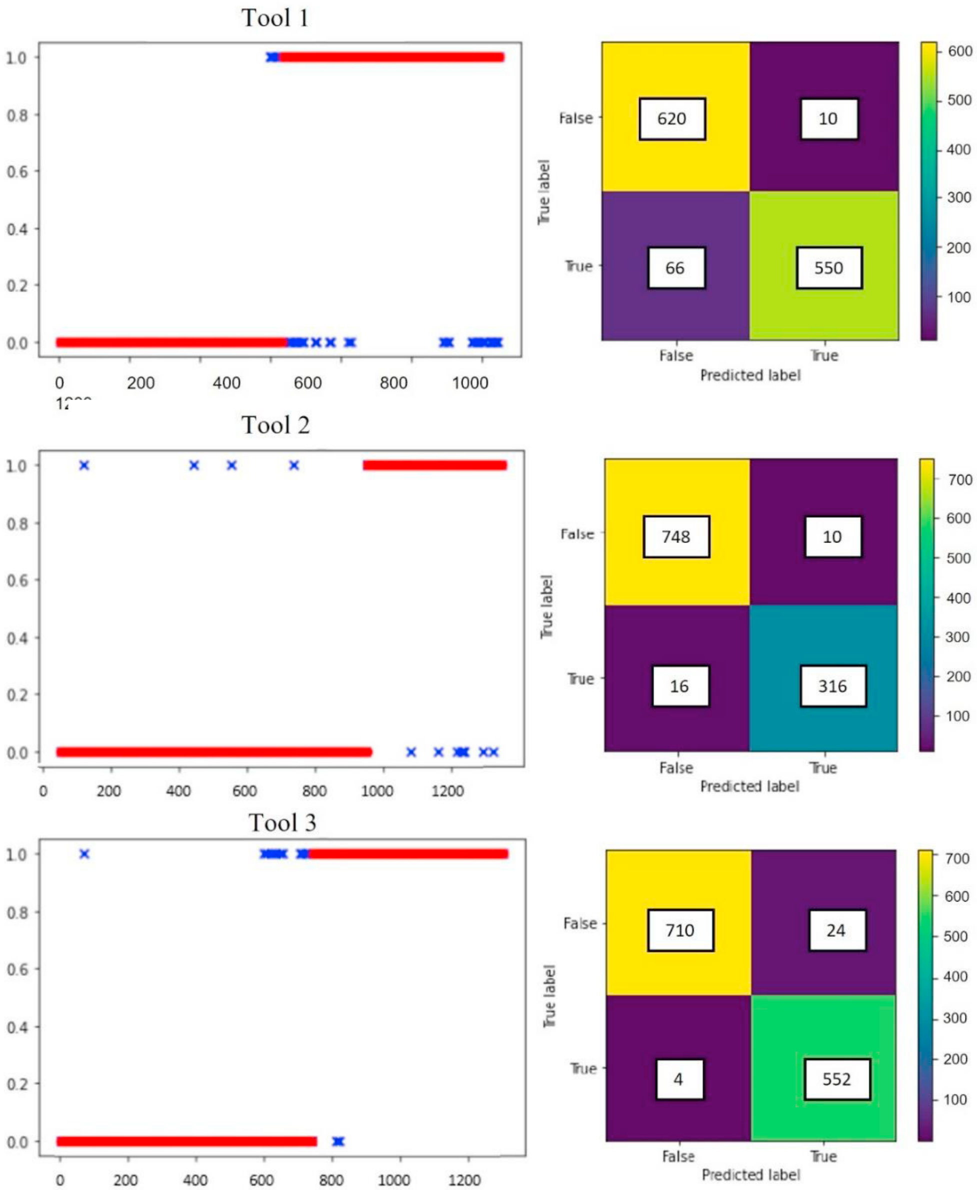


Fig. 6. Label calculation with WL index.

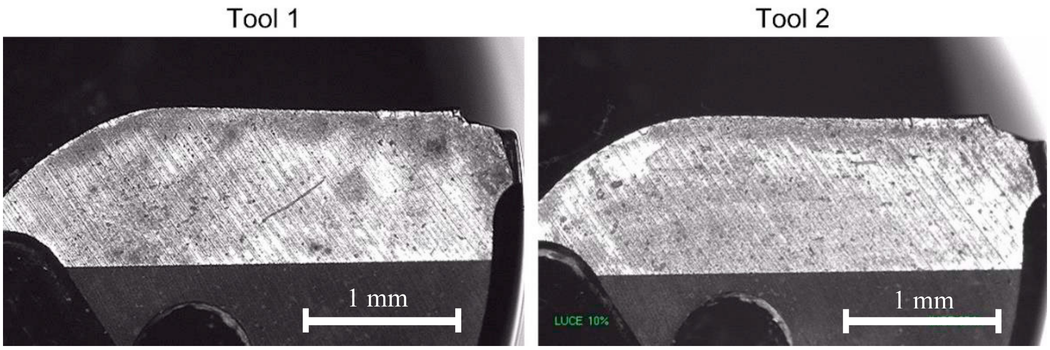


Fig. 7. Observed edge cracks on the tools.

5. Conclusions

A ML model able to predict the status of tool wear was successfully defined and implemented on an industrial study case. It was employed to monitor the flank wear in drilling by tuning an algorithm through the comparison between offline and online measurements. Several mathematical variables were computed by using the acoustic, vibration, spindle power and spindle torque as input and they were used to train ML models based on NN and RF. RF results to be the most reliable model and it was employed in the testing phase, achieving promising results. Further studies will be performed to correctly consider the effect of different tool wear mechanisms, such as the cutting edge cracking.

Acknowledgements

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