http://doi.org/10.24867/JPE-2022-01-020

Journal of Production Engineering
Vol.25 No.1

JPE (2022) Vol.25 (1) Original Scientific Paper

Milošević, M., Lukić, D., Ostojić, G., Lazarević, M., Antić, A.

APPLICATION OF CLOUD-BASED MACHINE LEARNING IN CUTTING TOOL CONDITION MONITORING

Received: 02 May 2021 / Accepted: 12 August 2021

Abstract: *One of the primary technologies in the Industry 4.0 concept refers to Smart maintenance or predictive maintenance that includes continuous or periodic sensor monitoring of physical changes in the condition of manufacturing resources (Condition monitoring). In this way, production delays or failures are timely prevented or minimized. In this context, the paper present a developed cloud-based system for monitoring the condition of cutting tool wear by measuring vibration. This system applies a machine learning method that is integrated within the MS Azure cloud system. The verification was performed on the data of the calculated central moments during the turning process, for cutting tool inserts with different degrees of wear.*

Key words: *Cloud manufacturing, machine learning, I 4.0, smart maintenance, condition monitoring.*

Primena mašinskog učenja zasnovanog na oblaku u praćenju stanja reznog alata. *Jedna od primarnih tehnologija u konceptu Industrije 4.0 odnosi se na Pametno održavanje ili prediktivno održavanje koje uključuje kontinuirano ili periodično senzorsko praćenje fizičkih promena u stanju proizvodnih resursa (Monitoring stanja). Na ovaj način se kašnjenja u proizvodnji ili kvarovi blagovremeno sprečavaju ili minimiziraju. U tom kontekstu, u radu je predstavljen razvijen sistem zasnovan na oblaku za praćenje stanja istrošenosti reznog alata merenjem vibracija. Ovaj sistem primenjuje metod mašinskog učenja koji je integrisan u MS Azure cloud sistem. Verifikacija je izvršena na podacima izračunatih centralnih momenata u toku struganja, za izmenjive pločice na reznom alatu sa različitim stepenom habanja.*

Ključne reči: *Proizvodnja u oblaku, mašinsko učenje, I 4.0, pametno održavanje, praćenje stanja.*

1. INTRODUCTION

A necessary step in achieving the main goal of Industry 4.0 - the creation of smart factories, is the application of smart manufacturing methods, intelligent tools and smart services [1]. For this purpose, the basic task is to conceptualize efficient smart maintenance system as one of the basic technologies that will be applied in smart manufacturing and which bases its functions on monitoring the physical parameters of condition in a manufacturing process. The final goal is to increase the flexibility of manufacturing companies in the direction of developing sustainable manufacturing driven by intelligent services, as well as predict, prevent or minimize delays and potential failures in production.

Novel research in this area has focused on creating a framework for an intelligent manufacturing environment to be used in the implementation of the Industry 4.0 concept [1]. Smart manufacturing uses various methods based on artificial intelligence. Therefore, a number of intelligent tools and services related to monitoring the condition of a production are introduced and applied in a manufacturing process. For this purpose, it is necessary to improve the system for monitoring cutting tool wear in the workspace of the machine tool, i.e. to create a framework for intelligent predictive cutting tool maintenance. This system includes monitoring the condition of cutting tool wear with the vibration measuring equipment. The data collected by measuring the vibration of the tool are analyzed using machine learning methods, which make the base of Smart maintenance technology. In this way, cutting tool failures and unplanned, costly delays in a manufacturing process are timely prevent, remove and eliminate.

2. CLOUD-BASED MACHINE LEARNING

Azure Machine Learning Studio allows create and test different machine learning models for a some data set. This is a platform for managing a machine learning system in the cloud. Software, platform, and infrastructure are provided by *Microsoft Azure*, supporting numerous programming languages and cloud-based tools and frameworks. By applying ML Studio it is possible:

- Develop a machine learning model using data from one or more sources.
- Transform and analyze data with statistical functions in order to determine the set of results (it is an iterative process in which the correction of parameters changes the results until a efficient trained model is obtained).

Fig.1 shows the basic procedure for applying machine learning for one experiment.

In order to develop a model of predictive analysis, data from one or more sources are used, transformed and analyzed, and a set of results is generated by applying statistical functions. By modifying the different functions and their parameters, the obtained results converge until a trained, efficient model is created. ML Studio provides an interactive, visual

Note: The manuscript was presented at the 14. International Scientific Conference MMA held in Novi Sad, Serbia, 23.-25. September, 2021.

workspace for easy creation, testing, and iterations on a predictive analysis model, Fig.2.

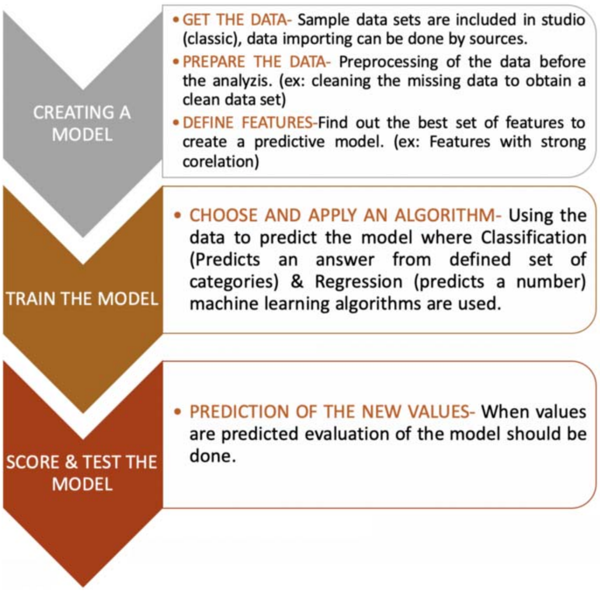

Fig. 1. Azure ML workflow of a machine learning predictive model create [2]

The user combines datasets and modules for analysis in an interactive workspace, linking them into a machine learning training experiment. When the results are satisfying then the training experiment is translated into a predictive experiment in the form of a web service, so that other users can access to the created model.

The metrics for regression models are generally designed to estimate the amount of error. A model is considered to fit the data well if the difference between observed and predicted values is small. The pattern of the residuals (the difference between any one predicted point and its corresponding actual value) can indicate potential bias in the model [2].

To estimate regression models in the ML Studio, the following metrics are used [2,3]:

- ***Mean absolute error (MAE)*** measures how close the predictions are to the actual outcomes; thus, a lower score is better.
- ***Root mean squared error (RMSE)*** creates a single value that summarizes the error in the model. By squaring the difference, the metric disregards the difference between over-prediction and under-prediction.
- ***Relative absolute error (RAE)*** is the relative absolute difference between expected and actual values; relative because the mean difference is divided by the arithmetic mean.
- ***Relative squared error (RSE)*** similarly normalizes the total squared error of the predicted values by dividing by the total squared error of the actual values.
- ***Coefficient of determination***, often referred to as R^2, represents the predictive power of the model as a value between 0 and 1. Zero means the model is random (explains nothing); 1 means there is a perfect fit. However, caution should be used in interpreting R^2 values, as low values can be entirely normal and high values can be suspect.

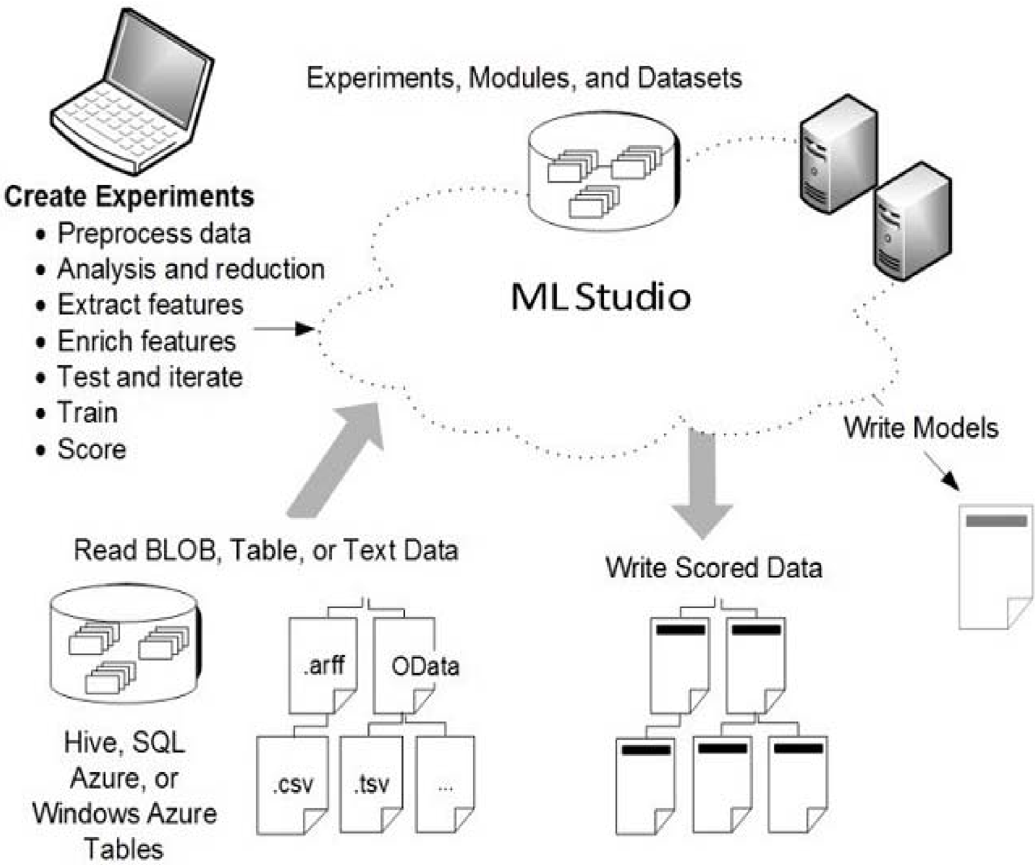

Fig. 2. ML Studio interactive workspace [2]

3. SENSOR SYSTEM FOR MONITORING OF CUTTING TOOL VIBRATION

The sensor system for monitoring of the cutting tool vibration has the following characteristics:

- Uses adequate sensors to measure vibration acceleration in order to better detect the dynamic characteristics of the cutting process and implement it in the monitoring system.
- Uses algorithms based on artificial intelligence in the field of cutting tool wear monitoring, which are based on the application of a priori knowledge about the condition of cutting tool wear.
- Finds a satisfying model of extracting vectors of input characteristics by applying transformations in the time-frequency domain.

The sensor part of the data pre-processing module consists of an accelerometer for measuring the vibration acceleration mounted on the tool handle, Fig.3. A part of the subsystem for data pre-processing also includes an A/D converter card which receives analog information from the sensor, converts it into digital information and forwards it to the measurement database.

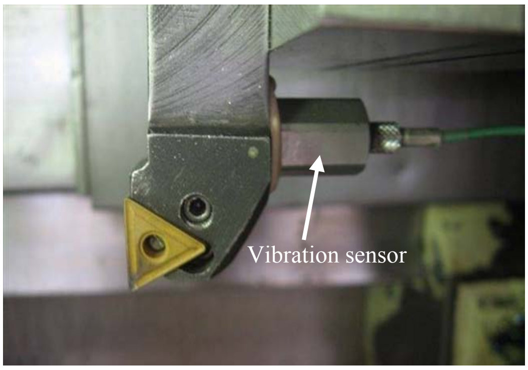

Fig. 3. Installation of sensor for measuring cutting tool vibration

The structure of the preprocessing subsystem can be observed through the three phases shown in Fig.4.

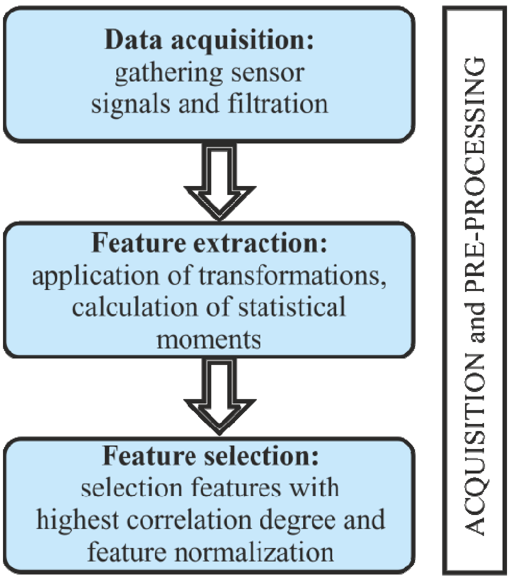

Fig. 4. Pre-processing data collected from sensor

In the first phase, data is collected from the sensor and the filter band is selected.

The second phase is the extraction of the features. The main goal of feature extraction is to significantly reduce the amount of "raw" data collected from sensor in the time and frequency domain. At the same time, relevant tool status information is retained in the selected features. It should be know that different extraction methods have different possibilities for obtaining a set of information about the cutting tool condition by processing the sensor signal.

Nowadays, numerous of industrial measuring systems, which are used to monitoring the wear of cutting tools, are supplied with a built-in signal filter (analog pre-signal processing). With such filters, the frequency band is usually limited to the area that the sensor covers the best. Additional signal filtering (digital pre-signal processing) within the operating range of the sensor is required to attenuate the frequencies of those signals that are an integrative part of the machining process and are not related to tool wear (machine vibration, deformation and material break, friction of material on the sides of the tool…).

The recorded signal was initially processed by a low-pass filter, where the frequency range up to 50 kHz was analyzed due to the characteristics of the applied sensor. A discrete Fourier transform was applied on the filtered signal and the spectral filtered signal shown in Fig.5 was obtained. For further analysis, the upper part of the signal spectrum, the high-frequency part, was separated from the obtained signal spectrogram because in that part of the spectrum there are discriminant features that characterize the condition of the cutting tool wear [4].

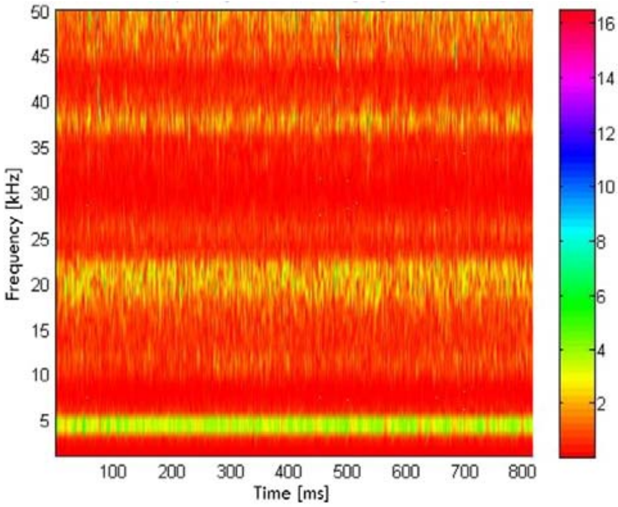

Fig. 5. Filtered signal spectrogram

From the measured results, the orientation of the central moments can be observed by the frequency of formation of chips lamellae, which are obtained by machining with a tool with different degrees of wear of the cutting insert according to individual filter sizes. The exception is the deviation from the orientation of the tool insert with the highest wear, which can be justified by the fact that the cutting insert is full degraded and that this insert has changed the type of chips.

4. ANALYSIS OF CENTRAL MOMENTS OF CUTTING TOOL WEAR IN ML STUDIO

The final output from the data acquisition and pre-processing module are the calculated central moments for the defined scales. The dataset part of the central moments values is shown in Table 1.

Central moments	New tool insert	Wear band (VB) 0,25mm	Wear band (VB) 0.55mm	Full degraded tool insert
Scale I				
Mean	-0.13794819926	-0.12472823415	-0.11436530596	-0.12541743628
Variance	4.33004452633	1.61527765463	0.59496679855	1.00174617608
Skewness	-1.47780598530	-0.96825146333	-0.41422192202	-1.21663428609
Kurtosis	0.11382051257	0.06486639025	0.04587497758	0.12541445114
Scale II				
Mean	-0.22383778716	-0.18795982515	-0.16372339460	-0.18678597239
Variance	3.06549712564	1.23954201485	0.36939617833	0.63390553200
Skewness	-1.17290133182	-0.77377167145	-0.48294701146	-1.06014195154
Kurtosis	0.08259091746	0.05210368214	0.04575176375	0.08659298047
Scale III				
Mean	-0.30352420900	-0.23958936267	-0.20836828770	-0.24357300170
Variance	1.56893965739	0.75401003960	0.17995614785	0.33778890834
Skewness	-1.07040434106	-0.63626635922	-0.57505774822	-1.13331518583
Kurtosis	0.06757675981	0.04609144501	0.04589097543	0.07824611322

Table 1. Segment of calculated central moments at particular scales for various stages of cutting tool wear

The values of the calculated central moments were applied as discriminant features: variance, skewness and kurtosis. These features were chosen because their values have a more pronounced change with the change in the cutting tool wear, i.e. have a better correlation with cutting tool wear compared to other features. By applying the classification in only one scale, a quality classification of the cutting tool wear condition can be performed, especially because there is only one physical source of information, i.e. vibrations.

Dataset on the central moments generated by processing and calculation after analysis of the tool vibration spectrum were recorded and as such were transferred to the ML Studio, Fig.6.

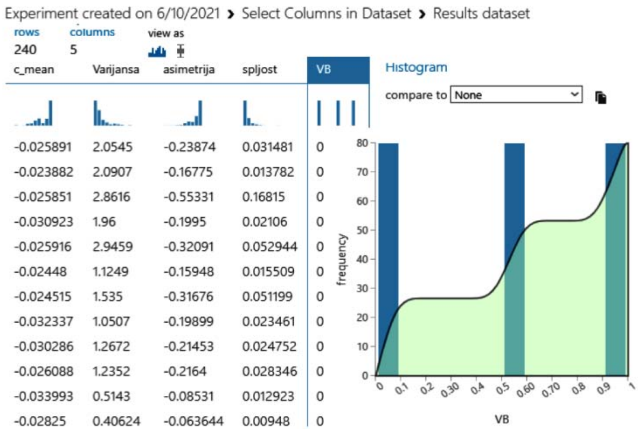

Fig. 6. Segment of calculated central moments imported in ML Studio

The project, actually an experiment was formed in the ML Studio environment, in which the steps of the algorithm for machine learning were defined, also include the metrics of the regression model. Finally, the project was started, after which the validation, training, scoring and evaluation were executed over the dataset on central moments related to the estimation of cutting tool wear, Fig.7.

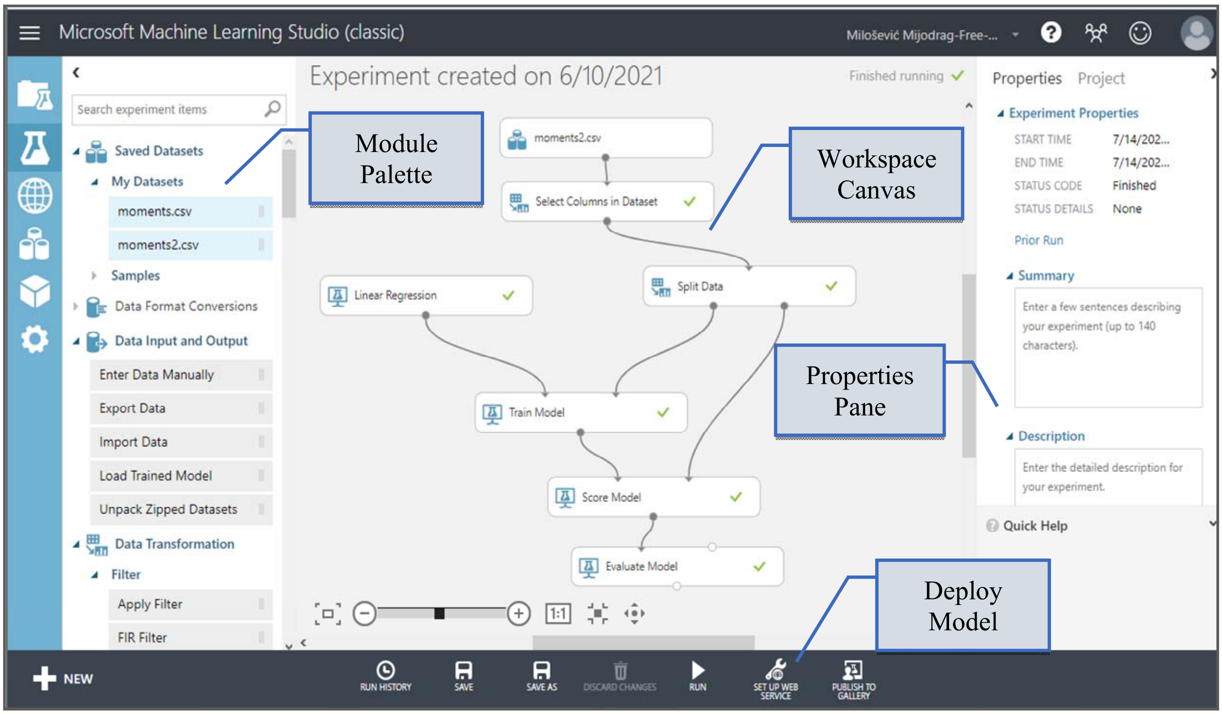

Fig. 7. Validation and evaluation of the machine learning experiment

The developed model of machine learning enables width estimate of the wear band on the cutting tool back surface, depending on the intensity of vibrations. Based on this model, it is possible to generate an intelligent web service that can exist within the system of smart manufacturing and manufacturing based on cloud technologies, Fig.8.

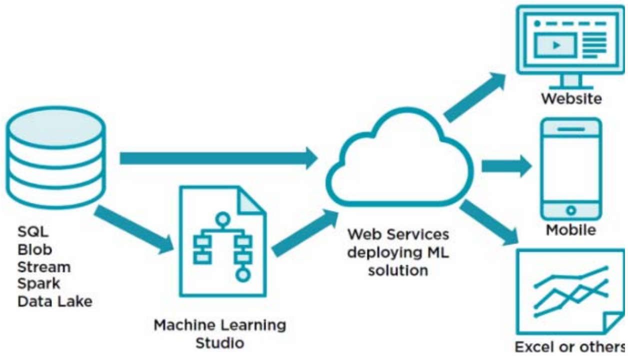

Fig. 8. Web service deployment in Azure ML Studio environment [2]

5. CONCLUSION

The presented system for predictive monitoring of the cutting tool wear is classified in the domain of smart predictive maintenance. Continuous sensor monitoring of the cutting tool vibrations in manufacturing process results in the extraction of statistical features and the calculation of central moments. Using the cloud-based machine learning technique, the degree of wear on the back surface of the cutting tool can be estimated on the basis of these features.

The defined framework present the basis for development of intelligent services and methods that are applied in a smart manufacturing environment.

6. REFERENCES

[1] Zhong, R. Y., Xun X., E., Klotz, Stephen T. Newman: *Intelligent manufacturing in the context of Industry 4.0: a review*, Engineering, Vol.3, No.5, pp. 616-630, 2017.

[2] https://docs.microsoft.com/en-us/azure/machine-learning, August 2021.

[3] Barnes, J.: *Microsoft Azure Essentials - Azure Machine Learning*, The Microsoft Press Store, ISBN:978-0-7356-9817-8, 2015.

[4] Antić, A., Popović, B., Krstanović, L., Obradović, R., Milošević, M.: *Novel texture-based descriptors for tool wear condition monitoring*, Mechanical Systems and Signal Processing, Vol. 98, pp.1-15, 2018.

ACKNOWLEDGMENTS

This paper is part of a research on the projects: *"Application of smart manufacturing methods in Industry 4.0"*, No.142-451-3173/2020 and *"Application of edge computing and artificial intelligence methods in smart products"*, No. 142-451-2312/2021, supported by Provincial Secretariat for Higher Education and Scientific Research of the Autonomous Province of Vojvodina.

Authors: **Assoc. Prof. Mijodrag Milošević**, **Assoc. Prof. Dejan Lukić**, **Full Prof. Gordana Ostojić**, **Full Prof. Milovan Lazarević**, **Full Prof. Aco Antić**, University of Novi Sad, Faculty of Technical Sciences, Department of Production Engineering, Trg Dositeja Obradovića 6, 21000 Novi Sad, Serbia, Phone: +381 21 485-2346.

E-mail: mido@uns.ac.rs;
lukicd@uns.ac.rs;
goca@uns.ac.rs;
laza@uns.ac.rs;
antica@uns.ac.rs