Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 99 (2021) 189–195

www.elsevier.com/locate/procedia

14th CIRP Conference on Intelligent Computation in Manufacturing Engineering, CIRP ICME '20

Drilling process monitoring: a framework for data gathering and feature extraction techniques

Aitor Duo[a], Tiziana Segreto[b], Alessandra Caggiano[c], Rosa Basagoiti[a], Roberto Teti[b], Pedro J. Arrazola[a]

[a]*Mondragon Unibertsitatea, Faculty of Engineering, Loramendi 4, 20500 Arrasate-Mondragon (Gipuzkoa), Spain*
[b]*Dept. of Chemical, Materials and Industrial Production Engineering, University of Naples Federico II, Piazzale Tecchio 80, Naples 80125, Italy*
[c]*Dept. of Industrial Engineering, University of Naples Federico II, Piazzale Tecchio 80, Naples 80125, Italy*

* Corresponding author. Tel.: +34-627-859-865. E-mail address: aduo@mondragon.edu

Abstract

Today's industrial transformation is taking advantage of the benefits of information and communication technologies (ICT) to evolve into a more decision-making environment in manufacturing. Efficiency, agility, innovation, quality and cost savings are the goals of this transformation in one of the most employed manufacturing processes as is the case of machining. Drilling processes are among the last operations in the different manufacturing stages of machined parts, where an undetected problem can lead to the production of a defective part. Data analysis of sensor signals gathered during drilling processes provides information related to the cutting process that can anticipate non-desired phenomena. This work illustrates the experimental setup for sensorial data acquisition in drilling processes, signal processing techniques and feature extraction methodologies for faster and more robust decision-making paradigms.

Peer-review under responsibility of the scientific committee of the 14th CIRP Conference on Intelligent Computation in Manufacturing Engineering, 15-17 July 2020.

Keywords: Drilling; Sensors; Signal processing; Feature extraction; Feature selection

1. Introduction

The digital transformation demands greater decision-making capacity on production processes to increase productive capacity, sustainability and greater efficiency. This has lead industries to adapt their production processes to meet the quality standards demanded by the customers. Machining processes are not an exception to this transformation and in the last decades monitoring techniques have provided remarkably successful results [1-4].

The drilling process is one of the most common machining processes together with turning and milling. The cutting speed in drilling operations is variable along the cutting edges, starting from zero at the tool center up to Vc_{max} at the periphery of the tool. The mechanisms for chip generation will therefore be very different depending on the input zone [5]. A drill bit has usually two-edges, which produce the cut simultaneously as in a turning process, while at the center of the tool the cut is made by plastic deformation [6].

The physical components (cutting tool, material, fixture, type of coolant and machine tool) and quantitative parameters (cutting conditions) define the behaviour of the cutting process. At the output of the cutting process, there are the industrial parameters of the workpiece (dimensional tolerances, geometrical tolerances, surface finish, burr, delamination or residual stresses) and the tool properties (tool wear or tool breakage) to be controlled in order to meet the requirements set for a given part. The scientific parameters (temperature, cutting forces, power, acoustic emission, sound pressure, vibrations, etc.) are used to control these industrial parameters.

The scientific parameters contain information related to the nature of the cutting process. The different phenomena occurring during the operation are recorded in these signals and therefore could be explained if the appropriate features are extracted. This allows for the acceleration of decision-making and the prediction of irreversible phenomena.

Tool wear is one of the most studied parameters; it has been observed by several studies that thrust force and torque increase with tool wear growth [7-9]. Thus, they are good

Peer-review under responsibility of the scientific committee of the 14th CIRP Conference on Intelligent Computation in Manufacturing Engineering, 15-17 July 2020.
10.1016/j.procir.2021.03.123

indicators for tool wear monitoring. Although there is a pressing need for more advanced signal processing techniques [10], vibration signals [11], acoustic emission signals [12] and spindle current [13] have provided successful results in tool wear monitoring. At high cutting speeds, tool wear accelerates, thus decreasing the useful life of the working tool. Increasing the cutting speed raises the temperature and the stress generated during the cutting process, hastening the erosion process and causing the generation of low quality holes [14, 15].

Surface roughness is a popular measure of the technical requirements of a part [16-18]. However, it is harder to find a relation with signals obtained from sensors because most conventional cutting processes produce surfaces with asymmetrical profiles [19]. Thus, each of the generated surfaces could have different contact properties. Roughness monitoring systems assume the same roughness properties for given cutting conditions, considering only the *Ra* (average roughness of profile) as output value. This parameter is the best known, but it does not reflect the real properties of the generated surface. Garcia Plaza et al [20] utilized features extracted from the vibration signal by singular spectrum analysis. Deshpande et al [12] used vibration, sound pressure and cutting force for surface roughness prediction. Vrabel et al employed cutting conditions, tool wear and thrust force for Ra parameter prediction [13]. However, currently there are no identified signals that have a clear relationship with the surface roughness parameters of the machined part. In addition, the amount of data obtained from roughness measurements is too small (it is a time demanding task) for the creation of models using machine learning algorithms. Therefore, advanced signal processing techniques, feature extraction methods and pattern recognition procedures, should be investigated to find such relationships with a robust character.

In drilling, surface roughness is more complicated than in other processes. The tool, when penetrating into the hole, exerts a rubbing on the machined part. In addition, the extraction of the chip also exerts a rubbing on the surface of the hole, changing the generated roughness profile.

This paper shows different techniques for monitoring the drilling process, including the simultaneous acquisition of both internal (spindle power, process parameters, position, speed, acceleration and tool tip jerk) and external (vibrations, acoustic emissions and cutting forces) signals from the machine and from the process together with signal processing and feature extraction strategies. Accordingly, a drilling process monitoring framework is presented and discussed.

2. Experimental set-up

The amount of data available for processing and exploitation in terms of process monitoring systems has been increasing. The precision of the sensors and the amount of information available from the machine tool itself is an excellent opportunity for the creation of systems characterised by greater decision making capability. According to ISO/IEC/IEEE 60559:2011, a double floating point of 8 bytes covers the range from 4.94065645841246544e-324 to 1.79769313486231570e308 (positive or negative). Knowing this and assuming each sample is stored based on this type of data and signals are digitized at 1 MHz sampling rate, 1 GB is detected in 125 s. For this reason, appropriate manipulation and extraction of information is important to properly select the signal features that best represent the physical quality of the cutting process under control and to store the relevant data containing significant information about the cutting process.

Table 1 shows a setup for sensorial data acquisition in drilling processes. In the setup, the most utilised sensors for machining process monitoring are installed for a post-analysis search of patterns allowing to identify the physical output parameters of actual interest for industrial applications.

Table 1. Internal (machine) and external (sensors) signals available for pattern recognition and related sampling frequencies for each of sensor signals.

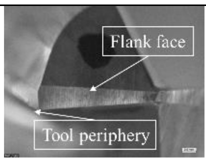
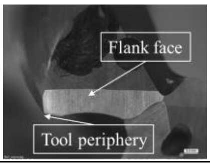
Tri-axial accelerometer (PCB J356A45)	**Acoustic emission sensor** **(**Kistler 8152C**)**	**Kistler rotational dynamometer** (Kistler 9123)	**Fagor CNC8070** (Internal signals)
			
Machine vibrations: • X axis vibration • Y axis vibration • Z axis vibration	Elastic energy produced during the cutting process	**Cutting forces and torque:** • Fz (Thrust force) • Mz (Torque) • Fx (X axis force) • Fy (Y axis force)	**Internal signals:** • Spindle power • Motor current • Torque feedback **Process parameters:** • Spindle speed • Feed speed • Tool tip position • Tool tip speed • Tool tip acceleration • Tool tip jerk
Fs= 25.6 KHz	Fs= 2 MHz	Fs= 10 KHz	Fs=250 Hz

A Kistler 8152C acoustic emission sensor, a PCB J356A45 tri-axial accelerometer and a Kistler 9123 4-component rotational dynamometer were installed for sensor signal acquisition. In addition, several internal CNC signals were collected: Z axis motor torque, spindle motor power feedback, active power supplied by the drive and power percentage used with respect to the maximum power available in the servo system. The following process parameters were also recorded: spindle speed, feed speed, as well as tool tip position, speed, acceleration and jerk along the three axes.

The simultaneous acquisition of the internal and external signals was possible using analogue signals obtained from the machine. The trigger is activated when the acquisition of the internal signals begins, so that simultaneously the acquisition of the external signals is started.

Two different tool geometries were employed (Kendu R204.6D and Kendu BH04.5D), the work material was a BLS 35CrMo4 low S steel, and all holes were made under wet conditions. Table 2 shows the cutting conditions used for each of the two tool geometries.

Table 2. Cutting tool geometries and cutting conditions.

Tool geometry		Cutting conditions
R204.6D		Vc= 70 m/min f= 0.15 mm/rev Hole depth= 5 mm Ø= 8 mm
BH04.5D		Vc= 100 m/min f= 0.15 mm/rev Hole depth= 5 mm Ø= 8 mm

During the cutting tests, the tool was measured periodically to evaluate the development of tool wear. The measuring point was at the periphery of the flank face of each cutting edge, as shown in Fig 1.

Measuring the flank wear provides an approximate evaluation of the actual tool wear by using the average flank wear land, *Vb*, or the maximum wear land, Vb_{max}, parameters measured on the tool flank face perpendicularly to the cutting edge. As wear is accelerated by higher cutting speed, it derives that the tool suffers a greater wear where the cutting speed is maximum.

After the drilling tests, the surface roughness of the generated surfaces was measured using an Alicona IFG4 3D confocal profilometer. This type of metrology allows for the measurement of surface roughness at different cross sections of the machined surface. In addition, it allows to observe the different surface errors that could occur during the drilling process. To carry out the analysis, the holes selected for the measurement were extracted from the part by means of electrical discharge machining (EDM) cutting (Fig. 2). Then, the hole was cut in two halves using a precision cutter. Fig. 2 shows the process for extraction and measurement made on different cross sections of the holes.

Table 3 reports the different parameters calculated for each of the obtained surface roughness profiles. This is intended to give a more comprehensive view of the surface roughness profile distribution. The parameters in grey take into account only a specific point of the whole distribution of the profile. The other parameters are more descriptive as they take into account all the data points of the distribution.

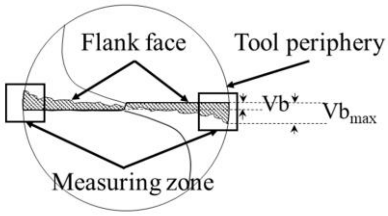


Fig. 1. Tool wear measuring point on Vc_{max} section.

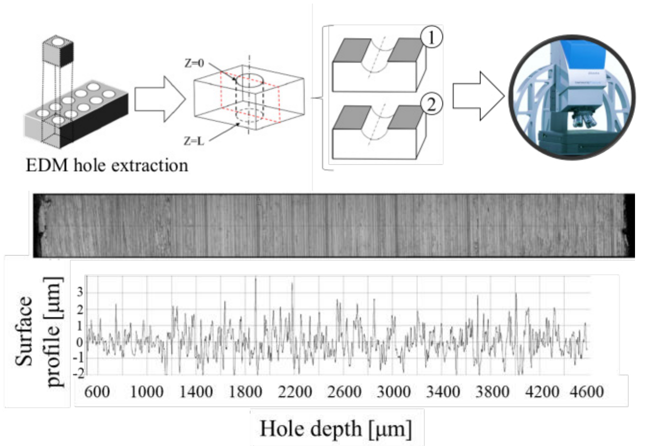


Fig. 2. Hole cutting procedure for Alicona inspection and an example of recorded surface profile measurement.

Table 3. Surface roughness parameters from the profile measured on the machined surface of the part.

Name	Description	Unit

Ra	Average roughness of profile	μm
Rq	Root-Mean-Square roughness of profile	μm
Rt	Maximum peak to valley height of roughness profile	μm
Rz	Mean peak to valley height of roughness profile	μm
Rmax	Maximum peak to valley height of roughness profile within a sampling length	μm
Rp	Maximum peak height of roughness profile	μm
Rv	Maximum valley height of roughness profile	μm
Rc	Mean height of profile irregularities of roughness profile	μm
Rsm	Mean spacing of profile irregularities of roughness profile	μm
Rsk	Skewness of roughness profile	-
Rku	Kurtosis of roughness profile	-
Rdq	Root-Mean-Square slope of roughness profile	-
Rt/Rz	Extreme Scratch/Peak value of roughness profile, (>=1), higher values represent larger scratches/peaks	-

3. Feature extraction

One of the biggest challenges after acquiring different types of sensor signals from a cutting process is given by the extraction of features that best represent the process to be analysed. The statistical features of the acquired signals are statistical indicators that preserve and explain important elements of the signal [23].

The extraction of features from the acquired signals can be carried out in the time domain and/or in the frequency domain. Fig. 3 shows a schematic overview for the feature extraction procedure followed in this work. In the time domain, statistical parameters are selected in order to explain or provide information about the phenomena that generated the acquired signals [24]. In the frequency domain, the parameters representing the variation of the frequency content related to the phenomena under control are chosen.

Feature extraction is the task of processing the acquired sensor signals to yield a group of descriptors capable to keep relevant information obtained from a specific industrial measurement relative to the cutting process.

3.1 Time domain

Time domain features provide data about the distribution of a signal, maintaining the relevant information about the monitoring unit. Statistical features are the most uilised: *mean, root mean square (rms), maximum, minimum, standard deviation, skewness, kurtosis and crest factor*.

3.2 Dimensionality reduction

Advanced approaches based on feature extraction, i.e. aimed at generating a lower number of relevant features in comparison with the very numerous initial sensorial data, have proven to be highly valuable [25-27].

One of the most effective feature extraction technique for dimensionality reduction is the principal component analysis (PCA) procedure [26-30]. PCA is an unsupervised linear projection method allowing to perform a mapping from the input vectors $\boldsymbol{x}$ in the original d-dimensional space to new vectors $\boldsymbol{z}$ in the q-dimensional space (with $q < d$), with minimum loss of information. In practice, PCA identifies new variables along new directions, namely the principal components that are linear combinations of the original variables. With the aim to preserve the variance embedded in the original variables, the principal components are computed as the normalized eigenvectors of the covariance matrix of the original variables and ranked according to how much of the variation existing in the data they comprehend.

3.3 Frequency domain

The analysis of the frequency content of a signal provides information about the events that occur in a cutting process, providing insight on properties that are hard to discern or see in time domain representations. Discrete Fourier transform is frequently used for this type of analysis; sometimes it is applied with windowing to have a periodic signal and reduce the leakage effect [31].

3.4 Time frequency domain

The Fourier transform is useful only for stationary signals (statistical properties without changes in time) but sometimes sensor signals in machining are non-stationary and a time-frequency domain analysis is utilised to detect the frequency changes over time.

The wavelet transform (WT) is widely used to analyze sensor signals in the time-frequency domain and can be mainly classified into continuous (CWT), discrete (DWT) and wavelet packet transform (WPT) [32]. The key feature of WT resides in its ability to decompose a signal through scaling and translation processes without changing the information content present in the original signal. Generally, a signal is decomposed into approximations and details using a mother wavelet function where the approximations are the high-scale, low-frequency components of the signal and the details are the low-scale, high frequency components [18, 33, 34].

WPT is a DWT generating more frequency bands and enhancing the extraction of relevant information from the original signal. In this case, the signal decomposition is structured as a tree with multiple levels, whereby at each new level a new decomposition is performed on low-frequency and high-frequency components (packets) [35, 36] as shown in Fig. 4.

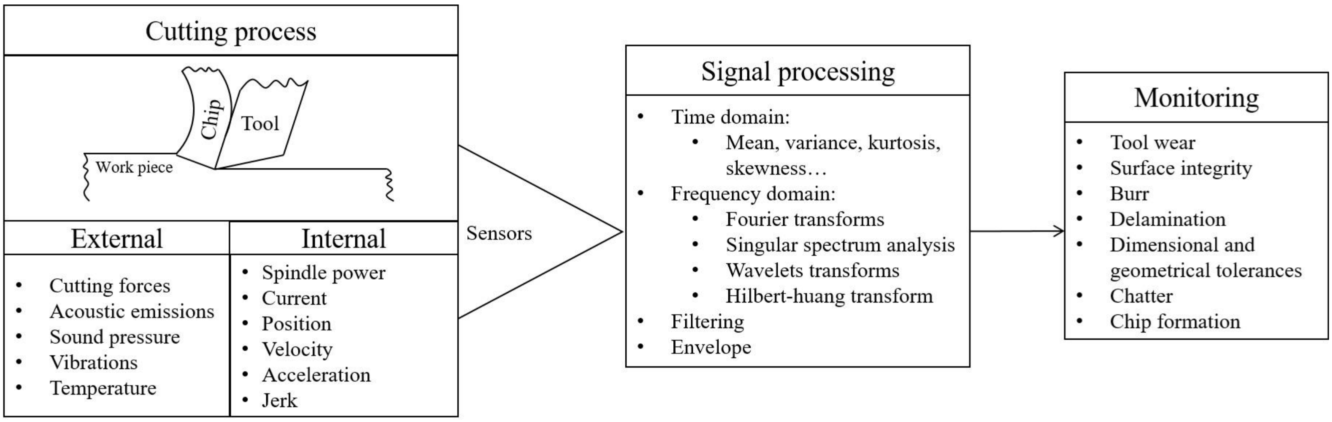


Fig. 3. Signal processing for feature extraction (adapted from [24]).

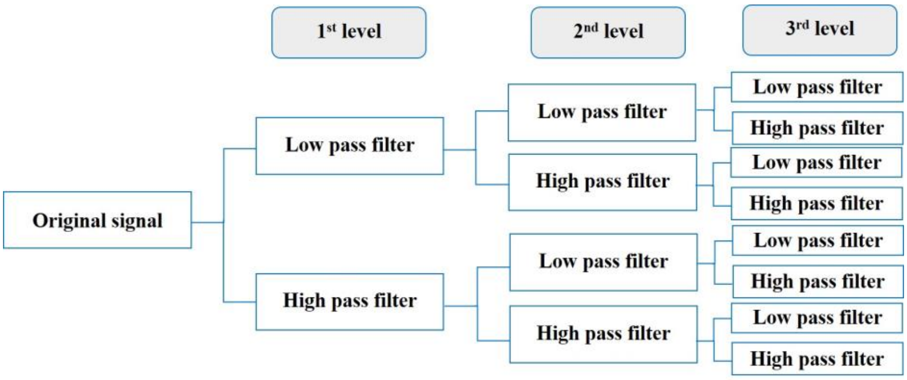


Fig. 4. WPT decomposition tree at three levels.

4. Feature selection

After acquiring the internal and/or external signals and extracting the signal features, the number of obtained features can be very large. Proper selection of the most relevant features is needed to reduce feature dimensionality and better represent the phenomena under control.

Feature subset selection is the process of identifying and removing as many irrelevant and redundant features as possible regarding the monitoring unit.

In machine learning, it is essential to reduce the feature set dimensionality to simplify the modelling, reduce the problem complexity and shorten the training time [37-39]. Simpler models are also more robust on small datasets and are less affected by variance due to noise or outliers [26, 27].

Assuming that each drilled hole constitutes an instance of a dataset where features extracted from the raw data for this specific hole are the columns of the dataset and the target or class column reports the tool wear level. To remove irrelevant features, a feature selection criterion is required which can measure the relevance of each feature to the output class/target or its redundancy regarding the other features. From a machine learning viewpoint, if a system is trained with irrelevant variables, it will use this information for new data leading to poor generalization. In [40] the features were defined as:

- Relevant: are features, which have an influence on the output, and their role cannot be assumed by the rest.
- Irrelevant: are those features not having any influence on the output, and whose values are generated at random for each example.
- Redundant: a redundancy exists whenever a feature can take the role of another.

Teti et al. [1] report that in only 15% of the cases some technique to select representative features was used for tool condition monitoring. Overall, applying feature selection will always provide benefits such as granting insight into the data, better classifier model, enhance generalization and identification of irrelevant variables. Mehmood et al. [41] comment that there is no method for selecting variables consistently superior to the others; it is probably more an interaction between the method and the data properties.

4.1 Filtering methods

The existing filtering algorithms are computationally cheap but they fail to identify and remove all redundant features. In addition, there is a risk that the features selected by a filtering method can decrease the correlation coefficient of the learning algorithm [40]. The most used filtering method for variable selection is the Pearson's correlation coefficient that assumes a Gaussian distribution for each variable and reports on their linear relationships.

4.2 Wrapper methods

Wrapper methods wrap the feature selection around the induction algorithm to be used, employing cross-validation to predict the benefits of adding or removing a feature from the utilized feature subset [40].

The sequential selection algorithms start with an empty set (forward selection) or full set (backward selection) and add features or remove features until the maximum objective function is obtained. A problem with forward selection is that it may fail to include attributes that are interdependent, as it adds variables one at a time. However, it may locate small effective subsets quite rapidly, as the early evaluations, involving relatively few variables, are fast. In contrast, in backward selection inter-dependencies are well managed, but early evaluations are relatively expensive [42].

4.3 Embedded methods

Some induction algorithms include implicitly a search for optimal features with respect to the target. It is the case of random forest trees that allows to obtain a ranking of the most important variables to create a model.

Apart from that, regularization is a form of regression that discourages learning a more complex or flexible model in order to avoid the risk of overfitting. There are two main regularization algorithms: LASSO and ridge regression. The main difference is that the LASSO regression is better than the ridge regression at reducing the variance if there are useless features.

5. Conclusions and future work

This work reports a complete set-up in which internal and external signals of drilling processes are collected. In addition, the most utilized signal processing techniques of feature extraction and selection for cutting process monitoring are illustrated.

Signal acquisition for cutting process control has become important over the last few decades. In addition to reducing manpower, it allows to obtain information about the state and quality of the cutting process. Monitoring a process leads to the reduction of time and costs, in addition to making estimates about the quality of the machined part.

Only few works explore feature selection techniques in this field. Exploring different feature selection methods can be of great help as they allow to reduce the high dimensionality of the data as well as to obtain a better generalisation of the models that will be employed later.

Regarding future work, the main focus will be on applying different feature extraction and selection methods to feed machine learning algorithms and get insight in drilling process monitoring.

In particular, WPT, which generates more frequency bands with improved extraction of relevant information from the original signal, will be considered. In addition, dimensionality reduction will be carried out via PCA techniques based on singular value decomposition, which is a computationally efficient method for determining principal components. This will allow to reduce the feature set dimensionality with the aim to simplify modelling, decrease problem complexity and shorten training time in view of the application of decision making paradigms.

Acknowledgements

This work was developed by the group of Intelligent Systems for Industrial Systems (IT-1357-19), the group of High-Performance Machining (IT-1315-19) of Mondragon Unibertsitatea, the Fraunhofer Joint Laboratory of Excellence on Advanced Production Technology (Fh J_LEAPT UniNaples) at the Dept. of Chemical, Materials and Industrial Production Engineering and the Dept. of Industrial Engineering of the University of Naples Federico II, Italy. This work was carried out with the support of the INTOOL II project (KK-2020/00103) and partially funded by the PRODUCTIVE 4.0 project subsidised by ECSEL (737459) and MINECO (PCIN-2017-071).

References

[1] Teti R, Jemielniak K, O'Donnell G, Dornfeld D. Advanced Monitoring of Machining Operations. CIRP Annals 2010, 59/2: 717-739.
[2] Teti R, Jawahir IS, Jemielniak K, Segreto T, Chen S, Kossakowska J. Chip Form Monitoring through Advanced Processing of Cutting Force Sensor Signals. CIRP Annals 2006, 55/1: 75-80.
[3] Byrne G, Dornfeld D, Inasaki I, König W, Teti R. Tool Condition Monitoring (TCM) - The Status of Research and Industrial Application. CIRP Annals 1995, 44/2: 541-567.
[4] Teti R. Tool wear monitoring through acoustic emission. CIRP Annals 1989, 38/1: 99-102.
[5] Zhao Q, Qin X, Ji C, Li Y, Sun D, Jin Y. Tool life and hole surface integrity studies for hole-making of Ti6Al4V alloy. Int J Adv Manuf Technol 2015, 79: 1017-1026.
[6] Swinburne R. Metal cutting principles, 2nd Edition, Oxford University Press Inc., 2005.
[7] Caggiano A, Centobelli P, Nele L, Teti R. Multiple Sensor Monitoring in Drilling of CFRP/CFRP Stacks for Cognitive Tool Wear Prediction and Product Quality Assessment. Procedia CIRP 2017, 62: 3-8.
[8] Arrazola PJ, Garay A, Fernandez E, Ostolaza K. Correlation between tool flank wear, force signals and surface integrity when turning bars of Inconel 718 in finishing conditions. Int J Mach Mater 2014, 15 (1-2): 84-100.
[9] Caggiano A, Napolitano F, Nele L, Teti R. Multiple sensor monitoring for tool wear forecast in drilling of CFRP/CFRP stacks with traditional and innovative drill bits. Procedia CIRP 2018, 67: 404-409.
[10] Mekid S, Schlegel T, Aspragathos N, Teti R. Foresight Formulation in Innovative Production, Automation and Control Systems. The Journal of Foresight - The Journal of Futures Studies, Strategic Thinking and Policy 2008, 9/5: 35-47.
[11] Harun MHS, Ghazali MF, Yusoff AR. Analysis of tri-axial force and vibration sensors for detection of failure criterion in deep twist drilling process. Int J Adv Manuf Technol 2017, 89: 3535-3545.
[12] Ravindra HV, Sudev LJ. Tool Wear estimation in drilling using acoustic emission signal by multiple regression and GMDH. Mech Eng 2008: 1-10.
[13] Ao Y, G. Qiao G. Prognostics for drilling process with wavelet packet decomposition. Int J Adv Manuf Technol 2010, 50: 47-52.
[14] Rahim EA, Sharif S. Investigation on tool life and surface integrity when drilling Ti-6Al-4V and Ti-5Al-4V-Mo/Fe. Int J Series C Mech Systems, Machine Elements Manuf 2006, 49, 2: 340-345.
[15] Caggiano A, Angelone R, Teti R. Image Analysis for CFRP Drilled Hole Quality Assessment. Procedia CIRP 2017, 62: 440-445.
[16] Benardos PG, Vosniakos GC. Predicting surface roughness in machining: A review. Int J Mach Tools Manuf 2003, 43: 833-844.

[17] Segreto T, Karam S, Teti R, Ramsing J. Feature extraction and pattern recognition in acoustic emission monitoring of robot assisted polishing. Procedia CIRP 2015, 28: 22-27.
[18] Segreto T, Karam S, Teti R. Signal processing and pattern recognition for surface roughness assessment in multiple sensor monitoring of robot-assisted polishing. Int J Adv Manuf Technol 2017, 90: 1023-33.
[19] Zhang S, Wang W, Zhao Z. The effect of surface roughness characteristics on the elastic-plastic contact performance. Tribol Int, 2014, 79: 59-73.
[20] García Plaza E, Núñez López PJ. Surface roughness monitoring by singular spectrum analysis of vibration signals. Mech Syst Signal Process 2017, 84: 516-530.
[21] Deshpande YV, Andhare AB, Padole PM. Application of ANN to estimate surface roughness using cutting parameters, force, sound and vibration in turning of Inconel 718. Applied Sciences 2019, 1 (1): 104.
[22] Vrabel M, Mankova I, Beno J, Tuharský J. Surface roughness prediction using artificial neural networks when drilling. UDIMET 720, Procedia Eng 2012, 48: 693-700.
[23] Balsamo V, Caggiano A, Jemielniak K, Kossakowska J, Nejman M, Teti R. Multi Sensor Signal Processing for Catastrophic Tool Failure Detection in Turning. Procedia CIRP 2016, 41: 939-944.
[24] Martin KF. A review by discussion of condition monitoring and fault diagnosis in machine tools. Int J Mach Tools Manuf 1994, 34: 527-51.
[25] Caggiano A, Angelone R, Napolitano F, Nele L, Teti R. Dimensionality reduction of sensorial features by principal component analysis for ANN machine learning in tool condition monitoring of CFRP drilling. Procedia CIRP 2018, 78: 307-312.
[26] Bishop CM. Neural networks for pattern recognition, Oxford University Press. Oxford, UK, 1995.
[27] Alpaydin E. Introduction to machine learning, MIT Press, USA, 2014.
[28] Jolliffe IT. Principal component analysis, 2nd Edition, Springer Series in Statistics, Springer Verlag New York, 2002, 30: 487.
[29] Segreto T, Simeone A, Teti R. Chip Form Classification in Carbon Steel Turning through Cutting Force Measurement and Principal Component Analysis. Procedia CIRP 2012, 2: 49-54.
[30] Simeone A, Segreto T, Teti R. Residual stress condition monitoring via sensor fusion in turning of Inconel 718. Procedia CIRP 2013, 12: 67-72.
[31] Li H, Chen Y. Handbook of manufacturing engineering and technology, 2013.
[32] Gao RX, Yan R. Wavelets: theory and applications for manufacturing, Springer US, 2011.
[33] Segreto T, Karam S, Simeone A, Teti R. Residual stress assessment in inconel 718 machining through wavelet sensor signal analysis and sensor fusion pattern recognition. Procedia CIRP 2013, 9: 103-108.
[34] Jemielniak K, Teti R, Kossakowska J, Segreto T. Innovative Signal Processing for Cutting Force Based Chip form Prediction. Intelligent Production Machines and Systems - 2nd I*PROMS Virtual International Conference, 3-14 July 2006: 7-12.
[35] Karam S, Centobelli P, D'Addona DM, Teti R. Online Prediction of Cutting Tool Life in Turning via Cognitive Decision Making. Procedia CIRP 2016, 41: 927-932.
[36] Karam S, Teti R. Wavelet Transform Feature Extraction for Pattern Recognition of Chip Form in C Steel Turning. Procedia CIRP 2013, 12: 97-102.
[37] Caggiano A, Zhang J, Alfieri V, Caiazzo F, Gao R, Teti R. Machine learning-based image processing for on-line defect recognition in additive manufacturing. CIRP Annals 2019, 68/1: 451-454.
[38] Segreto T, Caggiano A, Teti R. Neuro-fuzzy system implementation in multiple sensor monitoring for Ni-Ti alloy machinability evaluation. Procedia CIRP 2015, 37: 193-198
[39] Teti R, D'Addona DM. Grinding wheel management through neuro-fuzzy forecasting of dressing cycle time. CIRP Annals 2003, 52/1: 407-410
[40] Karagiannopoulos M, Anyfantis D, Kotsiantis SB, Pintelas PE. Feature selection for regression problems, 8th Hell Eur Res Comput Math its Appl, HERCMA 2007: 20-22.
[41] Mehmood T, Liland KH, Snipen L, Sæbø S. Review of input variable selection methods for artificial neural networks. Chemom Intell Lab Syst 2012, 118: 62-69.
[42] Liu H, Motoda H. Feature Selection for knowledge discovery and data mining. Featur Sel Knowl Discov Data Min, Springer US, 1998.