EKSPLOATACJA I NIEZAWODNOŚĆ
MAINTENANCE AND RELIABILITY

Eksploatacja i Niezawodnosc – Maintenance and Reliability

Volume 23 (2021), Issue 4

journal homepage: http://www.ein.org.pl

Article citation info:
Kozłowski E, Antosz K, Mazurkiewicz D, Sęp J, Żabiński T. Integrating advanced measurement and signal processing for reliability decision-making. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2021; 23 (4): 777–787, http://doi.org/10.17531/ein.2021.4.20.

Integrating advanced measurement and signal processing for reliability decision-making

Indexed by:
Web of Science Group

Edward Kozłowski[a], Katarzyna Antosz[b], Dariusz Mazurkiewicz[c], Jarosław Sęp[b], Tomasz Żabiński[d]

[a]Lublin University of Technology, Faculty of Management, ul. Nadbystrzycka 38, 20-618 Lublin, Poland
[b]Rzeszow University of Technology, Faculty of Mechanical Engineering and Aeronautics, ul. Powstańców Warszawy 8, 35-959, Rzeszów, Poland
[c]Lublin University of Technology, Mechanical Engineering Faculty, ul. Nadbystrzycka 36, 20-618 Lublin, Poland
[d]Rzeszow University of Technology, Faculty of Electrical and Computer Engineering, ul. W. Pola 2, 35-959 Rzeszów, Poland

Highlights

- Force and torque sensors analysed as an alternative to the vibration measurement.
- Effective condition prediction when integrated with adequate signal processing.
- Decision trees with various types of wavelets selected for predictive models.
- High accuracy method proposed to trace tool condition in real-time.

Abstract

An advanced milling machine multi-sensor measurement system as a condition monitoring tool was presented. It was assumed that the data collected from the 3-axis force and torque sensor can be used as a new approach and an alternative to the typical vibration signal based health monitoring and remaining useful life prediction (RUL), when integrated with machine learning techniques that are regarded as a powerful solution. Measurement system integration with the proposed signal processing method based on decision trees with different types and levels of wavelets for the cutter reliability decision-making process was presented together with proving their ability to trace the tool condition accurately. Prediction errors achieved with the use of different signal sources and data processing methods were presented and compared.

Keywords

force and torques measurement, condition monitoring, cutting tool, remaining useful life, prediction.

1. Introduction

Innovative technological machines are constructed as advanced mechatronic systems facing extremely high demands with respect to their performance, reliability and product quality. In both, their construction and operation, the problem of maximum productivity, where several factors such as efficiency, production costs or resources and energy consumption must be taken into account, is important too, all in the context of sustainable manufacturing requirements [21, 32]. Machine tools together with other technological machines used in production systems of high technology industry form complex systems functioning as Industry 4.0 elements. Such terms as Industrial Internet of Things (IIoT) or Machine to Machine Communication (M2M) do not only describe the current industrial revolution but they also characterize any modern machine tool. According to the paradigm of the fourth industrial revolution complemented by the mentioned high demands in quality and reliability, machine tools are equipped with several sensors, diagnostic and monitoring systems.

The measuring methods of machine tool key elements wear are classified as direct (intermittent, offline) and indirect [28, 45, 49]. For example, tool wear is measured based on various sensor signals containing cutting force, torque, vibration, acoustic emission, sound, surface roughness, temperature, displacement or spindle power. The features of the signals correlating to the tool wear are captured to monitor tool condition and to do this, a mass of signal processing methods were used, such as time series modeling, Fast Fourier Transform and time–frequency analysis, the amount of data gathered and calculation involved in corresponding parameters with tool wear is enormous. According to the detailed analysis presented in [49], up to now, many types of sensors and signal processing techniques are used in machine tool and especially in cutting tool condition monitoring and RUL prediction. However, most of these sensors are wired, mounted inconveniently on the machine during the machining operations, and the prognostic information is not easy to be integrated into the manufacturing system [28, 31, 45, 49]. One of the problems is huge amount of data gathered. As a result, we face two types of research challenges concerning machine tools systems which are actually strongly interconnected. First of all, we force the problems related to their adequate measurement techniques for service life, health monitoring and reliability, especially with respect to predicting future states in order to enable the inference and implementation of executive activities in terms of failure-preventing servicing [24]. In addition, potential new solutions according to digital era requirements have to go beyond typical tool wear monitoring methods in real-time by tracking for example force model coefficients during the cutting process [30, 32]. On the other hand, diagnostic or maintenance systems require an operator to make reliable predictions and decisions under uncertainty. All these

E-mail addresses: E. Kozłowski - e.kozlovski@pollub.pl, K. Antosz - katarzyna.antosz@prz.edu.pl, D. Mazurkiewicz - d.mazurkiewicz@pollub.pl, J. Sęp - jsztmiop@prz.edu.pl, T. Żabiński - tomz@prz.edu.pl

aspects create the so called information overload problem, which can be solved with the use of data mining and existing data reduction techniques. Unfortunately, in complex production systems machinery operating under diverse conditions requires more advanced measurement and data processing approaches. As it was pointed by Zhao et al. [50], as a key component in modern manufacturing system, machine health monitoring has fully embraced the big data revolution. In order to extract useful knowledge, to create information based on it and, finally, to make appropriate decisions from the big data, machine learning techniques were regarded as a powerful solution. Machine learning has a potential for improving products and processes, enabling successful predictions using past experience, data and information. It encompasses several algorithms and tools used for a vast array of different data processing tasks [6, 40]. However, as mentioned by Ahamad et al. [1], the Big Data analytics require innovative tools that address the challenges faced by data volume, variety and velocity. Especially, when data fusion - integration of data and knowledge from several sources is necessary to be taken into consideration [23, 48]. These techniques may act as an effective bridge connecting advanced machinery sensors systems, big data and intelligent machine health monitoring systems. On one hand, it requires monitoring systems equipped with adequate sensors in order to collect the data. On the other hand, the transition from raw industrial big data to knowledge-based executive actions without any human action also requires the development of new analytical tools. This means another need of new expert and intelligent systems. For the purpose of mechanical systems development, studies must be conducted particularly on the measurement systems construction, and further the development of the integrated analytical solutions for intelligent modules that take advantage of a data analysis and intelligent decision support tools in order to predict and prevent a potential failure of machines or their crucial elements [24]. Machine tools are considered as a representative example of such studies needs and their real-world applications. For example, the new methods enable early prediction of the machine tool remaining useful life, its current condition classification, or both of them simultaneously.

For this purpose, numerous research works have been carried out providing new knowledge, although not without several weaknesses that should be solved. Condition monitoring techniques such as temperature, vibration or acoustic signal analysis, play an important role as indicators of a developmental failure, and have a wide range of different applications for the purpose of fault diagnosis. These different applications in technological machines such as machine tools or in any other mechanical systems, allow to compare the proposed methods and achieved results. Vamsi et al. [43] simulated the non-stationary load profile acting on a wind turbine. The vibration, acoustic signal and lubricating oil signals were simultaneously acquired. The raw signals were processed using a wavelet-based feature extraction technique. Next, the efficiency of each of these condition monitoring techniques under stationary and non-stationary loads were compared by using Support Vector Machine (SVM) as the classification technique. A decision tree algorithm was used to identify among the extracted features the dominant one (which was a standard error). SVM was used to classify the features among the fault levels. The main purpose of these investigations was to verify diagnostic capabilities of vibration signal analysis, compared to other techniques in the fault detection of a gear tooth root crack and a gear tooth chip. The authors [2] did not go beyond the standard diagnostic. The RUL prediction with the use of the collected data and modelling techniques as a decision support tool, unfortunately were not taken into consideration. The remaining useful life prediction via the combined use of the SVM as a classification tool and AutoRegressive and Integrated Moving Average (ARIMA) based identification as an expert system tool for the real-time monitoring of a manufacturing process was presented by Kozłowski et al. [24]. The objective of the study was to develop a new method for the proper estimation and representation of uncertainty in the RUL prediction. Therefore, in the analysed case, sensor data management involved the application of the SVM in order to construct a classifier for the cutter condition assessment, investigation of the effect of an acoustic signal correlation displacement length on the diagnostic error and the number of support vectors, and, finally, the development of the RUL prediction method. Several different advances in modelling of metal machining processes were also analysed in details by Arrazola et al. [2], as a result of a significant progress in developing industry-driven predictive models. The authors claim that the operation-level predictive models still need to be developed, especially for direct, industrial applications. As a part of a similar research project, mechanics of the milling system with serrated end-mills were studied by Pelayo et al [34], using force and surface topography models. A stationary milling force model was developed to predict the resulting machined surfaces. The authors point that the available cutting tools in standard catalogues are not homogeneous from one seller to another. Large differences are seen on the tool's features suggesting that there is not a unified criterion. It requires more effective measurement systems but also more universal analytical tools. The spindle bearing system as one of the most important parts of a machine tool was the subject of dynamic modelling by Xi et al. [47]. Based on the developed spindle bearing system model, the dynamic response of the system with different cutters and under different cutting conditions was simulated and compared with the experiment measured results. The presented results show that the simulated responses are in accordance with the experiment measured responses. However, they were achieved only in the laboratory conditions that do not directly reflect actual industrial production. According to [22], when avoiding chatter and improving machining efficiency and accuracy, the machining process analysis is extremely important. This type of analysis is essential in order to enable high productivity without sacrificing surface quality and inducting significant surface errors. Its exact implementation depends on the dynamics modelling with a reliable requirement of the system's dynamic parameters. With regard to this, a novel model testing strategy was proposed for obtaining the system's dynamic parameters. A triaxial acceleration sensor was used there and the related parameter processing techniques were proposed. Unfortunately, for validation, only two cutters with different diameters were employed in the experiments what makes the achieved results very limited.

As proved by Bousdekis et al. [4], the emergence of Industry 4.0 led to a wide use of sensors which facilitate manufacturing operations. Machining technology is one of the core examples. Predictive maintenance has significantly benefited from these technological advancements with the use of real-time detection and prediction algorithms regarding future failures. For the last few years, there has been an increasing interest on the decision making algorithms triggered by failure predictions, especially in production engineering. From the presented above state-of-the-art analysis we can make a similar conclusion as in [16], i.e.: machines without vibrations in the industrial environment are something non-existent. During machining operations, these vibrations are directly linked to the problems in systems having rotating or reciprocating parts, such as bearings, engines, gear boxes, shafts, turbines and motors. The vibration analysis has proved to be a measure for any cause of inaccuracy in manufacturing processes and components, or any maintenance decisions related to the machine. However, we should remember that a vibration signal analysis, on which most researchers are focused, is not the only one existing condition monitoring technique. Technological machines and machine tools as their typical example are equipped with several different sensors. The data gathered with them could be alternatively used in effective structural health monitoring. These aspects should be additionally discussed from the perspective of the internet of things-based intelligent decision support systems need [17], as a tool for data processing in manufacturing. With regard to the above presented research gaps and research challenges related to them, contributions of this work are twofold. An advanced milling machine multi-sensor system as a condition monitoring tool was presented. Its integration with the proposed signal processing method based on decision trees with different types and levels of wavelets for the cutter reliability decision-making process was presented as well. The assumed indicators of achieving the research goal are: low calculation time and data processing complexity, a universal analytical tool, data gathered directly reflecting typical industrial production, and finally a high accuracy model to assess the condition of the cutter state in real-time.

The research presented in the article is based on the cooperation of the authors with the aviation industry, in which providing the quality of the manufactured components, including aircraft engine components, is a critical factor due to a potential threat to the lives of the aircraft passengers that is connected to this issue. In turn, the final and inter-process quality control introduces significant costs. What's more, it doesn't provide a full guarantee of the quality that, in many cases, could be only obtained by carrying out destructive tests. Therefore, it is purposeful to perform the works that will enable the development of the methods which increase the effectiveness of a technological process supervision, even at the expense of installing additional sensors, including the construction of machining handle instruments with the built-in sensors of e.g. force and torque. Component machining, including large components, always requires the use of appropriate instruments which position and hold the machining component to the machine tool workstation. The aviation industry is open to designing the instruments in a way to allow for installing in them appropriate sensors as soon as it is possible to achieve the benefits mentioned above.

The aim of the research covered in this article is to develop an effective and dedicated measurement system for monitoring critical machining procedures implemented in the aviation industry with the use of a single type tool. The proposed solution allows to achieve high efficiency for a particular machining procedure with the limited solution generality. The article consists of the introduction, followed by a chapter describing the experimental setup and data processing with the use of the selected techniques. Finally, prediction errors achieved with the use of different signal sources and data processing methods were presented and compared.

2. Experimental evaluation

In the first phase of the research presented, an advanced milling machine multi-sensor system was designed and constructed. It was assumed that the data had to be collected from different signal sources for the purpose of health monitoring and later on for the RUL prediction. The system should not only be universal from the research perspective but should also conform to the industrial conditions. For the wide analytical purposes a typical industrial milling machine working in real industrial conditions was equipped with such sensors as (Fig. 1): accelerometers collecting signals from the lower spindle bearing, upper spindle bearing, Z axis, upper motor bearing and lower motor bearing; an acoustic emission sensor, 3-axis force and torque sensor, spindle velocity and spindle load sensor.

The data collected with the use of this milling machine and multi-sensor condition monitoring system were used for the previously presented research results [24, 25]. Their aim was to apply vibration and acoustic signals analysis in health monitoring, cutter state classification or its remaining useful life prediction. For the purpose of the presented in the this article sensor system and signal processing integration for cutter reliability decision-making process, we have assumed that the data collected from the 3-axis force and torque sensor can be also applied. It may be used as an effective alternative to the typical vibration signal based health monitoring and the RUL prediction.

2.1. Experimental setup and data description

The main goal of the experiment was to collect the data describing the cutter state during a milling process. The state of the cutter was categorized into two classes: sharp and blunt. The experiment was carried out on an industrial Haas VM-3 CNC

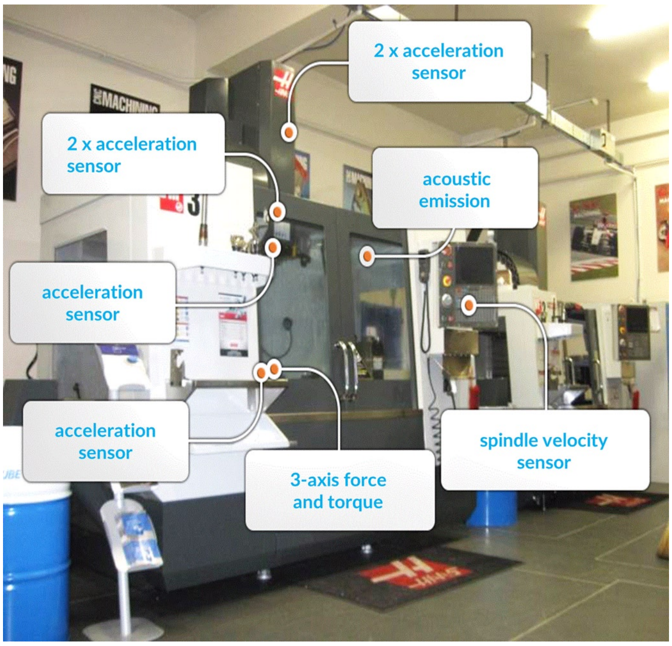

Fig. 1. Industrial CNC milling machine with a set of condition monitoring sensors [51]

machine. This machine is equipped with a 12,000 RPM direct drive spindle. The rotational speed of the spindle during machining was equal to 860 rpm. A multi-component CL16 ZEPWN sensor was used for the tests. The sensor enables force measurement in the range of 10 kN and torque measurement in the range of 1 kNm. The accuracy class of the sensor is 0.5, and the sensitivity is 1mV/V. The following signals were collected from the multi-component sensor: signals from the force sensor (P1x, P2y, P3z) and torque (M1x, M2y, M3z). A platform for rapid prototyping of intelligent diagnostic systems was used to collect data during milling experiments [51]. The platform includes Beckhoff industrial computer, an EtherCAT-based distributed I/O system. A hard disk of the engineering workstation was used to store the gathered data, collected in the real time with a sampling interval of 2 ms. The duration of the signal buffer stored in one file was 640 ms. During the experiments the data were collected from various real production tasks in the milling process on the machine.

2.2. Data processing

During the experiment a set of the collected data included 2172 observations. The data were gathered from the force sensor (signals: P1x, P2y, P3z) and torque (signals: M1x, M2y, M3z). These data were analysed in accordance with the methodology used to discover knowledge from the measurement database. The knowledge discovery in databases is a process of which the main task is a comprehensive data analysis, starting from the proper understanding of the problem under study, through the data preparation, execution and analysis of appropriate models, up to their evaluation. Then, the identified information is transformed into the knowledge that can be used to build decision support systems [3, 9]. In this paper the knowledge discovery process was divided into three stages: data pre-processing, data mining (processing), analysis of the results and evaluation of the created models (post-processing) (Fig. 2).

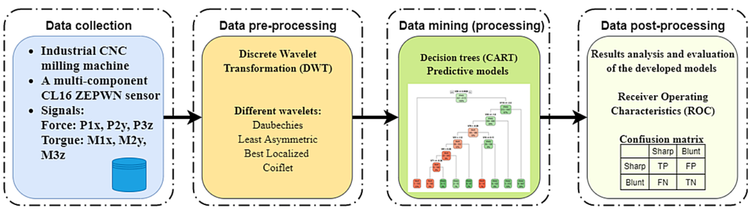

Fig. 2. Data processing methodology

In the first stage, the data obtained with the use of discrete wavelet transformation (DWT) were pre - processed. Different types and levels of wavelet were used [10]. The second stage of the knowledge discovery process was data mining. According to [26], which gives an overview of the methods used at this stage, primarily the methods related to the statistical data analysis, artificial intelligence and machine learning can be applied. Generally, these methods can be divided as follows:

- classic statistical methods, which include, among others: linear regression, multiple regression, analysis of variance,
- methods based on the use of artificial intelligence, machine learning and deep learning; for example: classification trees, regression trees, random forests, artificial neural networks, genetic algorithms, evolutionary algorithms, fuzzy sets, rough sets, enhanced and fuzzy trees, support vector machines and Bayes classifiers.

The authors of the aforementioned work [26] after analysing the results obtained in many publications, point out that in the case of large data sets, the methods from the second group are the most effective and most often used for data processing. In this paper, decision trees for data processing were used. In many publications, i.e. [7, 38], this method is widely used and it is considered as one of the best data mining algorithms. The results of their application in various research areas indicate their advantages such as: easy and transparent data interpretation, the ability to identify variables importance and ability to analyse large amounts of data [39, 41].

The third stage of the knowledge discovery was the interpretation and evaluation of the developed models. Receiver Operating Characteristics (ROC) was used as a tool to help to analyse the performance of predictive models. This method is often recommended for assessing the quality of models [8, 15, 36, 37].

2.2.1. Discrete Wavelet Transformation (DWT)

The data gathered from the force sensor (P1x, P2y, P3z) and torque (M1x, M2y, M3z) were preprocessed with the use of the wavelet analysis. The wavelet transformation is based on wavelet functions. Wavelet functions are irregular, asymmetric and, most of all, they are not periodic. The main goal of the wavelet transformation consists in the decomposition of the tested signal into component functions. Instead of harmonics, wavelet functions are used with a different scale (scale / frequency) and position (time / space) [10, 12]. The wavelet coefficients describe the extent to which the wavelet function is with a certain scale and position is similar to the considered signal fragment. The wavelet transformation consists in determining the coefficients for wavelets of various scales and positions.

Let $\mathbb{N}$ denote a set of natural numbers, $\mathbb{R}$ - set of real numbers, $\mathbb{Z}$ - set of integer numbers. Let $\{x_t\}_{t\in\mathbb{Z}}$ be a time series and $\Psi(t)$ ortogonal wavelet basis - mother wavelet and $\phi(t)$ denotes the scaling function (father wavelet) corresponding to wavelet Ψ. For any $j\in\mathbb{Z}$ we define a sequences $\{\Psi_{jk}\}_{k\in\mathbb{Z}}$ and $\{\phi_{jk}\}_{k\in\mathbb{Z}}$ as follows:

$$\Psi_{jk}(t)=\frac{1}{2^{j-1}}\Psi\left(\frac{t}{2^j}-k\right) \tag{1}$$

and

$$\phi_{jk}(t)=\frac{1}{2^{j-1}}\phi\left(\frac{t}{2^j}-k\right) \tag{2}$$

Then the time series we can present as:

$$x_t=\sum_{k=-\infty}^{\infty}c_{jk}\phi_{jk}(t)+\sum_{i=-\infty}^{j}\sum_{k=-\infty}^{\infty}d_{ik}\Psi_{ik}(t) \tag{3}$$

where c_{jk} is a scaling coefficient, d_{ik} is a detailed coefficient.

In many cases we perform a wavelet transformation for a time series with a finite number of observations $\{x_t\}_{1\le t\le n}$. A decomposing level j meets the condition $1\le j\le m=\max\{s\in\mathbb{N}:2^s\le n\}$. To simplify, we assume that $n=2^s$.

From the equations (1) and (2) we can see, that $\Psi_{jk}(t)$ and $\phi_{jk}(t)$ take non-zero values on the interval $\left(2^jk,2^j(k+1)\right]$. From above the time series $\{x_t\}_{1\le t\le n}$ we can present as follows:

$$x_t=\sum_{k=0}^{\frac{n}{2^j}-1}c_{jk}\phi_{jk}(t)+\sum_{i=0}^{j}\sum_{k=0}^{\frac{n}{2^i}-1}d_{ik}\Psi_{ik}(t) \tag{4}$$

for $1\le j\le m$. Based on the equation (4) we see that the time series $\{x_t\}_{t\in\mathbb{Z}}$ can be presented in different forms due to the level $j\in\mathbb{Z}$.

According to [17], we define the time series projection operator $\{x_t\}_{1\le t\le n}$ for the level j in the base $\{\phi_{jk}(t)\}_{0\le k\le\frac{n}{2^j}-1}$:

$$P^jx_t=\sum_{k=0}^{\frac{n}{2^j}-1}c_{jk}\phi_{jk}(t) \tag{5}$$

More about the DWT can be found in [11, 35, 44].

2.2.2. Decision trees

Decision trees were used to develop predictive models for the processed signals. Decision trees are a family of data mining and machine learning methods that can be used for both classification and regression tasks. The classification task is performed for a variable characterized by a predetermined set of possible states or values, otherwise it is defined as a regression task. Decision trees use different algorithms. In this study, the CART (Classification and Regression Trees) algorithm was used, as presented in [5]. CART splits the observation sample for the target variable as a binary tree structure with non-intersecting subsamples called nodes, according to specific rules.

The construction criteria are used to stop the tree growth and to avoid the model overfitting. These include: a minimum number of observations in the parent node, a minimum number of observations in the child node, tree depth, a cross-validation type, reaching the specified error type and others. In the case of machine learning, the standard recommendation is to use 10 fold cross-validation. The resulting model includes all target cases classified in the terminal nodes of the tree. In order to classify a given data set with the help of decision trees, the conditions should be formulated in such a way as to obtain the greatest gain of information or the smallest Gini index. Therefore, the process of selecting an attribute is based either on the Gini index or on obtaining information [13, 19]. The Gini index is a measure used to measure the frequency with which the randomly selected items would be misclassified. The Gini index is defined as follows [18, 20]:

$$Q_G(m)=\sum_{j=1}^{s}p_{mi}(1-p_{mi})=1-\sum_{j=1}^{s}p_{mi}^2 \tag{6}$$

where p_{mi} is a conditional probability for j – th class in a node, s – a number of classes. In node m with n_m observations the conditional probability for j – th class is equal to:

$$p_{mi}=\frac{\#\{y=c_i:x\in R_m\}}{n_m} \tag{7}$$

2.2.3. Receiver Operating Characteristics (ROC) analysis

Receiver Operating Characteristics (ROC) indicators were used as a tool to help to determine the performance of predictive models. The ROC curve is a graph characteristic for a given classifier, showing TP (True Positives) and FP (False Positives) values on the Y and X axes. Classification errors are defined as FP (False Positives) and FN (False Negatives). They mean appropriately classifying objects from the positive to negative class and assigning cases from the negative to positive class. The values of TP, TN, FP and FN create the confusion matrix presented in Table 1.

Table 1. Confusion matrix

Predicted classes	Real classes	
	Positive	Negative
Positive	TP (True positive)	FP (False positive)
Negative	FN (False negative)	TN (True Negative)

Based on the confusion matrix (Table 1), the following assessment indicators were used to assess the quality of classification models analysing the results from most of the classifiers of machine learning [14, 29, 36, 42, 46]:

- Accuracy (Acc), which is determined as the sum of TP and TN, it indicates that the results are correctly classified to all the analysed data. This indicator evaluates the prediction ability of the model:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

True Positive Rate (TPR) is the rate that determines the fraudulent free transactions classified as fraudulent:

$$TPR = \frac{TP}{TP + FN} \tag{9}$$

- True Negative Rate (TNR) is the rate that determines the fraudulent free transactions classified as legitimate:

$$TNR = \frac{TN}{TN + FP} \tag{10}$$

- Positive Predictive value (PPV) is an indicator that describes the relationship between the number of true positives and the total number of positives: true positives and false positives:

$$PPV = \frac{TP}{TP + FP} \tag{11}$$

- Negative Predictive Value (NPV) is an indicator that describes the relationship between the number of true negatives and the total number of negatives: true negatives and false negatives:

$$NPV = \frac{TN}{TN + FN} \tag{12}$$

- Prevalence (PV) is an indicator that determines the frequency of occurrence of the distinguished class:

$$PV = \frac{TP + FN}{TP + TN + FP + FN} \tag{13}$$

- Detection Rate (DR) is an index that measures the ratio of true positives to the total number of predictions:

$$DR = \frac{TP}{TP + TN + FP + FN} \tag{14}$$

- Detection Prevalence (DPV) is an index defined as the number of predicted positive cases divided by the total number of predictions:

$$DPV = \frac{TP + FP}{TP + TN + FP + FN} \tag{15}$$

The ROC analysis is most often used to show how a change in the threshold value of a classifier affects its ability to classify. Using the ROC analysis, it is possible to select an optimal threshold value, also known as the cut-off point. Looking at the ROC curve only in this context, performing the ROC analysis would make sense only for a model that gives a numerical value on the output indicating the degree of belonging to the class (scoring). The ROC curve can also be used as a measure of the quality of a classifier by determining the Area under Curve (AUC) [29, 42].

3. Results and discussion

The main aim of the task was to recognize if the cutter was blunt or not, based on the observation of the signals obtained from sensors. From sensor for each signal P1x, P2y, P3z, M1x, M2y and M3z the sequence contained 320 observations was created. The sample realisation of signals are presented in Figure 3.

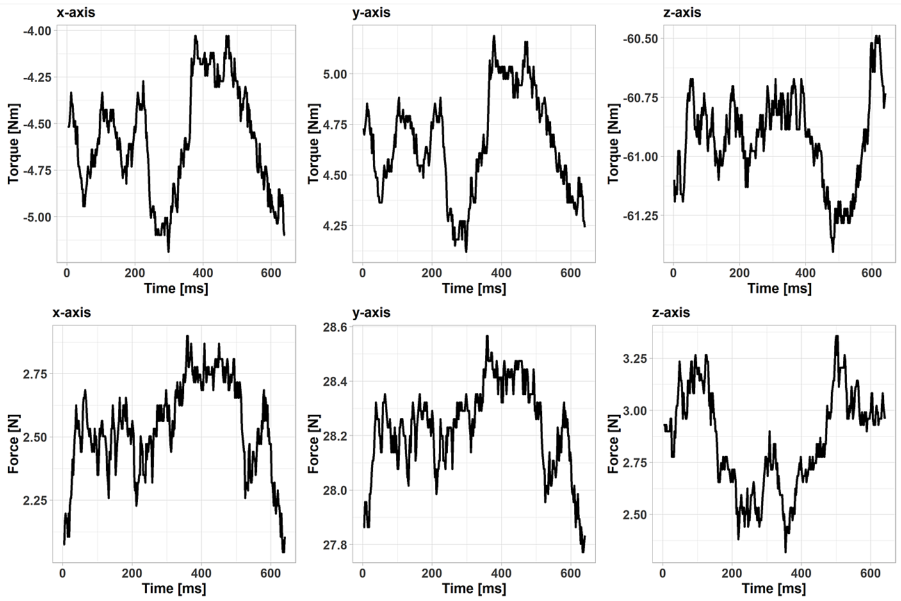

Fig. 3. Sample realisation of P1x, P2y, P3z, M1x, M2y and M3z signals

To analyse the relationship between the main characteristics of data and cutter state, the statistical analysis was performed. The Kruskal-Wallis test for hypothesis testing was used and the basic statistics were analysed. The Table 2 and Table 3 present the basic signal statistics for the cutter state.

Table 2. The basic signal statistics for a sharp cutter

Signals	M1x	M2y	M3z	P1x	P2y	P3z
min	−0.1171427	−0.0228960	−0.6303399	0.0010815	0.2567350	0.0149973
max	0.0029251	0.1296336	−0.5869904	0.0713316	0.3263204	0.0405637
mean	−0.0529555	0.0403286	−0.6181026	0.0248948	0.2874076	0.0282353
std	0.0310903	0.0302851	0.0062023	0.0172853	0.0095725	0.0055035
0.25%	−0.0803710	0.0146124	−0.6218952	0.0100079	0.2840958	0.0235235
0.5%	−0.0514923	0.0402213	−0.6191194	0.0209323	0.2882440	0.0283904
0.75%	−0.0248435	0.0671787	−0.6148348	0.0389972	0.2938729	0.0329296

Table 3. The basic signal statistics for blunt cutter

	M1x	M2y	M3z	P1x	P2y	P3z
min	−0.1439127	−0.0656999	−0.6350875	0.0030977	0.2707327	0.0058511
max	0.0510880	0.1436246	−0.5717976	0.1140984	0.4079226	0.0521933
mean	−0.0511779	0.0389308	−0.6186331	0.0421332	0.3625294	0.0280621
std	0.0480753	0.0476963	0.0080547	0.0259049	0.0452849	0.0108821
0.25%	−0.0882373	0.0005646	−0.6243047	0.0233395	0.3643719	0.0192413
0.5%	−0.0545385	0.0386228	−0.6188666	0.0355519	0.3847081	0.0277085
0.75%	−0.0106254	0.0772895	−0.6136879	0.0590801	0.3919459	0.0366029

Table 4. Kruskal-Wallis test results for torque and force signals

	M1x	M2y	M3z	P1x	P2y	P3z
chi-squared	0.0619675	0.5523552	2.1087337	250.9589	687.9325	0.715012
p-value	0.8034128	0.4573570	0.1464605	0.0000	0.0000	0.397785

The Kruskal-Wallis test to compare the mean of the received torque and force signals was used. The test results are presented in the Table 4.

Analyzing the above data, it should be noted that at the significance level α = 0.01 for M1x, M2y, M3z and P3z signals, there are no reason for rejecting the null hypothesis, that there is no statistically significant difference between the mean values for the sharp and blunt cutters (p-value >0.01). That's why it should be noted that on the basis of the mean of the received signals it is not possible to determine the condition of the cutter. Therefore, signals were pre-processed by the application of a wavelet analysis.

For the possible wavelet a data set $D=\{(w_i,y_i)\}_{1\le i\le n}$, was defined, where for $i-th$ sample the value $y_i\in\{0,1\}$ denotes the cutter state, but $w_i\in\mathbb{R}^m$ denotes the vector of predictors based on wavelet pre-processing. When the cutter was sharp then we put $y_i=0$, otherwise if the cutter was blunt then $y_i=1$. For designing a decision tree the data set which contains 2172 samples was used. For the chosen wavelet and filtering level $l\in\mathbb{N}$ the signals from sensors were pre-processed, i.e. the same preprocessing was applied to the observation sequences from P1x, P2y, P3z, M1x, M2y and M3z signals.

Thus, for each sample the sequences of approximation coefficients $\left\{c_{lk}^{j,s}\right\}_{1\le k\le n}$ and detail coefficients $\left\{d_{lk}^{j,s}\right\}_{1\le k\le n}$ were estimated, where $1\le j\le 2172$ and $s\in\{P1x,P2y,P3z,M1x,M2y,M3z\}$.

For the signal decomposition the following different wavelets were applied:

- Daubechies 2,4,6,8,10,12,14,16,18,20;
- Least Asymmetric 8,10,12,14,16,18,20;
- Best Localized 14,18,20;
- Coiflet 6,12,18,24,30.

For the detail coefficients the mean $m_j^s=\sum_{k=1}^{n} d_{lk}^{j,s}$ and variance $S_j^s=\sum_{k=1}^{n}\left(d_{lk}^{j,s}-m_j^s\right)^2$ were determined. The vector of predictors was defined as:

$$w_j=\left\{m_j^{P1x},S_j^{P1x},\left\{c_{lk}^{j,P1x}\right\}_{1\le k\le n},m_j^{P2y},S_j^{P2y},\left\{c_{lk}^{j,P2y}\right\}_{1\le k\le n},\ldots,m_j^{M3z},S_j^{M3z},\left\{c_{lk}^{j,M3z}\right\}_{1\le k\le n}\right\} \tag{16}$$

The set $D=\{(w_i,y_i)\}_{1\le i\le 2172}$, where $y_i\in\{0,1\}$, $w_j\in\mathbb{R}^{6(n+2)}$, is a learning set based on which classification trees were designed. The realizations of some features in the dataset for sharp and blunt cutters differ significantly. The density function and the distribution for one of the analyzed features are shown in Figure 4.

Significance of differences between sharp and blunt cutters based on possible feature which distribution is presented on figure 4 was confirmed by Kolmogorov-Smirnov and Kruskal-Wallis tests. For Kolmogorov-Smirnov test the statistic D is equal 0.7297983, for Kruskal-Wallis test the statistic χ^2 is equal 935.8446284. For both tests p - value is to approximately 0. Hence, at the significance level of 0.01, it should be assumed that the values of the presented feature for sharp and blunt cutters differ significantly.

The following tree construction criteria were used: a classification tree (method = 'class') and the following parameters that control the tree designing procedure: a complexity parameter (cp = 0.005), a minimum number of observations that have to exist on the node in order to be able to attempt a split (minsplit = 7), a number of variables competing at the output (maxcompete = 10), a number of surrogate variables (maxsurrogate = 10), a method of determining which surrogate variables will be used (usesurrogate = 2), and a maximum depth

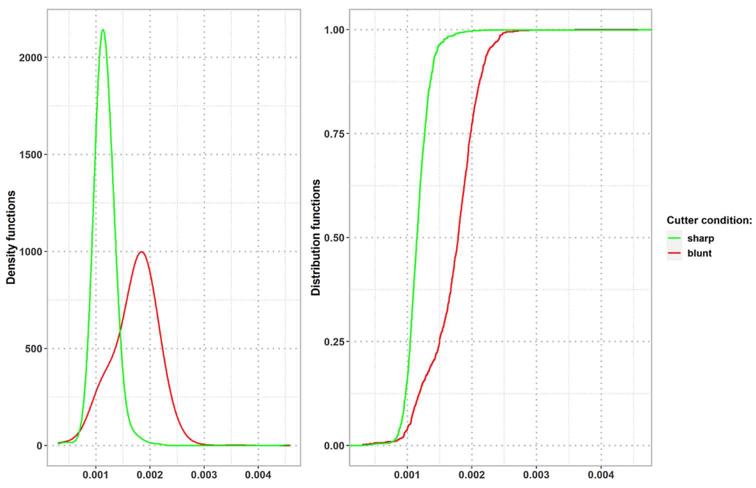

Fig. 4. Analysis of the distribution of an exemplary feature

of a tree (maxdepth = 7). A decision tree was generated for the defined parameters.

In order to evaluate the quality of recognition, the following ratios were estimated: accuracy, sensitivity (True Positives Rate), specificity (True Negatives Rate), positive predictive value, precision, negative predictive value, prevalence, detection rate and detection prevalence. Additionally, 10-fold cross validation was done. For each wavelet, the number of variables used in the training set (n.var) and the number of variables used in the tree (n.used) were checked. In order to carry out the cross validation procedure, the learning set was divided into 10 portions. The classification tree was created every time based on the training set containing 9 portions. However, the accuracy was determined based on the test set containing only one portion. Each time the test set was different. For the obtained accuracy sequence the mean and standard deviation were estimated. The values of these parameters were attached to Table 5 as Acc.cv and Acc.sd respectively. The obtained results are presented in Table 5.

When analysing the results presented in Table 5, it should be noted that the first indicator (accuracy - Acc) shows that the highest value was obtained for the Daubechies 20 wavelets at level l = 4 (Acc = 0.9926).On the other hand, the lowest Acc value was obtained for the Coiflet 30 wavelet, level l = 3 (Acc = 0.9797). The results for the sensitivity (TPR) of the classifiers look similar. The ability to detect objects from the selected class is the highest for the Daubechies 20 wavelets at level l = 4 (TPR = 0.9904) and the lowest for Coiflet 30 wavelets level l = 3. The analysis of the TNR and PPV indicator shows its highest value for the Coiflet 6 wavelet at level l = 5. The highest probability of belonging of an object to the category recognized by the classifier as a not distinguished class in the actual non-displayed class (NVP) was obtained for Daubechies 20 wavelets at level l = 4. Though, the number of predicted positive cases (DPV) was obtained for Best Localized 14 wavelets at level l = 4. The value of the PV indicator for all the analysed wavelets was at a comparable level, that is ≈ 0.4314. Fig-

Table 5. The values of prediction models quality indicators

	level	n.var	n.used	Acc	TPR	TNR	PPV	NPV	PV	DR	DPV	Acc.cv	Acc.sd
d2	5	120	9	0.9862	0.9808	0.9903	0.9871	0.9855	0.4314	0.4231	0.4286	0.9630	0.0104
d4	5	120	7	0.9834	0.9691	0.9943	0.9923	0.9769	0.4314	0.4180	0.4213	0.9713	0.0067
d6	5	120	7	0.9843	0.9723	0.9935	0.9913	0.9792	0.4314	0.4194	0.4231	0.9722	0.0115
d8	5	120	7	0.9802	0.9616	0.9943	0.9923	0.9715	0.4314	0.4148	0.4180	0.9706	0.0090
d10	5	120	8	0.9853	0.9723	0.9951	0.9935	0.9793	0.4314	0.4194	0.4222	0.9669	0.0096
d12	4	168	10	0.9890	0.9829	0.9935	0.9914	0.9871	0.4314	0.4240	0.4277	0.9623	0.0122
d14	4	168	8	0.9848	0.9744	0.9927	0.9902	0.9808	0.4314	0.4203	0.4245	0.9685	0.0130
d16	4	168	8	0.9866	0.9829	0.9895	0.9861	0.9871	0.4314	0.4240	0.4300	0.9719	0.0100
d18	4	168	8	0.9834	0.9701	0.9935	0.9913	0.9777	0.4314	0.4185	0.4222	0.9663	0.0092
d20	4	168	12	0.9926	0.9904	0.9943	0.9925	0.9927	0.4314	0.4273	0.4305	0.9684	0.0121
la8	5	120	6	0.9853	0.9755	0.9927	0.9902	0.9816	0.4314	0.4208	0.4250	0.9768	0.0080
la10	5	120	8	0.9894	0.9808	0.9960	0.9946	0.9856	0.4314	0.4231	0.4254	0.9795	0.0100
la12	4	168	8	0.9862	0.9808	0.9903	0.9871	0.9855	0.4314	0.4231	0.4286	0.9735	0.0107
la14	4	168	7	0.9848	0.9712	0.9951	0.9934	0.9785	0.4314	0.4190	0.4217	0.9708	0.0112
la16	4	168	7	0.9843	0.9701	0.9951	0.9934	0.9777	0.4314	0.4185	0.4213	0.9677	0.0085
la18	4	168	9	0.9876	0.9808	0.9927	0.9903	0.9855	0.4314	0.4231	0.4273	0.9689	0.0126
la20	4	168	7	0.9816	0.9648	0.9943	0.9923	0.9738	0.4314	0.4162	0.4194	0.9705	0.0071
bl14	4	168	7	0.9857	0.9840	0.9870	0.9829	0.9878	0.4314	0.4245	0.4319	0.9747	0.0116
bl18	4	168	7	0.9820	0.9658	0.9943	0.9923	0.9746	0.4314	0.4167	0.4199	0.9677	0.0115
bl20	4	168	10	0.9871	0.9808	0.9919	0.9892	0.9855	0.4314	0.4231	0.4277	0.9658	0.0101
c6	5	120	7	0.9908	0.9840	0.9960	0.9946	0.9880	0.4314	0.4245	0.4268	0.9782	0.0096
c12	4	168	7	0.9820	0.9658	0.9943	0.9923	0.9746	0.4314	0.4167	0.4199	0.9659	0.0101
c18	4	168	9	0.9885	0.9829	0.9927	0.9903	0.9871	0.4314	0.4240	0.4282	0.9694	0.0088
c24	3	276	8	0.9834	0.9691	0.9943	0.9923	0.9769	0.4314	0.4180	0.4213	0.9650	0.0107
c30	3	276	7	0.9797	0.9594	0.9951	0.9934	0.9700	0.4314	0.4139	0.4167	0.9657	0.0076

Legend: *Prediction model with the highest Acc value* (green)
Prediction model with the lowest Acc value (red)

ure 5 shows the decision tree for the wavelets with the highest value of the accuracy coefficient (Daubechies 20 wavelets for the level l = 4).

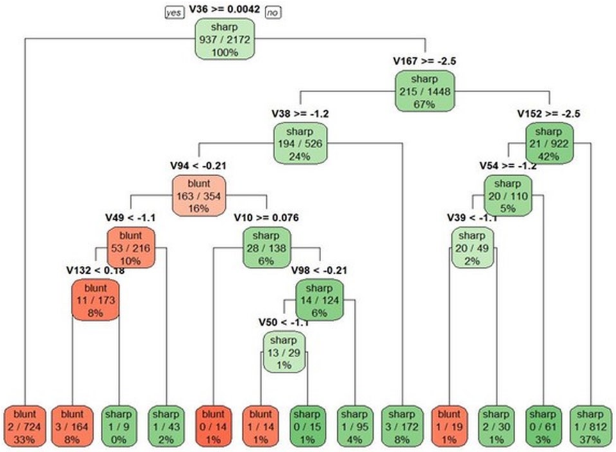

Fig. 5. A decision tree for the wavelets with the highest value of the accuracy coefficient (Daubechies 20 wavelets for the level l = 4)

Analysing Figure 5 it should be noted that with the defined 168 variables only 12 were used (Table 2) for the tree construction. The developed tree has 12 split nodes and 13 terminal nodes, and, thus, it generates 13 decision rules defining the cutter state. The ranking of the variables importance was used to build the tree in the training set for Daubechies 20 wavelets for the level l = 4 and presented in Figure 6. The highest values indicate the largest variable influence on the cutter state. In this case, from 168 variables used (Table 2) the most important variables are: V38, V54, V45, V47, V43, V46, V39, V40, V41, V36 and V92. The importance of the variable determines the participation of the variable in the created decision tree. Importantly, the specific meaning of a variable applies only to the analysed decision tree for which it was determined.

Variables included in the decision tree nodes do not necessarily mean its high importance. It can be observed that among these most important variables, only V38 and V39 were included in the analysed tree out of all 12 variables (nodes) in the tree. The variables which are to be included in the tree largely depend on the set of variables and its specificity. Input fields that contain relevant information may not be included in the decision tree and, thus, the quality of the forecast will not be affected. The analysis of the importance of the variables allowed to identify those input variables that have the greatest impact on creating the decision tree, and, thus, have an impact on the condition of the cutter state.

Table 6 presents the confusion matrix for the Daubechies 20 wavelets level l = 4. The sharp cutter is assumed to be a negative case (N), while a blunt cutter is a positive case (P). The confusion matrix analysis shows that 16 out of 2172 analysed variants were incorrectly classified, which means that the prediction error is ≈ 0.74%. This value indicates a very high predictive ability of the developed classifier.

On the other hand, the highest value of the accuracy indicator (Acc.cv = 0.9795) after the application of a 10-fold cross-validation was obtained for the Least Asymmetric 10 wavelets for the level l= 5. Figure 7 shows a decision tree created for the training set for the coefficients obtained on the basis of data processing using Least Asymmetric 10 wavelets.

Analysing Figure 7 it can be noted that with the defined 120 variables only 7 were used (Table 5) for the tree construction. The developed tree has 7 split nodes and 8 terminal nodes. It means that 8 decision rules define the cutter state. Table 7 shows the analysis results of the cutter state using a 10-fold cross-validation. In one of the analysed cases, the training set contained 1947 records, while the test set contained 225.

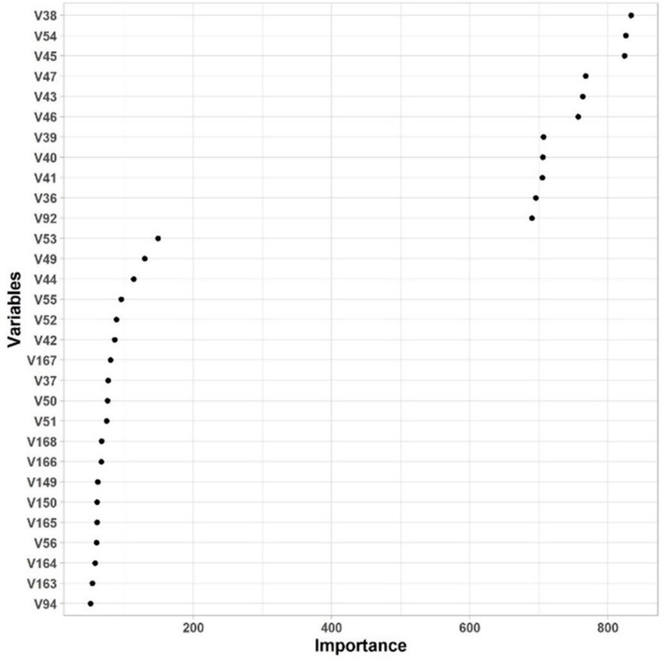

Fig. 6. The ranking of variable importance for a decision tree (Daubechies 20 wavelets for the level l = 4)

Table 6. Confusion matrix for classification tree designed on from wavelets Daubechies 20

		Reference	
	State	Blunt	Sharp
Prediction	Blunt	928	7
	Sharp	9	1228

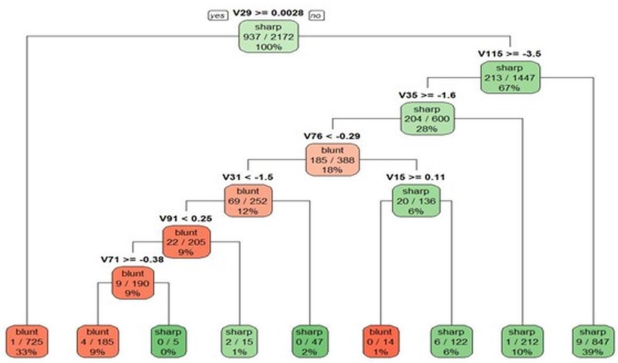

Fig. 7. A decision tree with the highest accuracy value after 10-fold cross-validation (Least Asymmetric 10 wavelets for level l=5)

Table 7. The chosen confusion matrix for the classification tree designed on the coefficients obtained from wavelets Least Asymmetric 10

		Reference	
	State	Blunt	Sharp
Prediction	Blunt	91	1
	Sharp	3	130

The analysis of the confusion matrix shows that 4 out of 225 set records analysed variants were incorrectly classified. Moreover, the lowest Acc.std value (Acc.std = 0.0067) (Table 2) was obtained for Daubechies 4 wavelets at level l = 5, which means that the changes in the Acc indicator value with the 10-fold cross-validation were the smallest. It should be assumed that the predictive model for these wavelets is the most stable. However, the value of the accuracy indicator for this model was only Acc = 0.9834, which means the prediction error is ≈ 1.7%.

4. Conclusions

Technological machines designed for the Industry 4.0 applications, among which are also machine tools, are advanced mechatronic systems equipped with several sensors. The data gathered from them are usually used for diagnostic, monitoring and other purposes including their components remaining useful life prediction, condition classification, or both of them. Typical condition monitoring techniques (temperature, vibration or acoustic signal analysis) play an important role as data sources and indicators of a developmental failure, and having a wide range of different applications. Among them, a vibration signal analysis is usually applied as a measure for any cause of inaccuracy in manufacturing processes and components, or any maintenance decisions related to the machine. On the other hand, technological machines are equipped with several different sensors, from which the data gathered could be alternatively used in effective structural health monitoring. That is why, the aim of this article was to verify how effective appropriate data processing of such alternative signals collected from the multi-component sensor: signals from the force sensor and torques could be. All this with a strong relation to the expected solutions necessary in digital transformation, which will help to eliminate current barriers such as heterogeneous data streams that cannot be well processed to realize the automated decision support due to the lack of strong analytic capabilities Another research challenge in this area should also be considered, that is the development of predictive data analytics techniques in order to aggregate and process the sensor data to assist in the maintenance operations or scheduling. It requires advanced information analytics for the networked machines that will finally be able to perform more efficiently and collaboratively. Vast research is conducted in this area. However, it is mainly theoretical considerations where new methods or mathematical models are usually verified only with the use of simulation data. Although there are many works investigating SHM or RUL in production engineering, they are usually limited to small and academic problems. Monitoring smart structures poses a big challenge in terms of fault or damage detection, due a huge amount of noisy data collected from many sensors on a periodic basis.

For the purpose of the presented sensor system and signal processing integration for a cutter reliability decision-making process, we assumed that the data collected from the 3-axis force and torque sensor can be also used as an alternative to a typical vibration signal based health monitoring and the RUL prediction, while integrated with machine learning techniques that are regarded as a powerful solution. An industrial milling machine multi-sensor system as a condition monitoring tool was presented. Its integration with the proposed signal processing method based on decision trees with different types and levels of wavelets for the cutter reliability decision-making process was a part of the research results discussed. In the first stage, the data gathered were pre-processed with the use of discrete wavelet transformation. The main goal of the wavelet transformation consists in the decomposition of the tested signal into component functions. Different types and levels of wavelet were used. Next, decision trees (a family of data mining and machine learning methods that can be used for both classification and regression tasks) were applied for data processing in order to develop predictive models for the processed signals. The third stage of the knowledge discovery was the interpretation and evaluation of the developed models. Receiver Operating Characteristics (ROC) was used as a tool to assess the performance of the developed predictive models. The presented confusion matrix for the classification tree designed on the coefficients obtained from wavelets Least Asymmetric 10 allowed to achieve a prediction error equal to 1.7%. On the other hand, much better results were achieved in the case of the classification tree designed with the use of Daubechies 20 wavelets. Only 16 out of 2172 analysed variants were incorrectly classified, which means that the prediction error was equal to 0.74%.

The data gathered during the same industrial production process but coming from other sensors were also analysed for classification and prediction on earlier research stages. The comparison of the results achieved before with these, presented in the current work, will allow to verify the research hypothesis i.e.is it possible to use the data collected from the 3-axis force and torque sensor as an alternative to the typical vibration signal based health monitoring and RUL prediction? In [25] the prediction was evaluated by the SVM application. Cutter condition identification was done by registering and processing vibroacoustic data, in conjunction with torque measurement using a three-axis sensor mounted in the chuck. A correlation analysis, which is related to the spectral analysis, was used to identify the parametric property of an vibroacoustic signal, but torque signals were identified as ARIMA models. This information was used to create a data set. Additionally, for the prediction based on SVM the modified kernel function as a linear combination of kernels representing the acoustic signal and torque data was used. The prediction error achieved was equal to 2.1 %. In [9] SVM was applied only for the preprocessed vibroacoustic signals. In this case the achieved prediction error was equal to 2.6%. In [24] the prediction was assessed by a logistic regression application into the preprocessed vibroacoustic signals. The classification error was obtained at the level of 8.6%. The comparison of the results achieved previously and in the current analysis indicates a very high predictive ability of the analysed tree and alternative condition monitoring data source. A novel approach for a predicting tool remaining useful life was also proposed by Li et al. [27], who emphasize that most current approaches for the predicting tool RUL are based on historical failure and truncation data, while for the new types of tools or when a similar tool has just been launched, such failure and truncation data are limited or even unavailable. In order to address this problem, a novel method for the prediction of the tool RUL using limited data was proposed and, for this purpose, a time window was constructed to track the tool condition using sensor data, with its size to be dynamically adjusted according to the wear factor and increase rate. Then, a deep bidirectional long short-term memory neural network in which sequential data are predicted and smoothed by forwards and backwards directions respectively, was developed to encode temporal information and identify long-term dependencies. On this basis, multi-step ahead rolling predictions were employed to predict the tool RUL. The presented results [27] show that with this method it is possible to predict the tool RUL However, its weakness stems from the time consuming and complicated multi-step framework of the proposed prediction algorithm. In addition, this algorithm is also quite sensitive to changes in tool working conditions. The mean absolute error and root mean square error of the method proposed by [27] were 0.1130 and 0.1592. They are much higher than prediction errors achieved in this study.

To sum up, the novelty aspect and most important achievements of the research results presented in the article are:

1. It was proved with the use of real world industrial production process data that the 3-axis force and torque sensors can be considered as a data source alternative to the typical vibration signal for health monitoring and RUL prediction, while integrated with adequate pre- and post-processing methods.
2. The possible application of different types and levels of wavelets for signal processing with their efficiency analysis in industrial condition monitoring were presented and discussed.
3. Different predictive models were developed with the use of decision trees for the signals processed with various types and levels of wavelets proving their ability to accurately trace a tool condition.
4. The ROC analysis was used to identify the most stable predictive model and the model with the lowest prediction error selection method.

5. The prediction error of the proposed method is lower than those for the previously proposed approaches evaluated, while the time necessary to achieve high accuracy predictions and analysis complexity as well as the associated cost are much lower. Limited calculation time and data processing complexity reduction are significant results of the proposed method.

In Industry 4.0 vision, data digitalization and data processing are expected to bring major changes in manufacturing in general, and the spread of novel technologies will enable a stepwise increase of productivity in manufacturing companies. From this perspective, the described milling machine multi-sensor system and the proposed data processing model may be considered as a decision-making process tool in determining cutting tools service life, extending the time of their effective use in a production process, making this way the replacement time as optimal as possible.

***Acknowledgement*:**

The research was partially financed in the framework of the project Lublin University of Technology - Regional Excellence Initiative, funded by the Polish Ministry of Science and Higher Education (contract no. 030/RID/2018/19)".

References

1. Ahamd A, Paul A, Din S, Rathore MM, Choi GS, Jeon G. - Multilevel data processing using parallel algorithms for analyzing Big Data in high-performance computing. International Journal of Parallel Programming 2018; 46: 508-527, https://doi.org/10.1007/s10766-017-0498-x.
2. Arrazola P, Özel T, Umbrello D, Davies M, Jawahir I. - Recent advances in modelling of metal machining processes. CIRP Annals 2013; 62: 695-718, https://doi.org/10.1016/j.cirp.2013.05.006.
3. Borucka A, Wiśniowski P, Mazurkiewicz D, Świderski A. - Laboratory measurements of vehicle exhaust emissions in conditions reproducing real traffic. Measurement 2021; 174: 108998, https://doi.org/10.1016/j.measurement.2021.108998.
4. Bousdekis A, Lepenioti K, Apostolou D, et al. - Decision making in predictive maintenance: Literature review and research agenda for Industry 4.0. IFAC-PapersOnLine 2019; 52: 607-612, https://doi.org/ 10.1016/j.ifacol.2019.11.226.
5. Breiman L, Friedman JH, Olshen RA, Stone CJ. - Classification and Regression Trees. Chapman and Hall/CRC: Boca Raton, FL, USA 1984.
6. Carleo G, Cirac I, Cranmer K, Daudet L, Schuld M, Tishby N, Vogt-Maranto L, Zdeborova L. - Machine learning and the physical sciences. Reviews of Modern Physics 2019; 91: 045002.
7. Choi S, Battulga L, Nasridinov A, Yoo K-H. - A Decision Tree Approach for Identifying Defective Products in the Manufacturing Process. International Journal of Contents 2017; 13: 57–65, https://doi.org/10.5392/IJoC.2017.13.2.057.
8. Costa EP, Lorena AC, Carvalho ACPLF, Freitas AA. - A review of performance evaluation measures for hierarchical classifiers. Evaluation Methods for Machine Learning II: papers from the AAAI-2007 Workshop, AAAI Press 2007: 82–196.
9. Dargan S, Kumar M, Ayyagari MR, Kumar G. - A survey of deep learning and its applications: a new paradigm to machine learning. Archives of Computational Methods in Engineering 2020; 27: 1071-1092, https://doi.org/10.1007/s11831-019-09344-w.
10. Daubechies I. - Orthonormal bases of compactly supported wavelets. Communications on Pure and Applied Mathematics 1998; 41: 909–996.
11. Daubechies I. - Ten lectures on wavelets. Society for Industrial and Applied Mathematics 1992, https://doi.org/10.1137/1.9781611970104.
12. Edwards T. - Discrete Wavelets Transform: Theory and Implementation. Stanford University 1991.
13. Farid DM, Zhang L, Rahman CM, Hossain MA, Strachan R. - Hybrid decision tree and naïve Bayes classifiers for multi-class classification tasks. Expert Systems with Applications 2014; 41: 1937–1946, https://doi.org/10.1016/j.eswa.2013.08.089.
14. Fawcett T. - An introduction to ROC analysis. Pattern Recognition Letters 2006; 27: 861–874, https://doi.org/10.1016/j.patrec.2005.10.010.
15. Fawcett T. - Using rule sets to maximize ROC performance. Proceedings 2001 IEEE International Conference on Data Mining ICDM 2001: 131–138, https://doi.org/ 10.1109/ICDM.2001.989510.
16. Goyal D, Pabla B. - The vibration monitoring methods and signal processing techniques for structural monitoring: a review. Archives of Computational Methods in Engineering 2016; 23: 585-594, https://doi.org/ 10.1007/s11831-015-9145-0.
17. Guo Y, Wang N, Xu ZY, Wu K. - The internet of things-based decision support system for information processing in intelligent manufacturing using data mining technology. Mechanical Systems and Signal Processing 2020; 142: 106630, https://doi.org/10.1016/j.ymssp.2020.106630.
18. Hastie T, Tibshirani R, Friedman J. - The elements of statistical learning. Springer-Verlag New York Inc 2009, https://doi.org/ 10.1007/978-0-387-84858-7.
19. Hssina B, Merbouha A, Ezzikouri H, Erritali M. - A comparative study of decision tree ID3 and C4.5. International Journal of Advanced Computer Science and Applications, Special Issue on Advances in Vehicular Ad Hoc Networking and Applications 2014; 4: 13–19.
20. James G, Witten D, Hastie T, Tibshirani R. - An introduction to statistical learning. Springer-Verlag GmbH 2013, https://doi.org/10.1007/978-1-4614-7138-7.
21. Jasiulewicz-Kaczmarek M, Antosz K, Wyczółkowski R, Mazurkiewicz D, Sun B, Qian C, Ren Y. - Application of MICMAC, Fuzzy AHP and Fuzzy TOPSIS for Evaluation of the Maintenance Factors Affecting Sustainable Manufacturing. Energies 2021; 14(1436): 1-31, https://doi.org/10.3390/en14051436.
22. Jiang S, Sun SY. - Stability analysis for a milling system considering multi-point-contact cross-axis mode coupling and cutter run-out effects. Mechanical Systems and Signal Processing 2020; 141: 106452, https://doi.org/10.1016/j.ymssp.2019.106452.
23. Koch W. - Tracking and sensor data fusion. Methodological framework and selected applications. Springer Verlag, Berlin 2014.
24. Kozłowski E, Mazurkiewicz D, Żabiński T, Prucnal S, Sęp J. - Assessment model of cutting tool condition for real-time supervision system. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2019; 21: 679-685, https://doi.org/10.17531/ein.2019.4.18.
25. Kozłowski E, Mazurkiewicz D, Żabiński T, Prucnal S, Sęp J. - Machining sensor data management for operation-level predictive model. Expert Systems with Applications 2020; 159: 1-22, https://doi.org/10.1016/j.eswa.2020.113600.
26. Lepenioti K, Bousdekis A, Apostolou D, Mentzas G. - Prescriptive analytics: literature review and research challenges. International Journal of Information Management 2020; 50: 57-70, https://doi.org/10.1016/j.ijinfomgt.2019.04.003.
27. Li H, Wang W, Li Z, Dong L, Li Q. - A novel approach for predicting tool remaining useful life using limited data. Mechanical Systems and Signal Processing 2020; 143: 1086832, https://doi.org/10.1016/j.ymssp.2020.106832.

28. Liu R, Kothuru A, Zhang S. - Calibration-based tool condition monitoring for repetitive machining operations. Journal of Manufacturing Systems 2020; 54: 285-293, https://doi.org/10.1016/j.jmsy.2020.01.005.
29. Matthews BW. - Comparison of the predicted and observed secondary structure of T4 phage lysozyme. Biochimica et Biophysica Acta (BBA) - Protein Structure 1975; 405: 442-451, https://doi.org/10.1016/0005-2795(75)90109-9.
30. Mazurkiewicz D. - Empirical and analytical models of cutting process of rocks. Journal of Mining Science 2000; 36: 481-486, https://doi.org/10.1023/A:1016620810143.
31. Nath C. - Integrated tool condition monitoring systems and their applications: a comprehensive review. Procedia Manufacturing 2020; 48: 852-863, https://doi.org/10.1016/j.promfg.2020.05.123.
32. Neugebauer R, Denkena B, Wegener K. - Mechatronic systems for machine tools. CIRP Annals 2007; 56: 657–686, https://doi.org/10.1016/j.cirp.2007.10.007.
33. Nouri M, Fussell BK, Ziniti BL, Linder E. - Real-time tool wear monitoring in milling using a cutting condition independent method. International Journal of Machine Tools and Manufacture 2015; 89: 1-13, https://doi.org/10.1016/j.ijmachtools.2014.10.011.
34. Pelayo GU, Trejo DO. - Model-based phase shift optimization of serrated end mills: minimizing forces and surface location error. Mechanical Systems and Signal Processing 2020; 144: 106860, https://doi.org/10.1016/j.ymssp.2020.106860.
35. Percival DB, Walden AT. - Wavelet methods for time series analysis. Cambridge University Press 2000.
36. Powers DM. - Evaluation: From precision, recall and F-measure to ROC, informedness, markedness and correlation. Journal of Machine Learning Technology 2011; 2: 37-63.
37. Provost F, Fawcett T, Kohavi R. - The case against accuracy estimation for comparing classifiers, Proceedings of the ICML-98, Morgan Kaufmann, San Francisco 1998: 445-453.
38. Raghavan V. - Application of decision trees for integrated circuit yield improvement. In the 13th Annual IEEE/SEMI Advanced Semiconductor Manufacturing Conference, Advancing the Science and Technology of Semiconductor Manufacturing ASMC 2002; 02CH37259: 262–265, https://doi.org/ 10.1109/ASMC.2002.1001615.
39. Ronowicz J, Thommes M, Kleinebudde P, Krysiński J. - A data mining approach to optimize pellets manufacturing process based on a decision tree algorithm. European Journal of Pharmaceutical Sciences 2015; 73: 44–48, https://doi.org/10.1016/j.ejps.2015.03.013.
40. Schuld M, Sinayski I, Petruccione F. - An introduction to quantum machine learning. Contemporary Physics 2015; 56: 172-185, https://doi.org/10.1080/00107514.2014.964942.
41. Shao Q, Rowe RC, York P. - Comparison of neurofuzzy logic and decision trees in discovering knowledge from experimental data of an immediate release tablet formulation. European Journal of Pharmaceutical Sciences 2017; 31: 129–136, https://doi.org/10.1016/j.ejps.2007.03.003.
42. Sokolova M, Japkowicz N, Szpakowicz S. - Beyond Accuracy, F-Score and ROC: A Family of Discriminant Measures for Performance Evaluation. In: Sattar A., Kang B. (eds) AI 2006: Advances in Artificial Intelligence. AI 2006, Lecture Notes in Computer Science 2006; 4304, https://doi.org/10.1007/11941439_114.
43. Vamsi I, Sabareesh GR, Penumakala PK. - Comparison of condition monitoring techniques in assessing fault severity for a wind turbine gearbox under non-stationary loading. Mechanical Systems and Signal Processing 2019; 124: 1-20, https://doi.org/10.1016/j.ymssp.2019.01.038.
44. Walnut DF. - An introduction to wavelet analysis. Springer Nature 2004.
45. Wang Y, Zheng L, Wang Y. - Event-driven tool condition monitoring methodology considering tool life prediction based on industrial internet. Journal of Manufacturing Systems 2021; 58: 205-222, https://doi.org/10.1016/j.jmsy.2020.11.019.
46. Wu X, Kumar V, Ross J, Quinlan J, et al. - Top 10 algorithms in data mining. Knowledge and Information Systems 2008; 14: 1–37, https://doi.org/10.1007/s10115-007-0114-2.
47. Xi S, Cao H, Chen X. - Dynamic modelling of spindle bearing system and vibration response investigations. Mechanical Systems and Signal Processing 2018; 114: 486-511, https://doi.org/10.1016/j.ymssp.2018.05.028.
48. Zhang C, Qian Y, Dui H, Wang S, Chen R, Tomovic MM. - Opportunistic maintenance strategy of a Heave Compensation System for expected performance degradation. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2021; 23(3): 512–521, http://doi.org/10.17531/ein.2021.3.12.
49. Zhang C, Yao X, Zhang J, Jin H. - Tool condition monitoring and remaining useful life prognostic based on wireless sensor in dry milling operations. Sensors 2016: 16: 795, https://doi.org/103390/s16060795.
50. Zhao R, Yan R, Chen Z, Mao K, Wang P, Gao RX. - Deep learning and its applications to machine health monitoring. Mechanical Systems and Signal Processing 2019; 115: 213-237, https://doi.org/10.1016/j.ymssp.2018.05.050.
51. Żabiński T, Mączka T, Kluska J. - Industrial Platform for Rapid Prototyping of Intelligent Diagnostic Systems. Trends in Advanced Intelligent Control, Optimization and Automation - Polish Control Conference, eds. W. Mitkowski, J. Kacprzyk, K. Oprzędkiewicz, P. Skruch 2017: 712-721, https://doi.org/10.1007/978-3-319-60699-6_69.