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ASSESSMENT MODEL OF CUTTING TOOL CONDITION FOR REAL-TIME SUPERVISION SYSTEM

MODEL OCENY STANU NARZĘDZIA SKRAWAJĄCEGO DLA SYSTEMU NADZORU W CZASIE RZECZYWISTYM

Further development of manufacturing technology, in particular machining requires the search for new innovative technological solutions. This applies in particular to the advanced processing of measurement data from diagnostic and monitoring systems. The increasing amount of data collected by the embedded measurement systems requires development of effective analytical tools to efficiently transform the data into knowledge and implement autonomous machine tools of the future. This issue is of particular importance to assess the condition of the tool and predict its durability, which are crucial for reliability and quality of the manufacturing process. Therefore, a mathematical model was developed to enable effective, real-time classification of the cutting blade status. The model was verified based on real measurement data from an industrial machine tool.

Keywords: *predictive maintenance, logistic regression, elasticnet, maximum likelihood method, ROC, AUC.*

Dalszy rozwój inżynierii produkcji, w szczególności obróbki skrawaniem, wymaga poszukiwania nowych innowacyjnych rozwiązań technologicznych. Dotyczy to w szczególności zaawansowanego przetwarzania danych pomiarowych pochodzących z systemów diagnostycznych i monitorujących. Rosnąca ilość danych gromadzonych przez wbudowane systemy pomiarowe wymaga opracowania skutecznych narzędzi analitycznych, aby efektywnie przekształcać dane w wiedzę i wdrażać autonomiczne obrabiarki przyszłości. Kwestia ta ma szczególne znaczenie dla oceny stanu narzędzia i przewidywania jego trwałości, które są kluczowe dla niezawodności i jakości procesu produkcyjnego. Dlatego opracowano nowy model matematyczny, którego zadaniem jest skuteczna klasyfikacja stanu ostrza narzędzia skrawającego realizowana w czasie rzeczywistym. Opracowany model został zweryfikowany na podstawie rzeczywistych danych pomiarowych z przemysłowej obrabiarki.

Słowa kluczowe: *predykcyjne utrzymanie ruchu, regresja logistyczna, elasticnet, metoda największej wiarygodności, ROC, AUC.*

1. Introduction

Machining as a manufacturing technology has invariably played a significant role in the manufacturing processes of many enterprises. It is estimated [3] that expenditure on machining account for approximately 5% of the GDP in the developed countries. Therefore, machining technology is constantly evolving. It results from numerous research concerning i.e. the accuracy of the machined parts [5], or the stability of the high-speed machining process [30].

Despite a number of research and innovations regarding technologically advanced cutting tools, or more demanding materials to be machined, further striving to increase productivity and quality decreasing total costs at the same time, requires search for innovative solutions, including those of an optimizing character. Therefore, recently, the number of scientific research in the field of machining is growing. They concern advanced processing of collected measurement data coming from diagnostic and monitoring systems of technological machines. On the one hand, this is the result of the rapid development of measurement and analytical techniques [10, 17, 23], and the growing importance of broadly understood durability and reliability. On the other hand, it is the result of expectations related to the implementation of solutions based on the idea of Industry 4.0. Machine to machine communication, smart technologies, or the need to develop cyber-physical systems (CPS), taking into account the broadly understood principle of sustainable development [14-16], pose a number of new research challenges. According to Lee at al. [22], recent advances in manufacturing industry have paved way for a systematical deployment of CPS systems, within which information from all related perspectives is closely monitored and synchronized between the physical factory floor and the cyber computational space. This requires advanced information analytics for networked machines, which finally will be able to perform more efficiently and collaboratively.

Currently available advanced technological solutions in measurement sensors and data collection and processing systems [24-26, 28, 29] as well as widespread use of industrial computer networks open up an opportunity for potential future smart factories. However, the increasing amount of collected data requires effective analytical tools

[6]. Vast amount of research are also conducted in this area, however, they are mainly theoretical considerations, where new methods or mathematical models are usually verified only based on simulation data. As Arrazola et al. [3] noted that industry application of mathematical models is very limited in manufacturing technology analyzed from the point of view modelling of metal machining operations, due to the fact that direct application of currently available predictive models for specific operations on the shop floor is limited, as most models developed by researchers are only laboratory-validated, and not shop floor-tested. Taking into account the above factors as well as the growing role of reliability and quality of the manufacturing process, in which the durability of the cutting tool plays a key role, a mathematical model was developed to effectively classify the cutting blade. The model was verified based on actual measurement data. This way contribution to industrial data elaboration for predictive maintenance was successfully provided.

2. Problem formulation

The study primarily aimed to determine the cutter state. The answer to the question if the cutter is sharp or not is necessary to define its function, since the response variable is qualitative. Thus the values of this function should be included in a set of two elements describing the possible states of the cutter. The response variable has a categorical value in the case considered. Prediction of cutter state based on data obtained from sensors (accelerometers, microphones, etc.) can be referred to as classification problem.

Numerous classification techniques (classifiers) might be used to predict inclusion in the appropriate class. Logistic regression was used to determine the cutter state. In logistic regression allows to calculate the probability with which the response variable belongs to appropriate category. Therefore, instead of determining cutter state, the probability of each possible state was estimated. In other words, application of logistic regression allows to determine the distribution of response variable based on observation of input variables. Some observable input variables are strongly correlated which will be discussed later in the paper. The elasticnet method was used to minimize this problem. The following subsections present the mathematical aspects required to build a classifier of cutter state.

2.1. Logistic regression

Let us consider the data set, where the realization of the response variable belongs to a binary set. For any finite element we analyze the training set $D=\left\{\left(x_{(i)},y_i\right)\right\}_{1\leqslant i\leqslant n}$, where $\left\{x_{(i)}\right\}_{1\leqslant i\leqslant n}$ denotes a series of input variables, $\left\{y_i\right\}_{1\leqslant i\leqslant n}$ is a series of response variable, where $x_{(i)}\in R^m$, $y_i\in\{0,1\}$ for $1\leqslant i\leqslant n$, denote number of samples, m denotes a number of measurements obtained from transducers (sensors). If the cutter is blunt, then we take $y_i=1$ otherwise we put $y_i=0$. The training set can be presented as $D=\{Y,X\}$, where:

$$Y=\begin{bmatrix} y_1\\ y_2\\ \vdots\\ y_n\end{bmatrix},\quad X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m}\\ x_{21} & x_{22} & \cdots & x_{2m}\\ \vdots & \vdots & \vdots & \vdots\\ x_{n1} & x_{n2} & \cdots & x_{nm}\end{bmatrix}=\begin{bmatrix} x_{(1)}\\ x_{(2)}\\ \vdots\\ x_{(n)}\end{bmatrix}.$$

Observing the signal $x_{(i)}\in R^m$ obtained from sensors, it is necessary to classify the cutter state. The task is to find such a classifier $f:R^m\to\{0,1\}$, which would allow to classify the cutter into categories $y=1$ or $y=0$ based on observation $x\in R^m$.

Let (Ω,F,P) be a probability space. On this space a random variable Y with binomial distribution, i.e. $Y:\Omega\to\{0,1\}$ (see e.g. [27]) is defined. In the presented case logistic regression is a regression model, where response variable Y has a binomial distribution. Logistic regression (see e.g. [4, 9, 13]) describes probability of realization of dependent variable Y based on observation of input variables X. Therefore, it is necessary to determine success $P(Y=1|X)$ and defeat $P(Y=0|X)$ probabilities accordingly. In literature [4, 12] the formula:

$$\Theta(X)=\frac{P(Y=1|X)}{P(Y=0|X)}=\frac{P(Y=1|X)}{1-P(Y=1|X)} \tag{1}$$

is called the odds. Thus, the odds is defined as the ratio of success probability to defeat probability. The aim of logistic regression consist in determining the probability of success $p(X)=P(Y=1|X)$ based on observation X. Because the probability of success is $p(X)\in(0,1)$, therefore from formula (1) the odds is $\Theta(X)\in(0,\infty)$ but $ln(\Theta(X))\in(-\infty,\infty)$. The logarithm of odds is called log-odds or logit.

For models of logistic regression the linear dependencies between logit and input variables are analyzed:

$$ln\Theta(X)=ln\left(\frac{p(\beta,X)}{1-p(\beta,X)}\right)=X\beta\ , \tag{2}$$

where $\beta=(\beta_1,\ldots,\beta_m)\in R^m$. When linear system (2) contains an intercept, then in matrix X the column that corresponds to intercept contains ones. From (2) a success probability is calculated as follows:

$$p(\beta,X)=\frac{e^{X\beta}}{1+e^{X\beta}}. \tag{3}$$

The maximum likelihood method is usually used to estimate the unknown parameters β in logistic regression (3). Thus the likelihood function is defined as:

$$L(\beta,Y,X)=\prod_{i=1}^{n}p\left(\beta,x_{(i)}\right)^{y_i}\left(1-p\left(\beta,x_{(i)}\right)\right)^{1-y_i}. \tag{4}$$

The application of maximum likelihood method consists in solving the task:

$$\max_{\beta} L(\beta,Y,X). \tag{5}$$

As a result the estimators of unknown parameters β for system (2) are obtained. Instead of solving the task (4), the auxiliary task needs to be solved:

$$\max_{\beta} l(\beta,Y,X), \tag{6}$$

where the objective function is defined as the logarithm of likelihood function:

$$l\left(\beta,Y,X\right)=\sum_{i=1}^{n}\left(y_i x_{(i)}\beta-ln\left(1+e^{x_{(i)}\beta}\right)\right). \tag{7}$$

To solve the auxiliary task (6) (determine the unknown parameters β) Newton-Raphson algorithm was applied. Application of this algorithm follows that the unknown parameters β are estimated iteratively. In the step $j+1$ the estimators are determined from the formula:

$$\beta_{j+1}=\beta_j+\left(\frac{\partial^2 l}{\partial\beta\partial\beta^T}\left(\beta_j\right)\right)^{-1}\frac{\partial l}{\partial\beta}\left(\beta_j\right),$$

where $\frac{\partial l}{\partial\beta}\left(\beta\right)$, $\frac{\partial^2 l}{\partial\beta\partial\beta^T}\left(\beta\right)$ denote a first and second partial derivatives of the objective function (7).

2.2. Elasticnet

Usually the measurements obtained from sensors are correlated (referred to as the multicollinearity problem). If the input variables (predictors) in linear system (2) are correlated, the direct solution of the task (6) based on the application of Newton-Raphson algorithm does not bring about the expected effect. Additionally, the forecasts based on this model are unstable. Thus the problem depends on the selection of appropriate predictors, which should be included in the regression model (2). On the one hand, these predictors should influence the value of response variable, on the other they should not generate multicollinearity.

In literature there are many techniques (e.g. singular value decomposition, regularization, least angle regression) to solve the problem (6) of multicollinearity. One of possible ways to reduce multicollinearity between predictors is the application of the elasticnet method (see e.g. [12, 13]). This method consists in including the penalty, which depends on values of estimators, in objective function. This technique implies a shrinkage of estimators of unknown parameters. From above when predictors are correlated then we solve the task:

$$\max_{\beta}\sum_{i=1}^{n}\left(y_i x_{(i)}\beta-ln\left(1+e^{x_{(i)}\beta}\right)\right)-\lambda P_\alpha\left(\beta\right) \tag{8}$$

where $\lambda>0$ and value $P_\alpha\left(\beta\right)$ denote the penalty. For $0\leqslant\alpha\leqslant1$ the penalty $P_\alpha\left(\beta\right)$ is defined as a linear combination of vector norm of estimators β in spaces L_1, L_2 and given by the formula $P_\alpha\left(\beta\right)=\frac{1-\alpha}{2}\beta_{L_2}+\alpha\beta_{L_1}$. If $\alpha=0$, then a classical Tikhonov regularization (ridge regression) is used, while $\alpha=1$, then Least Absolute Shrinkage and Selection Operator (LASSO). The elasticnet is a connection between ridge regression and LASSO. As will discussed later, the application of elasticnet method allowed to receive classifier based on logistic regression (2) with more accurate and stable detection of cutter state.

2.3. Acoustic signal analysis

Acoustic signal properties were identified by correlation analysis which is related to spectral analysis (see e.g. [11]). Therefore, the time series $\left\{x_t\right\}_{t\in N}$ were considered which denote acoustic pressure and is (weakly) stationary in a broad sense with realizations in the set of real numbers R . The autocovariance function of the time series is determined as follows:

$$\gamma_\tau=E\left(x_t-Ex_t\right)\left(x_{t+\tau}-Ex_t\right) \tag{9}$$

and the autocorrelation function is determined as:

$$r_\tau=\frac{\gamma_\tau}{\gamma_0} \tag{10}$$

for any lag $\tau\in N$. Below two theorems are presented which can be helpful to distinguish acoustic signals.

Theorem 1 (Herglotz). Let γ_τ , $\tau\in N$ denote the autocovariance function of weakly stationary time series. There exists right continuous and non decreasing function $F:\left[-\pi,\pi\right]\to\left[0,\infty\right)$ such that $F\left(-\pi\right)=0$ and:

$$\gamma_\tau=\int_{-\pi}^{\pi}e^{i\omega\tau}dF\left(\omega\right) \tag{11}$$

The proof of Theorem 1 is given in [27]. The function $F\left(\omega\right),\omega\in\left[-\pi,\pi\right]$ is a spectral function, however if:

$$F\left(\omega\right)=\int_{-\pi}^{\omega}f\left(s\right)ds \tag{12}$$

the function $f\left(s\right)$ is a spectral density function. The relationship between the autocovariance function γ_τ , $\tau\in N$ and the spectral density function $f\left(s\right)$ is given below.

Theorem 2. If the autocovariance function γ_τ , $\tau\in N$ has realization in the set of real numbers, then the spectral density function $f\left(\omega\right),\omega\in\left[-\pi,\pi\right]$ is defined as follows:

$$f\left(\omega\right)=\frac{1}{2\pi}\left(\gamma_0+2\sum_{j=1}^{\infty}\gamma_j cos(j\omega)\right)=\frac{\gamma_0}{2\pi}\left(1+2\sum_{j=1}^{\infty}r_j cos(j\omega)\right) \tag{13}$$

The proof of Theorem 2 can be found e.g. [21, 27]. From theorem 2 for needs to make classifier, each acoustic signal was identified by correlation sequence $\left\{r_\tau\right\}_{1\le t\le k}$. The stationary property was checked for each acoustic signal by application Augmented Dickey-Fuller (ADF) test (see e.g. [11, 18]). Additionally, the significance of correlation sequence $\left\{r_\tau\right\}_{1\le t\le k}$ for acoustic signal $\left\{x_t\right\}_{t\in N}$ was analyzed by application of Ljung-Box test (see e.g. [11]).

3. Numerical example

The aim of research was to analyse the possibility of designing a classifier, which would recognize the cutter state. In order to develop a classifier, 2173 signals (series of acoustic pressure) obtained from microphone were analyzed, where 937 cases were concerned for blunt cutters and 1236 for sharp cutters. Each series $\left\{x_t^j\right\}_{1\le t\le n}$ had 16000 measurements ($n=16000$) collected with 25 kHz sampling frequency and was identified by sequence of correlation values $r^j=\left\{r_t^j\right\}_{1\le t\le m}\in\left[-1,1\right]^m$ for $0\le j\le2173$. It was assumed that the maximal lag is equal to 200 ($m=200$) [31]. Exemplary realization of signal and sequence of correlation is depicted on Figure 1.

Remark 3. For each analyzed acoustic series $\left\{x_t^j\right\}_{1\le t\le n}$, $0\le j\le 2173$ an ADF test was performed. The results show that the probability of null hypothesis H_0 (the series is non-stationary) does not exceed 0.01 for every series. Hence, we accept that the series describing acoustic signals are stationary.

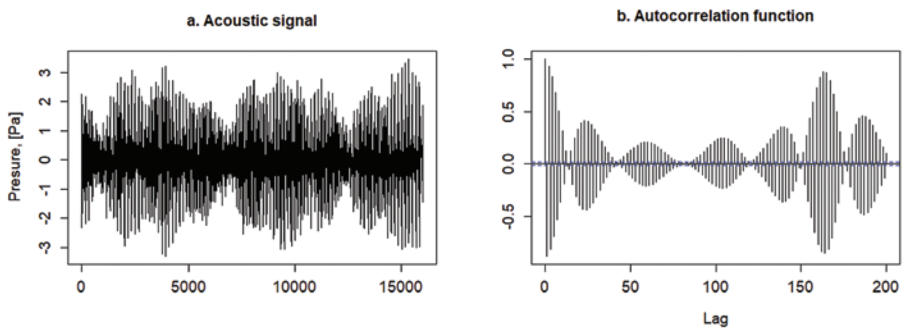

Fig.1 . Realization and autocorrelation for an acoustic signal $\left\{x_t^j\right\}_{1\le t\le n}$

Remark 4. Additionally, Ljung-Box test was performed to examine the null hypothesis H_0, that elements of acoustic series $\left\{x_t^j\right\}_{1\le t\le n}$, $0\le j\le 2173$ are independent. The results show that for each of the analyzed series the probability of null hypothesis H_0 does not exceed 0.01, thus the elements in acoustic series are not independent. From above there exist significant correlations between the elements for lags $\tau\ge 0$)

As a result, learning dataset $D=\left\{\left(r^j,y_j\right):r^j\in[-1,1]^m,y_j\in\{0,1\},1\le j\le 2173\right\}$ was created, where $r^j=\left\{r_t^j\right\}_{1\le t\le m}$ is a sequence of values of the autocorrelation function for j – th sample, $y_j=0$ for the sharp cutter and $y_j=1$ for the blunt cutter. Thus, observing the sequence , the question if the cutter is blunt must be answered. For this purpose the elasticnet method was applied to estimate unknown parameters in linear model (2) by solving the task (8). Additionally, 10-fold cross validation (see e.g. [12, 13]) was performed to validate stability of the obtained model (thereby to assess of accurately work of model for data).

Below the reconstruction based on application of logistic regression is presented. For correlation sequence of acoustic signal obtained from sensors the probability that the cutter is blunt is calculated as follows:

$$\hat{P}\left(Y=1|r\right)=\frac{e^{r\hat{\beta}}}{1+e^{r\hat{\beta}}} \tag{14}$$

where $\hat{\beta}\in R^m$ denotes the estimator of unknown parameters β for logistic regression (2).

Accordingly, for probability $\hat{P}\left(Y=1|r\right)$, the question of the cutter state must be answered – if it is blunt or sharp, due to the cut-off level (threshold classification) $l\in[0,1]$:

$$state=\begin{cases}sharp, & for\hat{P}\left(Y=1|r\right)<l,\\ blunt, & for\hat{P}\left(Y=1|r\right)\geqslant l\end{cases} \tag{15}$$

Main aim of classification of the cutter state is recognizing that the cutter is blunt. The accuracy (quality of identification) was assessed for different thresholds $0\le l\le 1$. For this purpose the relative error was defined as ratio number of incorrect detection to number of samples (fraction of incorrect detection). The relative error is complement of accuracy (calculated as 1 – accuracy) (see e.g. [1, 2, 7]). Accuracy is a fraction of correct detection from model. Relative error and accuracy give a basic information about goodness of fit of classification model. The smallest relative error corresponds to threshold 0.46. Figure 2 depicts the dependence between relative error and threshold. Below basic terminology and ratios to describe the quality of binary classifier are presented. In this paper, Sharp class is treated as a negative example (N) and Blunt as a positive example (P). To create a confusion matrix we determine the following values: TP (True Positive) denotes number of sample with correct detection for blunt cutter, TN (True Negative) - number of sample with correct detection for sharp cutter, FP (False Positive) - number of sample where sharp cutter was recognized as blunt (number of false alarms), FN (False Negative) - number of sample where blunt cutter was recognized as sharp (number of miss). Basic ratios is calculated as follows:

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN},\ Sensivity=\frac{TP}{TP+FN},\ Specificity=\frac{TN}{TN+FP},$$

$$PositivePredictiveValue=\frac{TP}{TP+FP},\ NegativePredictiveValue=\frac{TN}{TN+FN},$$

$$Prevalence=\frac{TP+FN}{TP+TN+FP+FN},\ DetectionRate=\frac{TP}{TP+TN+FP+FN},$$

$$DetectionPrevalence=\frac{TP+FP}{TP+TN+FP+FN},\ BalancedAccuracy=\frac{Sensivity+Specificity}{2},$$

$$FalseAlarmRate=\frac{FP}{TP+FP}.$$

Table 1 presents a confusion matrix (identification result of cutter state). The relative error of classification is equal to $\frac{(77+106)}{2173}\approx 0.0842$ (below 8.5%), thus accuracy is $1-0.0842=0.9158$. For cut-off level 0.5, the relative error did not exceed 8.6%. Figure 3 presents boxplots (quantiles ¼ and ¾, median and outliers) of probability values obtained by application (8) for cutters.

Table 1. Confusion matrix for classification level 0.46

	Reference: blunt	Reference: sharp
Prediction: blunt	860	77
Prediction: sharp	106	1130

Table 2 presents identification ratios for logistic regression model. The sensitivity (recall or probability of detection) has been calculated as proportion of number of exact (relevant) recognitions for blunt cutters to the number of samples which actually had blunt cutter. On the other hand the specificity has been calculated as proportion of number of exact (relevant) recognitions for sharp cutters to the number of samples which had sharp cutter. The positive predicted value (preci-

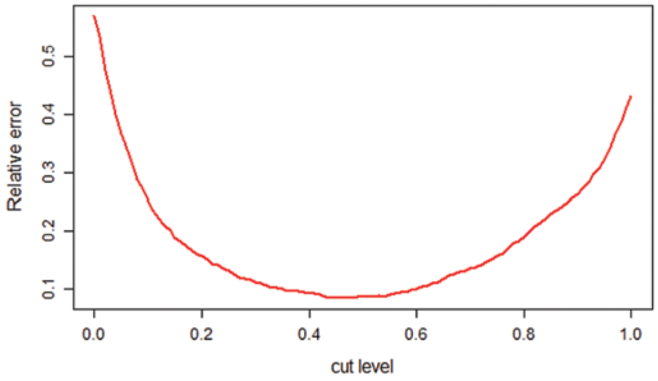

Fig. 2. Relative error dependence on cut level

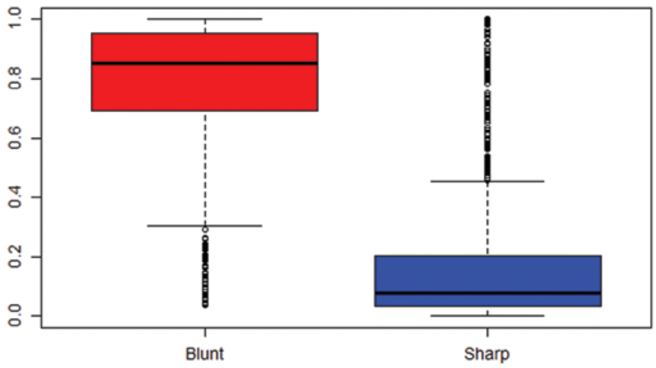

Fig. 3. The result of cutter state detection

sion) is a ratio of number of exact (relevant) recognitions for blunt cutters to the number of samples recognized as blunt. The precision characterizes a purity of performed classifier (purity in retrieval performance). The parameters presented in table 2 are discussed thoroughly in [1, 2, 7, 8]. Additionally, McNemar's chi-squared test was performed for symmetry of rows and columns for confusion matrix presented in table 2. In presented case the McNemar's chi-squared statistic is equal to 4.2842 and p.value is 0.03847. It means that at a significant level 0.05, we have no basis to reject the null hypothesis. Additionally, κ -statistic was calculated. κ -statistic presents the proportion of disagreements expected by chance that did not occur. For recognition based on logistic regression model the parameter κ is equal to 0.829.

Table 2. Basic ratios of quality for logistic regression model

Parameter	Value
Accuracy	0.9158
Sensitivity	0.9178
Specificity	0.9142
Positive Predicted Value	0.8903
Negative Predicted Value	0.9362
Prevalence	0.4312
Detection Rate	0.3958
Detection Prevalence	0.4445
Balanced Accuracy	0.9160
False Alarm Rate	0.0858

Additionally, exact binomial test was also made. Null hypothesis maintains that the probability of success (recognition of blunt cutter) is consistent with prevalence (samples from training data, where the proportion of blunt cutters to all cutters is equal to $\frac{937}{2173} = 0.4312$). At significant level 0.05 we have no basis to reject the null hypothesis.

Figure 3 illustrates the diagnostic ability of classifier based on logistic regression model (see e.g. [7]). Receiver Operating Characteristic (ROC) curve shows the relationship between sensitivity and specificity for every possible cut-off levels. The diagonal line in Figure 3 represents a strategy of randomly guessing cutter state. Thus the presented classifier based on logistic regression is much better then guessing. The bend on the ROC curve corresponds to threshold of 0.465. Area under ROC curve (AUC) denotes general measure of predictiveness. The AUC value for classifier is equal to 0.916.

4. Summary

The extremely dynamic development of technology resulted in wide use of advanced computer systems and sophisticated diagnostic systems equipped with intelligent sensors. Monitoring the parameters of the technological process and diagnostics of key machines and production equipment means that each enterprise collects significant and constantly growing quantities of various types of data. Raw data obtained in this way is a large collection and usually difficult to use directly, requiring appropriate analytical methods. The collected data is, however, a resource of extremely valuable information, which after proper processing and inference should become knowledge, on the basis of which it is possible to increase the efficiency of the com-

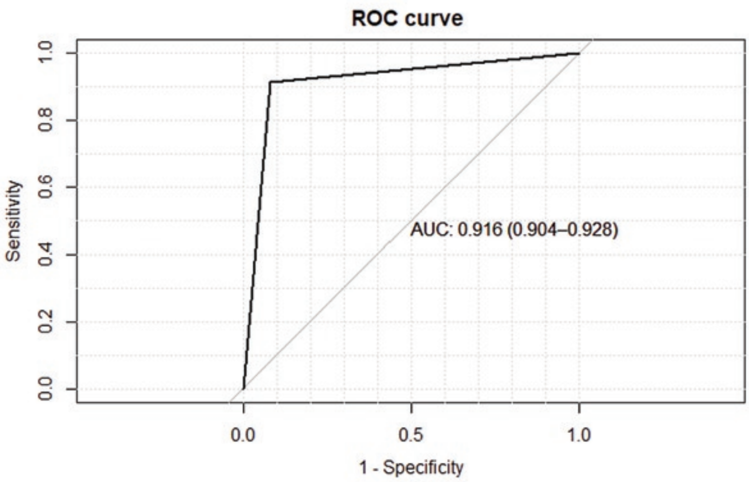

Fig. 4. Receiver operating characteristic curve

pany's operation and effectively build a competitive advantage.

Industrial data sets for the implementation of Industry 4.0 solutions are the basis for the functioning of cyber-physical systems, meaning the automation of the processing of collected data. Their functioning requires the development of appropriate analytical tools, especially important for the efficient functioning of CMMS (Computerized Maintenance Management Systems) class predictors. Predictive maintenance is a preventive maintenance method that uses a variety of techniques to inform the owner, service provider or operator about the current and, preferably, future status of their physical resources. The issue of durability and reliability in machining is undoubtedly one of the most important issues also in the context of predictive maintenance and real-time monitoring of technological processes, especially due to the growing role of various diagnostic and measurement systems, in which every numerically controlled machine tool is equipped. Therefore, the authors undertook the task of developing a solution enabling effective identification of the condition of the cutting tool, allowing further determination of the optimal moment of its replacement. Presented method gives a simple way to detect the cutter state. The study gives promising results - sensitivity and specificity exceed 0.9, furthermore precision is equal to 0.89 and false alarm rate is equal to 0.08. The presented analytical solution, verified on the basis of real data from an industrial machine tool, can be used as part of the system for recognizing the wear rate of the cutting tool during the production process based on the analysis of an acoustic signal or any other symptoms. Obtaining sufficiently high effectiveness of identification, classification and forecasting for the needs of the advanced CMMS class system, however, requires further work. This issue is particularly important for the ongoing work [19, 20] over an innovative prediction tool for failure using mathematical models selected autonomously by an intelligent algorithm based on information criteria, as well as forecast errors and forecast error indicators. As well as the work [31] aimed at developing algorithms for real-time diagnostics and predictions of the state of technological processes.

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