Use of Cutting Force and Vibro-acoustic Signals in Tool Wear Monitoring Based on Multiple Regression Technique for Compreg Milling

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This study focused on a computerised TCM (tool condition monitoring) system as a part of automated monitoring of the machining processes in the wood industry. The system's principal task was to evaluate the actual state of tool wear without disrupting the normal course of machine tool exploitation for cutting force and vibro-acoustic signals analysis. During the experiment, five physical quantities that are generated during machining were measured and recorded: cutting forces in two directions (Fx, Fy), ultrasonic stress waves (acoustic emission - AE), acoustic pressure in the range of audible frequencies (noise - N), and acceleration of mechanical vibrations (V). Six pairs of tools were used in the experiment. One tool from each pair was experimental, the other was a control tool. Out of the five physical quantities generated during machining that were tested as an indirect source of information on the tool condition, signals of cutting forces and mechanical vibrations proved the most useful. Both acoustic emission and noise signals emerged as wholly inadequate as evidence to predict tool wear.

Keywords: Machining; Tool wear; Tool condition monitoring

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INTRODUCTION

The automation of production processes is becoming a priority in the manufacturing of products made of wood-based materials. Computer numerical control (CNC) machine tools or automated production lines are routinely used for such automation. One of the problems that remains unsolved in this kind of production is the automated monitoring of the machining processes, and tool condition monitoring is a high priority (Iskra and Hernández 2012). It is worth noting that tool wear is a particularly important research topic that it is traditionally given a lot of attention (Szwajka and Trzepieciński 2016, 2017a,b). It is evident that gradual deterioration of the cutting edge results in decreased machining quality and increases the risk of a sudden catastrophic tool failure, which in turn may lead to such consequences as unplanned tool stoppage in problematic circumstances. Woodworking tool wear online measurement is an essential step in improving wood industrial automation (Wei *et al.* 2018). Therefore, a subject of interest in recent years is the idea of special computerised tool condition monitoring (TCM) systems designed to function in an on-line mode. Their principal task is to evaluate the current state of tool wear without disrupting the normal course of machine tool exploitation. Such systems are typically based on an indirect identification of the cutting edge's wear on the measurement and analysis of cutting forces or vibro-acoustic signals generated in the cutting zone

(Jemielniak *et al.* 2012). For wood-based materials, advanced scientific research into TCM systems machining has been conducted for years (Lemaster and Jackson 2000a, 2000b). They have chiefly consisted of systematic attempts to determine the most useful signals and their features that would allow for an unequivocal, fast, and reliable identification of the tool condition during the machining process (Wilkowski and Górski 2011; Kurek *et al.* 2016; Świderski *et al.* 2017). However, any reports of commercial or at least prototype TCM systems that could be applied in machine tools for wood-based boards are yet to materialise. Designing such systems requires further research using various tools and various wood-based materials.

Under these circumstances, it is advisable to develop a tool wear identification model in relation to the cutting force and vibro-acoustic signals analysis for compreg milling. Compreg is a special processed wood made of veneers impregnated with phenolic resins and compressed to reduce shrinking and swelling as well as to increase density and strength. Compreg is relatively easy to machine and is used for making berths of railway coaches and seats, boxes of heavy equipment, industrial pallets, marine decks and cabins, and many other products (Wilkowski and Górski 2011).

EXPERIMENTAL

Materials

A machining centre CNC (Jet 130; Busellato, Thiene, Italy) was used in the experimental studies. A machine tool was equipped with a single edge cutter head that was 40 mm in diameter (Faba SA, Baboszewo, Poland) with an exchangeable carbide cutting edge KCR08 (Fig. 1)

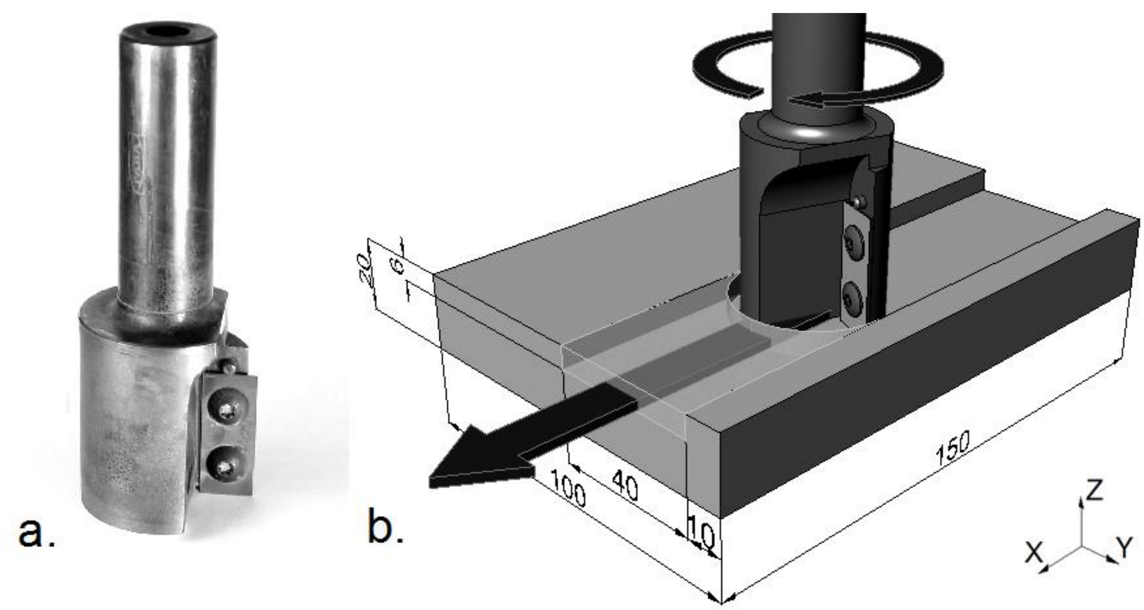

Fig. 1. General view of the cutter head (a.) and the scheme of the workpiece machining (b.); in the bottom right corner: 3-axis coordinate system used in CNC machine tool

The material used for experimental machining was 20-mm-thick compreg (Sklejka-Pisz Paged Sp. z o.o., Pisz, Poland). Its selected physical and mechanical properties were determined in accordance with valid standards that are shown in Table 1.

Table 1. Physical and Mechanical Parameters of Compreg

Density (kg/m^3)	1340	EN 323 (1993)
Modulus of Rupture (MOR) (N/mm^2)	138	ISO 16978 (2003)
Modulus of Elasticity (MOE) (N/mm^2)	12400	ISO 16978 (2003)
Brinell's Hardness (HB)	23.4	EN 1534 (2000)
Swelling After 24 h (%)	4.5	EN 317 (1993)

The workpieces were specimens made of compreg with measurements of 100 mm × 150 mm. In the experiments, a groove 6-mm-deep and 40-mm-wide was milled in the samples (Fig. 1). The machining was conducted with a rotational spindle speed of 18000 rpm. The feed rate on the cutting edge was 0.15 mm/rev. The above parameters were adopted as recommended by the cutter head manufacturer (Faba SA, Baboszewo, Poland) for the precise milling of wood-based materials. During the experiment, five physical quantities that are generated by machining were measured and recorded: machining forces in two directions, *i.e.*, parallel to the X- and Y-axes defined according to Fig. 1 (F_x, F_y), ultrasonic stress waves (usually called acoustic emission - AE), acoustic pressure in range of audible frequencies (noise - N), and acceleration of mechanical vibrations (V). The measurements were possible with a special experimental setup that is presented in Fig. 2. The machined object was fixed on a platform, and a Kistler 9601 (Winterthur, Switzerland) sensor was installed on the inside of the platform to measure the forces in three directions (as mentioned above, only two of its channels were used to measure the forces F_x and F_y). The output signals from this sensor were transmitted to a Kistler 5036 (Winterthur, Switzerland) amplifier. The noise was measured with a standard B&K 4189 microphone (Nærum, Denmark) (frequency range: 6.6 Hz ÷ 20 kHz) that was placed just below the milling table at a distance of 200 mm from the cutting zone, and a B&K Type 2690-A Nexus microphone conditioner amplifier (Brüel & Kjær, Nærum, Denmark). To measure the vibrations of the platform that served as a jig (a device that holds a piece of work), a Kistler 8141A (Winterthur, Switzerland) accelerometer and a Kistler 5127B (Winterthur, Switzerland) amplifier were used. All four signals (F_x, F_y, N, and V) were sent to a connector box Nr 1, and then digitally recorded *via* an acquisition card NI PCI-6111 (the frequency of sampling was 50 kHz). To measure and record acoustic emission, a Kistler 8152B contact sensor (frequency range: 50 ÷ 400 kHz), a Kistler 5125B amplifier (Winterthur, Switzerland), a connector box Nr 2, and an NI PCI-6034E acquisition card (Austin, Texas, USA) (with a 2 MHz frequency of sampling) were used. The signal recording was conducted in the NI LabView (National Instruments Corporation, ver. 2015 SP1, Austin, Texas, USA) environment.

Six pairs of tools were used in the experiment. One tool from each pair was experimental, the other was a control tool. The experimental tools (marked with the symbols TE01 ÷ TE06) were gradually worn in a way that reflected normal exploitation in real industrial conditions, *i.e.*, the machining of various wood-based materials without using the platform shown in Fig. 2. At some intervals, the standard tool wear indicator (VB), defined in Fig. 3, was measured by means of a workshop microscope (TM-505; Mitutoyo, Kawasaki, Japan).

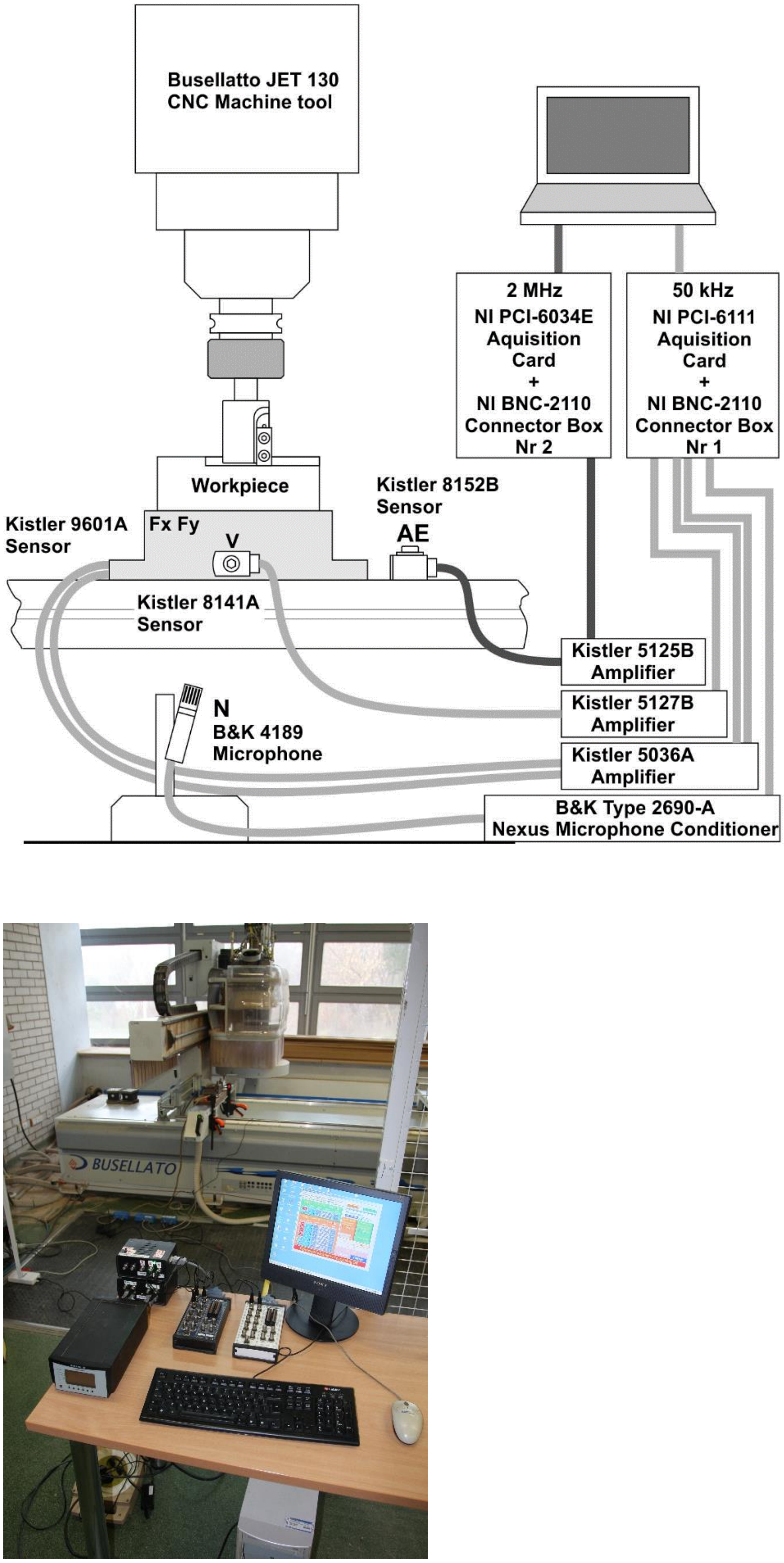

Fig. 2. Schematic and photo of the measuring setup

The control tools (marked with the symbols TC01 ÷ TC06) were always brand new. Under the experimental procedure, nine series of workpieces were grooved (as shown in Fig. 1) by means of each experimental tool, with four workpieces per each series. Each series was made with a different wear status (*i.e.*, different VB values) that is shown in Table 3. At the conclusion of each four-workpiece series, a fifth workpiece was produced using the adequate control tool. The machining of each mentioned above workpiece was performed in the experimental setup shown in Fig. 2. In this way, all cutting forces (F_x, F_y) and vibro-acoustic signals (V, N, and AE) were recorded.

All of the VB values (observed for the particular experimental tools) for which measurement signals were recorded are shown in Table 3. With the method described above, 270 workpieces were produced (as each of the six pairs of tools was used to make 45 workpieces, 36 of which were made with an experimental tool, and nine with a control tool).

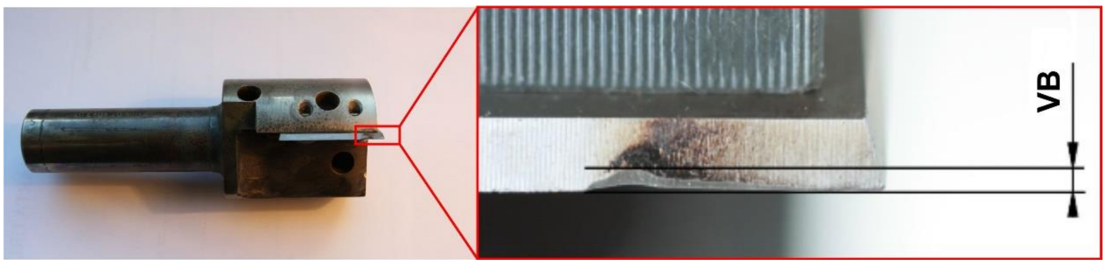

Fig. 3. Indicator of tool wear; VB (mm)

Table 3. Values of VB Observed for Particular Experimental Tools During Measurement of Cutting Force and Vibro-acoustic Signals

Number of Measuring Series	VB (mm) for 6 Experimental Tools (TE01 ÷ TE06)					
	TE01	TE02	TE03	TE04	TE05	TE06
1	0	0	0	0	0	0
2	0.080	0.100	0.065	0.080	0.080	0.090
3	0.095	0.140	0.090	0.115	0.105	0.110
4	0.140	0.150	0.140	0.130	0.145	0.150
5	0.225	0.215	0.215	0.225	0.225	0.230
6	0.245	0.245	0.245	0.245	0.240	0.245
7	0.320	0.320	0.305	0.305	0.325	0.315
8	0.345	0.340	0.345	0.330	0.350	0.340
9	0.370	0.350	0.360	0.350	0.360	0.350

For each recorded signal, 40 features were calculated (identified as f01 to f40). All features were calculated with the standard functions available in the MATLAB Signal Processing Toolbox (MathWorks, v. R2018a, Natick, MA, USA). Given that five different signals were recorded, this rendered a total set of 200 potential regressors (explanatory variables). The term potential is adequate because from the beginning it was clear that some part of them should be rejected due to diagnostic insignificance or redundancy, which is a standard selection problem when diagnostic features are generated in an automatic way. To order these data, a special (uniform) coding system for particular variables was adopted, using the letter V and a four-digit code. Thus, an ordered set of experimental data was created that could be used to develop and test multiple linear regression models as a base of TCM. Generally multiple linear regression is a statistical technique which gives the answer to a following question: "To what extent do E_1, E_2, … (two or more explanatory, independent variables) can predict *D* (single dependent variable)?". This technique estimates *D* according to the strictly linear model based on Eq. 1,

$$D = \beta_0 + \beta_1 \cdot E_1 + \beta_2 \cdot E_2 + \ldots + \beta_p \cdot E_p \tag{1}$$

where $E_1 \div E_p$ are p explanatory variables (predictors) and $\beta_0 \ldots \beta_p$ are linear regression coefficients. In the all models developed in the study the dependent variable was tool wear indicator (VB) and explanatory variables were features calculated for recorded signals (i.e. aforementioned variables named using the letter V and the four-digit code).

RESULTS AND DISCUSSION

The analysis of the research results started with a preselection of potential explanatory variables. At that stage, variables that were too weakly correlated with the VB (minimum $R^2 = 0.8$) were discarded, followed by those that were too highly correlated with each other (maximum $R^2 = 0.9$). Only 10 variables out of the 200 passed the preselection. Table 4 presents a list of those variables along with a reference to the standard functions of MATLAB applied to their calculation. It was worth noting that the AE signal was the only one to prove itself totally inadequate, that is, none of its features passed the preselection.

Table 4. Variables that Passed the Preliminary Selection Stage

ID	Specification	Matlab
V1004	Root-mean-square level of F_x signal	Rms (F_x)
V1012	Sample skewness of F_x signal	Skewness (F_x)
V2002	Max. value of F_y signal	Max (F_y)
V2003	Min. value of F_y signal	Min (F_y)
V3003	Min. value of *V* signal	Min (*V*)
V3008	Standard deviation of *V* signal	Std (*V*)
V3013	Quotient of the mean and the standard deviation of *V* signal	Mean (*V*) / std (*V*)
V4006	Difference between the max. and min. values of *N* signal	Peak2peak (*N*)
V4008	Standard deviation of the noise signal	Std (*N*)
V4013	Quotient of the mean and the standard deviation of *N* signal	Mean (*N*) / std (*N*)

The next step was the final selection of regressors, which involved statistical comparison of the effectiveness for different variants of the linear regression model (as a base of TCM) creation using a multifactor analysis of variance (ANOVA). The basic effectiveness criterion adopted was the root mean squared error (RMSE) of the regression model that was calculated using Eq. 2,

$$\text{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(VB_{T_i} - VB_{P_i}\right)^2} \tag{2}$$

where VB_T is the real (true) tool wear, VB_P is the expected (estimated) tool wear, and *m* is the sample size.

It was assumed that the regression model could make use of any combination of ten variables that passed the preselection stage. The model could be developed based on a different number of tools. To account for that factor, the parameter n_T was introduced, which was equal to the number of pairs of tools (where a pair of tools is to be construed as one experimental tool and one control tool) that took part in model creation. For simplicity, the signals recorded for particular experimental tools were integrated with the signals recorded for their respective control tools, which created six inseparable subsets of data. The parameter n_T may equal 1, 2, 3, 4, or 5, except in the case of $n_T = 6$, because then all tool pairs would be applied to develop the model, which would preclude testing it on those data that were not used to create the model. It was also assumed that the model could be developed using calculations of explanatory variables based on machining individual workpieces or on the moving mean from results obtained for several subsequent workpieces. This meant that the different window sizes for a moving average filter (MM = 1 ÷ 4) could be used. This rendered 20460 variants of the model structure. A multiple linear regression model was developed for each of these variants (built on the number of tools – nT appropriate for a given variant) and tested on the pairs of tools that had not been used to create the model. The test took account of not only the real (*de facto* random) sequence in which the particular pairs of tools were exploited, but also other theoretically possible sequence variants. For example, for $n_T = 1$ (which meant creating the model on one pair and testing it on five remaining pairs), the model was constructed and tested as many as six times. Each time, it was constructed on a different pair of tools and tested on the remaining tools. The effectiveness of all six variants was averaged and a single RMSE value was calculated.

The regression error (RMSE) was treated as a dependent variable in the statistical analysis based on an ANOVA (y = RMSE). In contrast, 10 factors (independent variables $x_1 \dots x_{10}$) that affected the dependent variable were taken into account. These were binary variables with only two values: 0 or 1. The values of $x_1 \dots$ x10 were determined by the individual use ($x_i = 1$) or the individual rejection ($x_i = 0$) of ten pre-selected regressors (respectively: V1004, V1012, V2002, V2003, V3003, V3008, V3013, V4006, V4008, and V4013). For example, $x_1 = 1$ when V1004 was used in the model and $x_1 = 0$ in the opposite situation.

Summarizing: all estimation models developed in the study (for all variants of n_T and MM parameters) were formally based on the Eq. 3,

$$VB_P=a_0+a_1\cdot x_1\cdot V1004+a_2\cdot x_2\cdot V1012+a_3\cdot x_3\cdot V2002+a_4\cdot x_4\cdot V2003+a_5\cdot x_5\cdot V3003+ \\ +a_6\cdot x_6\cdot V3008+a_7\cdot x_7\cdot V3013+a_8\cdot x_8\cdot V4006+a_9\cdot x_9\cdot V4008+a_{10}\cdot x_{10}\cdot V4013 \quad (3)$$

where VB_P is the expected (estimated) tool wear, $a_0 \dots a_{10}$ are regression coefficients (calculated by means of linear least squares method), V1004 … V4013 are ten selected predictors defined in table 4, $x_1 \dots x_{10}$ are ten binary (with only two values: 0 or 1) factors explained in the previous paragraph.

The main effects of each factors are shown in Fig. 4. Each of the factors proved to be statistically significant.

Based on the results of a multi-factor ANOVA, it was found that only the six following explanatory variables were worth considering when creating a model: V1004, V1012, V2002, V2003, V3008, and V3013. This meant that four out of the ten pre-selected regressors were definitively rejected. In this manner, the final selection of explanatory variables was made. Thus, the acoustic emission (AE) measurement and noise (N) measurement proved totally inadequate.

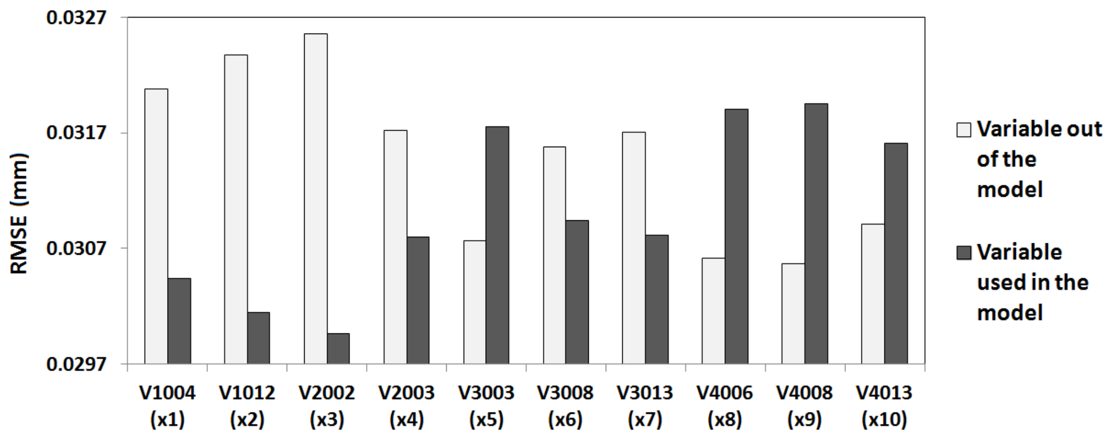

Fig. 4. The main effect of independent variables (factors x1 ÷ x10) on the dependent variable (RMSE)

Figures 5 and 6 detail the effect of two previously defined factors, *i.e.*, n_T and MM, on the selected indicators quantifying the quality of tool wear identification model, which was based on the six final predictors. Besides RMSE (defined by means of formula no. 1), the coefficient of determination (R^2) was provided between the real VB and the expected VB, and the mean absolute percentage error (MAPE) was calculated using Eq.4,

$$\text{MAPE} = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{VB_{T_i} - VB_{P_i}}{VB_{T_i}}\right| \cdot 100 \tag{4}$$

where VB_T is the real (true) tool wear, VB_P is the expected (estimated) tool wear, m is the sample size.

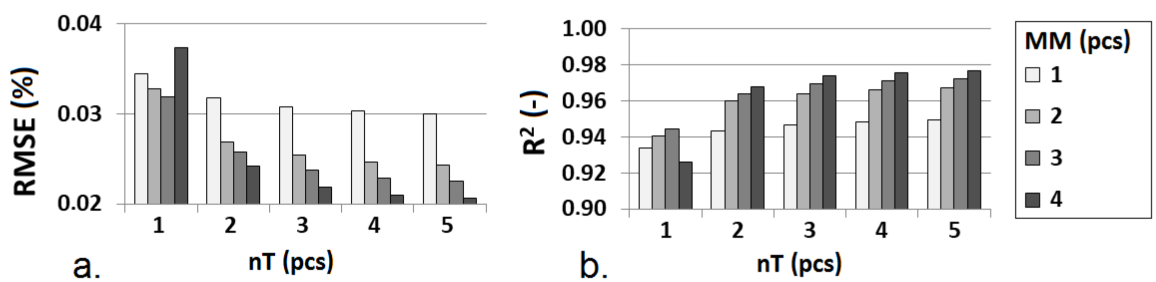

Fig. 5. The effect of the number of tool pairs used to develop regression model (nT = 1 ÷ 5) and a window size for a moving average filter (MM = 1 ÷ 4) on the RMSE of the model (a.) and on R^2 between real and expected tool wear (b.)

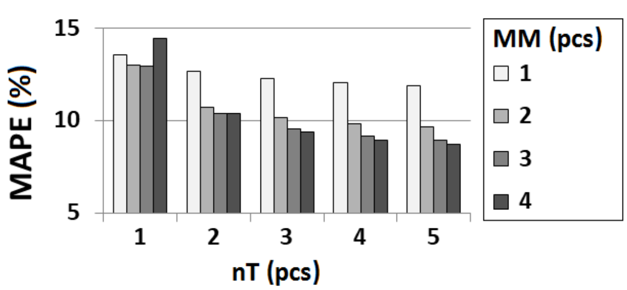

Fig. 6. The effect of the number of tool pairs used to develop regression model (n_T = 1 ÷ 5) and a window size for a moving average filter (MM = 1 ÷ 4) on the MAPE of the model

Because division by zero is not possible, calculations of the value of MAPE omitted cases in which the real VB value equalled 0, which meant that brand new tools were omitted. This did not constitute a significant methodological issue in the diagnostics of brand new tools; even though it was possibly interesting from the scientific point of view, it is not vital in the manufacturing practice. The MAPE value was considered especially important as it often serves as a basis for assessment of the practical usefulness of predictive models. It is usually assumed that acceptable MAPE values (proving acceptable practical usefulness of a model) should be lower than 10%. On this basis, it can be stated with a certain approximation that models adequately useful in practice would be constructed on at least three pairs of tools ($n_T \geq 3$), with application of a moving mean from the results obtained for at least two subsequent workpieces (MM $\geq$ 2). The best effects can be obtained with a model created on five pairs of tools and with averaged results for four subsequent workpieces (for $n_T = 5$ and MM = 4; $R^2 = 0.98$; RMSE = 0.021 mm; and MAPE = 8.7 %).

CONCLUSIONS

1. Out of five physical quantities that were generated while machining and tested as an indirect source of information on the tool condition, the signals of cutting forces and mechanical vibrations proved to be the most useful. Acoustic emission and noise signals emerged as wholly inadequate for sensing of tool wear.
2. Models adequately useful in practice could be constructed on at least three pairs of tools ($n_T \geq 3$), with application of a moving mean derived from the results obtained for at least two subsequent workpieces (MM $\geq$ 2). In those instances, the MAPE value stood at 10% or lower, which was considered as a sign of practical usefulness.
3. The best effects ($R^2 = 0.98$, RMSE = 0.021 mm, and MAPE = 8.7 %) were obtained with a model created on five pairs of tools and with averaged results for four subsequent workpieces.

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