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Krzysztof JEMIELNIAK[1*]

CONTEMPORARY CHALLENGES IN TOOL CONDITION MONITORING

Implementation of robust, reliable tool condition monitoring (TCM) systems in one of the preconditions of introducing of Industry 4.0. While there are a huge number of publications on the subject, most of them concern new, sophisticated methods of signal feature extraction and AI based methods of signal feature integration into tool condition information. Some aspects of TCM algorithms, namely signal segmentation, selection of useful signal features, laboratory measured tool wear as reference value of tool condition – are nowadays main obstacles in the broad application of TCM systems in the industry. These aspects are discussed in the paper, and some solutions of the problems are proposed.

1. INTRODUCTION

Nowadays industry demands continuous improvements of product quality, dependability, and manufacturing efficiency. It makes implementation of robust tool condition monitoring (TCM) systems in manufacturing processes like turning, milling or drilling inevitable. Such system must allow for the exchange of worn tools in time, application of higher and application of more effective cutting parameters due to reduction of costly catastrophic tool failures is reduced. In spite numerous papers have been published (see eg. [1]) presenting many approaches to tool wear monitoring, the problem is still far from solved.

The typical structure of a tool condition monitoring (TCM) system is presented in Fig. 1. The primary source of information about tool condition is those process variables dependent on tool wear which can be used as tool wear symptoms. The most often used are cutting force dependent measures like power, torque, acoustic emission, and vibration [1–3]. These quantities are measured during a cutting process, using special sensors which produce electrical signals. There are many commercially available sensors and more and more modern machine tools are equipped with embedded sensors [4].

Analogue, electrical signals are preprocessed (amplification, anti-aliasing filtering) and converted into digital representation – time series. Number of signal features can be extracted from these time series in time, time-frequency or frequency domain.

[1] Warsaw University of Technology, Department of Automation and Metal Cutting, Poland
[*] E-mail: krzysztof.jemielniak@pw.edu.pl
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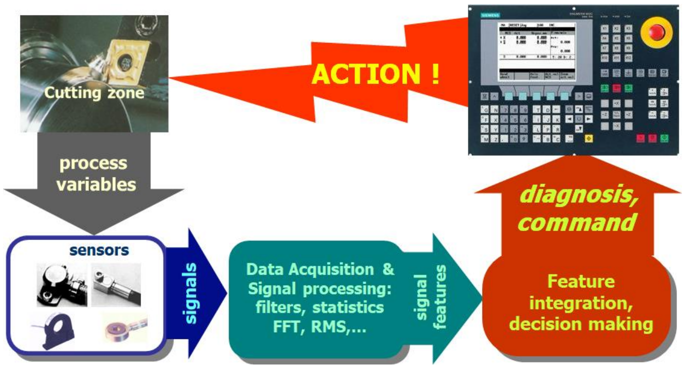

Fig. 1. Tool wear monitoring system

In the time domain, most often used are statistic signal features like average, effective value (root mean square – RMS), power, amplitude, crest factor, variance, skew, kurtosis and others [1, 5–7], or auto regressions (AR), moving average (MA) and auto regressive moving average (ARMA) models (see e.g. [1, 8]). In frequency and time-frequency domain signal features are usually extracted using a discreet, windowed Fourier Transform (FFT, STFT), see e.g. [1, 9, 10], discreet wavelet transform (DWT), e.g. [1, 11–13] or Hilbert-Huang Transform (HHT) [11, 14]. However, more and more sophisticated methods are continually being developed and proposed, like ν-support vector regression [11], Principal Component Analysis (PCA) [15, 16], Singular Spectrum Analysis (SSA) [17], permutation entropy [18], fractal analysis [19], supplying more and more signal features.

It does not seem, that new methods of signal feature extraction delivers significantly better results than already known, advanced ones. E.g. authors of [19] showed that features obtained using the fractal analysis are more useful that conventional statistical ones, which is easy to believe, but it might be assumed, that more advanced methods like PCA, DWT or HHT would not be worse.

The signal features are subject of integration, decision making, resulting in diagnosis of tool condition. Various methods can be used, such as statistical methods, auto-regressive modeling, pattern recognition, expert systems and others [1, 11]. Artificial intelligence (AI) plays a key role in the development of modern tool wear monitoring systems [1, 11, 20]. The most frequently chosen methods are neural network (NN) [3, 8, 9, 19], Mamdani fuzzy logic (FL) [21], Takagi-Sugeno-Kang (TSK) FL [22] or a combination of FL and an automatic generating method, i.e., genetic algorithm (GA) [23]. Recently Hidden Markov Models [24], Support Vector Machine [11, 16], Self-Organizing Map (SOM) [12], fuzzy clustering, ensemble learning, incremental learning, transfer learning, and depth learning are applied [6, 11, 25]. Most of the papers (including mentioned above) describing application of AI method for signal feature integration in TCM monitoring use scanty number of SFs, usually less than ten. Application of any number of signal features is possible using hierarchical algorithms [26]. In the first stage of the algorithm, the tool wear is estimated separately for each signal feature. In the second stage, the results obtained in the first one, are integrated into the final tool wear evaluation. Such hierarchical strategy of TCM based on not necessarily positive, the rising and monotonic signal features [27] was presented in [28] and verified in many applications and installations [13, 29–31].

All these methods have a similar objective – matching the estimate of average cutting tool wear with the directly measured wear value. Again, it seems that the quality of signal features is much more important than signal feature integration method [20, 22].

Despite hundreds of papers devoted to TCM have been published, it is still far from successful, broad industrial application. The major attention is paid to mentioned above two aspects of TCM systems: signal feature extraction and feature integration, as it is scientifically advanced and attractive. However, there are three weak points in the TCM system procedure usually underestimated, neglected even in the latest publications, including critical reviews of the state of the art [11, 25]:

- analyzed parts of the acquired signal are arbitrary selected by a researcher, neglecting number of data and necessary computing time,
- useful signal features are arbitrary selected for further integration,
- system is trained using signal features vs. tool wear measured in laboratory condition.

The objective of this paper is to discuss these aspects of the signal processing and feature integration techniques applied in tool wear monitoring, being major obstacles for effective industrial application of TCM systems.

2. SIGNAL SEGMENTATION

The signal acquired during machining consists of sequences of positioning movements and working feed (Fig. 2). The presence of working feed can be easily identified on the base of digital signals from CNC controller. During the working feed, air cutting (idle) and actual cutting (removing metal) should be distinguished. Duration of air cutting can vary between workpieces. Thus, an important stage of the signal preprocessing is automatic detection of the actual cutting. The simplest, most often used method of cutting recognition is detection of the signal value crossing of the preset threshold [16, 32, 33].

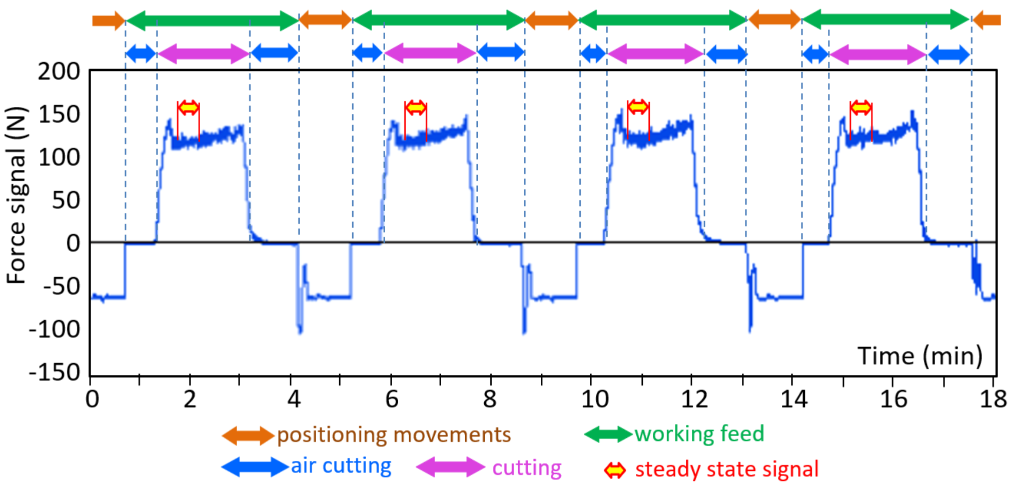

Fig. 2 The cutting force signal registered during subsequent cuts [31]

The threshold value is calculated as part of maximum signal value, which makes the method not applicable automatically, online, as the max value is not known before the cutting starts. In many industrial applications different disturbances of the signals may occur, which is another disadvantage of this method. Signal from piezoelectric transducer (e.g. cutting force) may fall or rise during an air cut or even become negative during cutting due to complex cross coupling between sensor sensitive directions. Therefore, cutting detection should be based on more than one signal, and more than one signal feature. Bombiński et al. [31] presented the algorithm which allows for detection of cutting based on all available signals. The method is presented in Fig. 3, where F_c signal is analyzed as an example. It is based on low pass filtered signal values and standard deviation. 40 ms after receiving a signal "working feed on" from the CNC, average value S_{av} of the sensor signal S are calculated from the 120 ms segment of the signal and subtracted from the signal as an offset, thus during air cutting the signal should oscillate around zero. At the same time the standard deviation σ_0 is calculated as a measure of signal disturbances characterizing the sensor installation. It might be dependent on the spindle rotational speed, feed, position of the current etc. Therefore, standard deviation σ_0 can be used for determination of the threshold values for cutting detection.

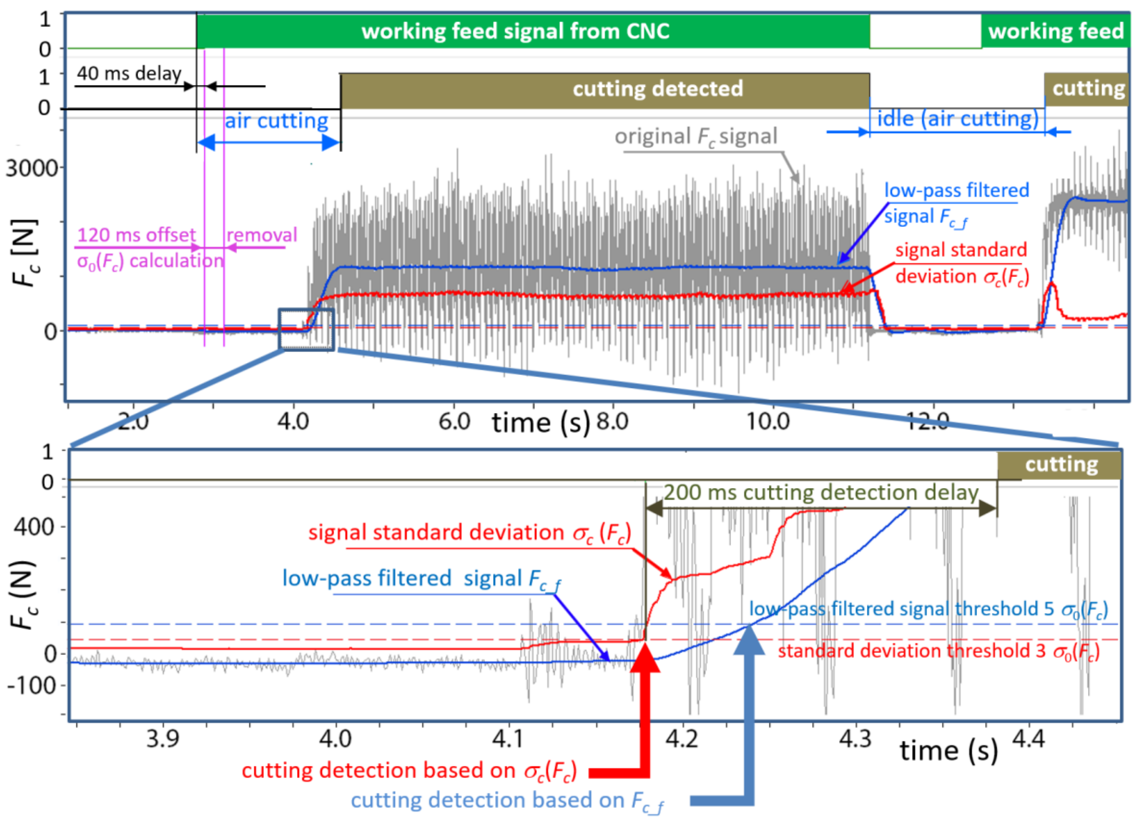

Fig. 3. The cutting detection method [31]

The actual cutting detection starts after the offset removal. Every 2 ms two signal features are calculated. The first one is S_f (here F_{c_f}) – signal filtered with low pass, 1 Hz

Butterworth II order filter. This feature represents moving average value of the signal and it is the most effective in the absence of the signal drift or change of sign of the signal value due to cross coupling mentioned above. The second feature is σ_c (here $\sigma_c(F_c)$) – standard deviation of a 400 ms fragment of the signal, which is independent of the signal drift or sign changes. If there are more available sensor signals, all of them are used for the cutting detection. The system recognizes the beginning of cutting if $S_f > 5\sigma_0$ or $\sigma_c > 3\sigma_0$ for any of the signals more than 200 ms. In the example presented in Fig. 3 the earliest threshold crossing appeared at 4.175 s for the standard deviation of the F_c thus the cutting was recognized at 4.375 s. Interruption of the cutting is recognized after all filtered signals and standard deviations which were above their thresholds, falls below the thresholds. If some signals have a strong drift tendency, cutting detection based on filtered signal might be switched off during the system installation. The same applies to detection based on standard deviation for very disturbed signals. None of these are done by the machine tool operator, and cutting detection is performed automatically without any user tuning or even knowledge.

Even during machining with constant cutting parameters, acquired signals may vary. Two methods could be applied here. One is averaging the signal values from larger time. E.g. to reduce the influence of runout in milling Dong et al. [5] calculated signal features from the force samples in one spindle rotation instead of one tooth period. Similarly, in [12], where tool failure detection in interrupted turning was analyzed, several data points taken into consideration contained the measured AE data from at least one full revolution of the workpiece. The second method, often used in commercial TCM systems is selection of steady state part of the signal by the operator [32–35]. Jemielniak et al. [30] observed, that despite constant cutting conditions during single micro-milling cut, AE signals were not constant, thus separate signal features were calculated for all cut and for the first and second 1/3 of the cut.

Another problem is the amount of data and calculation time. Considering the acquisition of several signals and calculation of several signal features from each of them, including time consuming transformation into the frequency domain (FFT, DWT, HHT) amount of data and calculation time can become unacceptable. On the other hand, especially for tool wear estimation, it is good enough to process short parts of the signal only several times during the tool life.

A crucial problem in selection of useful signal fragments is its automatization. Bombiński et al. [31] developed the algorithms for automatic selection of short, steady state, representative signal segments. The signals acquired during cutting in the first, training operation were divided into 1 second segments (Fig. 4). Then the effective value of each segment (B) was compared to proceeding (A) and succeeding (C) segment giving local fluctuation coefficient:

$$Fl_B = \left|\frac{RMS[A]}{RMS[B]} - 1\right| + \left|\frac{RMS[C]}{RMS[B]} - 1\right| \quad (1)$$

The fluctuation Fl is a measure of the segment usability for tool wear monitoring – the lower the better. For strictly a steady state signal it would be zero. The best segments are selected from the signal registered during cutting uniformly distributed through the entire cut.

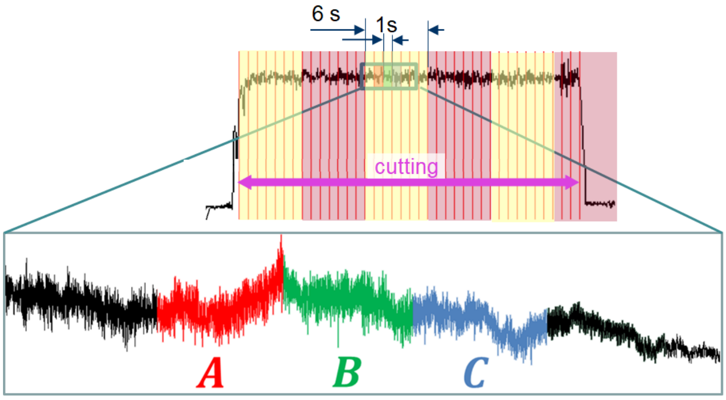

Fig. 4. Selection of steady state signal fragments [31]

Therefore segments are collected in clusters, six segments each and the best segment from every cluster is selected as its representative. For long operation, there would be many segments, overloading computer memory and increasing computing time without any added value. Therefore, if operation contains more than 2 min (120 segments in 20 clusters) not more than 20 best segments are selected for further processing. When the number of segments exceeds 128, they are clustered in pairs and the better of the two is selected. This segmentation algorithm allows for selection of the all sensor signal fragments from all operations corresponding to the same moment of the operation duration respectively. This selection is carried out only during the first tool life, while the system training. During this and all following tool lives, all available signal features are calculated from all selected signal segments and only the SFs are kept in computer memory. The original signals are erased, which reduces memory consumption.

3. TOOL CONDITION REFERENCE VALUE

The objective of TCM system is the evaluation of the tool condition. For system training some tool condition reference value is needed, with which the system indications can be compared. A majority of researches use direct measurements of tool wear [1, 6, 19]. Sometimes ranges of tool wear are used like "initial worn" – "normal (medium) worn" – "severe worn" [7, 16, 24]. However, such tool wear measures as *VB* or *KT* are seldom used in factory floor conditions, which makes all these works laboratory, difficult to introduce in the industry. Therefore, Warsaw University of Technology (WUT) introduced the concept of the used up portion of tool life (ΔT), defined as the ratio of the cutting time as performed so far to the overall tool life span [27–30]. During system training signals or signal features are collected as functions of time, number of operations, cuts or machined parts:

$$SF(t) \text{ or } SF(n) \tag{2}$$

Machining continues until the tool reaches its critical condition evaluated in the way used so far (before installation of TCM system). Machining time to the tool failure is the tool life T measured in minutes or number of cuts, operations or machined parts N. Independent variable of function (2) becomes used up portion of tool life ΔT:

$$\Delta T = \frac{t}{T} \text{ or } \Delta T = \frac{n}{N} \tag{3}$$

It is worth mentioning, that the end of tool life can be identified by tool wear measurements or by any other means, appropriate in particular factory floor conditions like burs, surface finish, dimensional accuracy, etc. Moreover, used up portion of the tool life is much more informative and useful for machine tool operator, who do not really needs to know the exact value of *VB* or *KT* but is interested in degree of tool life utilization.

4. SIGNAL FEATURE SELECTION

As it is really not possible to predict which signal features (SFs) will be useful in a particular case, largest possible number of SFs should be extracted from the available signals. The majority of them are not correlated with tool wear, useless. Therefore, TCM system must be equipped with effective feature selection procedure. The selected features should be relevant, sensitive to the tool or process condition.

Sick [9] noticed that in 38% out of 138 analyzed publications, features were selected without any reason (or based on literature review), in 26% signal features were defined after analysis of measured signals, in 21% the most appropriate of these features were selected without considering the behavior of the subsequent wear model. Only in 15% of publications the optimal set of features was found after the analysis of the influence of different features on the estimation of tool wear.

Therefore SFs should be preliminary tested for their correlation with the tool wear. Some researchers [6, 10, 16] apply Pearson's correlation coefficient r to find those features that can best characterize the tool wear. The correlation coefficient between a selected feature SF and the tool wear value w is can be expressed as follows:

$$r^2 = \frac{[\sum_i (SF_i - \overline{SF})(w_i - \overline{w})]^2}{\sum_i (SF_i - \overline{SF})^2 \sum_i (w_i - \overline{w})^2} \tag{4}$$

where $\overline{SF}$ and $\overline{w}$ are the mean values of signal feature and tool wear, respectively. The correlation coefficient r is a measure of the strength of linear dependence between x and y thus even if SF is perfectly correlated with the tool wear, but the correlation is not linear, the correlation coefficient is lower than 1.

Jemielniak et al. [3] grouped SF values against four ranges of the tool wear *KT* and used the coefficient of determination for SF classification. Coefficient of determination is a statistical measure of how well any SF-tool wear model approximates the real data points or – in other words – how much this model is better than just signal feature average value $\overline{SF}$:

$$R_s^2 = \frac{RSS}{TSS} = \frac{TSS - ESS}{TSS} = \frac{\sum_i (SF_i - \overline{SF})^2 - \sum_i (SF_i - \widehat{SF}_i)^2}{\sum_i (SF_i - \overline{SF})^2} \tag{5}$$

where: $TSS = \sum_i (SF_i - \overline{SF})^2$– total square sum, $ESS = \sum_i \left(SF_i - \widehat{SF}_i\right)^2$- residual square sum, RSS = TSS – ESS – regression square sum, SF_i, $\overline{SF}$ – single and mean value of the signal feature, $\widehat{SF}_i$ – single SF value evaluated on the base of any SF-tool wear model.

Very important, convenient characteristic of this coefficient is its independence from applied signal feature – tool condition model. There is no tool condition in equation (5). In [4] average values of SF within the group were applied as SF-tool wear model. Similar meaning has a Fisher's discriminant ratio applied by [7].

The coefficient of determination can be of course used also do continuous SF-tool condition models. It was applied in comprehensive methodology of signal feature selection developed in WUT [18, 29, 30]. Low-pass filtered signal feature SF_f was accepted as $\widehat{SF} = SF(\Delta T)$ model, which allowed avoiding any uncertain suppositions about the mathematical formula of this model. SF_i and SF_{fi} – single values of SF and SF_f respectively in the formula (5) were normalized in time (0-100% of the used part of tool life ΔT, i=0..100). These SFs, for which $R_s^2 > 0.4$ can be assumed as satisfactory correlated with the tool wear, thus usable for TCM – see examples in Fig. 5 [29].

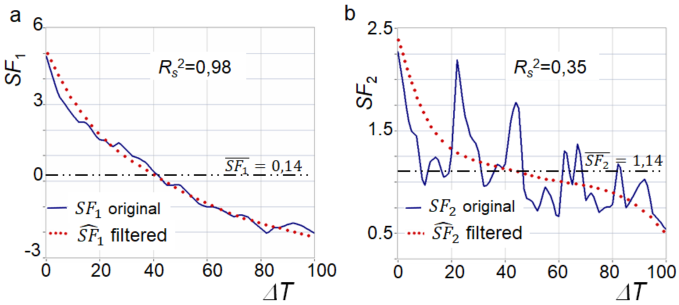

Fig. 5. Examples of signal feature usability evaluation a – useful SF, b – useless SF [29]

On the one hand, the more SFs correlated with the tool condition, the better. On the other hand, especially in neural networks based systems, the more features, the more training samples are needed. If the system is supposed to monitor the tool wear already after the first, training tool life, amount of training samples may be not big enough to properly train a big network necessary for a large number of inputs (signal features) [1, 28]. Thus he second objective of signal selection is to remove redundant signal features. Scheffer and Heyns [12] noticed that automated feature selection method often select features that are too similar or dependent on one another, and therefore do not achieve the goal of proper sensor fusion. In such cases, they recommended few rules based on "engineering judgment" which means resignation from automatic feature selection and manual intervention of the scientist. Such procedure is hardly acceptable in factory floor condition, making a TCM system purely laboratory. Nevertheless, they pointed important issue.

Accordingly, selected SFs should not be strongly correlated one with each other to avoid multiplication of the same information. In WUT methodology these SFs which meet the $R_s^2 > 0.4$ criterion, are sorted into descending order, according to the R_s^2 values. Then the first (best) is selected and Pearson's correlation coefficients r^2 between this SF and every other are calculated. SFs with r^2>0.8 are rejected as too much correlated with the best one. From among the remaining signal features, again the best one is selected, and the SFs correlated with it are rejected. The procedure is repeated until no signal feature meeting the $R_s^2 > 0.4$ criterion remains.

After completion of the third tool life, feature selection is repeated, using all available data, thus R_s^2 coefficients are calculated for three tool lives and averaged. Now application of second, even more important SF usability criterion can be applied: repeatability. It is evaluated using another determination coefficient R_r^2:

$$R_r^2 = \frac{\sum_j \sum_i \left(\widehat{SF}_{ij} - \overline{\widehat{SF}}\right)^2 - \sum_j \sum_i \left(\widehat{SF}_{ij} - \overline{\widehat{SF}_i}\right)^2}{\sum_j \sum_i \left(\widehat{SF}_{ij} - \overline{\widehat{SF}}\right)^2} \tag{6}$$

where: $\widehat{SF}_{ij}$ is $\widehat{SF}$ (filtered SF value) in *i*-th point (*i*=0..100) and *j*-th tool life (*j*=1..3),

$\overline{\widehat{SF}_i} = \frac{1}{3}\sum_j \widehat{SF}_{ij}$ is average of $\widehat{SF}$ in *i*-th point in all three tool lives,

$\overline{\widehat{SF}} = \frac{1}{303}\sum_j \sum_i \widehat{SF}_{ij}$ – is average of all $\widehat{SF}$ values in three tool lives.

These SFs, for which R_r^2>0.6 are assumed as repeatable enough. All SFs meetings, both criteria are sorted according to the R_r^2 values. Elimination of SFs correlated one to each other is based on three tool lives data. Examples of repeatable and not repeatable SFs are presented in Fig. 6.

The selected features are subject of signal feature integration – the decision making algorithm.

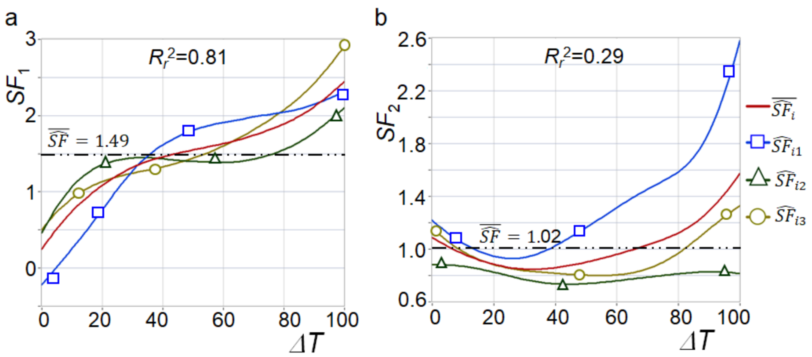

Fig. 6. A signal feature repeatability evaluation: a) – accepted SF, b) – rejected SF [29]

Generally, the reliability and user friendliness are the most important concerns of those who actually are using some form of TCM [1, 36]. Most laboratory systems presented in the literature are "manually" tuned and cannot work without the author. Thus, it is obviously vital to minimize the complexity of operation of any future TCM system so that it can be applied on many different machines for many different applications and can be used by a machine tool operator without any knowledge of the complex strategy involved. Any threshold value determination, signal feature selection and as well as their integration, should be performed by the system without any operator intervention, who should only point the end of the first, training tool life.

5. CASE STUDY

In [31] a tool wear monitoring strategy developed at Warsaw University of Technology, based on a large number of signal features was applied. Experiments were performed on turning center VENUS 450 equipped with an industrial cutting force sensor (Kistler 9601A31) installed under the turret and acoustic emission (AE) sensor (Kistler 7815B121) see Figure 7a. Four sensor signals were measured: three force signals, F_c, F_f and F_p and AE_{RMS} signal. The workpieces were C 45 steel bars, 160 mm diameter.

The plan of operation is presented in Fig. 7b. It consisted of 22 subsequent rough, shaping cuts with the depth of cut a_p = 1.5 (13 cuts) and 2 mm (9 cuts), the feed f = 0.1 mm/rev and cutting speed v_c = 150 m/min, and one finishing cut with the same feed and cutting speed but various depths of cut. Toolholders SCGCL equipped with cemented carbide inserts CNMG 10408 BP30A were used. Machining of one workpiece lasted 4.6 min, in which 3.6 min was cutting time. Eight tools were worn out after machining 8, 10, 10, 12, 10, 9, 14 and 10 workpieces respectively.

Figure 7c presents an example of the cutting force signal F_c and results of segmentation procedure in this case. During the first operation (top row in Fig. 7c) 165 segments were identified. The best nineteen segments selected after this operation are shown in the second row. After 7 operations, there were 19×7=133>128 signal segments in computer memory, so they were decimated by two, leaving only 10 segments per operation, which lasted to the end of the first tool life (8 operations).

Each of four measured signals was processed using three-level Wavelet Packet Transform (WPT) decomposition to obtain fourteen coefficients, called approximations *A* and details *D*. Then from all of them and the original signals the following signal features were calculated and selected automatically using procedure presented in section 4:

- logarithmic energy (e.g., $F_{c/DD.E}$ – the energy of wavelet coefficient *DD* of F_c signal),
- effective value (e.g., $F_{f/\mathrm{ADA.RMS}}$ – RMS value of coefficient ADA of F_f signal),
- standard deviation (e.g., $F_{f/A.st\_dev}$ – st.dev. value of coefficient A of F_f signal),
- mode (e.g. $AE_{/s.\mathrm{mode}}$ mode value of original AE_{RMS} signal),
- count 1, 2 and 3 – threshold crossing rate i.e. number of times the signal crosses the 30%, 50% or 70% of max value (e.g., $F_{p,\mathrm{ADA,Count1}}$),
- pulse 1, 2 and 3 – pulse width i.e. the percentage of time during which the signal remains above thresholds, (e.g., $\mathrm{F}_{c/\mathrm{ADA,Pulse1}}$).

In Fig. 8a feed force F_f signals acquired in the three of eight operations are presented, and 1st, 4th and 7th segments are marked. In each segment different numbers of different signal features were selected - examples are presented in Fig. 8b, (blue lines). After the first tool life, for every SF in every segment separate model based on 2rd degree polynomial was calculated (black, continuous lines in Fig. 8b).

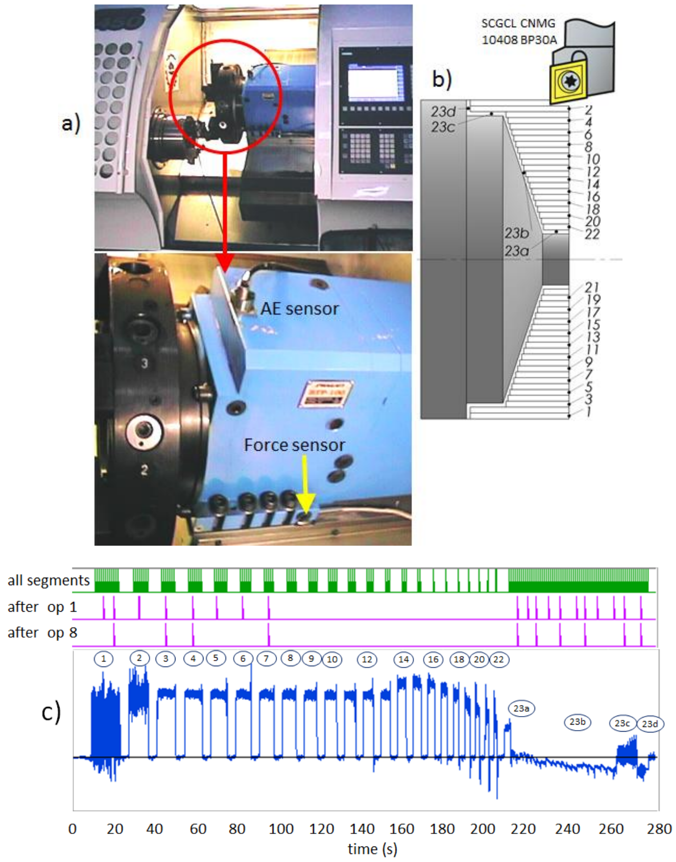

Fig. 7. (a) Sensor installation, (b) plan of operation and (c) segment elimination procedure [31]

During subsequent tool lives, the system works in monitoring mode. After acquiring of each selected segment, the used up part of tool life is calculated on the base of every SF model separately. For example, after acquiring the first segment in the third operation ΔT estimated using the first and the second signal features: $AE_{/s.\mathrm{mode}}$ and $F_{f/A.E}$ are $\Delta T_{1,1,3}$ and $\Delta T_{1,2,3}$ respectively (see Fig. 8b). Then they are averaged to give an estimation of the used part of tool life at this point of time, here it would be $\Delta T_{1,3}$ see Fig. 8c. The tool wear monitoring results are presented in Fig. 8c as the used up portions of tool lives evaluated by the system, ΔT_{est}, versus the actual values of ΔT.

As the first tool life was used only for system training. The results of the seven following tool lives are presented there. The accuracy of the tool wear monitoring evaluation can be assessed using the root mean square error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum(\Delta T_{ev} - \Delta T)^2} \tag{7}$$

The ΔT values are expressed as percentages; thus, the RMSE can be interpreted as average percentage errors. The RMSE are also presented in Fig. 8c. Presenting the tool wear evaluation during operation is especially important in the aerospace industry where machining of one workpiece can last several minutes, and sometimes several tools (tool lives) must be used to complete one operation.

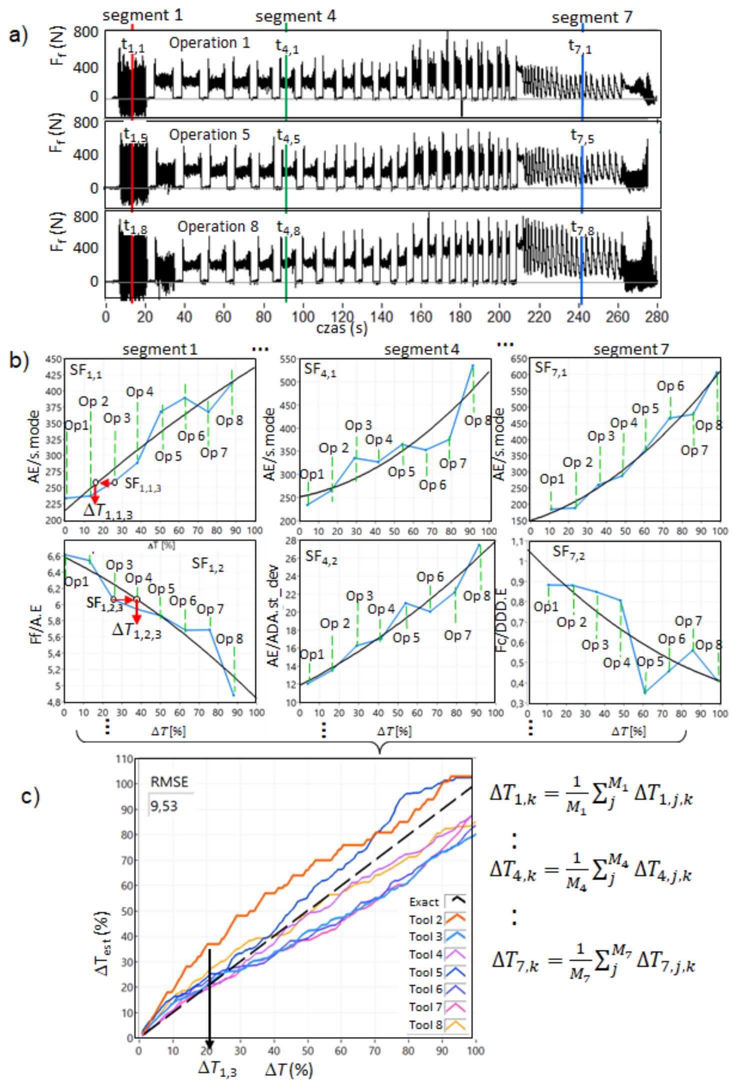

Fig. 8. (a) Feed force signals in three operations, (b) examples of signal features selected and modelled automatically in segment 1, 4 and 7, (c) used up part of the tool life estimation in tool lives 2–8 [31]

The presented case study proved the effectiveness of the tool wear monitoring system signal processing procedure – from cutting detection, via signal segmentation, automatic signal feature extraction and selection to tool wear evaluation. It was also tested even under very difficult cutting conditions, where the number of tool lives is less than the number of machined parts [29]. It was also implemented in several other applications like [28], including micromachining [30]. Recently it was applied in the aerospace industry in factory floor conditions [37].

6. CONCLUSIONS

The majority of papers on tool condition monitoring concern signal feature extraction and integration (decision making algorithms). Parts of the acquired signal that cover actual cutting in steady state conditions and selection of useful features are usually performed by a researcher arbitrary, which makes them hard to apply in factory floor condition. These procedures must be automated and work without operator intervention or even knowledge.

Reference tool condition used for system training should not be tool wear measured by a microscope, as it is not applicable in the industry. Used up portion of the tool life is a convenient indicator of a tool condition, much more informative than the direct value of a sensor signal or any signal feature, and more practical than tool wear measures (*VB*, *KT*) which are not usually measured at the factory floor conditions.

Solving these problems are much more important for industrial application of TCM systems than inventing new methods of signal feature extraction and AI based decision making algorithms.

REFERENCES

[1] TETI R., JEMIELNIAK K., O'DONNELL G., DORNFELD D., 2010, *Advanced monitoring of machining operations*, CIRP Annals – Manufacturing Technology, 59/2, 717–739.

[2] Li X., 2002, *A brief review – acoustic emission method for tool wear monitoring during turning*, Int. J. Mach. Tools Manufact., 42/2, 157–165.

[3] JEMIELNIAK K., KWIATKOWSKI L., WRZOSEK P., 1998, *Diagnosis of Tool Wear Based on Cutting Forces and Acoustic Emission Measurements as Inputs to a Neural Network*, J. of Intelligent Manufacturing, 9/5, 447–455.

[4] CAO H., ZHANG X., CHEN X., 2017, *The concept and progress of intelligent spindles: A review*, Int. J. Mach. Tools Manufact., 112, 21–52.

[5] JEMIELNIAK K., OTMAN O., 1998, *Catastrophic Tool Failure Detection Based on AE Signal Analysis*, Annals of the CIRP, 47/1, 31–34.

[6] LI N., CHEN Y., KONG D., TAN S., 2017, *Force–based tool condition monitoring for turning process using –support vector regression*, Int. J. Adv. Manuf. Technol., 91, 351–361.

[7] XIE Z., LI J., LU Y., 2018, *Feature selection and a method to improve the performance of tool condition monitoring*, Int. J. Adv. Manuf. Technol., doi.org/10.1007/s00170-018-2926-5.

[8] DONG J. et al., 2006, *Bayesian–inference–based neural networks for tool wear estimation*, Int. J. Adv. Manuf. Technol., 30/9–10, 797–807.

[9] SICK B., 2002, *On-line and indirect tool wear monitoring in turning with artificial neural networks: a review of more than a decade of research*, Mechanical Systems and Signal Processing, 16/2, 487–546.

[10] SCHEFFER C., HEYNS P.C., 2004, *An industrial tool wear monitoring system for interrupted turning*, Mechanical Systems and Signal Processing, 18/5, 1219–1242.

[11] ZHOU Y., XUE W., 2018, *Review of tool condition monitoring methods in milling processes*, Int. J. Adv. Manuf. Technol., 96, 2509–2523.

[12] SCHEFFER C., HEYNS P.C, 2001, *Wear monitoring in turning operations using vibration and strain measurements*, Mechanical Systems and Signal Processing, 15/6, 1185–1202.

[13] JEMIELNIAK K., KOSSAKOWSKA J., URBAŃSKI T., 2011, *Application of wavelet transform of acoustic emission and cutting force signals for tool condition, monitoring in rough turning of Inconel 625*, Proc. IMechE Part B: J. Engineering Manufacture, 225, 123–129.

[14] HUANG N., SAMUEL S., (ed.), 2005, *Hilbert-Huang Transform and its Application*, World Scientific Publishing.

[15] SHI D., GINDY N.N., 2007, *Tool wear predictive model based on least squares support vector machines*, Mechanical Systems and Signal Processing, 21, 1799–1814.

[16] CAGGIANO A., 2018, *Tool wear prediction in Ti-6Al-4V machining through multiple sensor monitoring and PCA features pattern recognition*, Sensors, 18, 823.

[17] SALGADO D.R., ALONSO F.J., 2006, *Tool wear detection in turning operations using singular spectrum analysis*, J. of Materials Processing Technol., 171/3, 451–458.

[18] Li X. et al., 2008, *Complexity measure of motor current signals for tool flute breakage detection in end milling*, Int. J. Mach. Tools Manufact., 48/3–4, 371–379.

[19] CAGGIANO A., RIMPAULT X., TETI R., BALAZINSKI M., CHATELAIN J.-F., NELE L., 2018, *Machine learning approach based on fractal analysis for optimal tool life exploitation in CFRP composite drilling for aeronautical assembly*, CIRP Annals – Manufacturing Technology, 67/1, 483–486.

[20] BALAZINSKI M., CZOGALA E., JEMIELNIAK K., LESKI J., 2002, *Tool condition monitoring using artificial intelligence methods*, Eng. App. of Art. Int., 15/1, 73–80.

[21] BARON L., ACHICHE S., BALAZINSKI M., 2001, *Fuzzy decisions system knowledge base generation using a genetic algorithm*, Int. J. of App. Reasoning, 28, 125–148.

[22] REN Q., BARON L., BALAZINSKI M., JEMIELNIAK K., 2011, *TSK Fuzzy Modeling for Tool Wear Condition in Turning Processes: An Experimental Study*, Eng. App. of Art. Int., 24/2, 260-265.

[23] ACHICHE S., BALAZINSKI M., BARON L., JEMIELNIAK K., 2002, *Tool wear monitoring using genetically-generated fuzzy knowledge bases*, Eng. App. of Art. Int., 15/3–4, 303–314.

[24] GAO D., LIAO Z., LV Z., LU Y., 2015, *Multi-scale statistical signal processing of cutting force in cutting tool condition monitoring*, Int. J. Adv. Manuf. Technol., 80, 1843–1853.

[25] SIDDHPURA A., PAUROBALLY R, 2013, *A review of flank wear prediction methods for tool condition monitoring in a turning process*, Int. J. Adv. Manuf. Technol., 65, 371–393.

[26] KUO R.J., COHEN P.H., 1999, *Multi-sensor integration for on-line tool wear estimation through radial basis function networks and fuzzy neural network*, Neural Networks, 12/2, 355–370.

[27] JEMIELNIAK K., 2006, *Tool wear monitoring based on a non-monotonic signal feature*, Proc. IMechE Part B: Journal of Engineering Manufacture, 220, 163–170.

[28] JEMIELNIAK K., BOMBIŃSKI S., 2006, *Hierarchical strategies in tool wear monitoring*, Proc. IMechE Part B: Journal of Engineering Manufacture, 220, 375–382.

[29] JEMIELNIAK K., URBAŃSKI T., KOSSAKOWSKA J., BOMBIŃSKI S., 2012, *Tool condition monitoring based on numerous signal features*, Int. J. of Advanced Manufacturing Technology, 59/1–4, 73–81.

[30] JEMIELNIAK K., BOMBIŃSKI S., ARISTIMUNO P.X., 2008, *Tool Condition Monitoring in Micromilling Based on Hierarchical Integration of Signal Measures*, CIRP Annals – Manufacturing Technology, 57/1, 121–124.

[31] BOMBIŃSKI S., BŁAŻEJAK K., NEJMAN M., JEMIELNIAK K., 2016, *Sensor signal segmentation for tool condition monitoring*, Procedia CIRP, 46, 155–160.

[32] http://www.toolmonitoring.com/pdf/praesentation/Nordmann_presentation_ENG.pdf, [Accessed: 11-Nov-2018].

[33] http://www.artis.de/en/, [Accessed: 11-Nov-2018].

[34] http://www.artis.de/en/, [Accessed: 11-Nov-2018].

[35] BRANKAMP K., 2008, BRANKAMP CMS 100 User Manual, Brankamp System Prozessautomation.

[36] REHORN A.G., JIANG J., ORBAN P.E., 2005, *State-of-the-art methods and results in tool condition monitoring: a review*, Journal of Advanced Manufacturing Technology, 26/7–8, 693–710.

[37] JEMIELNIAK K., et al. 2013-2016, *Advanced techniques of manufacturing of aircraft transmission – INNOGEAR*, Project No. INNOLOT/I/10/NCBR/2014, co-financed by the European Regional Development Fund under the Operational Programme Innovative Economy.