Application of wavelet transform of acoustic emission and cutting force signals for tool condition monitoring in rough turning of Inconel 625

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Abstract: Nickel-based superalloys are widely used in the aircraft industry since they are exceptionally thermal resistant, retaining their mechanical properties at temperatures of up to 700 °C. On the other hand, since they are very difficult to machine, tool life is typically short and can finish abruptly. As catastrophic tool failure can destroy an expensive workpiece, automatic tool condition monitoring (TCM) has become particularly critical. This paper presents an application of the wavelet packet transform (WPT) for extracting useful TCM features from the cutting forces and acoustic emission (AE) signals during rough turning of Inconel 625. New, improved methods of signal feature (SF) relevancy evaluation were proposed based on determination and correlation coefficients. Out of several SFs calculated from bandpass signals, the most useful for TCM were automatically selected. The selected features were used for tool condition monitoring.

Keywords: tool condition monitoring, cutting forces, acoustic emission, wavelet transform

1 INTRODUCTION

For many years, difficult-to-machine alloys have caused serious problems in the aviation and other manufacturing industries. Nickel-based superalloys are widely used in the aircraft industry since they are exceptionally thermal resistant, retaining their mechanical properties at temperatures of up to 700 °C [**1**]. However, they are very difficult-to-cut materials due to their high shear strength, work-hardening tendency, inclusion of highly abrasive carbide particles in the microstructure, strong tendency to weld and form a built-up edge, and low thermal conductivity [**2**, **3**]. Tool wear is not repeatable and has a tendency to end catastrophically by chipping or breakage. Thus, tool wear monitoring plays a very important role in guaranteeing undisturbed production machining of nickel-based alloys like Inconel 625.

Tool and process condition monitoring has been one of the most important focuses of research efforts for more than 20 years. An excellent summary of early work on this topic can be found in reference [**4**]. Much research has been done since then, and there are many commercially available tool condition monitoring systems [**5**]. However, these are generally not considered to be sufficiently reliable for broad applications. Most of these systems apply 'one process–one signal feature' strategies. On the other hand, it is commonly agreed that reliable tool wear evaluation based on one signal feature (SF) is impossible, because any feature depends not only on the tool wear but also on a variety of other process parameters with random natures. Therefore, the relationship between tool wear and a measured value is very complex and has a statistical nature, rather than a strictly predictable one. Hence, the key issue in tool condition monitoring (TCM) is finding multiple signal features correlated with tool condition [**6**]. Various methods for tool wear monitoring have been developed, most of which are based on acoustic emission (AE), cutting forces, and vibrations [**5–7**]. Many approaches have been taken to analyse these signals. Over the past 15 years, the wavelet transform has become one of the emerging and fast-evolving mathematical and signal processing tools. It has been used for surface metrology [**8**], chip form monitoring [**9**], and grinding wheel

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condition monitoring [**10**]. An interesting review of many applications of the wavelet transform in fault diagnosis and condition monitoring is presented in Peng and Chu [**11**]. Recently, it is more and more often applied to tool wear monitoring. Kwak [**12**] applied discrete wavelet decomposition to detect tool failure and to conduct the de-noising of the cutting force signal in a turning process. Li and Patri [**13**] applied the wavelet packet transform to tool wear monitoring in boring. They used the root mean square (r.m.s.) value of the bandpass of an AE signal to assess the tool state. Scheffer and Heyns [**14**] used a wavelet packet transform based on the strain and vibration signal to assess tool wear in turning. Several signal features indicative of tool wear were automatically extracted from a wavelet packet analysis. A correlation coefficient between the feature and the ideal trend was used for the automatic selection of the best features. Li *et al.* [**15**] applied a fast wavelet transform algorithm to recognize the tool wear states in automatic machining processing. They showed that a wavelet analysis based on this fast algorithm was more sensitive, more reliable, and faster than a Fourier analysis in recognizing the tool wear states for different cutting conditions.

The objective of the present study was the application of improved methods of feature extraction, selection, and integration based on the wavelet transform of raw AE and cutting force signals, for tool wear monitoring in the rough turning of Inconel 625.

2 DISCRETE WAVELET TRANSFORM

The discrete wavelet transform was developed by Mallat with a fast algorithm based on the conjugate quadratic filters [**16**]. The wavelet transform can decompose a signal into different components in different time windows and frequency bands through the wavelet scale function, and scaled and shifted versions of the mother wavelet. The discrete wavelet transform (DWT) decomposes a signal into the scaling coefficients (approximations A) and wavelet coefficients (details D) by the convolution of the signal and the impulse responses of the lowpass and highpass filters. The filter's outputs are subsampled by 2. At the first level, the original signal is decomposed into A_1 and D_1, and then approximation A_1 is decomposed again into A_2 and D_2. Generally, the approximations (A_{j+1}) and details (D_{j+1}) at level $j+1$ can be expressed by convolutions

$$A_{j+1}[n] = \sum_{k=-\infty}^{\infty} h[2n-k]A_j[k] \tag{1}$$

$$D_{j+1}[n] = \sum_{k=-\infty}^{\infty} g[2n-k]A_j[k] \tag{2}$$

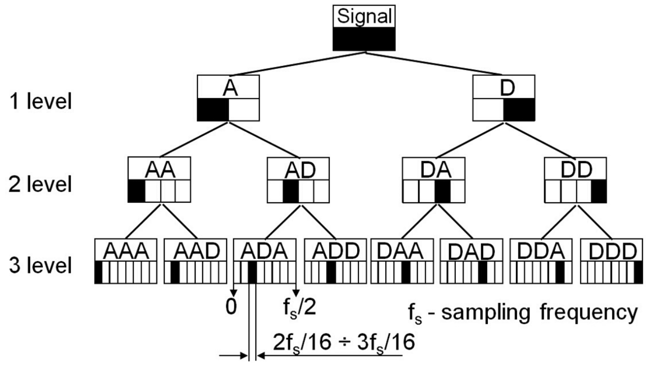

Fig. 1 Three-level wavelet packet transform (WPT) decomposition, where blackened fields indicate the frequency band of the original signal

where h and g are the impulse responses of the lowpass and highpass filters respectively, which are discrete equivalents to the scaling function and wavelet.

Another type of wavelet transform is the wavelet packet transform (WPT), where the approximations and details are both decomposed, providing many more frequency bands (Fig. 1). Since this provides more opportunities to find useful signal features, it was used in this research. From a mathematical point of view, the structure of the computations in a WPT is exactly an octave-band filter band. Thus, the approximations and details are bandpass signals (see Fig. 1).

Several wavelet basis function types are available in the literature. After many experiments with a number of them, the coiflet 5 wavelet and three-level decomposition WPT were applied because they were the most informative.

3 EXPERIMENTAL SET-UP AND CONDITIONS

The experiments were performed on a turning centre (TKX 50N) equipped with an industrial AE sensor (Kistler 8152B121) mounted on the turret and a cutting force sensor (Kistler 9017B) mounted under the turret (see Fig. 2(a)). The tool was a CRSNL 3225P12 MN7 with whisker-reinforced ceramic inserts, RNGN 120700T01020 CC670 (Fig. 2(a)). The workpieces were impeller cases made of Inconel 625 (Fig. 2(b)), and machined with subsequent perpendicular cuts from diameter 406 to 268, with the depth of the cut $a_p = 2.5$ mm, feed $f = 0.2$ mm/rev, and cutting speed $v_c = 220$ m/min. Three such workpieces were machined, during which seven tools were worn out. All of the experiments were conducted until the appearance of a drastic decrease in the surface finish (Fig. 2(c)) or burr formation (Fig. 2(d)), which are indirect criteria for tool life estimation applied under factory floor conditions. The tool notch wear (a direct, laboratory criterion for tool life estimation)

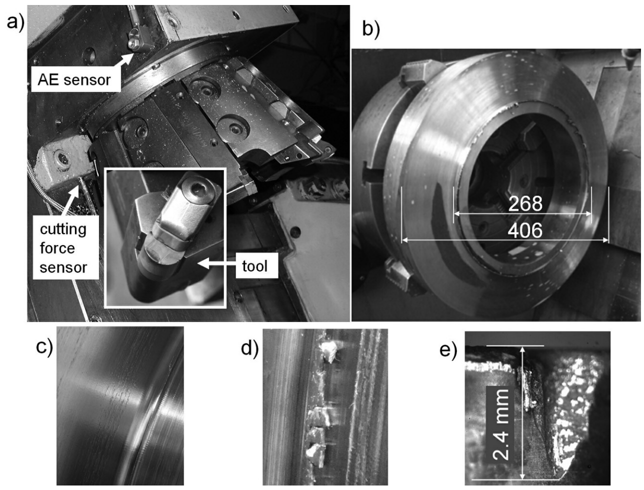

Fig. 2 Experimental set-up and tool life criteria: (a) tool and sensors, (b) the workpiece, (c) surface roughness, (d) burrs, and (e) tool wear

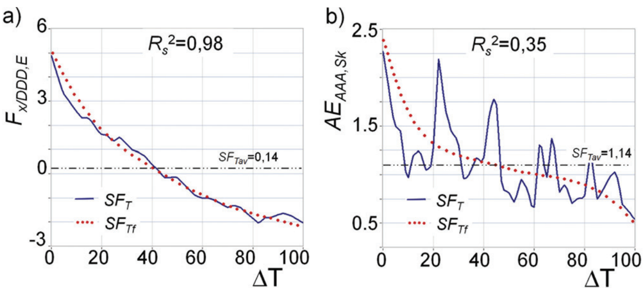

Fig. 3 Examples of signal features normalized in time (SF_T) and lowpass filtered (SF_{Tf}); (a) $F_{x/DDD,E}$: energy of coefficient DDD of F_x signal; (b) $AE_{AAA,Sk}$: skew of coefficient AAA of AE signal

was also measured (Fig. 2(e)). As the notch wear appeared on the side of the cutting edge opposite to that creating the machined surface, it was not correlated with the surface finish. It also was not correlated directly with the burr formation. All three phenomena (notch wear, surface finish, and burr formation) appeared autonomously, making determination of the tool life end difficult, subjective, and dependent on the machine tool operator's experience. Therefore, the application of a TCM system would be very useful. Here, the used-up portion of the tool life (ΔT), defined as the ratio of the cutting time as performed so far (t) to the overall tool life span (T), was used as the tool condition measure.

A raw AE (AE_{raw}) signal was acquired with a sampling frequency of 2 MHz using a DAQ card, NI PCI 6111. As this sampling frequency produces an enormously large amount of AE data, only 0.05 s (100 000 samples) out of every 10 s period was recorded and analysed. Two cutting force signals (F_x and F_z) were acquired simultaneously with a sampling frequency of 30 kHz using an NI-PCI 6221 DAQ card at the same points of time during 1.66 s (50 000 samples). Each cut lasted 96 s. Eight signal recordings taken from the middle parts of each cut were used for further analysis based on wavelet transforms.

4 EXTRACTION AND SELECTION OF SIGNAL FEATURES

As the outputs of the wavelet transforms have relatively large sizes, informative features must be extracted from the coefficients (bandpass signals). Wavelet coefficients are usually treated as separate signals, each characterized by the signal features (SFs) used for time domain signals [**17**]. Here, the following six signal features were calculated from the three-level decomposition WPT coefficients:

(a) effective value (root mean square, r.m.s.);
(b) logarithmic energy (E);
(c) skewness: the third statistical moment of a distribution (Sk);
(d) kurtosis: the fourth statistical moment of a distribution (Ku);
(e) ring-down count (Rd): number of times the signal crosses the threshold level calculated as 30 per cent of the maximum–minimum of the wavelet coefficient value during the first measurement (first 100 000 samples) for each tool life independently;
(f) pulse width (Pw): the percentage of time during which the signal remains above this threshold.

For three-level decomposition, there are 14 WPT coefficients and 84 signal features for each signal (AE_{raw}, F_x, and F_z) – altogether 252 SFs. Although the number of signal features was quite large, most of them were very distorted or barely sensitive to the tool condition. The decision-making algorithm of the TCM system should not be overburdened with those features, which would cause unnecessary computation or hinder the subsequent classification process. The selected features should be relevant, sensitive to the tool condition. To measure this relevancy, some model of the relationship between the signal feature and the tool wear or used-up portion of the tool life, ΔT, is necessary. Here, a lowpass filtered SF course was accepted as an SF(ΔT) model, which made it possible to avoid any uncertain suppositions about the mathematical formula of this model. As the filter characteristics depend on the number of elements in the filtered time series, filtering was preceded by the normalization of the SF in time to 0–100 per cent of the tool life to SF_T. Figure 3 shows examples of the signal features normalized in time (SF_T) and lowpass filtered (SF_{Tf}).

Now, the signal feature usability for tool condition monitoring can be evaluated using a coefficient of determination, R_s^2, which is a statistical measure of how well the $SF_{Tf}(\Delta T)$ model approximates the real $SF_T(\Delta T)$ relationship

$$R_s^2 = \frac{\sum_i (SF_{Ti} - SF_{Tav})^2 - \sum_i (SF_{Ti} - SF_{Tfi})^2}{\sum_i (SF_{Ti} - SF_{Tav})^2} \quad (3)$$

where $\sum_i (SF_{Ti} - SF_{Tav})^2$ is the total square sum, $\sum_i (SF_{Ti} - SF_{Tfi})^2$ is the residual square sum, SF_{Ti} and SF_{Tfi} are single values of SF_T and SF_{Tf} respectively ($i = 0, \ldots, 100$), and SF_{Tav} is the average value of SF_T.

As mentioned above, seven tools were worn out (seven tool lives obtained) during the experiments. It was decided to use the first three for the TCM system training, while the other four were used for testing the tool condition monitoring accuracy. Thus, average values of R_s^2 were calculated and used as the first criterion for automatic SF selection. These SFs, for which average values of $R_s^2 > 0.4$ were assumed to be satisfactory, correlated with the tool condition (smooth enough). Figure 3 presents an example of a signal feature that was accepted at this stage ($F_{x/DDD,E}$: energy of coefficient DDD of F_x signal, $R_s^2 = 0.98$) and a feature that was rejected as poorly correlated with the tool condition ($AE_{AAA,Sk}$: skew of coefficient AAA of AE signal, $R_s^2 = 0.35$).

The second criterion for an SF selection was its repeatability. Another coefficient of determination, R_r^2, was used for this purpose for signal features that met the first criterion

$$R_r^2 = \frac{\sum_j \sum_i (SF_{Tfji} - SF_{3Tfav})^2 - \sum_j \sum_i (SF_{Tfji} - SF_{Tfavi})^2}{\sum_j \sum_i (SF_{Tfji} - SF_{3Tfav})^2} \quad (4)$$

where SF_{Tfji} is the value of SF_{Tf} at the ith point ($i = 0, \ldots, 100$) and jth tool life ($j = 1, \ldots, 3$), $SF_{Tfavi} = \frac{1}{3}\sum_j SF_{Tij}$ is the average SF_{Tf} at the ith point, and $SF_{3Tfav} = \frac{1}{303}\sum_j \sum_i SF_{Tij}$ is the average of all of the SF_{Tf} values for three tool lives.

The signal features that were sufficiently repeatable ($R_r^2 > 0.6$) were selected for further consideration. Figure 4 presents examples of accepted (repeatable) and rejected (not repeatable) SFs.

Array $SF_{Tfav}(\Delta T)$ of 101 signal feature values normalized in time (0–100 per cent of ΔT), filtered, and averaged is now considered to be a representation of the signal feature–used-up portion of tool life.

Every SF, even those well correlated with tool wear, can sometimes be disturbed randomly. Therefore, the number of features should be sufficiently high to cover these possible random disturbances of any SF. On the other side, the selected signal features should not be strongly correlated with each other, to avoid repeating the same information or giving the same phenomenon too much importance [18–20]. The following procedure was adopted to eliminate similar SFs. All of the signal features selected so far were sorted into descending order, according to their R_r^2 values. Then, the first (best) was selected and correlation coefficients r^2 between this SF and every other were calculated. SFs with $r^2 > 0.75$ were rejected as too correlated with the best one. From among the remaining signal features, again the best one was selected, and the SFs correlated with it were rejected. This procedure was repeated until no signal feature meeting the $R_r^2 > 0.6$ criterion remained.

The procedure described above, wavelet transform and signal feature calculation, selection, and elimination, was performed fully automatically without any intervention by the operator. Finally, out of 252 signal features only 15 were left that were considered useful for tool condition monitoring: $F_{x/DDD,rms}$, $F_{x/ADA,Ku}$, $F_{z/D,Ku}$, $F_{z/AD,Pw}$, $F_{z/DAA,Rd}$, $F_{x/DAA,rms}$, $F_{z/DAA,Ku}$, $F_{z/DA,Rd}$, $F_{z/AD,Ku}$, $F_{z/DDD,rms}$, $AE_{DDA,E}$, $F_{x/DAA,Ku}$, $AE_{DD,Ku}$, $F_{x/ADD,Ku}$, and $F_{z/DA,E}$. It is worth noting that the most effective SFs were obtained from the F_z signal (8 SFs). The F_x signal was not much worse (5 SFs), while the AE signal produced only 2 SFs. The most productive type of SF was the kurtosis (7 SFs), while the skewness did not give any useful SF. All of these observations are summarized in Table 1.

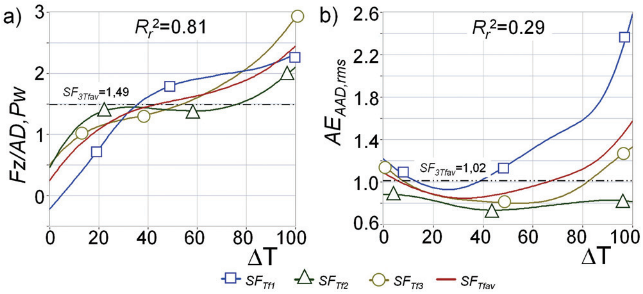

Fig. 4 Signal feature repeatability evaluation: (a) accepted SF – $F_{z/AD,Pw}$, pulse width of coefficient AD of F_z signal ($R_r^2 = 0.81$), (b) rejected SF – $AE_{AAD,rms}$, effective value of coefficient AAD of AE signal ($R_r^2 = 0.29$)

Table 1 The numbers of useful signal features obtained from different signals

	AE	F_x	F_z
R.m.s.	0	2	1
Energy	1	0	1
Skewness	0	0	0
Kurtosis	1	3	3
Ring-down count	0	0	2
Pulse width	0	0	1
Σ	2	5	8

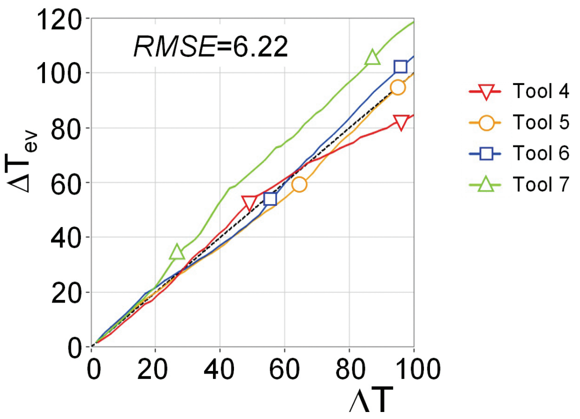

Fig. 5 Used-up portion of the tool life evaluated by the TCM system (ΔT_{ev}) versus actual one (ΔT) after training on all signals from the first three tool lives and testing on the remaining four

5 TOOL CONDITION ESTIMATION

The automatically selected signal features were fed to the decision-making algorithm of the TCM system, which evaluated the used-up portion of tool life (ΔT). The hierarchical TCM algorithm, described in reference [**7**], was applied here. In the first step of this algorithm, ΔT was calculated using the current signal feature value and the direct relationship between the signal feature and ΔT, $\mathrm{SF_{Tfav}}(\Delta T)$, for each SF separately [**21**]. In the second step, all of the ΔT values were averaged into a final tool condition evaluation. As three tool lives were used for the TCM system training, the remaining four were used for the system testing. Examples of this estimation are presented in Fig. 5 as the used-up part of a tool's life evaluated by the system (ΔT_{ev}) versus actual ΔT. Errorless estimation is shown by the straight, dashed line and deviations from this line are presented as the root mean square error (RMSE = 6.22).

As there were three signals measured, it is interesting to consider what would have happened if not all of them were available. First, the system was fed with the cutting forces signals only (Fig. 6(a)). It appeared that results were not much worse, which is not surprising, as AE provided only two signal features (see Table 1). When only one cutting force signal was used, the accuracy of the tool condition evaluation was significantly worse (RMSE = 10.81 for F_x only and RMSE = 9.82 for F_z only) but still reasonably good. Rather surprising is the relatively good result achieved when only the AE signal was available (Fig. 6(d)), despite the fact that only two SFs were then selected. Nevertheless, all of the results prove that WPT provides a powerful tool for signal feature extraction, which is very useful for tool condition monitoring. It was also again shown that the hierarchical algorithm applied here is very effective in this monitoring, as it was in two other applications [**18–20**].

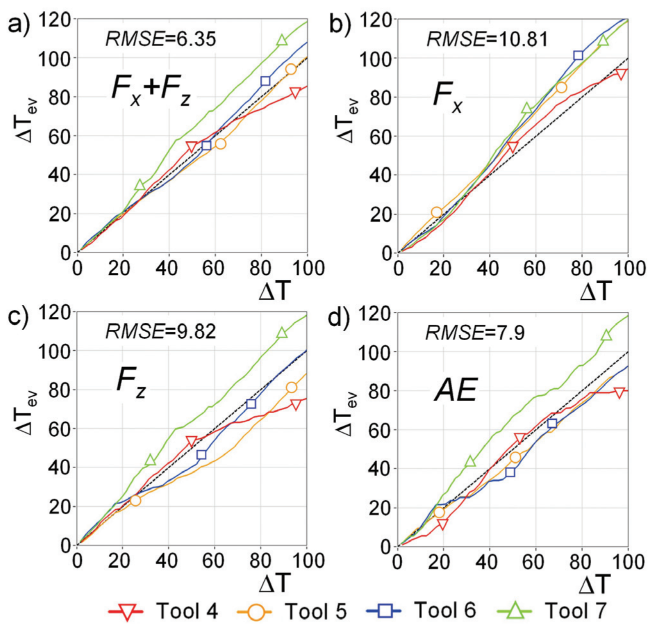

Fig. 6 Used-up portion of the tool life evaluated by the TCM system (ΔT_{ev}) versus actual one (ΔT) after training on selected signals from the first three tool lives and testing on the remaining four: (a) $F_x + F_z$, (b) F_x only, (c) F_z only, and (d) AE only

6 CONCLUSIONS

This paper presented an application of the wavelet packet transform of AE and cutting force signals in tool condition monitoring during the rough turning of Inconel 625. Several signal features (SFs) were extracted from wavelet coefficients. New, improved methods of SF relevancy evaluation were proposed based on determination and correlation coefficients. The coefficient of determination was used for selecting SFs that changed regularly and smoothly with the used-up portion of tool life, which was considered to be a measure of the correlation between the SF and ΔT. The same coefficient was also used for selecting repeatable SFs. The coefficient of correlation was applied to eliminate SFs that were similar (correlated) to better ones. Finally, the selected signal features were used in a hierarchical algorithm for tool condition evaluation.

The results of this research can be summarized as follows:

1. The proposed method of automatic signal feature extraction and selection provided informative SFs, which were successfully used in tool condition monitoring.

2. The most effective type of wavelet coefficient feature appeared to be kurtosis, while skewness did not produce any useful SF.
3. Most of the informative SFs were obtained from cutting force signals, while the AE signal provided only two SFs.
4. Tool condition monitoring based on the selected SFs appeared to be most successful when all three signals were available; however, even single signals appeared to be acceptable in this application.

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APPENDIX

Notation

a_p	depth of cut
A	approximation (DWT coefficient)
A_1	approximation (DWT coefficient) at level 1
A_2	approximation (DWT coefficient) at level 2
AE	acoustic emission
$\mathrm{AE}_{\mathrm{AAA,Sk}}$	skew of coefficient AAA of AE signal
$\mathrm{AE}_{\mathrm{DD,Ku}}$	kurtosis of coefficient DD of AE signal
$\mathrm{AE}_{\mathrm{DDA,E}}$	energy of coefficient DDA of AE signal
D	detail (DWT coefficient)
D_1	detail (DWT coefficient) at level 1
D_2	detail (DWT coefficient) at level 2
DWT	discrete wavelet transform
E	logarithmic energy
f	feed rate

F_z	cutting force signal measured in the cutting speed direction
F_x	cutting force signal measured in the feed direction
$F_{x/\mathrm{ADA,Ku}}$	kurtosis of coefficient ADA of F_x signal
$F_{x/\mathrm{ADD,Ku}}$	kurtosis of coefficient ADD of F_x signal
$F_{x/\mathrm{DAA,rms}}$	r.m.s. of coefficient DAA of F_x signal
$F_{x/\mathrm{DAA,Ku}}$	kurtosis of coefficient DAA of F_x signal
$F_{x/\mathrm{DDD,E}}$	energy of coefficient DDD of F_x signal
$F_{x/\mathrm{DDD,rms}}$	r.m.s. of coefficient DDD of F_x signal
$F_{z/\mathrm{AD,Ku}}$	kurtosis of coefficient AD of F_z signal
$F_{z/\mathrm{AAD,Ku}}$	kurtosis of coefficient AAD of F_z signal
$F_{z/\mathrm{AD,Pw}}$	pulse width of coefficient AD of F_z signal
$F_{z/\mathrm{D,Ku}}$	kurtosis of coefficient D of F_z signal
$F_{z/\mathrm{DA,E}}$	energy of coefficient DA of F_z signal
$F_{z/\mathrm{DA,Rd}}$	ring-down count of coefficient DA of F_z signal
$F_{z/\mathrm{DAA,Ku}}$	kurtosis of coefficient DAA of F_z signal
$F_{z/\mathrm{DAA,Rd}}$	ring-down count of coefficient DAA of F_z signal
$F_{z/\mathrm{DDD,rms}}$	r.m.s. of coefficient DDD of F_z signal
g	impulse response of the highpass filter
h	impulse response of the lowpass filter
Ku	fourth statistical moment of a distribution (kurtosis)
Pw	percentage of time during which the signal remains above threshold (pulse width)
r^2	correlation coefficient
Rd	number of times the signal crosses the threshold level (ring-down count)
R_r^2	coefficient of determination (repeatability)
R_s^2	coefficient of determination (smoothness)
r.m.s.	effective value (root mean square)
RMSE	root mean squared error
$\mathrm{SF_T}$	signal features normalized in time
$\mathrm{SF_{Tav}}$	average value of $\mathrm{SF_T}$
$\mathrm{SF}_{\mathrm{T}i}$	single value of $\mathrm{SF_T}$
$\mathrm{SF_{Tf}}$	signal features normalized in time and lowpass filtered
$\mathrm{SF}_{\mathrm{Tfav}i}$	average of $\mathrm{SF_{Tf}}$ in ith point
$\mathrm{SF}_{\mathrm{Tf}i}$	single value of $\mathrm{SF_{Tf}}$
$\mathrm{SF}_{\mathrm{Tf}ji}$	value of $\mathrm{SF_{Tf}}$ in ith point ($i = 0, \ldots, 100$) and jth tool life ($j = 1, \ldots, 3$)
$\mathrm{SF_{3Tfav}}$	average of all $\mathrm{SF_{Tf}}$ values in three tool lives
Sk	third statistical moment of a distribution (skewness)
t	performed cutting time
T	overall tool life span
TCM	tool condition monitoring
WPT	wavelet packet transform
v_c	cutting speed
x_i	single wavelet coefficient value
ΔT	used-up portion of the tool life
ΔT_ev	used-up part of the tool life evaluated by the TCM system
μ	mean
σ	standard deviation