Tool wear estimation in turning of Inconel 718 based on wavelet sensor signal analysis and machine learning paradigms

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Abstract

In the last years, hard-to-machine nickel-based alloys have been widely employed in the aerospace industry for their properties of high strength, excellent resistance to corrosion and oxidation, and long creep life at elevated temperatures. As the machinability of these materials is quite low due to high cutting forces, high temperature development and strong work hardening, during machining the cutting tool conditions tend to rapidly deteriorate. Thus, tool health monitoring systems are highly desired to improve tool life and increase productivity. This research work focuses on tool wear estimation during turning of Inconel 718 using wavelet packet transform (WPT) signal analysis and machine learning paradigms. A multiple sensor monitoring system, based on the detection of cutting force, acoustic emission and vibration acceleration signals, was employed during experimental turning trials. The detected sensor signals were subjected to WPT decomposition to extract diverse signal features. The most relevant features were then selected, using correlation measurements, in order to be utilized in artificial neural network based machine learning paradigms for tool wear estimation.

Keywords Inconel 718 · Tool wear · Multiple sensor monitoring · Wavelet packet transform · Machine learning · Artificial neural networks

1 Introduction

In modern machining processes, tool wear estimation is a crucial requirement to prevent machine tool failure and to produce parts with the required high quality. During machining operation, the employment of worn cutting tools can cause poor surface finish and insufficient dimensional accuracy of the product as well as unexpected catastrophic tool failure events. Moreover, cutting tool health tends to deteriorate more rapidly when the workpiece hardness is higher [1].

In the last years, the notable increase in the demand for materials with high strength and temperature resistivity in aerospace and gas turbine industries has led to an extensive use of nickel-based alloys. These alloys provide properties

of high strength, excellent resistance to corrosion and oxidation, and long creep life at elevated temperatures but are classified as a hard-to-machine materials [2–4].

Inconel 718 is a nickel-based alloy largely utilized to manufacture parts of nuclear reactors, gas turbines, rocket motors, spacecraft, pumps, tooling systems, etc. It combines corrosion resistance and high strength with outstanding weldability, including resistance to post-weld cracking. Moreover, this alloy has excellent creep-rupture strength at temperatures up to 700 °C. Besides these excellent properties, the machinability of Inconel 718 faces challenges in terms of high cutting forces and high temperature growth, built-up edge formation, strong work hardening, and rapid tool wear development [5, 6].

Rapid tool wear is a critical factor in terms of quality of the machined parts (with risk of workpiece scrap), short tool life, increase in energy consumption and tooling cost [2, 7, 8].

As a practical way out, many manufactures have chosen to utilize lower cutting parameter values and replace the cutting tool before approaching the critical wear limits [9].

Generally, tool wear measurements are performed by interrupting the machining process and making a judgment

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on tool wear level using offline inspection techniques such as optical microscope, profilometer, camera, etc. [10]. These direct measuring methods are generally carried out by the operator who stops the machining operation periodically with significant waste of production time and cost.

Today's tool condition monitoring (TCM) systems can be applied for the indirect measurement of tool wear during machining using sensorial instrumentation able to detect sensor signals related to tool wear development.

Numerous papers have been published on TCM during machining operations using diverse sensors such as dynamometer, accelerometer, motor load current, acoustics emission, temperature, vibrations, etc.; many of these research works are reviewed in [11–13].

An effective intelligent TCM system must be able to perform different functions: sensor signal data acquisition, sensor signal processing, features extraction and selection, and pattern recognition for decision making. The acquired raw sensor signals contain a lot of useless and/or misleading information, including noise and signal contamination, and need to be processed by filtering, amplification, analog-to-digital conversion, and segmentation procedures. Then, sensor signal features can be extracted in the time domain, frequency domain, and time–frequency domain [14]. In the time domain, statistical analysis, singular spectrum analysis and principal component analysis are widely used while the fast Fourier transforms and power spectrum density are the most common methods in the frequency domain.

To simultaneously analyze the signals in the time and in the frequency domains, wavelet transform (WT) has been largely applied to TCM [15]. Olortegui-Yume and Kwon [16] studied the crater wear development using wavelet-filtered images to identify the tool wear mechanisms in turning processes applied to AISI 1045 steel bars. In [17], a discrete wavelet transform was applied to turned surface images for tool flank wear prediction. A review of wavelet analysis applications for TCM is presented in [18].

In order to reduce the high number of features extracted from the analyzed sensor signals, it is necessary to select a subset of relevant features that maintains the correlation with the tool state. Various feature selection algorithms have been proposed in the literature such as Pearson correlation coefficient, Fisher's linear discriminant analysis, ridge regression, and least absolute shrinkage and selection operator [19].

Artificial intelligence (AI) and machine learning (ML) methods [20, 21] play a key role in the improvement of modern TCM systems [14, 22, 23]. In particular, several researchers have studied and applied diverse AI and ML methods for TCM such as fuzzy clustering approaches [24], genetic algorithms [25], Gaussian mixture models [26], neuro-fuzzy techniques [27, 28], self-organizing feature maps [29], hidden Markov models [30], support vector machine [31]. Artificial neural networks (ANNs) based ML

paradigms are very often applied due to their high capability in pattern recognition procedures.

As regards TCM during machining of Inconel 718, several research papers studied the diverse aspects of the cutting tool (geometry, material, surface, coatings) for the selection of the adequate tool to employ by minimizing the machining costs [2, 6, 10, 32, 33]. Other papers reviewed the surface integrity characteristics of machined nickel-based alloys by evaluating the influence of diverse cutting parameter values [3, 34–36].

However, the correlation of the acquired sensorial data with tool wear during machining of Inconel 718 for tool life prediction is little studied. In the recent literature, a tool wear monitoring system based on vibration and force sensors was utilized in [37] during hard turning of Inconel 718. The experimental trials were performed until the tool was completely worn out. The study showed that the force data are quite useful to establish a strong correlation between cutting force and tool wear.

In [38] the relationship between the tool wear evolution and the changes of the three cutting force components was studied during turning of Inconel 718, showing that the passive force is more representative due to the fact that the tool corner wear is associated with a strong ploughing action.

Kene and Choudhury [39] implemented a tool health monitoring system using multiple sensors signals in hard turning, presenting a novel analytical model of sensor data fusion. The results of this research confirm the effectiveness of using a fusion function over single sensor-based approaches.

A new cutting tool holder was designed in [40] to break continuous chips during turning of Inconel 718. The effect of the holder was examined by analyzing the cutting forces, cutting temperatures, surface roughness, and tool wear behaviour. A significant reduction in tool wear was observed using a high machining speed, a low feed rate, and high depth of cut.

In this paper, the tool wear estimation during experimental turning trials on Inconel 718 was performed by using an advanced sensor procedure, based on wavelet sensor signal analysis, and machine learning paradigms for decision making. Cutting force, acoustic emission, and vibration acceleration sensor signals were detected and processed. Cutting tool flank wear measurements were performed after each 2-min of turning in order to evaluate the tool condition. The pre-processed sensor signals were subjected to wavelet packet transform (WPT) decomposition in order to extract time–frequency domain features. A Pearson's coefficient algorithm was employed to select the features most correlated with the tool wear in order to reduce the high dimensionality of wavelet features. Then, the selected features were utilized to construct diverse feature pattern vectors to feed to ANNs-based ML paradigms. The performance of ANNs models in

estimating the tool wear level was evaluated under various combinations of the selected features.

2 Materials and experimental set up

The workpieces were cylindrical bars made of Inconel 718 with chemical composition and mechanical properties summarized in Table 1. Turning tests were performed on a CNC lathe using as cutting tools rhombic uncoated carbide inserts (Kennametal CNMG120408-K313) the characteristics of which are reported in Table 2.

The cutting parameters employed for the machining trials were selected according to the common cutting parameters adopted for turning of Inconel 718 (Table 3). In particular, three cutting speed values were considered: $v_c = 45, 50, 55$ m/min. The 45 m/min cutting speed corresponded to the highest speed industrially employed during turning of Inconel 718, whereas the 55 m/min cutting speed represented the maximum cutting speed for nickel-based alloys machining disclosed in the literature [5, 10, 14]; $v_c = 50$ m/min was selected as intermediate cutting speed value.

Three feed rate values, $f = 0.100, 0.125, 0.150$ mm/rev, were considered according to literature information [4, 5] and common shop floor values. The depth of cut, d , was kept equal to 0.3 mm for all turning trial conditions.

By combining the cutting parameters, 9 turning conditions were employed for cutting trials, which were repeated at least twice.

Table 1 Chemical composition and mechanical properties of Inconel 718

Chemical composition (wt)				Mechanical properties at room temperature	
Ni	50–55	Si	0.35	Ultimate tensile strength	1240 MPa
Cr	17–21	Mn	0.35	Yield strength	1036 MPa
Co	1	Cu	0.3	Elongation in 50 mm	12
Mo	0.65–1.15	C	0.08	Elastic modulus (Tension)	211 GPa
Al	0.2–0.8	P	0.015	Hardness	36 HRC
Nb+Ta	4.75–5.5	S	0.015		
B	0.006	Fe	Bal		

Table 2 Cutting tool geometry

Table 3 Cutting parameters for turning trials

Turning parameters			
Cutting speed, v_c (m/min)	45	50	55
Feed rate, f (mm/rev)	0.100	0.125	0.150
Depth of cut, d (mm)	0.3		

Each turning trial was carried out according to a step-wise procedure with step duration equal to 120 s. After each 120 s step, the operation was stopped and the tool flank wear was measured. Then, the turning steps were replicated until the maximum allowable tool flank wear, $VB_{\max} = 0.3$ mm, was reached.

The cutting length, Z , corresponding to the 120 s step during each turning trial was calculated as follows:

From equation: $T = \frac{Z}{n \cdot f}$, it is obtained: $Z = T \cdot n \cdot f$, where T is the cutting time and n is the number of revolutions per minute. The value of $n = \frac{v_c \cdot 1000}{\pi \cdot D}$, where v_c is the cutting speed, and D is the workpiece diameter. After calculating the cutting length Z for each turning step, an average value $\bar{Z}$ was considered and utilized in the CNC code: $\bar{Z} = \frac{\sum Z_{\text{step}}}{\text{number of steps}}$.

A total of 36 valid turning tests were performed using three cutting speeds, three feed rates, two tool states (fresh or worn) and two test repetitions ($3 \times 3 \times 2 \times 2 = 36$ tests) as summarised in Table 4. In particular, for each tool state (fresh or worn) 18 turning trials were carried out.

3 Sensor signal acquisition system

A multi-sensor monitoring system (Fig. 1) comprising three sensors of different nature (cutting force, acoustic emission, and vibration sensors) was employed during trials for tool state monitoring. In particular, the three cutting force component signals (F_x, F_y, F_z) in the feed, the radial and the tangential directions, respectively, were acquired through a triaxial cutting force sensor (Montronix FS-ICA) clamped in a slot between tool holder and its supporting fixture. The acquired cutting force signals were then amplified using a Montronix TSFA3-ICA force amplifier.

Corner radius, R_ϵ	0.8 mm
Cutting angle	80°
Insert size, D	12.70 mm
Cut edge length, L_{10}	12.90 mm
Insert thickness, S	4.76 mm
Insert hole size, D_1	5.16 mm

Table 4 Cutting parameters and test ID

Cutting speed	Feed rate	Test ID for fresh tool	Test ID for worn tool	Repetition
45	0.100	Test_1_fresh	Test_1_worn	2
45	0.125	Test_2_fresh	Test_2_worn	2
45	0.150	Test_3_fresh	Test_3_worn	2
50	0.100	Test_4_fresh	Test_4_worn	2
50	0.125	Test_5_fresh	Test_5_worn	2
50	0.150	Test_6_fresh	Test_6_worn	2
55	0.100	Test_7_fresh	Test_7_worn	2
55	0.125	Test_8_fresh	Test_8_worn	2
55	0.150	Test_9_fresh	Test_9_worn	2

Fig. 1 Multiple sensor system comprising the cutting force, vibration and acoustic emission sensors mounted on the tool holder

The detection of the acoustic emission (AE) signals was carried out with an AE sensing unit (Montronix BV-100 Series) screwed under the head of the tool holder. The analogue AE signals were amplified by a Montonix TSVA4G AE amplifier with band-pass filtering at 50–500 kHz. Moreover, the RMS values of the AE signals were obtained using a short time constant equal to 0.12 ms.

A multifunction data acquisition board (National Instruments USB-6221 A/D) was utilized to digitize the amplified

cutting force and AE sensor signals with sampling frequency 10 kHz.

An integrated triaxial vibration sensor (Montronix SpectraPulse) was magnetically attached to the tool holder for the acquisition of the three vibration acceleration components: a_x , a_y , a_z . This integrated vibration sensor system included, in addition to the actual sensor and the amplifier, an A/D conversion module with sampling rate of 3 kHz. In this way, the vibration acceleration signals were directly sent in digitized form to the PC via USB connection.

4 Tool wear measurements

Cutting tool wear measurements were performed using a profile projector (Nikon V-24A) after each 120 s turning step in order to evaluate the tool condition in terms of flank wear.

Figure 2 shows the tool insert positioning on the profile projector and the tool flank wear visualization and measurement on the profile projector screen.

The tool wear measurement procedure was repeated after each 120 s turning step until the maximum acceptable flank wear value, $VB = 0.3$ mm, was reached. In Figs. 3, 4 and 5, the tool flank wear measurements and the corresponding tool wear interpolated curves are reported for each cutting speed value: $v_c = 45$ m/min (Fig. 3), $v_c = 50$ m/min (Fig. 4), $v_c = 55$ m/min (Fig. 5), and the three feed rate values (0.100, 0.125, 0.150 mm/rev).

5 Sensor signal processing

The detected sensor signals from each turning trial were subjected to a pre-processing phase in order to identify the sensorial information only related to the actual machining (i.e. only when the tool really removes the work material). A signal segmentation procedure [3] was applied to filter out signal segments that do not correspond to actual machining operations. To this scope, the initial and final portions of each sensor signal (cutting force component, AE_{RMS} ,

Fig. 2 **a** Tool insert positioning and **b** tool flank wear visualization on the profile projector

Fig. 3 Tool wear curves for cutting speed $v_c = 45$ m/min and feed rate $f = 0.100, 0.125, 0.150$ mm/rev

Fig. 5 Tool wear curves for cutting speed $v_c = 55$ m/min and feed rate $f = 0.100, 0.125, 0.150$ mm/rev

Fig. 4 Tool wear curves for cutting speed $v_c = 50$ m/min and feed rate $f = 0.100, 0.125, 0.150$ mm/rev

and vibration acceleration component), related to transient machining conditions (e.g. tool engagement, tool retraction), were eliminated to get rid of misleading information [28, 33, 36].

In Fig. 6, the raw sensor signals for the three cutting force components, F_x , F_y , and F_z , and the AE_{RMS} , in the

case of cutting conditions $v_c = 45$ m/min and $f = 0.100$ mm/rev, are shown together with their segmentation time interval (represented by two dotted vertical red lines) for the removal of the head and tail parts of the sensor signals.

Each segmented signal was subdivided into six equal parts. From each signal subdivision part, one signal specimen of 3000 samplings was extracted. In this way, for each segmented signal, five signal specimens of 3000 samplings were obtained. In Fig. 7, the subdivision of the F_x , F_y , F_z cutting force components into six equal parts is reported, and the five 3000 sampling signal specimens extracted at each separation between signal subdivision parts are represented in yellow.

Thus, a total of 90 signal specimens (9 cutting conditions $\times 2$ repetitions $\times 5$ specimens = 90 signal specimens) for each tool condition (fresh or worn tool) were obtained for each sensor signal type (F_x , F_y , F_z , AE_{RMS} , a_x , a_y , a_z).

Fig. 6 F_x , F_y , F_z and AE_{RMS} raw sensor signals and their segmentation time interval (dotted vertical red lines) for the turning trial with $v_c = 45$ m/min and $f = 0.100$ mm/rev

Fig. 7 Cutting force components F_x , F_y , F_z : segmented signal subdivision into six equal parts and extraction of the five 3000 sampling specimens

6 Features extraction using wavelet packet transform

Wavelet packet transform (WPT) decomposition is a time–frequency domain analysis method which allows to separate relevant information from a sensor signal by scaling and translation procedures generating re-scaled waves, called “wavelets” [15–18]. The implementation of the WPT leads to a tree-structured decomposition, where a signal is passed through low-pass and high-pass filters which are recursively decomposed.

If $f(t) \in L^2(\mathbb{R})$ is a signal, $f(t)$ can be decomposed by using a mother wavelet function, ψ :

$$\psi_{st}(t) = \frac{1}{s} \psi\left(\frac{t-\tau}{s}\right) \quad (1)$$

where s is the frequency and t is the time shift.

The wavelet transform of $f(t)$ is defined by:

$$W_s[f(\tau)] = \int_{-\infty}^{\infty} f(t) \frac{1}{s} \psi\left(\frac{t-\tau}{s}\right) dt \quad (2)$$

$W_s[f(t)]$ decomposes a signal $f(t)$ into a weighted linear combination of a set of scaling functions and wavelet functions at

given location τ and frequency s . The wavelet transform is a time–frequency domain function describing the information of $f(t)$ in various time windows and frequency bands. Wavelet and scaling functions are generated from a single scaling function with two-scale difference equations:

$$\varphi(t) = \sqrt{2} \sum_k h(k) \varphi(2t - k) \quad (3)$$

$$\gamma(t) = \sqrt{2} \sum_k g(k) \varphi(2t - k) \quad (4)$$

where $h(k)$ and $g(k)$ are low-pass and high-pass filters coefficients. Coefficients associated with the scaling function (approximation coefficients) are related to low frequency information, while coefficients associated with wavelet function (detail coefficients) capture high-frequency information.

By using Eqs. (3) and (4), a signal can be decomposed at the 1st level into an approximation (A_1) and a detail (D_1). At the 2nd decomposition level, A_1 and D_1 are further decomposed into approximations (AA_2 and AD_2) and details (DA_2 and DD_2), and the process is repeated until the selected decomposition level is achieved. The approximation and detail coefficients generated at each level are

called packets. In Table 5, the wavelet packets generated for a 3rd decomposition level were reported.

In this paper, the WPT analysis was applied to each of the 7 sensor signals types (F_x , F_y , F_z , AE_{RMS} , a_x , a_y , a_z) using a Daubechies 3 as mother wavelet function [18]. The 7 sensor signals were decomposed up to the 3rd level obtaining 14 wavelet packets, for a total number of 98 wavelet packets.

The obtained wavelet coefficients for each packet were treated as separate signals and from them relevant features were extracted. Thus, five statistical features were extracted for each wavelet packet: standard deviation, skewness, kurtosis, root mean square, and energy (Table 6).

For each packet, 35 wavelet features (5 statistical features $\times$ 7 sensor signals types) were extracted and, in agreement with the 3rd level decomposition, the total number of the extracted signal features was 490 (14 packets $\times$ 35 wavelet features per packet).

7 Selection of features for WPT feature pattern vector construction

As the number of signal features extracted by the WPT method is very high (490 WPT signal features), a statistical criterion, namely the Pearson's correlation coefficient (r_p), was employed to select the relevant WPT features to be utilized in the construction of feature patten vectors (FPVs) for the development of ANNs based ML paradigms for decision making on tool wear conditions.

The Pearson's correlation coefficient is one of the most useful parameters to evaluate the association between the variables of interest, yielding information about the magnitude of the correlation as well as the direction of the relationship [12, 19].

The coefficient r_p was employed to measure the correlation between the extracted feature (X) and the output value (Y) using the following equation:

$$r_p = \frac{1}{N-1} \sum_{i=1}^N \frac{(X_i - \mu_X)}{\sigma_X} \frac{(Y_i - \mu_Y)}{\sigma_Y} \quad (5)$$

where μ_X , μ_Y and σ_X , σ_Y are the X and Y mean and standard deviation, respectively.

The extracted features (X) correspond to the WPT signal features while the output values (Y) coincide with the

Table 6 Features extracted from each wavelet packet

Feature	Expression
Standard deviation	$\sigma = \sqrt{\frac{1}{N} \sum (X_i - \mu)^2}$
Skewness	$Skewness = \frac{E(X-\mu)^3}{\sigma^3}$
Kurtosis	$Kurtosis = \frac{E(X-\mu)^4}{\sigma^4}$
Root mean square	$X_{RMS} = \sqrt{\frac{1}{N} (X_1^2 + X_2^2 + \dots + X_N^2)}$
Energy	$X_{ene} = \log \left(\sum_{i=1}^N (X(i))^2 \right)$

tool wear level. The correlation coefficient r_p was judged weak if $0 < |r_p| < 0.3$, moderate if $0.3 \leq |r_p| < 0.7$, and high if $|r_p| \geq 0.7$.

Figure 8 reports the r_p values obtained for each of the 5 statistical WPT features (standard deviation, skewness, kurtosis, root mean square, and energy) calculated for each of the 14 packets and for each of the 7 sensor signal types. As the obtained wavelet packets are 98, a total of 490 WPT signal features were extracted (98 packets $\times$ 5 statistical WPT features = 490 WPT features). To reduce the dimensionality of the extracted features, it is useful to examine Fig. 8 where the WPT signal feature Energy (En) (blue dots in the figure) is shown to be the most correlated feature ($|r_p| \geq 0.7$) for each wavelet packet and for each sensor signal type. On this basis, 115 WPT En signal features displaying a correlation value ≥ 0.7 were selected, which is a much lower number than 490 features.

The selected WPT signal features (Energy = En) were used to construct diverse FPVs to be employed in ANNs based ML paradigms for tool wear state estimation. Some of the FPVs were constructed following the sensor fusion approach, i.e. using signal features from sensors of different nature (force, acoustic emission, vibration) [33, 36, 37, 39]. In particular, for each of the 14 WTP packets, the constructed sensor fusion FPVs were:

- 3-element WPT FPV related to the cutting force components; e.g. for packet A_1 : {En[A_1] F_x , En[A_1] F_y , En[A_1] F_z }

Table 5 Wavelet packets for the 1st, 2nd, and 3rd decomposition level

Decomposition level	Wavelet packet							
1st	A_1	D_1						
2nd	AA_2	DA_2	AD_2	DD_2				
3rd	AAA_3	DAA_3	ADA_3	DDA_3	AAD_3	DAD_3	ADD_3	DDD_3

Fig. 8 Pearson's coefficient results for each of the 5 statistical WPT signal features: standard deviation, skewness, kurtosis, root mean square, and energy calculated for each of the 14 packets and for each of the 7 sensor signal types

- 3-element WPT FPV related to the vibration acceleration components; e.g. for packet A_1 : $\{En[A_1]a_x, En[A_1]a_y, En[A_1]a_z\}$
- 4-element sensor fusion WPT FPV related to the cutting force components and the AE_{RMS} ; e.g. for packet A_1 : $\{En[A_1]F_x, En[A_1]F_y, En[A_1]F_z, En[A_1]AE_{RMS}\}$
- 4-element sensor fusion WPT FPV related to the vibration acceleration components and the AE_{RMS} ; e.g. for packet A_1 : $\{En[A_1]a_x, En[A_1]a_y, En[A_1]a_z, En[A_1]AE_{RMS}\}$
- 7-element sensor fusion WPT FPV combining all sensor signal types; e.g. packet A_1 : $\{En[A_1]F_x, En[A_1]F_y, En[A_1]F_z, En[A_1]a_x, En[A_1]a_y, En[A_1]a_z, En[A_1]AE_{RMS}\}$

8 Artificial neural network based machine learning for tool wear estimation

Three-layer feed-forward back-propagation artificial neural networks (ANNs), largely utilized for pattern classification tasks [20, 21, 23], were used for the implementation of

machine learning paradigms to estimate the cutting tool wear conditions. To build this kind of ANNs, it is first necessary to define the structure of the three network layers (input, hidden and output layers) and then to select the kind of training and learning procedure.

Diverse ANNs configurations were constructed with the input layer containing a number of input nodes equal to the number of elements (3, 4, or 7-elements) of the selected WPT FPVs; the output layer had one node corresponding to the tool wear values, while the number of nodes at the hidden layer depends on the number of input layer nodes. In Table 7, the constructed WPT FPVs are reported together with the implemented ANNs configurations.

The ANN training phase was performed using the Levenberg–Marquardt optimization algorithm with the following parameters: the maximum number of the epochs was 1000; the performance goal was fixed at 0; the minimum performance gradient was set to 1×10^{-7} ; and the maximum Mu value was fixed at 1×10^{10} .

For the testing phase, the leave-k-out method [23] with $k=1$ was applied by removing from the training set one FPV

Table 7 Constructed WPT feature packet vectors and ANNs configurations

Sensor signal type	WPT feature pattern vector	N. of elements	ANN configuration
Cutting force components: F_x, F_y, F_z	$\{En[Packet]F_x, En[Packet]F_y, En[Packet]F_z\}$ from each of the 14 WPT packets	3	3-3-1; 3-6-1
Vibration acceleration components: a_x, a_y, a_z	$\{En[Packet]a_x, En[Packet]a_y, En[Packet]a_z\}$ from each of the 14 WPT packets	3	3-3-1; 3-6-1
Acoustic emission RMS: AE_{RMS}	$\{En[Packet]F_x, En[Packet]F_y, En[Packet]F_z, En[Packet]AE_{RMS}\}$ from each of the 14 WPT packets	4	4-4-1; 4-8-1
	$\{En[Packet]a_x, En[Packet]a_y, En[Packet]a_z, En[Packet]AE_{RMS}\}$ from each of the 14 WPT packets	4	4-4-1; 4-8-1
All sensor signal types: $F_x, F_y, F_z, a_x, a_y, a_z, AE_{RMS}$	$\{En[Packet]F_i (i=x, y, z); En[Packet]a_i (i=x, y, z); En[Packet]AE_{RMS}\}$ from each of the 14 WPT packets	7	7-7-1; 7-14-1

at a time, in order to use it as test case, whereas the remaining FPVs were employed for ANN training.

9 Results and discussion

The ANNs performance was evaluated using the mean absolute percentage error (MAPE), i.e. the absolute difference between target tool wear value (z) and ANN predicted value ($\hat{z}_t$) divided by the tool wear actual value, as defined by:

$$\text{MAPE} = \frac{100}{n} \sum_{t=1}^n \left| \frac{z_t - \hat{z}_t}{z_t} \right| \quad (6)$$

In Figs. 9, 10, 11, 12 and 13 and Table 8, the ANN MAPE results (%) for each of the 14 wavelet packets are reported for:

- 3-element FPV associated to the three cutting force components F_x , F_y , F_z (Fig. 9).
- 3-element FPV associated to the three vibration acceleration components a_x , a_y , a_z (Fig. 10).
- 4-element sensor fusion FPV associated to the three cutting force components and the AE_{RMS} (Fig. 11).
- 4-element sensor fusion FPV associated to the three vibration acceleration components and the AE_{RMS} (Fig. 12).
- 7-element sensor fusion FPV combining all sensor signal types (Fig. 13).

From Figs. 9, 10, 11, 12 and 13 and Table 8, it can be noted that very low ANN MAPE values were achieved for all WPT packets and for all the constructed WPT FPVs with an average value ranging from 5.17 to 7.73%, which denotes

Fig. 9 ANN MAPE results for the 3-element WPT FPV related to $\{F_x, F_y, F_z\}$ for each of the 14 wavelet packets with a number of hidden nodes equal to 3 and 6

Fig. 10 ANN MAPE results for the 3-element WPT FPV related to $\{a_x, a_y, a_z\}$ for each of the 14 wavelet packets with a number of hidden nodes equal to 3 and 6

Fig. 11 ANN MAPE results for the 4-element sensor fusion WPT FPV related to $\{F_x, F_y, F_z, AE_{RMS}\}$ for each of the 14 wavelet packets with a number of hidden nodes equal to 4 and 8

Fig. 12 ANN MAPE results for the 4-element sensor fusion WPT FPV related to $\{a_x, a_y, a_z, AE_{RMS}\}$ for each of the 14 wavelet packets with a number of hidden nodes equal to 4 and 8

Fig. 13 ANN MAPE results for the 7-element sensor fusion WPT FPV related to $\{F_x, F_y, F_z, a_x, a_y, a_z, AE_{RMS}\}$ for each of the 14 wavelet packets with a number of hidden nodes equal to 7 and 14

Table 8 ANN MAPE results (%) for each WPT packet by considering the diverse WPT FPVs and ANN models

WPT FPV	3-element FPV: {F _x , F _y , F _z }		3-element FPV: {a _x , a _y , a _z }		4-element sensor fusion FPV: {F _x , F _y , F _z , AE _{RMS} }		4-element sensor fusion FPV: {a _x , a _y , a _z , AE _{RMS} }		7-element sensor fusion FPV: {F _x , F _y , F _z , a _x , a _y , a _z , AE _{RMS} }		Packet average
	ANN model	3-3-1	3-6-1	3-3-1	3-6-1	4-4-1	4-8-1	4-4-1	4-8-1	7-7-1	
A ₁	5.80	5.85	7.90	4.83	5.12	5.13	5.04	3.97	4.73	7.53	5.59
D ₁	6.64	5.72	6.33	5.46	5.18	5.12	5.01	5.20	5.02	7.62	5.73
AA ₂	7.39	5.37	5.75	4.64	5.48	6.58	5.07	5.08	5.57	5.79	5.67
DA ₂	5.58	5.24	5.60	5.53	4.85	8.69	5.17	5.97	5.13	7.85	5.96
AD ₂	8.22	6.84	5.60	5.53	7.70	8.90	5.60	5.53	5.62	7.91	6.75
DD ₂	6.98	6.10	6.39	4.96	5.29	4.42	4.77	5.71	4.32	8.73	5.77
AAA ₃	6.78	5.42	5.75	4.61	5.11	6.07	5.11	6.65	5.78	8.21	5.95
DAA ₃	7.10	5.44	6.40	6.25	7.10	5.44	5.43	4.63	5.31	7.55	6.07
ADA ₃	7.42	5.64	5.65	5.87	5.25	6.48	5.65	5.87	5.56	8.81	6.22
DDA ₃	7.16	4.82	6.25	4.87	7.10	5.44	6.55	4.35	4.81	4.82	5.62
AAD ₃	6.34	6.86	8.24	6.66	5.59	6.65	7.63	5.86	5.31	8.71	6.79
DAD ₃	6.91	5.45	5.85	4.95	4.74	4.61	6.61	6.75	4.68	7.85	5.84
ADD ₃	7.32	5.15	5.79	4.72	7.24	5.35	5.79	4.72	5.12	8.89	6.01
DDD ₃	6.40	6.25	6.40	5.35	4.90	4.26	6.40	5.35	5.42	7.89	5.86
FPV average	6.86	5.73	6.28	5.30	5.76	5.94	5.70	5.40	5.17	7.73	

the high capability of the implemented ANNs to provide an accurate tool wear estimation.

As regards the MAPE values obtained considering the 3-element WPT FPVs associated to the three cutting force components F_x , F_y , F_z (Fig. 9, Table 8) and the three vibration acceleration components a_x , a_y , a_z (Fig. 10, Table 8), the lowest average MAPE value ($MAPE_{ave} = 5.30\%$) was obtained for the 3-element FPV related to a_x , a_y , a_z with ANN configuration 3-6-1, whereas the three cutting force components showed average MAPE values between 5.73% (3-6-1 ANN configuration) and 6.86% (3-3-1 ANN configuration).

The 4-element sensor fusion WPT FPV associated to the cutting force components plus the AE_{RMS} (Fig. 11, Table 8,) and the vibration acceleration components plus the AE_{RMS} (Fig. 12, Table 8) showed slightly lower average MAPE values than the 3-element WPT FPVs.

The best performance in tool wear estimation was obtained by considering all the sensor signal types in the 7-element sensor fusion WPT FPV ($MAPE_{ave} = 5.17\%$) with ANN configuration 7-7-1 (Fig. 13, Table 8). In this case, the increase of the number of hidden nodes in the 7-14-1 configuration reduced the ANNs performance, differently from all other cases, which might be caused by a too high number of hidden nodes (14).

By analysing the performance of the 14 wavelet packets (in terms of packet MAPE average value) for all the considered WPT FPVs and all the implemented ANNs configurations (Table 8), the A_1 packet at the 1st decomposition level provided the best average MAPE value equal to 5.59%,

followed by the DDA_3 packet at the 3rd decomposition level ($MAPE_{ave} = 5.62\%$) and the AA_2 packet ($MAPE_{ave} = 5.67\%$) at the 2nd decomposition level. The worst performance was obtained for the AAD_3 packet ($MAPE_{ave} = 6.79\%$) at the 3rd decomposition level.

10 Conclusions

The goal of this paper was to provide a tool wear estimation method during turning of hard-to-machine Inconel 718. For this purpose, three types of sensors (cutting force, acoustic emission, and vibration sensor) were mounted on the tool holder as near as possible to the tool cutting edge for the detection of sensorial data generated by the cutting process. The acquired sensor signals were pre-processed and analyzed using wavelet packet transform (WPT) decomposition to extract time–frequency domain signal features. After each two-minutes turning step, the cutting tool flank wear was measured to evaluate the tool condition. A Pearson's coefficient algorithm was adopted to select the WPT signal features most correlated with the tool wear level in order to reduce the high dimensionality of the obtained WPT features. The selected WPT signal features were utilized to construct diverse feature pattern vectors (FPV), including instances of sensor fusion FPVs, to feed to artificial neural networks (ANNs) for decision making on tool condition.

The performance of the ANN models was evaluated using the mean absolute percentage error (MAPE), and the results showed that the ANN outputs were in all cases in very good

agreement with the measured flank wear values, confirming the capability of the ANNs in providing an accurate tool wear estimation based on multiple sensor monitoring. In particular, the best ANNs performance was obtained with the 7-element sensor fusion WPT FPV, related to all the 7 sensor signal types, yielding an average MAPE value equal to 5.17% in the case of the 7-7-1 ANN architecture.

The accurate tool wear estimation achieved through the application of wavelet sensor signal analysis and ANN-based machine learning paradigms presented in this paper can allow for the realization of an effective intelligent tool condition monitoring system during turning of Inconel 718.

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