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A STATISTICAL DATA-BASED APPROACH TO INSTABILITY DETECTION AND WEAR PREDICTION IN RADIAL TURNING PROCESSES

METODA WYKRYWANIA NIESTABILNOŚCI I PRZEWIDYWANIA ZUŻYCIA W PROCESACH TOCZENIA PROMIENIOWEGO W OPARCIU O DANE STATYSTYCZNE

Radial turning forces for tool-life improvements are studied, with the emphasis on predictive rather than preventive maintenance. A tool for wear prediction in various experimental settings of instability is proposed through the application of two statistical approaches to process data on tool-wear during turning processes: three sigma edit rule analysis and Principal Component Analysis (PCA). A Linear Mixed Model (LMM) is applied for wear prediction. These statistical approaches to instability detection generate results of acceptable accuracy for delivering expert opinion. They may be used for on-line monitoring to improve the processing of different materials. The LMM predicted significant differences for tool wear when turning different alloys and with different lubrication systems. It also predicted the degree to which the turning process could be extended while conserving stability. Finally, it should be mentioned that tool force in contact with the material was not considered to be an important input variable for the model.

Keywords: *radial turning, tool-life improvement, instability detection, wear prediction, Linear Mixed Models.*

Badano siły występujące w procesie toczenia promieniowego. Celem badań było wydłużenie żywotności narzędzi tokarskich, przy czym główny nacisk kładziono na konserwację predykcyjną, a nie zapobiegawczą. Zaproponowano technikę prognozowania zużycia w różnych warunkach eksperymentalnych niestabilności, która polega na zastosowaniu metod statystycznych do przetwarzania danych dotyczących zużycia narzędzi podczas procesów toczenia. Wykorzystano dwie metody statystycznę: analizę z zastosowaniem reguły trzech sigm oraz analizę głównych składowych (PCA). Do prognozowania zużycia zastosowano liniowy model mieszany (LMM). Omawiane statystyczne podejścia do wykrywania niestabilności generują wyniki o dopuszczalnej dokładności, na podstawie których można formułować opinie eksperckie. Dane te można wykorzystywać do doskonalenia przetwarzania różnych materiałów poprzez monitorowanie w trybie on-line. W przedstawionych badaniach, LMM pozwolił przewidzieć znaczące różnice w zużyciu narzędzia podczas toczenia różnych stopów przy zastosowaniu różnych systemów smarowania. Umożliwił także prognozowanie stopnia, w jakim proces toczenia można przedłużać zachowując jego stabilność. Na koniec należy wspomnieć, że nie brano pod uwagę siły generowanej w kontakcie narzędzia z materiałem jako istotnej zmiennej wejściowej dla modelu.

Słowa kluczowe: *toczenie promieniowe, poprawa żywotności narzędzi, wykrywanie niestabilności, predykcja zużycia, liniowe modele mieszane.*

1. Introduction

New lighter and thinner alloys may be found in innovative aerospace, rail, and automotive components, among other industrial products. Generally known as superalloys, these materials can withstand higher temperatures and mechanical stress levels than ordinary alloys and are designed to reduce consumption and to increase productivity.

Superalloys are categorized as hard turning materials with a hardness index of at least 45 on the Rockwell C-scale *HRC*. The process of turning such alloys, produces high mechanical and thermal stress on cutting tool inserts, which influence cutting force, tool wear, surface integrity, and the accuracy of machining processes.

Although these materials in themselves will entail process instability, monitoring of tool conditions can detect both material and process-related instabilities. Reliable predictions can therefore be made using the same data sets. Process instabilities are often recorded at increased vibratory amplitudes, provoking undesired tool failures among other events that can damage both the workpiece and the machine tool [13].

Tool condition monitoring can track tool wear and thereby predict the Remaining Useful Life (*RUL*) of the tool, a very important issue for rapid machining processes involving superalloys. Together with the detection of instability, tool monitoring provides a valuable data source for improving the efficiency of superalloy turning processes.

In this paper, cutting-force signals are studied for the detection of instabilities during the hard-turning process and a tool-wear prediction model is proposed. The three superalloys tested in this study were as follows: *Inconel 718*, *Haynes 282* and *Waspalloy*.

The structure of this paper will be as follows. In Section 2, related work on radial turning process optimization, tool-wear prediction, and the improvement of tool life will be discussed. In Section 3, the industrial application will be explained and, in Section 4, the methodology used to detect instabilities and to predict tool wear. The results will be presented in Section 5. Finally, the conclusions will be discussed in Section 6.

2. Related Work

Many investigators have been exploring ways of predicting cutting-tool behaviors *RUL*, by establishing the length of time certain tooling processes will withstand wear [1]. *RUL* is the analysis of the remaining working time and number of executions of a tool, at a particular working age. The resulting information is used to predict whether the tool can still machine the piece to an acceptable finish. [15] developed a proportional hazard model for the remaining useful life of 25 identical tools during the turning of titanium metal matrix composites. The remaining useful life curves were developed for two different machining conditions: cutting speed and feed rate. [9] analyzed tool wear in the finish turning of AISI 1045 steel under different cooling conditions, to conclude that minimum quantity cooling lubrication (*MQCL*) provided significant improvements in the wear rate of the cutting tool and its productivity. [7] estimated the *RUL* of a bearing process with artificial neural network models that produced better bearing failure performance predictions. [19] compared multiple machine learning algorithms for tool-wear prediction and concluded that Random Forest generated higher accuracy than Artificial Neural Networks and Support Vector Regression. [11] developed mathematical models for describing surface finish and flank wear, employing multiple linear regression analysis during ceramic-tool machining of AISI-D2 steel. The nose geometry of the cutting tool strongly influenced the productivity and surface finish of the hard-turning process. [6] developed an online Neural Network model for tool-wear monitorization based on force ratio and cutting conditions. The algorithm was successfully verified during turning. [12] estimated tool conditions by applying neuro-fuzzy techniques, which yielded the best results for tool-wear estimation with cutting force and machining time variables. [20] developed a model based on particle-swarm optimization that fitted better than the back-propagation neural network for tool-life prediction.

Although tool-life prediction and *RUL* estimation are important in machining processes, stability is also one of the main topics for achieving the aim of obtaining good quality pieces, due to the fact that even if the remaining useful life of the tool is good, an instability may cause a machine failure. On this topic, [14] proposed a linear stability analysis in the frequency domain based on cutting forces. [4] developed a linear model based on the root locus method, called a chatter model for predicting stability in hard-turning processes. [17] proposed a method for measuring the stability of cutting processes that applied the power-spectrum density of dynamic cutting forces.

As may be seen from this literature review, many technologies have been developed over the years to predict tool wear, to improve tool life, and to detect stability during machining processes. Most of these technologies have been applied to a particular fault and have yielded good results for both stability and wear prediction. A hybrid mix of both predictive approaches is proposed in this paper, which will enable better prediction for stable tests and will prevent possible failure modes related to instability.

3. Industrial Application

This study is based on a radial turning process, applied to nickel-based superalloys. Even though only nickel-based superalloys enter into the case study (*Waspalloy*, *Inconel 718* and *Haynes*), the chemical composition of the superalloys differs slightly. Cutting tests were conducted at 30 m/min cutting speed, with a depth of cut of 2 mm and a feedrate of 0.1 mm/revolution. Each test had the same total amount of removed material, with a spiral cutting length (SCL) of 727 m, divided into six or four passes depending on the alloy. Standard uncoated cemented carbide inserts (Sandvik CoromantTCMW16T304, grade Sandvik H13A equivalent to ISO S20) were used with 0.4 mm tip radius.

The above-mentioned superalloys can be found in a wide variety of states, obtained by thermal heating and cooling processes. Annealing is the one that we will consider in this study. The physical process of annealing produces microestructural changes that include recrystallization and grain growth [5]. The crystallization structure of alloys treated at high temperatures and for long annealing periods will break up and the subsequent recrystallization processes will differ, depending on the rapidity of the annealing or cooling process. Note that while grain growth can be provoked through heat treatment, the same is not true for the reduction of grain size. Recrystallization and grain growth processes can both be controlled by regulating the heating and the cooling times.

Two states of grain size *Large Grain* (LG) and *Small Grain* (SG) can be distinguished in Figure 1. In terms of strength, *Aged* (A) refers to a stronger state than and *Solutioned* (S).

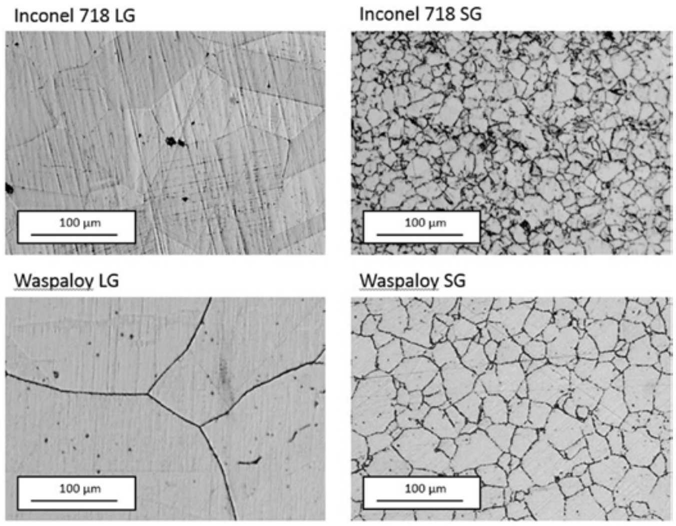


Fig. 1. Structural differences at a microscopic level between LG and SG in different superalloys.

Turning processes require lubrication to reduce high temperatures and to extend the life of tools subjected to high torque forces during the machining process. Both [16] and [10] discussed lubrication in their studies. In this case, the selected parameters for temperature reduction were a *conventional lubrication system* at a pressure of *6 bars* and a High Pressure Coolant *(HPC)* system at a pressure of *80 bars*. In radial turning processes, a pass is considered finished when the tool has moved from the surface of the material to the final point on the axis. A pre-determined number of passes made sequentially are called a test. The number of passes needed to complete a full test differed in acccordance with the materials that were studied in this paper. 6

Table 1. Number of tests for each superalloy (Inconel, Haynes, Waspalloy), grain size, strength (SGS, SGA, LGS, LGA) and type of lubrication (Conventional, HPC).

		SGS	SGA	LGS	LGA
Inconel	Conventional	2	2	2	2
	HPC	-	3	-	2
Haynes	Conventional	-	-	2	2
	HPC	-	-	1	1
Waspalloy	Conventional	2	2	1	1
	HPC	1	1	1	1

passes were required to complete a test on *Inconel 718* and *Waspalloy*, while 4 passes were needed for *Haynes*. Table 1 shows the number of tests for each superalloy, the grain size, and the lubrication systems.

The initial conditions set up in this study were the same for every superalloy in every state.

While each pass was running, the cutting force of the tool in contact with the superalloy was measured. This force was then decomposed into three components, *Fx, Fy, Fz*, which were perpendicular to each other. Once a pass had finished, tool wear was also measured, in two different ways: *flank wear* and *notch wear*. *Flank wear* was measured at nine different points where the tool enters into contact with the superalloy. *Notch wear* appears just after *flank wear* and is usually larger. Note that only *flank wear* is studied in this paper. *Notch wear* was not studied, due to it having no relation with the force signals generated during the process that are a key focus of this study.

Figure 2 illustrates, the three force components. These signals are taken from one particular pass: in general, the signals from any of the passes will be of a similar appearance.

The main purpose of this paper is to predict tool wear under different settings. Given the direct relationship between tool wear and process stability, we study process instability in terms of the force signal; not only for the complete test but also for each pass. Then we create a linear mixed model to compare the wear for different setting situations and to predict the expected wear.

Note that an expert will be able to label each complete pass as either stable or unstable. Once a pass is labeled as unstable the whole test is considered unstable.

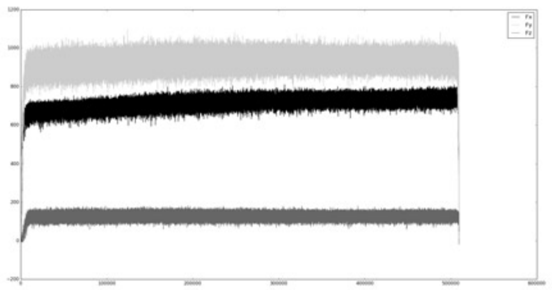


Fig. 2. Measured forces for a single pass for the three components.

4. Methodology

In this study, we have two goals: to identify the instability that can occur in irregular turning processes; and, to identify tool wear, the critical parameter during the turning process. The following sections explain the methodology to reach each goal.

4.1. Instability Detection

Instability has a direct relationship with tool wear linearity. An unstable process results in non-linear tool wear, causing a disturbance in the process.

First, we studied stability in each pass of every test, independently. Then, we analyzed the stability of the full test composed of several passes, comparing a given pass with the first pass, previously identified as stable or unstable.

4.1.1. Instability detection of a pass

Let the signals of the force components of a pass p be $(F_{xt}(p), F_{yt}(p), F_{zt}(p))_t$, recorded at a series of time-points $t = 1,...T$ for passes $p = 1,...,6$. The instability of any one given pass, p, must be detected. The instability of a pass is closely related to the outlying data values of the force components that were analyzed with the *three-sigma edit* rule [8].

This simple robust method allows us to obtain the median value of each force component, $Me_c = Median_t\{F_{ct}(p)\}$, and the corresponding absolute standard deviations, and can be expressed as:

$$|F_{ct}(p) - Me_c|,\ \ t = 1,...,T;\ c = x,y,z,$$

where, c is the axis of the force, t is the machined piece, and p is the pass.

The median value of these deviations is calculated and divided by 0.6745 as indicated in [8]:

$$MADN_c(p) = \frac{Median_t\left\{| F_{ct}(p) - Me_c\right\}}{0.6745}$$

The robust three-sigma edit rule (see [8]) establishes that observation $F_{ct}(p)$ is an outlier, if:

$$|F_{ct}(p) - Me_c| > r,$$

where, r is a threshold value. Under the normality assumption, $r = 3$ is often set (hence the “three-sigma rule”) and any observations beyond that threshold are considered outliers. Based on the three-sigma edit rule, a component force, c, at pass, p, is considered unstable, if:

$$Max_t(p) = \left\{\frac{| F_{ct}(p) - Me_c}{MADN_c(p)}\right\} > r. \tag{1}$$

In the case studied here, pass p is considered unstable if at least 2 of the 3 force components x, y or z are considered unstable. We explore different threshold values to establish the best one in this case. The goodness-of-fit is measured by the accuracy between the label given by the proposed approach (stable/unstable) and the expert’s label. It is determined by a confusion matrix (Table 2), where the rows show the predicted values and the columns show the expert classification. Accuracy is given as a percentage value representing an approximation between the state predicted by the approach and expert classification.

Table 2. Confusion matrix in a classification problem

	Real class	
Pred. class	Stable	Unstable
Stable	Tp	Fp
Unstable	Fn	Tn

$$Accuracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \tag{2}$$

The variability of the accuracy was measured by a moving blocks bootstrap approach [18]. This statistical technique is used to obtain bootstrap samples from correlated data. The signal is divided into contiguous blocks of length L. Following sampling with replacement from the blocks, the signals were then processed with a bootstrap technique. In this process, the threshold providing the highest accuracy is considered as the optimum value to detect the instability of a pass .

In this study, the above approach is only applied to the first pass of each test, due to the importance of this pass in the stability of the whole test.

4.1.2. Instability detection of a whole test

In this section, an instability-detection method is used to analyze the stability of the whole test. The approach is based on the comparison of any given pass of the test with the corresponding first pass of the test. First, the classical statistical technique of Principal Component Analysis (PCA) [3] is applied to reduce the dimension from the 3 force components to only two dimensions, so that the full signal of forces of the first pass can be easily visualized. PCA is based on combining linearly input features, in this case the force components of the first pass ($F_{ct}(1)$, $t = 1,...,T$; $c = x,y,z$), to obtain new ones ($C_k(1)$, $k = 1,2$) that are linearly independent between each other and maintain as much of the original information as possible. Second, subsequent passes are projected on the same space, so the progress of the test can be seen graphically. In addition to graphical classification, a quantitative measure is calculated: given $F_t(p) = (F_{xt}(p),F_{yt}(p),F_{zt}(p))$, the maximum distance from any time point, t, of this pass, p, to the centroid of the first pass is as follows:

$$D(p) = \max_t \left\{ \sqrt{\sum_c \left(F_{c,t}(p) - \overline{F_c(1)} \right)^2} \right\}.$$

These distances are obtained for each test and are used to determine the stability of the test; as a result, the test will be classified as unstable when the value $D(p)$ is twice the value of $D(1)$ in the first pass.

Validation of this model is done by comparing the stability classification that is obtained with the one offered by the expert. To do so, the confusion matrix is calculated and an accuracy value is obtained.

4.2. Tool-wear prediction

In this section, the objective is to model the radial turning according to some of the variables sensorized during the process and some others that depend on the material. Throughout the turning process for each piece, the wear at the end of each pass is recorded. The effect of each pass is the most important variable to take into account to build a model for the evolution of the wear. Nevertheless, factors that include the type of alloy, grain size, lubrication pressure, as well as forces on each component are considered. Since the wear is measured several times on the same piece or tool along the turning process, these measurements may be correlated. A linear mixed-effect model (LMM), capable of properly processing the data correlations, generated the model of tool wear.

A brief explanation would be that the dependent variable $\mathbf{w} = (w_{ip})_{ip}$ (in this study the wear, where w_{ip} stands for the tool wear, i, at the end of a pass, p) is formulated within the following general model in an LMM:

$$\mathbf{w} = \mathbf{X}\beta + \mathbf{Z}\mathbf{b} + \epsilon, \quad \mathbf{b} \sim N(\mathbf{0}, \mathrm{D}) \text{ and } \epsilon \sim N(\mathbf{0}, \mathcal{R}),$$

where $\mathbf{X}$ is a $n \times k$ matrix (k is the number of fixed effects), $\mathbf{Z}$ is a $n \times q$ matrix (q is the number of random effects) and D is the variance-covariance matrix ($q \times q$) of the random effects. The random effects (which are modeled by random variables) in these models permit the prediction of the behavior of particular units in the sample, as well as an estimation of variability between different units.

Inference for the model selection was performed with the Likelihood Ratio (LR) test for the fixed effects and by chi-squared distributions derived from Restricted Maximum-Likelihood Estimation-based LR tests for variances and covariances of the random effects (see [2] for details). The diagnosis of the model was not done by the analysis of the residuals. Instead, the Normalized Root Mean Square Deviation (NRMSD) statistic was used, to give a quantitative value of the approximation, where lower values indicate less residual variance.

5. Results

The results are organized into two main sections. In the first one, the results on instability detection are shown and, in the second, those concerning tool wear.

5.1. Instability Detection

As a first step, we studied the time series signal of each first pass considering different threshold values in equation (1). As mentioned in section 4.1.1, a threshold value has been searched for, in order to determine the optimum value for this specific process. The stable/unstable label obtained was compared with an expert opinion and the accuracy value was calculated. The standard deviation of the accuracy was measured on 200 bootstrap samples (see Table 3).

Table 3. Accuracy value and its bootstrap estimated standard deviation (std) for different thresholds

Threshold	Accuracy(std)
3	0.28 (0.000)
5	0.28 (0.032)
7	0.72 (0.047)
8	0.82 (0.039)
9	0.79 (0.017)
10	0.79 (0.018)

The results showed that the best threshold value was $r = 8$. Moreover the approach was not dramatically sensitive to the threshold value and values above $r = 8$ also yielded comparable results.

As a second step, the stability of the test based on the first pass was studied. The technique of Principal Component Analysis (PCA) produced a global summary of the forces in graphic form. Two PCA analyses can be seen in Figures 3 and 4, which present all the passes of a test for stable and unstable tests, respectively. A test is considered unstable when a particular value $D(p)$ of any pass, p, is over twice the maximum distance of the first pass, $D(1)$.

The maximum distance from the first pass centroid to any of the points of each pass is shown for both stable (Figure 5a) and unstable tests (Figure 5b). These values were obtained for the rest of the tests and the results following their comparison with the expert stability classification are shown in Table 4.

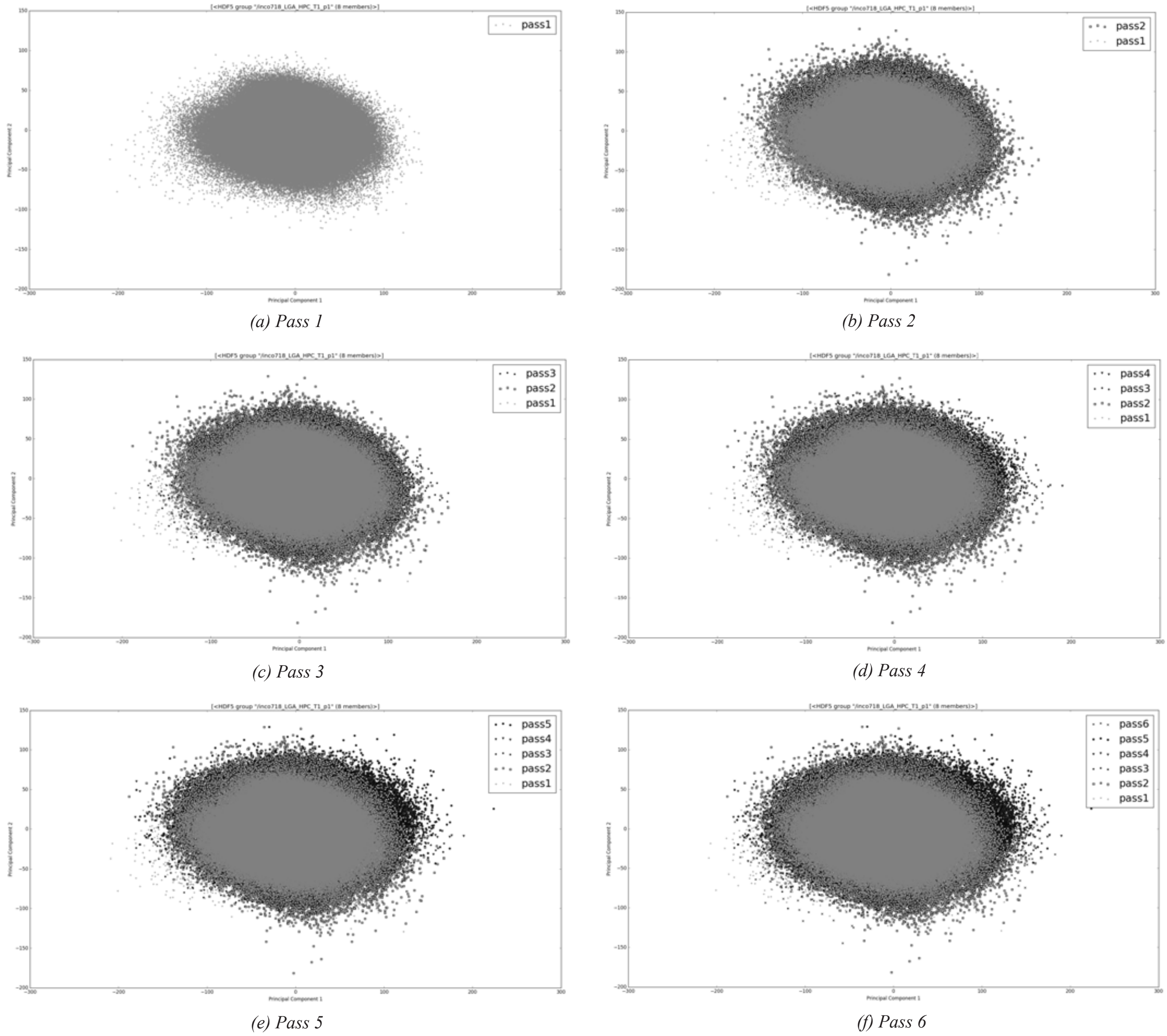
In Table 4, it can be seen that most of the tests are well classified, which accounts for 76% of the accuracy, calculated as the percentage of well classified values divided by the sum of all values (see equation. 2).

Table 4. Confusion matrix comparing the classification given by the expert (columns) and the obtained (rows) by comparing the maximum distances from the centroid of the first pass to the others: D(p).

	Expert's classification	
Pred. class.	Stable	Instable
Stable	13	5
Instable	2	9

5.2. Tool-wear prediction

During the radial turning process, each tool, i, is related with its experimental setup conditions ($i = 1,...,29$). Particularly, the type of superalloy and the lubrication system were of significant importance for tool wear throughout the model selection process, although the same could not be said for grain size, strength, and the forces that the



(a) Pass 1 *(b) Pass 2*

(c) Pass 3 *(d) Pass 4*

(e) Pass 5 *(f) Pass 6*

Fig. 3. Principal Component Analysis of a stable test, composed by 6 stable passes

tool withstands. Taking all these issues into account, the fitted model is as follows:

$$w_{ip} = \beta_0 + \beta_1 \text{Haynes}_i + \beta_2 \text{Waspalloy}_i + \beta_3 \text{Conventional}_i + b_{0i} + (\beta_4 + \beta_5 \text{Haynes}_i + \beta_6 \text{Waspalloy}_i + \beta_7 \text{Conventional}i)p + b1ip + \epsilon_{ip} ,$$

where:

- w_{ip} is the wear of the ith tool at the end of the pass p,
- Haynes_i and Waspalloy_i are dummy variables that indicate the type of superalloy that the ith tool is cutting, and Conventional_i is the dummy variable for the lubrication system of the ith tool,
- the random effects of the model are:

$$\begin{pmatrix} b_{0i} \\ b_{1i} \end{pmatrix} \sim N(0, \mathcal{D}) \;\; with \begin{pmatrix} d_{11} & 0 \\ 0 & d_{22} \end{pmatrix},$$

- the errors of the model have 0 mean but are heterocedastical

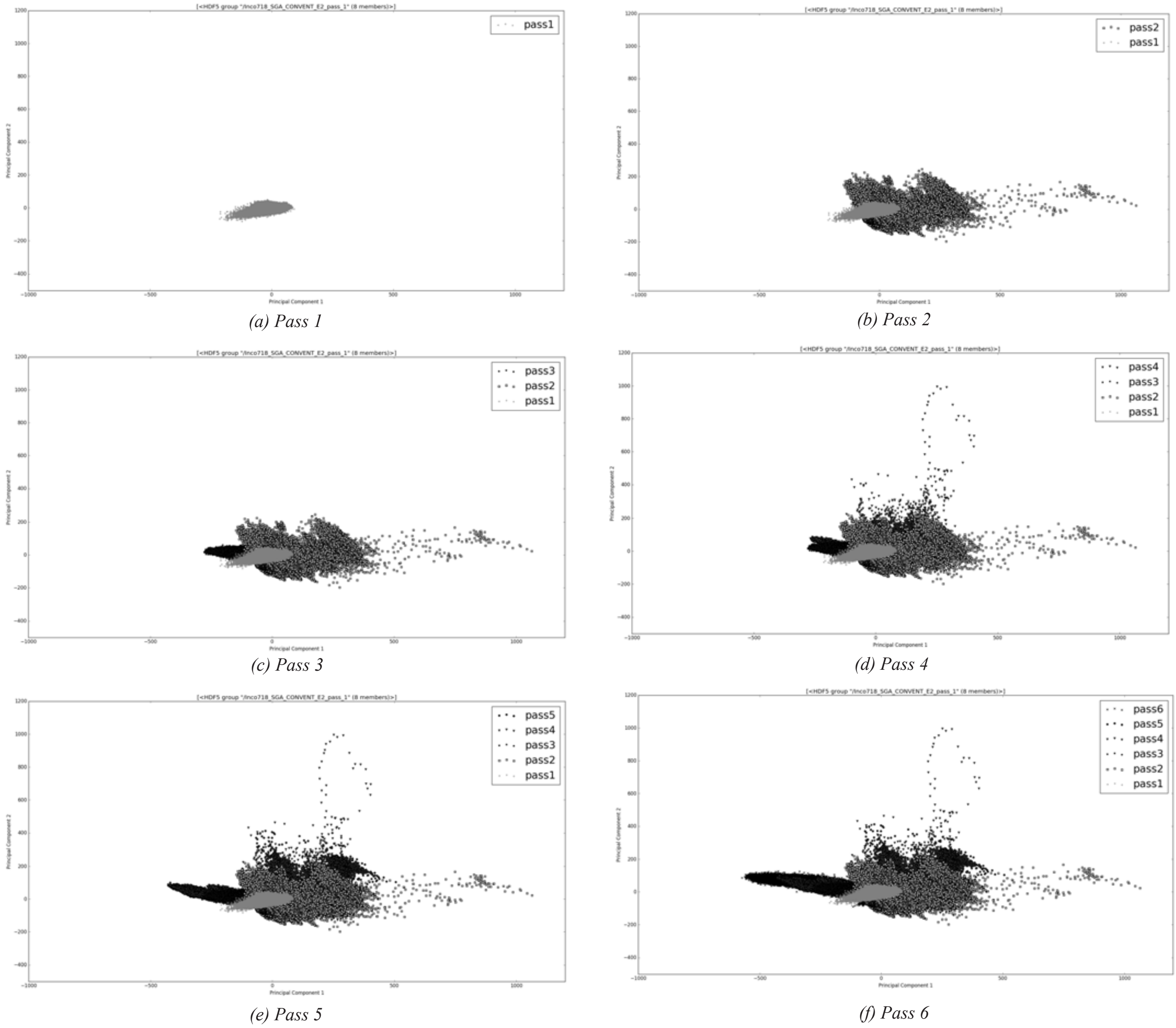
$$VAR\left(\epsilon_{ip}\right) = \sigma^2 \theta_i^2$$

with $\theta_i^2 = 1$ if the ith tool is stable and θ_i^2 6= 1 otherwise.

The estimations of the parameters of the model and 95% approximate confidence intervals are in Table 5 as well as the p-values for the fixed effects. The latter are obtained by Maximum Likelihood.

It is noteworthy that the variability between tools is much bigger than the residual variability, even for stable tests. For instance, by the intraclass correlation, 77% of the variability of the slope at each pass, p, is due to the variability between tools. Nevertheless, some general main effects can be assumed: each pass, p, on an *Inconel 718* alloy with HPC lubrication provokes mean tool wear of 19.4 mic. If the alloy is *Haynes* or *Waspalloy*, there will be less wear after each pass: mean average wear of 11.2 mic and 16.7 mic less, respectively. For a given alloy, when a conventional lubrication system was used, a higher mean wear of 13.2 mic compared with the HPC lubrication system was noted.

Using the model obtained and taking into account the maximum permitted tool wear (300 mic), it was easy to see that the tool could work properly with many more passes (a range from 10 to 81 passes depending on the tools). The prediction tendency for each of the

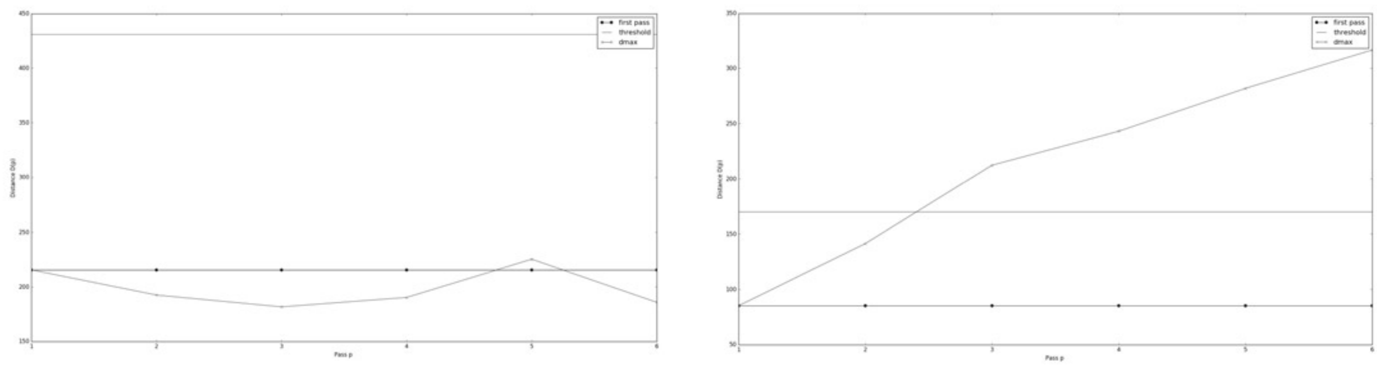


(a) Pass 1 (b) Pass 2

(c) Pass 3 (d) Pass 4

(e) Pass 5 (f) Pass 6

Fig. 4. Principal Component Analysis of an unstable test. The same axis in each of the 6 passes is shown, to highlight the variability of this process



(a) Stable test. (b) Unstable test

Fig. 5. Maximum distance to the centroid of the first pass D(1) for each pass D(p)

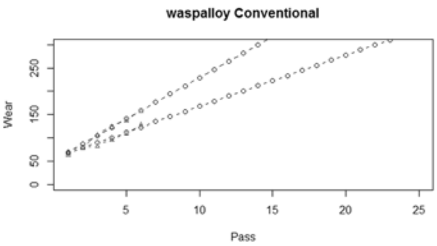
tests is shown in Figure 6. The Normalized Root Mean Square The deviation measure (*NRMSD*) for the stable tests was 13.3%, which means that the mean percentage error for measured wear using LMM was 13.3%.

6. Conclusions

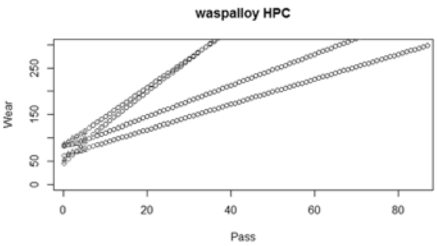
Two problems with a wide variety of industrial consequences for machining work have been discussed in this paper.

Table 5. Estimates of the LMM and approximate %95 confidence intervals

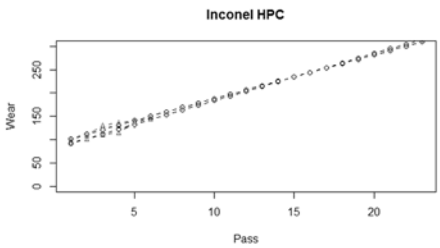
	Parameter	Estimation	*p*-value
Fixed effects	β_0	83.1 (71.4, 94.8)	< .0001
Superalloy	β_1 (Haynes)	9.7 (-5.5, 25.0)	0.0032
	β_2 (Waspalloy)	-10.6 (-24.7, 3.6)	
Lubrication	β_3 (conventional)	-18.7 (-30.5, -6.9)	0.0213
Pass p	β_4	19.4 (12.9, 25.9)	< .0001
Superalloy×Pass	β_4 (Haynes $\times p$)	-11.2 (-19.9, -2.6)	< .0001
	β_4 (Waspalloy $\times p$)	-16.7 (-24.0, -9.4)	
Lubrication ×Pass	β_7 (conventional $\times p$)	13.1 (6.5, 19.7)	0.0001
Random effects SD(b_{0i})	$\sqrt{d_{11}}$ $\sqrt{d_{22}}$	10.9 (6.4, 18.5)	
SD(b_{1i})		8.5 (6.3, 11.4)	
Errors	σ	4.6 (3.7, 5.7)	
	θ_i	5.4 (4.2, 7.1)	



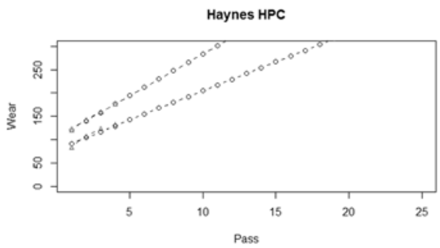
(a) Waspalloy Conventional



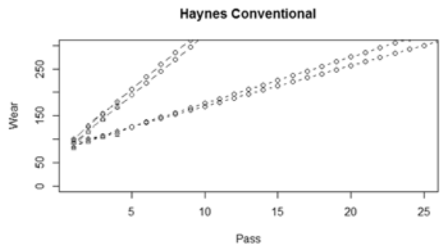
(b) Waspalloy HPC



(c) Inconel HPC



(d) Haynes HPC



(e) Haynes Conventional

Fig. 6. Prediction of the tool wear for each test as a function of the material and the lubrication system.

One aspect of this study is the development of a method for instability detection that can detect initial instability in radial turning processes. The three components of the measured force have been selected as the most important variables. These variables have been applied to two different methods with two goals; an off-line method, MADN, was used for first pass stability, which can be extended to the rest of the passes, and which produced an accuracy of 82% of the signals. Another methodology was based on PCA visualization, which provided an intuitive 2 dimensional representation of the forces. Applied on-line, it can function as a fault-detection method during machining processes and will, if necessary, end the process. The results applied to all the tests achieved an accuracy rate of 76%.

This result offers a better process-oriented view to the operator that is easier to understand. The algorithms can be directly integrated into the on-line monitoring tool, to analyze the effect of using a particular tool and material. The general approach in this work can be used in an experimental phase to improve the process with new materials.

A further aspect is that a tool-wear model based on a Linear Mixed Model has been applied. The model has shown that mean average tool wear differs, depending on the type of superalloy and lubrication system in use, as suggested in [16] and [10]. It is worth mentioning that the force of the tool in contact with the superalloy is not an important input variable in the model. The model has also been used to demonstrate that the tool can withstand a higher number of passes, with tool wear under 300 mic. while the stability of the turning process is held. As a consequence, the process could run longer without stopping, which would imply faster turning and less time to finish the piece. Finally, a confirmatory analysis using a larger amount of samples would be of interest, to reduce the uncertainty and variability of the different pieces.

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