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ORIGINAL ARTICLE

# Industrial application of a multitooth tool breakage detection system using spindle motor electrical power consumption

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**Abstract** This paper describes a multitooth tool diagnosis application to be used in the car industry. The main focus is on the optimal variable selection (noise, vibration, temperature, and tool drives electrical power consumption) of the tool's environment, and the signal processing by means of the segmentation of the electrical power consumption signals into groups of inserts according to the type of tools studied. The fault detection algorithms are based on statistical analysis of the spindle tool power consumption. Different statistical parameters are used in a change detection algorithm, while keeping in mind the need for a reliable and low-cost fault diagnosis system. Multitooth tools add an important degree of difficulty to the fault detection problem as opposed to simple tools because of the complexity introduced by the high number of inserts that the workpiece is machining at the same time, for different kinds of finishing and operations.

**Keywords** Tool breakage detection · Multitooth tools · Change detection · Electrical power consumption

## 1 Introduction

The need for higher automation and unmanned operation is well known in the manufacturing industry [1]. Machine tools represent one of the main examples of highly automated components [2]. In spite of this automation, the cutting process has an inherent degradation [3], which is one of the main problems to be overcome. The monitoring and diagnosis of the cutting process have been active research fields for many years [4], but the practical implementation in the workshop is still in progress [5]. There are a lot of commercial solutions directed to specific machining operations and cutting conditions that very often require re-calibrations to avoid false alarms [6]. This paper presents a real application of a methodology based on electrical power consumption analysis to detect faults that usually occur in multitooth tools. This application has been implemented for different kinds of operations, such as turning, milling, or broaching, and different cutting conditions with minimal adjustments. The proposed solution has been applied to different multitooth tools used in the manufacturing of crankshafts for the car industry. The greatest difficulty of detecting faults in this kind of multitooth tool is given by the combined effects of different inserts that attack simultaneously, as compared to the simple tool that uses only one insert. There also exists the desire to obtain a multitooth tool diagnosis application, which can be easily adaptable to the different types of machining operations that can be

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found in a production line, operating under different machining conditions.

## 2 Cutting process monitoring

In the machine tool field, the required high reliability is one of the main challenges to be tackled by unattended machining. In spite of the great level of automation integrated into this kind of machine, great care is required from the machine operator: workpiece tolerance deviations; ensuring a correct evacuation of the chips; changing of worn tools; and, if necessary, stopping the machine if abnormal working conditions appear (for example, chatter). So, to achieve the desired level of autonomy for machines, it is necessary to develop the monitoring and diagnosis of the cutting process.

A monitoring and diagnosis system is built using different blocks: a number of different sensors that extract relevant information from the cutting process; then an appropriate signal processing to enhance the key information; and, finally, a decision making process that analyzes the relevant signatures and gives the state of the cutting process. Taking into account these elements (cutting process, sensors, signal processing, and decision making), a short review of the main research contributions in the field of cutting process monitoring is now presented.

In the area of machine tool monitoring, most of the research work has been done under laboratory controlled cutting conditions. Just a small fraction of research work is developed under industrial conditions, which is the case of this particular paper. Working in an industrial environment presents several problems to be overcome, such as the low availability of the machines and the near impossibility of performing parameter variations. On the other hand, working in such conditions allows a great amount of information to be obtained due to the high production rate, and offers the opportunity to tackle the practical problems of implementation from the very beginning.

The main faults studied in the literature are tool wear, tool breakage, and chatter. This work focuses on the detection of insert breakage in a multitooth tool. The goal is a fast detection of catastrophic breakage in order to stop the machining process and avoid serious damage to the machine and its environment [7, 8], and to avoid the machining of defective workpieces.

The machining process can be seen as an energy balance between the cutting energy of the different kinds of drives (mechanical, electrical, and pneumatic) and the dissipated energy in its different forms (heat, noise, or vibration). To perform an adequate monitoring of the process, the sensors must be carefully selected in order to extract relevant information related to the phenomena under study (tool breakage, for example). In the literature, examples of several kinds of sensors can be found: *acoustic emission* [9, 10], *cutting force* [2, 11], *vibration* [12], *noise* [13], and *electrical power consumption* [8, 14], which is the case of the current paper.

After an adequate choice of sensors, the monitoring and diagnosis are performed by means of a signal-processing and decision-making scheme. The approaches that can be found in the literature are mainly *spectral analysis* [7, 13, 15], *wavelets* [10, 16], *neural networks* [11, 17], *fuzzy logic* [18], and time domain processing [15], as in the present paper, where a segmentation of the electrical power consumption takes place prior to a statistical analysis.

## 3 Multitooth tools

Many different kinds of tool are included under the term "multitooth tool." The tools analyzed in this paper are used in the car industry for mass production of different mechanical parts, such as the crankshaft or the camshaft of car engines. These are complex ad hoc tools built with many cutting inserts (up to 250, depending on the machine) of different kinds (roughing, finishing) and for different operations (turning, milling, or broaching) within the same tool, as shown in Fig. 1. The configuration of the tool is based on multiple tool holders specially designed for the particular operation of the mass production line. Such complexity is necessary to achieve the required high metal removal rate. This kind of tool adds complexity to the diagnosis problem. There

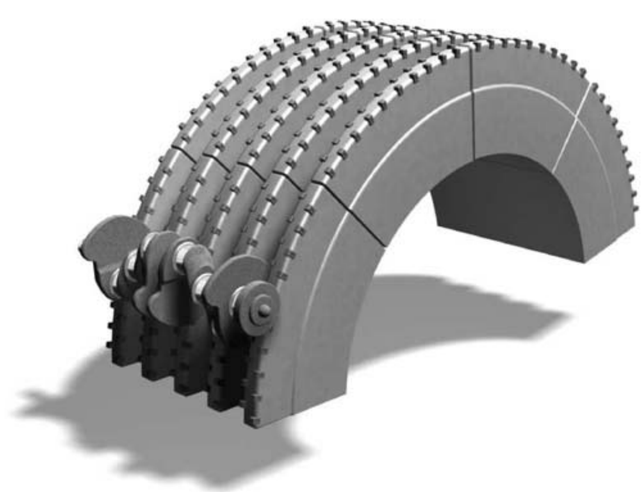

**Fig. 1** Example layout of multitooth tools used in the car industry

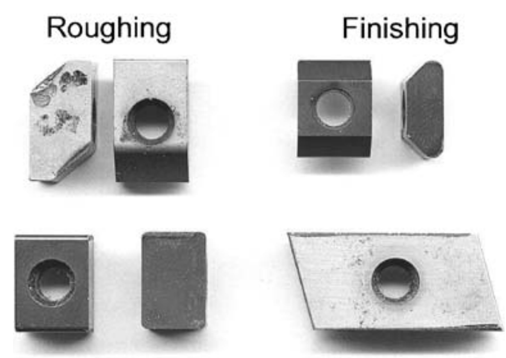


**Fig. 2** Example of inserts in the multitooth tool

are a great number of inserts working simultaneously, and the nature of the cutting is usually interrupted with their associated transients.

Different kinds of multitooth tools have been studied. For example, there are configurations that have been designed to mechanize the five main journals of a crankshaft at the same time. In particular, these tools have 220 inserts dedicated to roughing and 37 for finishing, distributed over five discs. The manufacturer of the tool (Widia Heinlein) established the useful life of the inserts at approximately 1,100 workpieces in the case of the roughing of the crankshaft supports. Another configuration designed to mechanize the crankpins of a crankshaft has 58 inserts dedicated to roughing and 14 for finishing distributed over two discs. The inserts are manufactured by Widia Heinlein, and some samples are shown in Fig. 2. More recent versions of this kind of tool have been developed with interchangeable tool holders, making them lighter, with a more flexible operation. This configuration has duplicated inserts that do not work at the same time and that could be used in the case of a sudden failure, for example, due to a tool breakage. The number of inserts is reduced by five (around 40 roughing inserts and 15 finishing inserts, depending on the kind of tool). Table 1 shows a summary of the different configurations of multitooth tools that have worked in this article.

**Table 1** Roughing and finishing inserts disrtribution in analyzed machines

| Machine | Roughing | Finishing |
|---|---|---|
| ME004,ME005 | 220 | 37 |
| ME006,ME007 | 58 | 14 |
| TN001,TN006 | 38 | 8 |
| TN002,TN003 | 30 | 12 |
| ME003 | 240 | |

## 4 Diagnosis of multitooth tools

The design of these tools is based on the achievement of a high-reliability operation. Moreover, due to the mass production work scheme, the machine and the tool are influenced by harsh conditions, frequent cutting parameter adjustments, and maintenance stops. All these determining factors must be taken into account in order to develop a robust diagnosis system. However, the inherent process of tool wear must be taken into account to achieve a highly unattended machining [12]. Then, the monitoring and diagnosis of the multitooth tool must be an essential task of the machining cycle [2], and this has been accomplished with a methodology (see Fig. 3) proposed by the authors that can be divided into different steps related to a specific signal, through statistical processing techniques and decision-making processes:

*Variable selection* from different sources of information within the machine tool environment [19] that show a correlation between the tool wear trend and these measures. In this work, different variables have been measured during tool life: vibration, temperature of the mechanized supports of the crankshafts, noise,

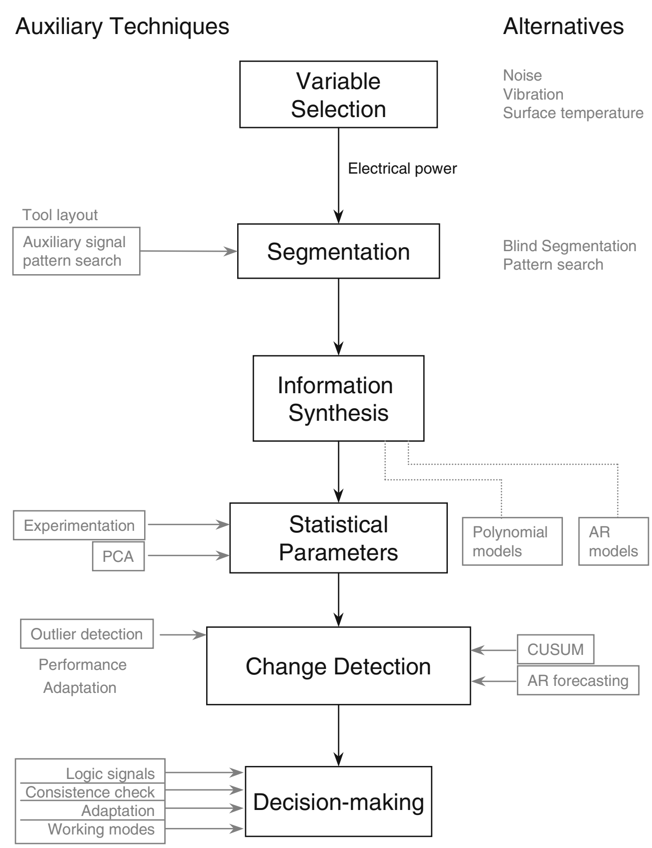


**Fig. 3** Proposed multitooth tool diagnosis scheme

and electrical power consumption of the tool drives. All showed a correlation with the degradation process of the tool, as can be seen in Fig. 6. It is clear, however, that electrical power consumption presented the best noise–signal ratio and was measured with lower cost sensors, just to mention two advantages of this measure.

*Segmentation* to analyze the state of the different inserts of the multitooth tool by extracting the electrical power consumption belonging to every zone of the tool. Due to the complexity of the multitooth tool, it is necessary to identify the electrical power consumption waveform for every zone or insert of the tool. With this segmented information, the subsequent tasks can be accomplished. This stage of the process is critical, so the electrical power consumption segments must be extracted in a reliable way. Different algorithms have been tested, and the use of an auxiliary signal (angular speed of the tool, for example) presented the best results.

*Information synthesis* of every electrical power consumption segment coming from the segmentation step through a model sensitive to electrical power consumption changes during the occurrence of a fault in the tool. Simple statistical parameters (mean electrical power consumption, maximum electrical power consumption, standard deviation, time peak, integral of the electrical power consumption segment) present high sensitivity to electrical power consumption changes, easy physical interpretation, and low computational cost.

*Statistical parameters* represent a minimal set of those calculated previously, so they are sensitive to electrical power consumption changes and gather the dynamic information of the process without redundant information (mean and maximum of every electrical power consumption segment).

*Change detection* of the statistical parameters, due to a fault in the tool. The chosen method will be tuned with the aid of different performance measurements, such as, for example, the mean time between false alarms (MTFA).

*Decision making* of the tool diagnosis through change detection. The effective declaration of an alarm during the cutting operation must be reliable, and this is done using consistency checks and auxiliary information (cutting parameter changes, planned maintenance operations, etc.) of the process.

This paper focuses mainly on the first three steps of the presented scheme. First, the results of the analysis of noise, vibration, temperature, and electrical feed power consumption are presented. Then, the problem of segmentation is outlined and different practical solutions are evaluated. Then, the appropriate information from the segmentation is extracted, which is the basis for the change detection and, hence, the diagnosis of the multitooth tool.

## 5 Variable selection

A tool condition monitoring system comprises several blocks. Of these, an optimal selection of sensors is of paramount importance in obtaining valuable information from the environment of the machine tool that should be correlated with the abnormalities that must be detected. In the current work, different signals have been analyzed and correlated with tool wear and the breakage of one or more inserts in the multitooth tool, as shown in Fig. 4. These are the signals analyzed:

*Noise:* measured in the environment of the tool using an omnidirectional microphone (Fig. 4b). This measure was also very helpful as the spectrogram revealed different facts about the machining cycle, such as the cutting speed, the layout of the tool showing the joint machining of groups of inserts, and clearly distinguished the roughing and finishing part of the work cycle, as shown in Fig. 5.

*Vibration:* measured with a radial accelerometer in the main shaft of the multitooth tool (Fig. 4c). As was stated firstly by the operators of the machine tool and then experimentally detected by the measurements, there was an initial increase of the vibration due to the wear of the fresh tool. At the end of the tool life, severe chatter occurred, also leading to a great increase in the global vibration.

*Temperature:* the progressive wear caused an increase in the temperature of the mechanized supports of the crankshaft. This temperature was measured automatically using a pyrometer connected to a data acquisition system (Fig. 4d), so the profile temperature of the mechanized surfaces was easily extracted. Then, the increase of the surface temperature (with respect to the ambient) was computed for every mechanized workpiece.

*Electrical power consumption:* this was measured from the output signals of the frequency converters for every motor that moves the multitooth tool and rotates the workpiece. Figure 4a depicts the root mean square (RMS) electrical power consumption of the two movements of the analyzed tool: feed and rotation. This

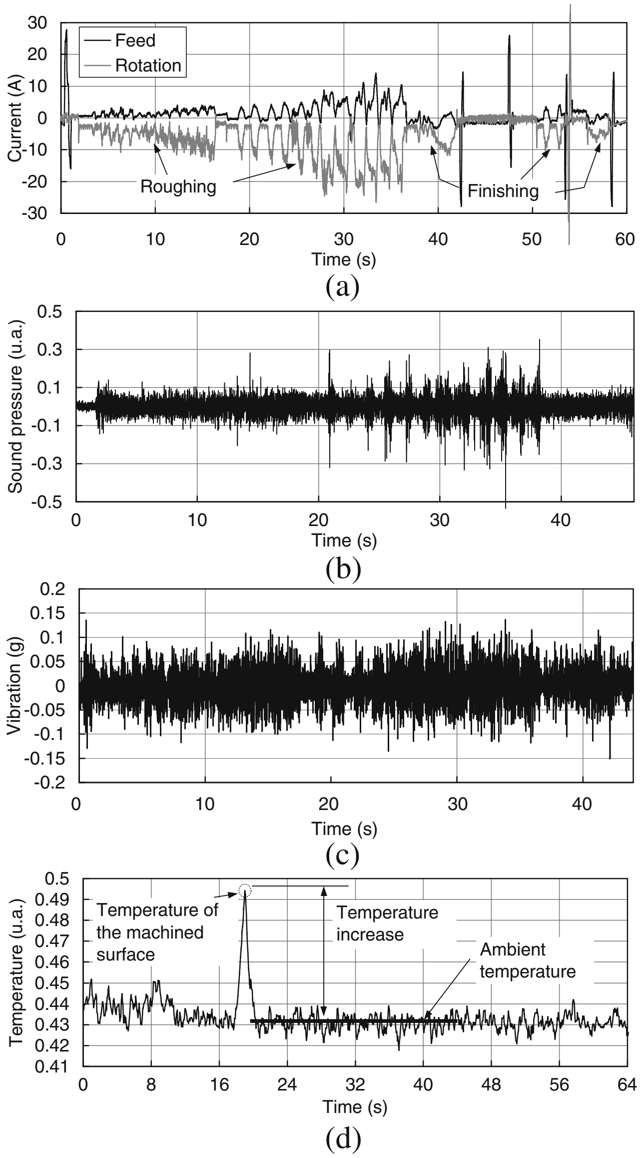


**Fig. 4** Measured signals in the multitooth tool environment. **a** Electrical power consumption; **b** sound pressure; **c** vibration; **d** temperature profile

kind of signal shows clearly the different parts of the cycle and the grouped attack of the inserts in the tool, as was shown with the spectrogram of the noise signals.

In all these cases, the measurements were made by a computer equipped with a data acquisition board and a specialized software that recorded the signals during the cycle time of every mechanized part in the production line. Figures 4 and 5 were recorded during the machining of a crankshaft. During this time, the workpiece rotates at a very high speed against the slow rotation movement of the tool. During this slow rotation, the different groups of inserts in which the

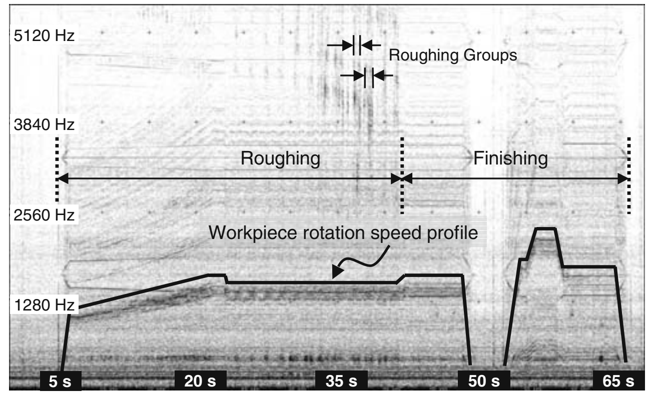


**Fig. 5** Noise signal spectrogram during the machining cycle of the crankshaft supports

multitooth tool is divided are attacking the workpiece with different programmed cutting parameters (cutting speed and depth of cut). Firstly, the roughing inserts come into work, and at the end of the machining cycle, the finishing inserts complete the work over the crankshaft supports.

The measurements took place over the useful life of several consecutive tools. After that, every set of signals was statistically analyzed to extract global information for comparison and to decide whether there is a

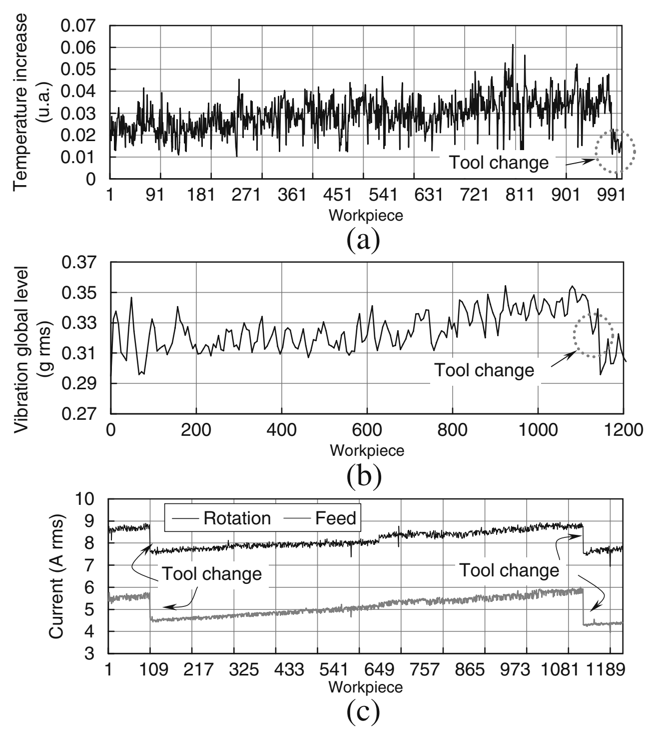


**Fig. 6** Evolution of the tool wear using the different measures. **a** Temperature; **b** vibration; **c** electrical power consumption

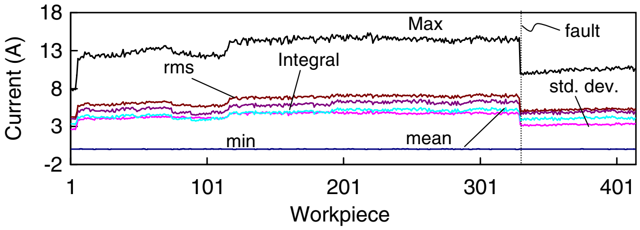


**Fig. 7** Example of statistical parameter change after a fault

correlation with the degradation of the tool. Figure 6 shows the result of this analysis of the signals analyzed:

- All of them showed a correlation with the wear that also caused a progressive increase in the measured signals.
- At the end of the useful life of the multitooth tool, the different signals suffer an abrupt decrease when the worn tool is replaced by a new one.
- The electrical power consumption showed the best signal-to-noise ratio.
- The measurement of the temperature presented the greatest limitations due to the situation where the measurements take place (at the exit of the machine tool) and is affected by production line stops. On the other hand, the sensors needed (pyrometers) are not cost-effective enough to be implemented on the factory floor.
- Vibration measurement gathers not only the state of the tool but also the state of all the kinematic chain responsible for the movement of the tool (gears, belts, ...). It is an invasive sensor whose installation in the analyzed machines is difficult.
- Noise measurement devices gather information from different sources and also interference coming from nearby machines. Prepolarized microphones are too delicate for the harsh cutting environment.

With these analyses, it is clear that the electrical power consumption is the best cost-effective measurement to be used for the tool condition monitoring of such multitooth tools. Several advantages can be obtained with this measurement: non-invasive sensing of the tool, low-cost and easy installation of the hall-effect sensors, high reliability and easy calibration of the sensor, and lower noise of the signals which are less influenced by external perturbations of the studied process (Fig. 7).

## 6 Segmentation

Besides the selection of the electrical power consumption as a cost-effective measurement, the previous analysis stated the grouped attack of the different inserts that are part of the tool. Every group of inserts is configured to work under different cutting conditions (feed and cutting speed) and to perform roughing or finishing. Then, to make an accurate diagnosis of the whole tool, it is necessary analyze the different segments of the measured electrical power consumption. That is why the segmentation stage comes into play. The segmentation process can be formulated as the automatic decomposition of a signal into stationary or transient pieces with a length adapted to the local properties of the signal [20].

### 6.1 Breakage correlation

The electrical power consumption signal has shown a clear correlation with the wear of the tool. Nevertheless, the aim of the monitoring system is to detect tool breakage. Using historical data of the electrical power consumption for all the workpieces machined by the machine tool and the visual evidence of broken inserts after the useful life of the tool, abrupt changes in segments of the whole signal of electrical power consumption have been found. Figure 8 depicts the electrical power consumption variation in the machining of three consecutive crankshafts (from workpiece number $n-2$ to $n$) by the tool presented in Fig. 1. When the workpiece (noted as $n-1$) is machined, the roughing insert begins to break; after that, when the workpiece number $n$ is machined, the cutting edge of the insert has disappeared, hence, the abrupt decrease in electrical power consumption. This decrease is visible in both movements of the tool and even in the motor that rotates the workpiece against the tool. For this

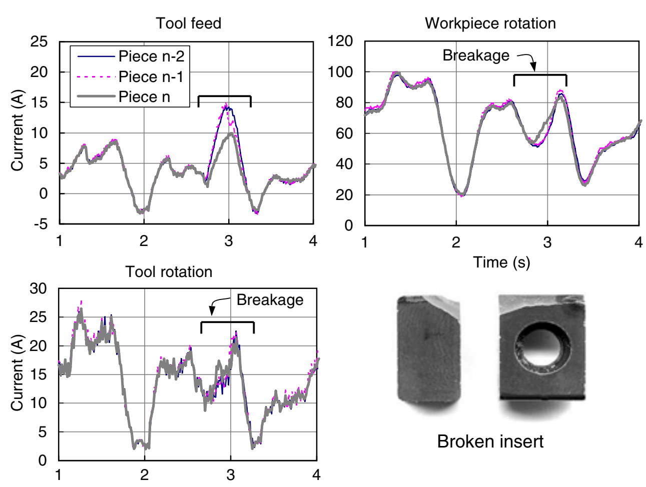


**Fig. 8** Abrupt electrical power consumption change after a breakage of a roughing insert during the machining of three consecutive workpieces (from workpiece number $n-2$ to $n$)

kind of breakage, the most sensitive direction is the feed movement of the tool. The sensitivity in the tool rotation and workpiece rotation is very low.

### 6.2 Segmentation alternatives

Once it is proved that there exist electrical power consumption changes due to a breakage as well as to wear, it is necessary to tackle the problem of segmentation. Firstly, the number of segments that must be extracted has to be defined. This is done according to changes in different aspects of the machining process, such as the different kinds of cutting inserts, the workpiece material, changes in the cutting conditions, changes in the PLC programming, different mechanized zones of the workpiece, and the layout of the tool. At this stage, it is very important to know the layout of the tool very precisely. Figure 9 shows an example of a multitooth tool where the different groups of inserts are associated with their corresponding electrical power consumption waveforms. The direction of the machining can also be seen. The group of inserts numbered from 0 to 10 are intended for roughing (in this case, the crank pins of a crankshaft); 11 and subsequent ones are in charge of finishing. Different alternatives for making the segmentation of the electrical power consumption signals have been explored:

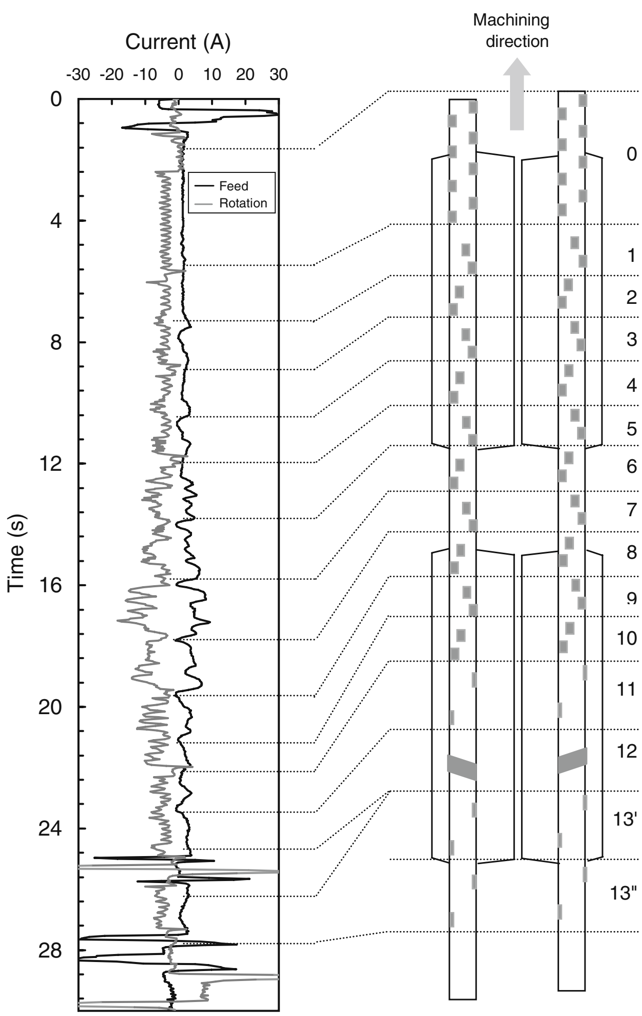


**Fig. 9** Example of multitooth tool layout and its associated electrical power consumption waveforms (feed and rotation of the tool)

- Blind segmentation: Using an electrical power consumption waveform as a reference, the time instant for every segment of the tool can be extracted, as shown in Fig. 9. This method is based on the fact that the start point of the signal is fixed for all subsequent mechanized workpieces.
- Pattern search: Looks for a specific pattern in the electrical power consumption, associated with a non-machining event such as, for example, a tool movement. It then uses the localization of such a pattern as the reference for the predefined segments.
- Auxiliary signals: Instead of using the electrical power consumption signal, an auxiliary signal can be used that is not directly affected by the machining, such as, for example, the sampled speed reference of the machining cycle, or its derivative.

After a set of tests, the blind segmentation algorithm presented the worst performance due to the fact that there exist movements of the tool that can shift in time, because of changes in workpiece material, stops in the working cycle, incomplete cycles, etc. This may cause errors in the segmentation process, assigning the electrical power consumption of a group of inserts to another one. Figure 10 compares the results of the

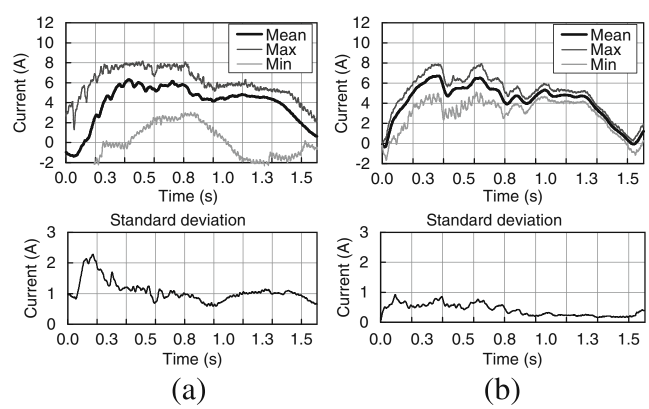


**Fig. 10** Comparison between blind segmentation (**a**) and auxiliary signal segmentation (**b**) for 100 consecutive workpieces using the rotation electrical power consumption of a group of roughing inserts

blind segmentation and the pattern search algorithm over the same segment of electrical power consumption signal during the machining of 100 consecutive workpieces. The pattern search makes it possible to detect changes in the cycle and to precisely determine the origin time of the different segments, eliminating unexpected patterns. On the other hand, a breakage could sometimes be interpreted as a tool movement and the segmentation would be wrong. To avoid this kind of problem, auxiliary signals that are not influenced by the machining events must be used.

## 7 Information synthesis

Once the different signal segments are extracted, the next step of the diagnosis scheme (see Fig. 3) is to obtain the model for every segment that should be sensitive to electrical power consumption changes due to a fault in the tool. Another goal of this step is to reduce the quantity of information used in the following steps of the diagnosis scheme. The different kinds of models tested were:

- Statistical analysis: The occurrence of a tool breakage is reflected as a global change in the electrical power consumption segment, so a calculation of different statistical parameters (mean, standard deviation, maximum, minimum, integral, and peak time) is a direct method to obtain a model for each electrical power consumption segment.
- Non-linear regression: After an analysis of the electrical power consumption signals, they can be modeled with a polynomial equation. A polynomial model is estimated using the electrical power consumption and the sampling time instants. For the machine tool studied, the model sensitivity to tool breakage is better for low-order polynomials (one to four). This kind of adjustment requires each electrical power consumption segment to be fitted individually.
- Autoregressive models: In order to imitate the dynamic characteristic of the electrical power consumption signal, a model based on the electrical power consumption of past instants is estimated.

The statistical model and the parameters of the polynomial model exhibit good sensitivity to abrupt changes in the electrical power consumption. The polynomial model requires a higher computational cost, and it is not straightforward to choose an appropriate model for every electrical power consumption segment. On the other hand, the interpretation of a statical parameter (e.g., maximum electrical power consumption) is straightforward and the computational cost is very low. The autoregressive models barely showed any correlation with the abrupt changes in the electrical power consumption segments modeled. Taking into account these conclusions, it can be said that statistical parameters are suitable characteristics for use in change detection for multitooth tool diagnosis.

## 8 Statistical parameters

Different statistical parameters have been calculated: mean, standard deviation, maximum, minimum, integral, power, RMS, and peak time. All of them were calculated using the feed and rotation electrical power consumption of the tool, and also for all the defined groups of inserts. Such a number of parameters is too large (more than 150 for the tool presented in Fig. 9), and the information provided is redundant in some cases. Given the dimension of the problem, it is necessary to reduce the amount of data used to detect failures in each group of the tool. Among the different parameters calculated, those that presented a greater sensitivity to the variations produced by the failures in the tools must be chosen. This work was performed jointly with experimental analysis of historical data and was also corroborated using statistical analysis based on the analysis of variance and principal component analysis. The experimental analysis was carried out by looking for known tool breakages in sampled historical data. This analysis revealed that the maximum electrical power consumption, its standard deviation, and the mean electrical power consumption were the most sensitive parameters. An analysis of the dispersion of the statistical parameters verified a clear linear relation between the mean, integral, power, and RMS.

## 9 Abrupt change detection problem

In this paper, the problem of fault detection in a multitooth tool is reformulated as a change detection problem using different statistical parameters of the electrical power consumption of the different groups of inserts that are part of the tool. The change detection is usually carried out using a so called *stopping rule*, as presented in Eq. 1; that is, a function of the random variables $y_k$ that exceed a preset threshold $\lambda$ in case of abrupt change. The parameter $t_a$ represents the estimated time of change at which the stopping rule is true for the first time [20].

$$t_a = \inf\{n : g_n(y_1, \ldots, y_n) \geq \lambda\} \tag{1}$$

This problem is frequently solved from a statistical point of view. First, the dynamic of the system under study must be modeled, then, using different statistical tests, the change detection of the corresponding estimated parameters can be carried out. The present problem is defined as the change detection of the different statistical parameters calculated from the measured electrical power consumption for every zone of the tool. Figure 7 represents a sudden decrease in the statistical parameters of electrical power consumption for a zone of the tool due to a breakage. To solve this change detection problem, the following requirements must be taken into account:

- The segmentations or electrical power consumption trends are non-stationary, so an adaptive detection scheme is needed.
- The changes must be reliably detected, and the false alarms due to occasional electrical power consumption changes must be avoided.
- A MTFA must be fixed.
- The change detection must be fast enough to avoid serious damage to the whole tool and machine.
- The changes can be abrupt decreases (in case of breakage), but also abrupt increases due to the loss of an insert or an abnormal wear rate caused by the breakage of previous inserts.

Among the different alternatives that can be used to detect abrupt changes, an algorithm based on linear regression outlier detection is presented.

### 9.1 Linear regression outlier detection

A first analysis of the electrical power consumption trends showed a gradual increase of the electrical power consumption with the number of workpieces, mainly due to tool wear. This kind of behavior could be modeled as a simple linear trend, represented by Eq. 2, where the index $k$ represents the zone of the tool, $p$ is the statistical parameter calculated from the segmentation process, $x$ represents the number of mechanized workpieces, and $I^{k,p}$ represents the statistical parameter of the electrical power consumption. The parameters $\beta_i$ can be easily calculated using least squares, as shown in Eq. 3.

The change detection can be carried out with the aid of the residuals obtained as the difference between the estimated electrical power consumption and the real one. To compare the residuals, they must be standardized as shown in Eq. 4. In this equation, the parameter $\hat{S}_{R(i)}$ represents the estimated residual variance calculated with the linear regression leaving out the $i$-th value. The $v_{ii}$ parameter is the $i$-th diagonal element of the $\mathbf{V}$ matrix used for the calculation of the model parameters $\beta_i$. This parameter is a function of the workpiece coordinates $x$.

This statistic follows a Student's $t$ distribution with $n-4$ degrees of freedom. The outlier is detected performing a statistical hypothesis testing for the residual $t_i$. The parameter for this test is the critical value based on the $t$ distribution.

This outlier detection scheme can be easily adapted to an online detection scheme estimating the linear trends over a finite memory of the last $L$ electrical power consumption values. The new values of statistical parameters $I^{k,p}$ (coming from the machining of new workpieces) can be compared using the estimated linear trends from past workpieces. In Fig. 11, an example of the online calculation of a standard residual over more than 1,000 workpieces and the corresponding maximum electrical power consumption parameter belonging to a group of inserts is presented. The fault events are marked with gray vertical lines. An appropriate choice of thresholds for the different residuals will make the fault detection effective. The new values of statistical parameters $I^{k,p}$ can be compared using the estimated linear trends from past workpieces.

$$I^{k,p}(x) = \beta_0^{k,p} + \beta_1^{k,p} x + e(x) \tag{2}$$

$$\hat{\beta} = \left(\mathbf{X}^{\mathrm{T}}\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{I} = \mathbf{VI} \tag{3}$$

$$t_i^{k,p} = \frac{e_i^{k,p}}{\hat{S}_{R(i)}\sqrt{1-v_{ii}}} \tag{4}$$

The parameters of this algorithm are the size of the memory, $L$, to calculate the linear regression and the threshold $t_c$, for the residual. To make this detection robust, an additional parameter can be added, such as the number of consecutive detected outliers. In quality

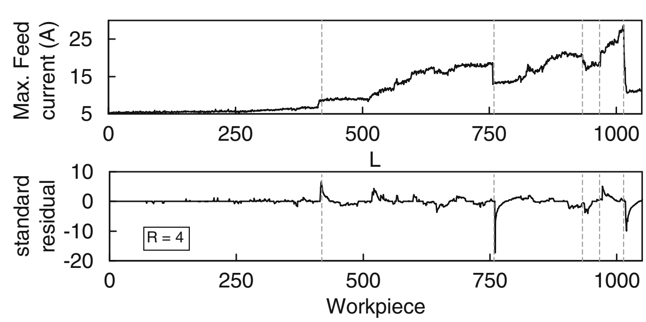


**Fig. 11** Example of linear regression residual calculated with the maximum electrical power consumption for a fixed $L$ of 70 workpieces

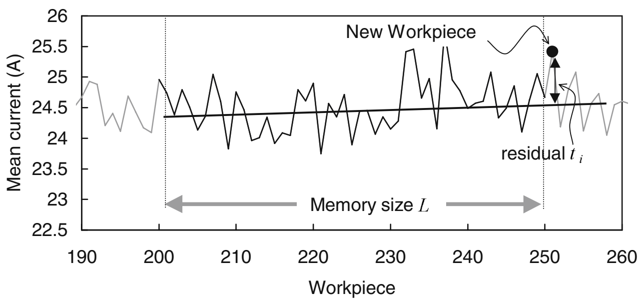


**Fig. 12** Parameters of the change detection algorithm based on linear regression outliers

control, this is called a *run test*. Figure 12 depicts the different parameters of the detection algorithm.

To choose these parameters, different considerations must be taken into account:

– To avoid the influence of the amount of data in residual evaluation, $L$ must be great enough to neglect the term $\sqrt{1-v_{ii}}$ in Eq. 4. This term approaches asymptotically to one with the increase of $L$.
– The increase of the window size $L$ leads to a stable estimation of the model variance, $\hat{S}_{R(i)}$, but at the expense of a loss in the local behavior of the model and its adaptive ability.
– The critical value of the residual $t_c$ can be set in terms of the global level of confidence for the residual test, $\alpha_T$, and Student's $t$ distribution interval $\pm t(1-\alpha_T/(2L), L-3)$.
– The memory $L$ and critical value $t_c$ are cross correlated. Small window sizes lead to high $t_c$ values and, hence, conservative diagnosis (only large current changes are detected). With large window sizes, the critical level $t_c$ loses its dependence on $L$, as is depicted in Fig. 13.

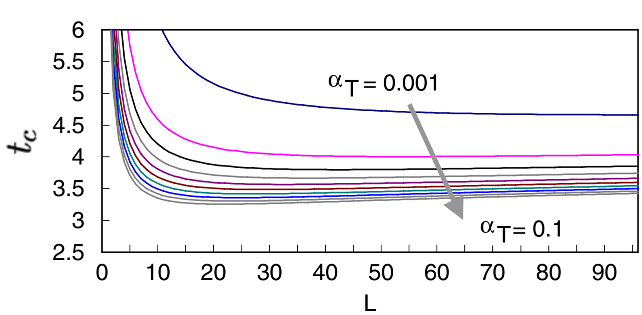


**Fig. 13** Critical value for the residual $t_i^{k,p}$ for different window sizes $L$, and different global levels of confidence $\alpha_T$

## 9.2 Optimal algorithm adjustment

Once the change detection algorithm has been presented, an optimal adjustment of their different parameters is necessary to achieve the objective, that is, to detect abrupt changes in the electrical power consumption trends and achieve the requirements shown in Section 9. The following performance measures can be evaluated in order to explore the influence of the different parameters of the algorithm [21]:

MTFA The mean time between false alarms that measures the alarm frequency when there is no change or fault.

MTD The mean time to detection (also known as detection delay) measures the time between the change and its detection in the electrical power consumption trend.

MDR The missed detection rate is the probability of not receiving an alarm, when there has been a change.

The optimal algorithm adjustment is performed fixing either MTFA or MTD, and the parameters of the algorithm should be chosen to minimize the other performance measure. Figure 14 presents the performance measures of the outlier regression detection algorithm. The figures were obtained through the analysis of historical data from more than 30,000 consecutive mechanized workpieces. The change detection algorithm was automatically evaluated by varying the different

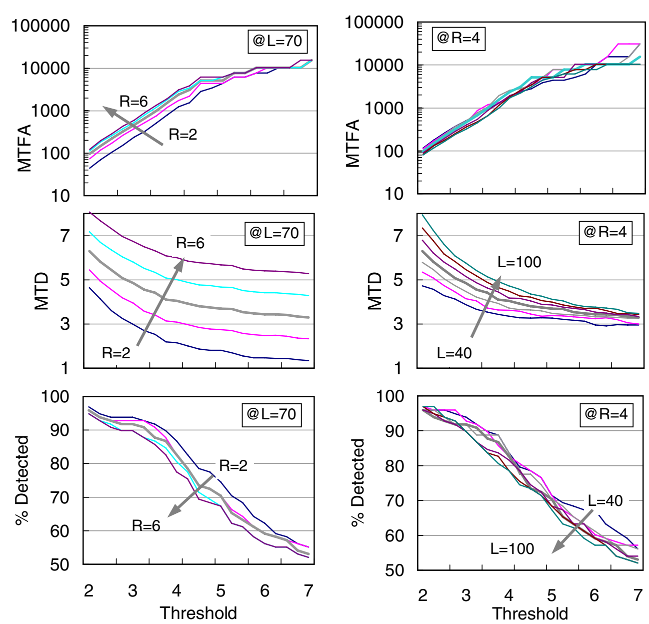


**Fig. 14** Performance measures for the linear regression algorithm with parameters: $L \in [40, 100]$, $R \in [2, 6]$, and $h \in [2, 7]$

parameters over predefined ranges. The horizontal axis represents the threshold set to detect the change and the vertical axis represents the performance measures expressed in workpieces. In the first column of the figures, the memory size $L$ is fixed at 70 workpieces, and in the second column, the run test $R$ is fixed at four workpieces. This kind of evaluation allows the influence of every parameter of the algorithm to be analyzed and then adjust them optimally to perform the detection and diagnosis of the insert breakage. One can fix, for example, the MTFA at 1,000 workpieces and then vary the rest of the parameters (in the presented case $L$ and $R$) to minimize the other two performance measures.

Examining the performance measures represented in Fig. 14, the following conclusions for the algorithm can be extracted:

- The increase of the threshold $h$ increases MTFA and decreases MTD, due to the fact that only the faults associated with a great current variation are detected. Furthermore, the MDR, represented as the percentage of detected fault, decreases.
- The *run test* parameter ($R$) adds reliability to the detection (greater MTFA) and increases the MTD.
- The influence of the window size $L$ on the MTFA is not clear and seems to be related to the *run test* $R$. For lower thresholds, $L$ hardly reduces the MTFA. The influence in the MTD and MDR is similar to that achieved with the *run test* parameter.

### 9.3 Adjustment on the plant floor

The presented methodology has been applied to the detection of tool breakage in a set of multitooth machine tools of a mass production line. Equation 4 shows the residual to be evaluated in order to perform the detection of insert breakage. The adjustment of the threshold for this residual can be done using Student's $t$ distribution if the residuals are Gaussian. However, the real residuals are not truly Gaussian. To overcome this limitation, the later performance study allowed to obtain the initial values for the thresholds based on a desired reliability and detection delay. However, as in any real diagnosis system, some fine tuning must be done to achieve the desired performance.

Figure 15 shows the thresholds for the tool presented in Fig. 1. In this figure, two kinds of thresholds can be seen. The positive ones are intended to detect abnormal increases of electrical power consumption in a group of inserts due to some premature increase of wear rate or some loose insert. The negative thresholds are set to detect an insert breakage within a group. An initial study of worn tools revealed that some of the groups (starting from group number 14) were more likely to fault (insert breakage) because of their cutting parameters. In these groups, the thresholds were fine-tuned so the breakages are detected. The first groups barely suffered faults, so their thresholds were increased to avoid false alarms and to have fewer parameters to be adjusted.

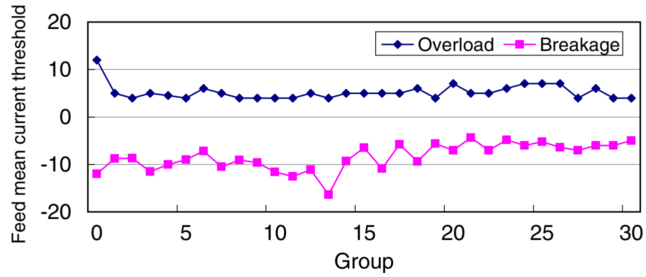


**Fig. 15** Thresholds for the feed mean current parameter of a multitooth tool

## 10 Conclusions

This paper has presented a real industrial application for the diagnosis of multitooth tools based on the electrical power consumption analysis, synthesized in a general scheme of work. The variable selection, from the different sources of information, showed that the electrical power consumption of the tool drives represented the best choice to perform an online detection of tool breakage. This signal exhibits the best signal-to-noise ratio, and it needs a non-invasive sensing, making it ideal for an industrial implementation on mass production lines. A statistical analysis of the segmentation of the different electrical power consumption segments allowed a minimal set of parameters sensitive to the breakage of the tools, that is, the maximum, standard deviation, and mean current for every segment of the tool belonging to every group of inserts in which the multitooth tool is divided. These current trends can be used in a change detection scheme to perform the effective detection of the breakage of an insert in the multitooth tool. The online detection of changes is done using a linear regression residual detection algorithm adapted to online operation. In spite of the fact that the needed thresholds can be derived from the theory, the real behavior of the residuals makes a final fine tuning of the detection parameters mandatory in order to achieve the desired performance of the algorithm. This performance has been measured for a wide range of parameters over real data to achieve a desired MTFA and MTD (detection delay). The authors have implemented the present methodology in an automatic diagnosis system used on the plant floor for machine tools used in mass production lines of car parts.

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