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IN-PROCESS QUALITY CHARACTERIZATION OF GRINDING PROCESSES: A SENSOR-FUSION BASED APPROACH

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ABSTRACT
The quality assessment of manufacturing processes has been traditionally based on sample measures performed on the process output. This leads to the common "product-based Statistical Process Control (SPC)" framework. However, there are applications of actual industrial interest where post-process quality measurement procedures involve time-consuming inspections strongly related to the operator's experience and/or based on expensive equipment. Cylindrical grinding of large rolls may be one of them. The final acceptability of a ground cylinder, in terms of surface finish, is a challenging task with traditional measuring tools, and it often depends on operator's visual inspections and on his subjective evaluations. In this frame, a paradigm shift is required to substitute troublesome post-process monitoring procedures with in-process and signal-based ones. In-process acquisition of sensor signals allows detecting undesired process phenomena affecting the product quality, and hence it can be potentially exploited to reduce the need for post-process SPC operations. In order to achieve reliable results, robust synthetic features must be identified and extracted from multiple correlated signals, and proper sensor fusion techniques should be applied. In industrial applications, robustness achievement represents a challenging task and it motivates continuous research efforts in this field. The paper reviews the quality control issues in surface quality monitoring of big ground rolls where process vibrations (i.e. chatter) are one of major concerns. A multi-sensor approach for vibration onset detection, based on the use of a multi-channel implementation of the Principal Component Analysis, is proposed. The potential benefits, the implementation issues, and the main criticalities are discussed by analysing data of a real industrial application.

NOMENCLATURE

K	Number of signals
$\mathbf{L}$	Eigenvalue matrix of $\mathbf{S}_{1:M}$
L	Number of datapoints in each time window
m	Number of retained principal components
M	Number of training samples
N	Number of time-windows
P, P'	Number of features
$\mathbf{S}_{1:M}$	Variance-covariance matrix of training data
SSE	Sum of Squared Error statistics
T^2	Hotelling's T^2 statistics
$\mathbf{U}$	Eigenvector matrix of $\mathbf{S}_{1:M}$
$\mathbf{x}_{kj}$	Data vector in the j^{th} time window, k^{th} signal
$\mathbf{Y}_k$	Feature matrix from the k^{th} signal
$\mathbf{y}_{kj}$	Feature vector from the j^{th} time window, k^{th} signal
$\tilde{\mathbf{Y}}$	Multi-channel feature matrix
$\tilde{\mathbf{Y}}_{1:M}$	Multi-channel feature matrix in training phase
$\hat{\tilde{\mathbf{y}}}_j(m)$	Reconstructed signal with m principal components
$\mathbf{z}_j$	Vector of scores for the j^{th} sample
α, α'	Type I error
λ_p	Eigenvalue of the p^{th} component

Subscripts

i	subscript index of datapoints ($i = 1,...,L$)
j	subscript index of samples/time windows ($j = 1,...,N$)
k	subscript index of signals ($k = 1,...,K$)
p	subscript index of monitored features ($p = 1,...,P$)

1. INTRODUCTION

Grinding of large and complex parts is a manufacturing process in which traditional dimensional measuring methods may be not sufficient to characterize the final acceptability of output products in terms of surface finish. Different authors proposed automated inspection systems based on machine vision or contact-less devices [1],[2], and different products are available off-the-shelf for specific purposes, either to support or to substitute operator's visual inspections. Nevertheless, the industrial implementation of those solutions is still limited in some applications, because of high sensor prices, time-consuming data acquisition and processing operations and other practical issues affecting the overall measuring accuracy and reliability [3]. In addition, the use of quality control methods based on post-process measures, performed at the end of the grinding cycle, yields a slow reactivity to changing process conditions, with negative impact on the overall process costs and productivity.

In order to overcome the limitations of visual inspections performed by human operators on the one hand, and the use of expensive and troublesome automated measuring systems on the other hand, there is an increasing interest within the Statistical Process Control (SPC) community for the implementation of tools that are based on in-process data-driven procedures. The result is a paradigm shift from traditional product-based methodologies toward in-process and signal-based ones.

A wide literature was devoted to grinding process monitoring by using in-process sensor signals [3-5]. In Roll Grinding, chatter onset in one of major concerns because it yields waviness marks on the cylinder surface, whose avoidance and detection may be quite challenging tasks. Furthermore, those marks and surface irregularities can have further impact on the subsequent rolling process, increasing the possibility to develop rolling vibrations and out-of-control products.

The use of in-process signals was proposed either to provide an indirect estimation of the surface quality, with particular regard to surface roughness [3 - 7], or to detect undesired vibrations that may affect the final product quality [8 - 12]. This study is focused on the latter problem.

When SPC techniques are applied to sensor signals, the goal is to detect any changing process condition with respect to a pattern estimated from data, which characterizes the natural process behaviour. The procedure involves two consecutive phases: a training step (Phase I), consisting of collecting data under natural (i.e. in-control) process conditions, and using them to design the control charts to be used in the second step, i.e. the monitoring step (Phase II).

In order to reduce the efforts devoted to Phase I, a very important goal consists of selecting synthetic indicators (i.e., the monitored variables) that are robust to time-varying cutting parameters and operative conditions. Such a robustness allows extending the applicability field of the designed control charts.

This paper introduces the quality control issues involving the surface finish of ground cylindrical rolls for steel rolling processes. In this frame, we discuss a process monitoring approach based on multivariate SPC techniques. In-process acquisition of multiple accelerometer signals is used to detect out-of-control vibration conditions, i.e. any anomalous accumulation of vibration energy. It is worth to notice that, from an SPC perspective, any unnatural deviation from the in-control behaviour should be signalled to activate a decision-making process about the required intervention. In case of In-Process SPC, unnatural vibration detection should be followed by (or integrated with) a further inference step to correlate the observed anomaly on the signals with the actual impact on the product quality. In this study, we focus on the first step, whereas future developments will be dedicated to the second inference step.

The use of Principal Component Analysis (PCA) - based approaches is discussed to deal with the fusion of multi-source information and to reduce the dimensionality of the problem by synthetizing the information content into a small number of features. Different kinds of synthetic indicators are considered to evaluate the capability of signalling unnatural process changes under time-varying cutting parameters. The proposed method is thought to be integrated into a chatter suppression system, or just to support the operator's decision making process. Real industrial data are used to discuss the potential benefits, the implementation issues and the main criticalities that shall be faced with in designing robust monitoring systems.

Section 2 briefly introduces the problems affecting the surface quality control of ground rolls; Section 3 reviews the process monitoring in grinding; Section 4 presents a real case study; Section 5 describes the proposed approach; Section 6 discusses the achieved results; Section 7 concludes the paper.

2. SURFACE QUALITY ASSESSMENT OF GROUND CYLINDRICAL ROLLS

In Roll Grinding, the final acceptability of the part is related to dimensional/geometrical tolerances and surface finishing features. The former ones are relatively easy to measure and to control. The assessment of surface finish quality, instead, represents a more troublesome task, which motivated considerable research efforts in the past decades [13].

One of the most important surface finishing features, is the roughness level that is regularly measured by means of contact or contactless devices. However, the product acceptability is often related to additional characteristics of the surface, related with its visual appearance (e.g., presence of alternating clear and dark areas, burned areas, waviness marks - or "chatter marks" -, etc.).

Fig. 1 shows a detail of the surface finish of a cylinder for hot rolling, where the waviness generated by chatter vibrations is clearly visible. The cylinder is of the same type described in Section 4, and the waviness wavelength is about 12 mm.

Onset of cutting instability (e.g. regenerative chatter [14] can easily lead to the generation of these waviness marks. This phenomenon is rather complex and is affected by the dynamic stiffness of both the machine and the workpiece. For instance, due to the varying dynamic compliance of slender rolls, this waviness may be different along their axial directions, leading to complex pattern on the surface.

Because of this, the execution of a limited number of local surface measurements may be not fully reliable for part acceptance purposes.

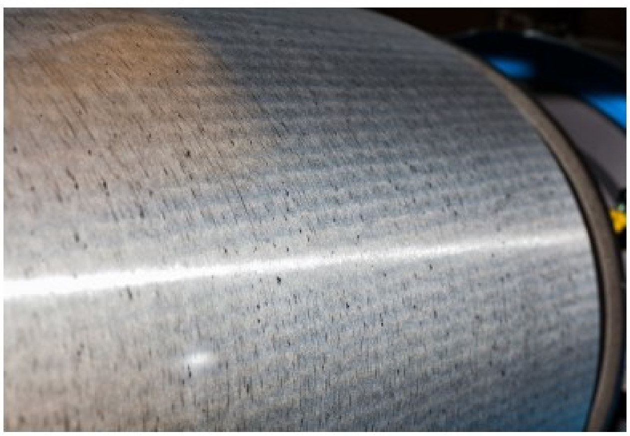

Fig. 1 – Surface waviness on a cylindrical roll for hot rolling caused by chatter vibrations

Fig. 2 shows a detail of a ground cylindrical roll for hot rolling, where the chatter marks are present only on a limited region (the right side of the figure).

Fig. 2 – Surface waviness localized on one side of a cylindrical roll

A standard grinding cycle for cylindrical rolls consists of a sequence of passes with a material removal rate that decreases over time, from first roughing steps to final finishing steps. The cutting parameters – which may change in each pass -, are usually selected on the basis of some empirical rules and on the operator's experience. In literature, some process optimization tools (e.g., see [15][16]), have been proposed to support the correct selection of the parameters, but this kind of tools are rarely adopted in industry. Visual inspections and surface finish measurements are foreseen during the cycle, after one (or more) grinding pass.

Such a surface quality assessment is strongly affected by the experience of the operator, by his subjective evaluations and by environmental factors, mainly consisting of the illumination conditions. Artificial illumination and strobe lamps are often used to highlight the presence of possible defects. Sometimes, chalk or other materials are spread over the surface in order to magnify the presence of these unnatural patterns that are not visible by the naked eye. A slow rotation of the cylinder may also help in detecting some waviness and chatter marks, and/or alternated clear and dark areas.

Such a time-consuming and non-objective procedure may be at least partially substituted by using advanced contactless inspection systems. However, a full characterization of large rolls is still a time-consuming, expensive and troublesome task in shop floors. This procedure may yield unreliable results whenever not sufficiently experienced operators are available, or when not sufficiently accurate systems are used. Thus, there is the need to redefine the quality control paradigms, and an increasing interest for the maximization of the information throughput provided by in-process sensor signals. The challenge consists of putting together process knowledge on vibration monitoring methods into a statistical quality monitoring framework that complies with industrial implementation requirements.

3. PROCESS MONITORING IN GRINDING

Process vibrations are one of the most critical issues in grinding processes [14]. There are two main kinds of chatter vibration in this field: forced vibrations and self-excited (unstable) vibrations [14 - 18]. Forcing factors may be either internal - including unbalances (e.g. grinding wheel or other rotating organs) - , or external (e.g., floor vibrations).

The regenerative effect is one of major causes of process instability in many cutting processes [14]. The waves generated on the workpiece surface, which are created by the relative vibration between the grinding wheel and the workpiece, result in a depth-of-cut modification after one workpiece revolution. The phase shift between the surface waves and the current relative vibration makes the process unstable when a given condition is reached. The regenerative effects may affect both the grinding wheel and the workpiece. Inasaki et al. [14], showed that the waves generated on the workpiece grow quite rapidly, whereas the self-excited vibration due to the regenerative effect on the grinding wheel yields a slower growing dynamics.

Process monitoring in grinding processes were discussed by many authors, with different objectives [3 - 12]. Commonly used sensors include acoustic emission sensors, spindle power sensors, accelerometers, temperature sensors and force sensors [3].

The largest portion of chatter-related literature in grinding is focused on chatter avoidance by cutting parameter selection [19] [20], and on chatter suppression [21] [22] [23].

Regarding the specific task of automated chatter detection, some authors discussed the use of data-driven algorithms. The proposed methods include artificial neural networks (ANNs) [8] [9], entropy-based algorithms [10] [11], and information rate-based algorithms [11]. A detection method based on the wavelet transform was proposed in [12].

Although recognizing the presence of chatter appears as a relatively simple task for a trained machine operator, only a relatively few methods of fully automatic chatter detection can be found in the grinding literature [22]. Nevertheless, automatic detection of chatter phenomenon is required to implement chatter suppression strategies. If not avoided or suppressed, the chatter vibrations lead not only to unacceptable surface finish, but also to excessive loads on cutting tools and spindles, causing tool and bearing failures. For a review of chatter suppression methods see [17].

One major issue for automatic chatter detection is represented by the influence of time-varying cutting parameters and operative conditions on the time series of monitored features. A robust detection algorithm requires the monitored statistics to be stable under chatter-free conditions, and the effect of chatter vibrations to be clearly separable from other natural process variation causes. A further problem consists of the selection of appropriate threshold levels. When no statistically rigorous approach is used to control the false alarm rate during the training phase, no clear evaluation of the detection performances can be made, reducing the effectiveness of the algorithm (e.g., in [20] and [21] experimental tests are used to choose a reasonable threshold, on an heuristic basis). Another problem consists of finding the proper way to capture and monitor the correlation structure among multiple features coming from different sensors. For such a task, ANNs are often used, but they are typically implemented in supervised learning mode. Supervised learning implies the need to collect process data that characterize not only the natural process condition (i.e., the chatter-free behavior), but also the unnatural phenomenon to detect (i.e., a sufficient amount of data under chatter conditions).

In-Process SPC techniques in general, and data-fusion methods in particular, are specifically designed to face with most of those problems.

4. A REAL CASE STUDY

An experimental campaign was performed to collect real data during cylindrical grinding processes under chatter-free conditions, and in presence of growing chatter vibrations.

The workpiece used for the experiments was a special alloyed steel roll for hot rolling, having an initial diameter of 500 mm and an axial length of 1700 mm.

The grinding wheel was an aluminum oxide one, having a nominal diameter of 700 mm and a width of 75 mm.

A qualitative scheme of the machine tool used for the experiments is shown in Fig. 3.

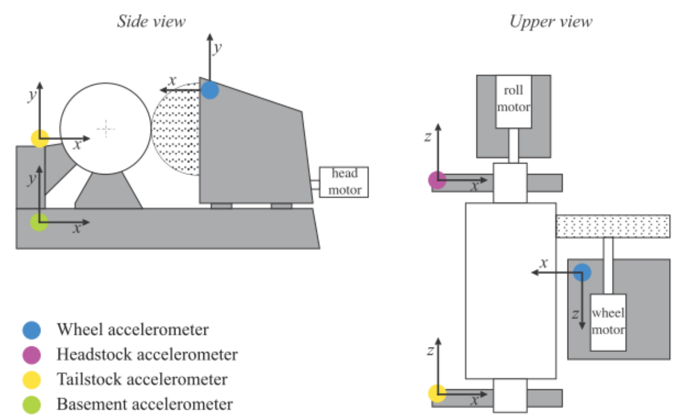

Fig. 3 – Simplified scheme of the grinding machine and sensor locations

Different runs were performed by varying the wheel speed and the infeed. The goal was to perform a number of complete grinding cycles under natural conditions (i.e., chatter-free mode), and with growing chatter vibrations. In order to induce out-of-control vibration conditions, wheel speed was tuned, until chatter is reached. According to [14], the experimental evidence has shown that chatter frequency is close to the main system resonance (which was known by previous modal analysis) and is almost synchronous with one of the wheel frequency harmonics. This empirical finding was used to drive the selection of the cutting parameters in different experimental runs. Notice that the dynamic characterization was used to support the experimental activity, but the proposed process monitoring strategy may be implemented without any prior empirical or analytical knowledge.

The ranges of the cutting parameters used in our experimental activity are reported in Table 1.

Table 1 – Cutting parameter ranges

Wheel speed [rpm]	Roll speed [rpm]	End Infeed [mm]	Continuous Infeed [mm]
680 - 1000	30	0.01 - 0.02	0.01 - 0.02

The most important parameters, which have a direct effect on the chatter dynamics, are the roll speed and the wheel speed. Other important parameters include the end-infeed and the continuous infeed (i.e. the parameter used to compensate the wheel wear), since they affect the chip thickness and the cutting forces.

Three accelerometers were mounted respectively on the wheel head, on the roll headstock and on the roll tailstock (see Fig. 3). A further accelerometer is mounted on the basement, but it is not used for chatter detection purposes. The data analysis here discussed involves the acceleration signals along the *x*-axis, which in theory [14] are the most sensitive to chatter vibrations. Signals were acquired with a sampling rate of 2 kHz.

The wheel accelerometer is the closest one to the chip – removal process, and its response is less sensitive to the axial location of the grinding wheel on the cylinder, differently from the other two sensors. Vibrations involving the whole machine structure and the workpiece mostly affect the headstock and the tailstock accelerometers. Because of this, the three sensors provide partially complementary information, and this motivates the study of multi-sensor fusion approaches.

The actual quality of the surface finish was assessed at the end of each cycle by exploiting extended visual inspections and contact-based measured.

Fig. 4 shows the frequency analysis of the surface waviness measured with a touching probe at a distance of 100 mm from one side of the roll, and at the middle of the roll, in chatter-free and chatter conditions.

The vertical red line corresponds to 50 upr, where upr stands for "*undulations per revolutions*". A frequency of about 50 upr represents the upper frequency level for large scale shape error features. Thus, the presence of surface waviness can be detected at frequencies higher than 50 upr. Fig. 4 shows that under chatter-free conditions no relevant waviness contribution is present, whereas when chatter grows in correspondence of a wheel speed of 630 rpm, waviness occurs at 126 upr.

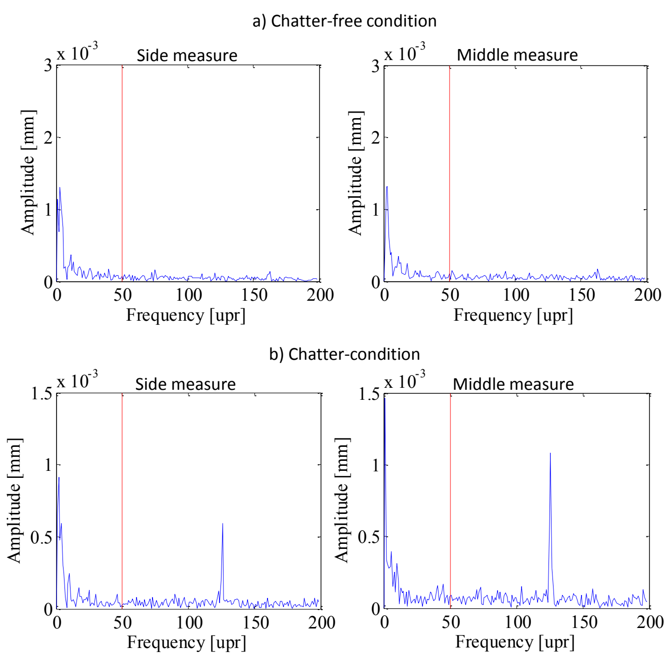

Fig. 4 – Frequency analysis of the touching probemeasures (on one side of the cylinder and at the middle of the cylinder) in chatter-free (a) and chatter conditions (b)

In addition, Fig. 5 shows the spectrogram of the wheel head accelerometer signals acquired in chatter-free and chatter conditions. The plots are based on the use of consecutive Hanning windows (5s duration), with a 90% overlap ratio. The figure shows that two frequency components grow over time under chatter conditions: a component at about 60 Hz, corresponding to the dominant chatter frequency, and one at about 200 Hz.

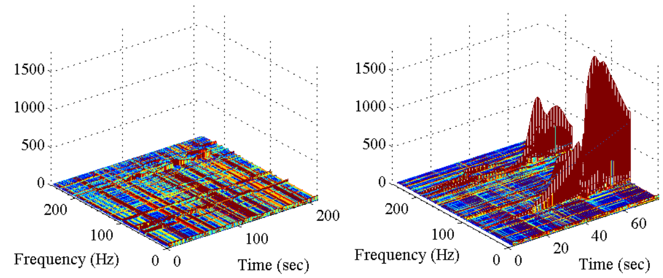

Fig. 5 – Spectrograms of the wheel head accelerometer under chatter-free (left) and chatter (right) conditions

5. THE PROPOSED APPROACH

5.1 Chatter indicator selection

In order to detect the occurrence of vibration phenomena, each monitored signal can be segmented into a number of consecutive time-windows of sufficient duration, with a given overlap ratio.

Let $\mathbf{x}_{kj} = [x_{kj1},...,x_{kjL}]^T$ be the data vector corresponding to the j^{th} time window ($j = 1,2,...$) extracted from the time series of the k^{th} signal, with $k = 1,2,...,K$, where K is the number of monitored signals. L is the number of datapoints included into the time window. The data vector $\mathbf{x}_{kj}$ can be processed to extract a number of features (i.e., chatter indicators) that synthetize its information content.

In this study, we consider and compare two kinds of potential chatter indicators, respectively extracted from the time-domain and the frequency-domain [24]. Time-domain indicators include the RMS, the Kurtosis, the Skewness, the peak-to-peak amplitude and the Crest Factor (Table 2).

Time-domain indices represent the less computationally expensive and easy to implement choice for most applications. However, the information content in the time domain may be not sufficient to properly characterize the nature of the phenomenon to be detected. In addition, we propose a set of frequency-domain indicators. Power spectrum indicators are frequently used for vibration monitoring, and they are also popular in industrial toolkits, thanks to their powerful interpretability. In this study, the choice of the frequency-domain indicators is driven by the fact that the chatter frequency is shown to be synchronous to the wheel speed. Therefore, by monitoring the energy of synchronous bands, one may expect to improve the capability of detecting incipient chatter vibrations.

Table 2 – Time-domain indicators

Indicator	Formula	Units
RMS	$\sqrt{\frac{1}{L}\sum_{i=1}^{L}\lvert x_{kji}\rvert^2}$	m/s^2
Kurtosis	$\dfrac{\frac{1}{L}\sum_{i=1}^{L}(x_{kji}-\bar{x}_{kj})^4}{\left(\frac{1}{L}\sum_{i=1}^{L}(x_{kji}-\bar{x}_{kj})^2\right)^2}$	-
Skewness	$\dfrac{\frac{1}{L}\sum_{i=1}^{L}(x_{kji}-\overline{x_{kj}})^3}{\left(\frac{1}{L}\sum_{i=1}^{L}(x_{kji}-\overline{x_{kj}})^2\right)^3}$	-
Peak-to-Peak	$\left\lvert\max_{i=1:L}\mathbf{x}_{kj}-\min_{i=1:L}\mathbf{x}_{kj}\right\rvert$	m/s^2
Crest Factor	$\dfrac{\max_{i=1:L}\lvert\mathbf{x}_{kj}\rvert}{\sqrt{\frac{1}{L}\sum_{i=1}^{L}\lvert x_{kji}\rvert^2}}$	-

The different proposed indicators in the frequency domain include: the relative synchronous energy value (RSEV), the relative maximum synchronous energy value (RMSEV), the absolute synchronous energy value (ASEV), the absolute maximum synchronous energy value (AMSEV) and the relative maximum harmonic synchronous energy value (RMHSEV). See Table 3. The synchronous energy is the energy in frequency bands centered at frequency values that are multiples of the wheel speed (expressed in Hz). The bandwidth at synchronous levels is 3 Hz.

All the indicators are computed on time-shifting windows of 5s duration and a 90% overlap ratio, for all the acquired signals.

A sensitivity analysis with respect to cutting parameters under chatter-free conditions was carried out for all the indicators. For sake of space, only a few examples are reported in Fig. 6. The figure shows the mean value and the corresponding 95% confidence intervals (dotted lines) of RMS and crest factor indicators (time-domain), and RMSEV and ASEV (frequency-domain). The ASEV indicator shows a negative correlation with wheel speed, when the infeed is equal to 0.01mm. The RMS indicator extracted from the wheel head accelerometer shows a positive jump when a wheel speed higher than 1000 rpm is used. The time-domain indicators extracted from the headstock and tailstock accelerometer signals have shown to be less sensitive to changes of the cutting parameters. Whereas, most of the frequency-domain indicators are quite sensitive to cutting parameter changes, regardless the location of the sensor. This is caused by a higher sensitivity of the power spectrum features to modifications that have some influence on the grinding process dynamics. A sensitivity analysis like the one synthetically depicted in Fig. 6 may help in assessing the robustness of selected indicators.

Table 3 – Frequency-domain indicators

Indicator	Formula	Units
Relative SEV	$\dfrac{\text{total synchronous energy}}{\text{total vibration energy}}$	%
Relative max SEV	$\dfrac{\text{max sync. energy(in one band)}}{\text{total energy}}$	%
Absolute SEV	total sync. energy	m/s^2
Absolute max SEV	max sync. harmonic energy	m/s^2
Relative max harmonic SEV	$\dfrac{\text{max synchronous energy(in one band)}}{\text{total synchronous energy(sum of all bands)}}$	%

However, the most robust indicators may be also the less sensitive to actual process changes. In this frame, a proper data fusion of available information is expected to provide a good detection power, even by using weak chatter indicators.

5.2 Data-fusion via Principal Component Analysis

Let $\mathbf{y}_{kj}=[y_{kj1},...,y_{kjP}]^T$ be the vector of chatter indicators extracted from the j^{th} time window ($j=1,2,...$) within the time series of the k^{th} signal, where $k=1,2,...,K$, and P is the number of extracted indicators. In general, a different set of indicators may be computed for each signal; in that case, the number P of indicators is a function of the selected signal ($P=P_k$).

A multi-channel dataset consists of K matrices $\mathbf{Y}_k=\{y_{kjp}\}$ of dimension $N\times P$, where $p=1,2,...,P$ and $j=1,2,...,N$, being N the number of acquired time windows. Such a dataset may be also treated as a multi-way array of dimension $K\times N\times P$. Regardless of the representation formalism, the dataset is characterized by two kinds of correlation: a correlation within the different indicators extracted from the same signal, and a correlation between the indicators extracted from multiple signals. In order to properly represent the evolution over time of the accumulated vibration energy, both the two kinds of correlation shall be captured. If one fails to capture the correlation structure among the monitored features, a potentially useful information content may be lost, and a reduced power in detecting actual process changes is achieved [25].

The PCA is a multivariate analysis technique that allows reducing the data dimensionality, and, at the same time, fusing together all the sensor outputs to achieve a better comprehension of the process [26].

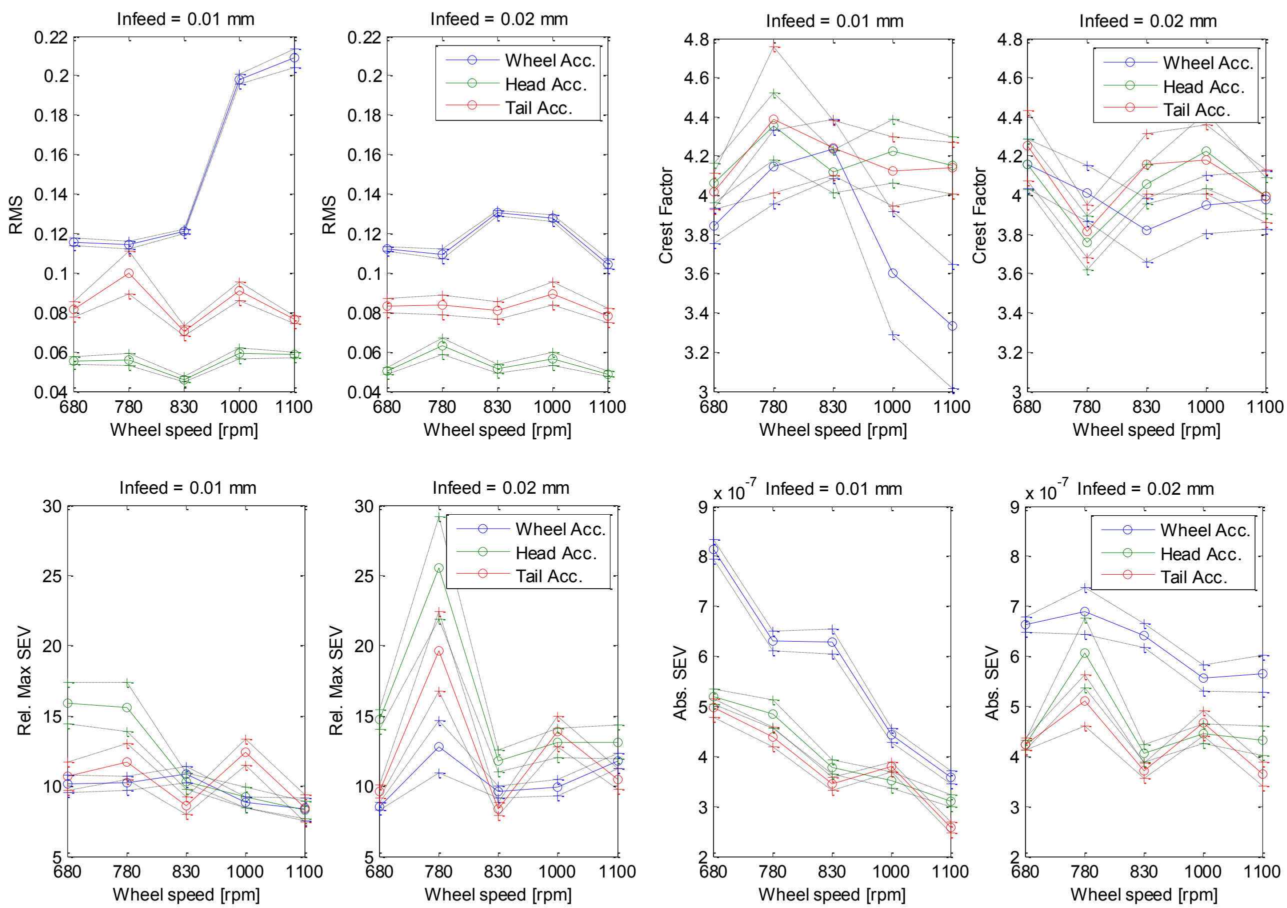

Fig. 6 – Sensitivity of a sub-set of indicators with respect to changing cutting parameters in chatter-free conditions

The dimensionality reduction capability is aimed at synthetizing the relevant information content into a small number of interpretable features. The result makes the overall signal analysis system efficient. Moreover, the interpretability of the synthetic features – the Principal Components (PCs), which are linear combinations of the original features – allows overcoming the black box limitations of artificial neural networks and other artificial intelligence paradigms.

In case of multi-channel datasets, different PCA extensions were proposed and discussed in literature. Multi-way formulations were proposed in [27 - 29]. Two main approaches to apply the PCA to such a kind of data are the Vectorized PCA (VPCA) approach, and the Multi-linear PCA (MPCA) approach [30] [31]. The VPCA involves the "*matricization*" operation [32], which consists of unfolding the multi-dimensional dataset into a bi-dimensional one. An example of the implementation of such a technique in a process monitoring application is discussed in [33]. The MPCA, instead, consists of performing the PCA directly on the original multi-way representation, without pre-processing the data by the unfolding procedure [29].

In [31], the authors showed that the VPCA may be the preferred solution in applications characterized by a limited number of signals, and possibly different number of features extracted from each signal. Therefore, the VPCA approach is here proposed.

The matricization operation simply consists of concatenating the K matrices corresponding to different signals into a single matrix $\tilde{\mathbf{Y}} = [\mathbf{Y}_1 \quad \mathbf{Y}_2 \quad \ldots \quad \mathbf{Y}_K]$, where $\tilde{\mathbf{Y}}$ has dimensions $N \times P'$, where $P' = KP$ if the same number of features is extracted from each signal, otherwise $P' = \sum_k P_k$.

The VPCA-based monitoring approach requires a training phase to estimate the PCA model that characterizes the natural conditions of the process [30]. Let M be the number of time windows acquired under in-control conditions. Then, the PCA-based method consists of performing a spectral decomposition of the sample variance-covariance matrix $\mathbf{S}_{1:M}$ of the $M \times P'$ data matrix $\tilde{\mathbf{Y}}_{1:M}$, i.e. finding the matrices $\mathbf{L}$ and $\mathbf{U}$ that satisfy the relationship:

$$\mathbf{U}^T \mathbf{S}_{1:M} \mathbf{U} = \mathbf{L} \qquad (1)$$

Where $\mathbf{L}$ is a diagonal matrix whose diagonal elements are the eigenvalues of $\mathbf{S}_{1:M}$ (λ_p; $p = 1,...,P'$), while $\mathbf{U}$ is an orthonormal matrix whose p^{th} column $\mathbf{u}_p$ is the p^{th} eigenvector of $\mathbf{S}_{1:M}$.

When the indicators refer to heterogeneous quantities, data standardization is required before computing the sample variance-covariance matrix $\mathbf{S}_{1:M}$. Standardization consists of subtracting to each column of $\widetilde{\mathbf{Y}}_{1:M}$ the corresponding sample mean value computed on the M samples, and dividing the result by the corresponding sample standard deviation. The projection of the j^{th} sample onto the PC orthogonal space is defined as follows:

$$\mathbf{z}_j = \mathbf{U}^T (\widetilde{\mathbf{y}}_j - \overline{\widetilde{\mathbf{y}}}) = [z_{j1},...,z_{jH}]^T \qquad (2)$$

Where $\widetilde{\mathbf{y}}_j$ is the j^{th} row of the data matrix $\widetilde{\mathbf{Y}}_{1:M}$ and $\overline{\widetilde{\mathbf{y}}}$ is the sample mean vector of $\widetilde{\mathbf{Y}}_{1:M}$. H is the maximum number of PCs that can be extracted, i.e. the maximum number of non-zero eigenvalues. H is upper-bounded by $\min\{P',M\}$.

The p^{th} eigenvector $\mathbf{u}_p$ contains the weights (loadings) associated with the p^{th} PC, and hence it weights the contribution of each indicator to the corresponding linear combination.

The first PC is the maximum variance linear combination; the second PC is the maximum variance linear combination having zero-correlation with the first one; and so on. The relative importance of each PC, i.e. the amount of explained variance, is represented by the value of the corresponding eigenvalue. Therefore, the relevant information content may be captured by a reduced number of PCs, providing the dimensionality reduction at the origin of the PCA popularity. Different methods have been proposed to automatically select a number m of PCs to be retained. A very effective one was proposed by Wold [34], based on a cross-validation algorithm. It is the method used in this study. For a comparison of methods see [35].

By retaining the first m PCs, each sample – i.e. each row of the matrix $\widetilde{\mathbf{Y}}_{1:M}$ – may be reconstructed as follows:

$$\hat{\widetilde{\mathbf{y}}}_j(m) = \overline{\widetilde{\mathbf{y}}} + \sum_{p=1}^{m} z_{jp}\mathbf{u}_p \quad \text{(j=1,2,…)} \qquad (3)$$

The process monitoring strategy requires the computation of two control statistics: one is the Hotelling's T^2 statistics, used to detect possible deviations along the directions of the first m PCs:

$$T_j^2(m) = \sum_{p=1}^{m} \frac{z_{jp}^2}{\lambda_p} \quad \text{(j=1,2,…)} \qquad (4)$$

The second is the Sum of Squared Errors (SSE) statistics, used to detect possible deviations in directions orthogonal to the ones associated to the first m PCs, given by:

$$SSE_j(m) = \left(\hat{\widetilde{\mathbf{y}}}_j(m) - \overline{\widetilde{\mathbf{y}}}\right)^Y \left(\hat{\widetilde{\mathbf{y}}}_j(m) - \overline{\widetilde{\mathbf{y}}}\right) \quad \text{(j=1,2,…)} \qquad (5)$$

The aim of the monitoring approach consists of computing the T^2 and SSE statistics for each computed time window, and then compare the computed values with a control limit. Any violation of the control limit is signaled as an alarm, i.e., an unnatural deviation from the stable conditions. Notice that the time window computation must be synchronous for all the monitored signals.

The selection of the control limits is based on the natural variability of the statistics estimated during the training phase. Those limits correspond to the empirical percentiles, which can be estimated by using a bootstrap-based procedure [36]. It consists of drawing B bootstrap samples of size M from the original one, computing the PCA model and the $T_j^2(m)$ and $SSE_j(m)$ statistics for each sample, and then using the collection of BM realizations to estimate the empirical cumulative distribution function. Therefore, the control limits are estimated as $(1-\alpha)\%$ percentiles of the empirical distributions, where $\alpha = 1 - \sqrt{1-\alpha'}$ and α' is the overall Type I error (i.e., the targeted false alarm rate). In this study, $\alpha = 0.027$ was used.

6. MAIN RESULTS

Fig. 7 shows the T^2 and SSE control charts based on the use of time-domain chatter indicators. Only the most robust indicators are used. They include the skewness indicator from the wheel head accelerometer, and the peak-to-peak and the crest factor from the other two sensors.

The control charts were trained on chatter-free conditions, and tested on both chatter-free and chatter conditions. The cutting parameters used in different scenarios are reported in Table 4. Two sets of consecutive passes with different cutting parameters were used during the three different test phases, i.e., training, testing in chatter-free conditions and testing with growing chatter. The difference between the two runs here discussed consists of the training dataset. Fig. 8 shows the T^2 and SSE control charts based on frequency-domain chatter indicators, for the same test scenario and designed by using the same settings of the time-domain based charts. Only the most robust indicators are used also in this case. They include the RMSEV and the RMHSEV from all the sensors.

Table 4 – Cutting parameters used in reported run tests

Run Test		Set of pass	Wheel speed [rpm]	End/Cont. Infeed [mm]
1	Training	#1	680	0.02
		#2	830	0.02
	Testing (chatter-free)	#1	830	0.01
		#2	970	0.02
	Testing (chatter)	#1	1000	0.02
		#2	910	0.01
2	Training	#1	680	0.02
		#2	680	0.01
	Testing (chatter-free)	#1	830	0.01
		#2	970	0.02
	Testing (chatter)	#1	1000	0.02
		#2	910	0.01

Fig. 7 shows that under chatter-free conditions the process results to be in-control. When the chatter vibrations start to grow, the T^2 and SSE statistics show a rapidly incresing trend. In Run Test 1, the control limit violation occurs after a couple of grinding passes, because of a slower growing dynamics at the selected cutting parameters. In Run Test 2, the increasing trend starts earlier, and the accumulation of vibration energy is detected very soon.

Fig. 8 shows that, by using the frequency-domain chatter indicators, some violation of the control limit occurs already during the chatter-free testing phase. Such a violation is associated with a periodic pattern of the T^2 statistics in Run Test 1, and with a mean shift coupled with a time-series autocorrelation change affecting the SSE statistic in Run Test 2. The observed control statistics pattern is due to the larger sensitivity of the frequency-domain indicators with respect to changes of the cutting parameters, as discussed in Section 4.

In all the test runs here reported, only the first two PCs were retained, as they were sufficient to capture the largest percentage of data variability.

The scatter-plots of the first two PCs respectively based on time-domain and frequency-domain indicators are shown in Fig. 9 and Fig. 10. Red points represent the data used to train the VPCA-based approach, whereas the black points consist of observations collected during the growing process vibrations.

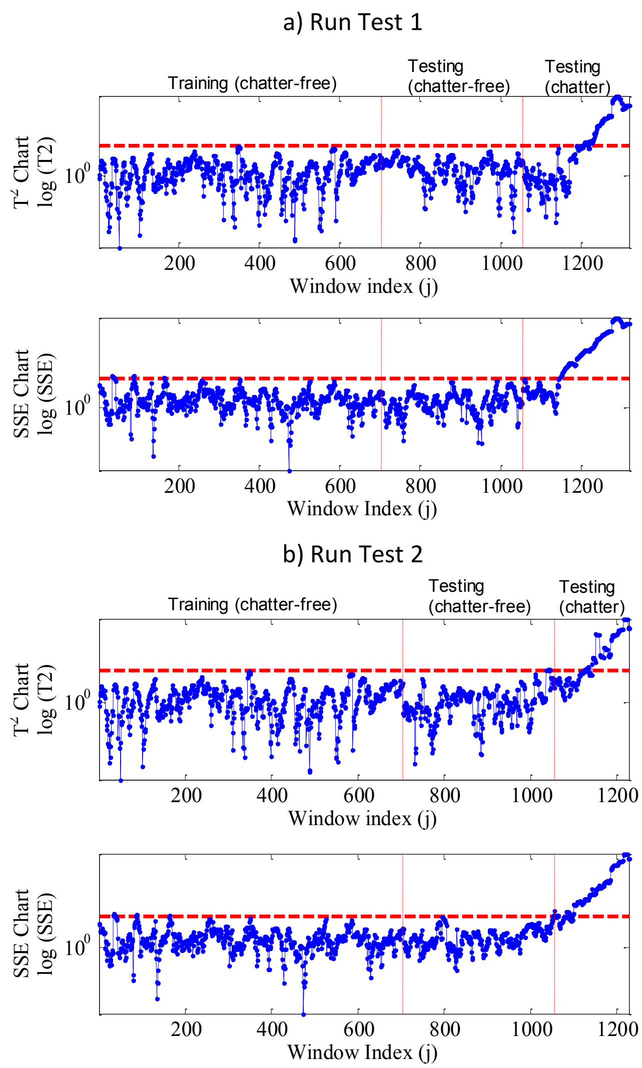

Fig. 7 – VPCA-based control charts by using the time-domain indicators

Fig. 9 and Fig. 10 show that the PCs based on both the two kinds of indicators are strongly affected by the vibration phenomena. In particular, the onset of chatter vibration yields a translation of the projected data in the bi-dimensional space spanned by the first two PCs. The capability of synthetizing the information coming from multiple indicators extracted from three sensors in a very small number of PCs is an interesting feature provided by the VPCA approach.

Furthermore, the contribution of each indicator on the retained PCs is known, being given by the corresponding weight of each PC loadings.

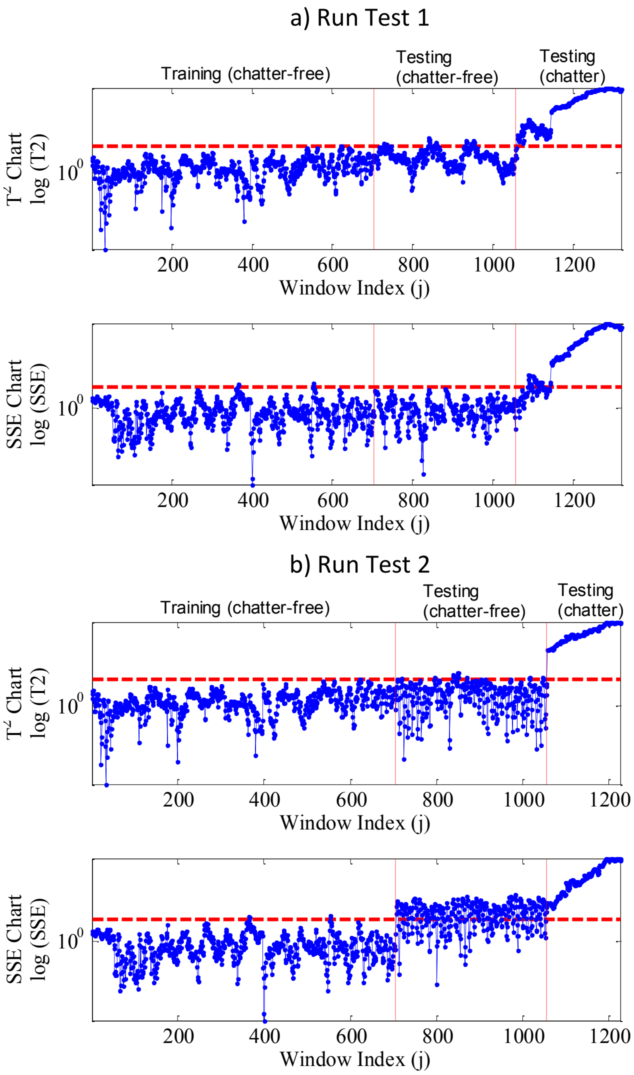

Fig. 8 - VPCA-based control charts by using the frequency-domain indicators

The entity of the maximum displacement from the chatter-free data cluster is higher when frequency-domain indicators are used. The effects of vibrations is higher when analyzed in the frequency-domain, but the higher dependence on current operative modes and cutting parameters represents a critical issue to be faced with. Because of this, a preliminary analysis about the dependence of potential indicators on the cutting parameters in the range of actual interest is expected to considerably improve the robustness and the reliability of any monitoring approach. The use of VPCA-based control charts provides a statistically appropriate way to define the alarm threshold levels, without introducing any ex-ante information based on the operator's experience, or any heuristic method.

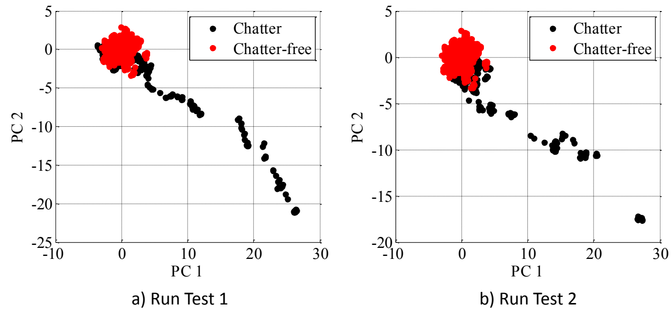

Fig. 9 – Projection of acquired data onto the space spanned by the first two PCs under chatter-free and chatter conditions (time-domain indicators)

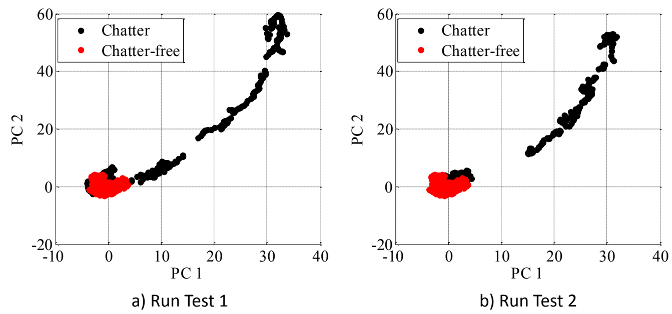

Fig. 10 – Projection of acquired data onto the space spanned by the first two PCs under chatter-free and chatter conditions (frequency-domain indicators)

7. CONCLUSIONS

Cylindrical grinding of rolls for steel rolling represents an industrial process where post-process quality assessment may be a troublesome and time-consuming task, often influenced by the human operator's experience. In most cases, the final acceptability of the roll is strongly related to its visual appearance, the presence of surface defects may be localized in restricted areas and only advanced and expensive inspection systems can substitute the expert judgment.

In this frame, a paradigm shift from traditional product-based SPC methodologies toward in-process and signal-based ones is required. However, when synthetic indicators extracted from available sensors are used to monitor the evolution of a grinding process over time, two main issues need to be faced with: the robustness of those indicators to cutting parameter changes, and the capability of properly capturing their correlation structure via a data-fusion approach. We used real-industrial data to demonstrate some of the difficulties encountered in the industrial environment. Our analysis showed that easy to compute features, including both time-domain and frequency-domain indicators, may depend on cutting parameters, in chatter-free conditions. However, we showed that by choosing a limited set of indicators that are little influenced by (or normalized with respect to) the current cutting conditions, and by exploiting an effective data fusion strategy, it is possible to rapidly detect growing chatter vibrations from multiple accelerometer sensors, without introducing computationally expensive techniques. The PCA-based control charts allows capturing the relevant information content into a small number of features, and defining the alarm thresholds by controlling the false alarm rate in a statistical data analysis framework. Further research streams are required to design automatic variable selection methods that allows implementing the overall process monitoring strategy leading to an actual machine tool autonomy improvement.

It is worth to notice that, the in-process detection of unnatural process changes should be coupled with the capability of correlating the observed behaviour with the actual product quality. This task involves an additional inference step, which needs to be investigated in future studies.

REFERENCES

[1] Wong P. L., Li, K. Y., In-process roughness measurement on moving surfaces, Optics & Laser Technology, 31, 543-548, 1999

[2] Lu R.S, Tian G.Y., Gledhill D., Ward S., Grinding surface roughness measurement based on the co-occurrence matrix of speckle pattern texture, Applied Optics, 45(35), 8839-8847, 2006

[3] Tönshoff, H. K., Friemuth, T., & Becker, J. C., Process monitoring in grinding. CIRP Annals-Manufacturing Technology, 51(2), 551-571, 2002

[4] Inasaki I., Sensor fusion for monitoring and controlling grinding processes, International Journal of Advanced Manufacturing Technology, 15, 730 – 736, 1999

[5] Anguiar P.R., Serni P.J.A., Dotto F.R.L., Bianchi E.C., In-process grinding monitoring through acoustic emission, Journal of the Brazilian Society of Mechanical Sciences, 23(1), 2006

[6] Lezanski, P., An intelligent system for grinding wheel condition monitoring. Journal of Materials Processing Technology, 109(3), 258-263, 2001

[7] Alagumurthi, N., Palaniradja, K., & Soundararajan, V., Optimization of grinding process through design of experiment (DOE) — A comparative study. Materials and Manufacturing Processes, 21(1), 19-21, 2006

[8] Kwak J.S., Ha M.K., Neural network approach for diagnosis of grinding operation by acoustic emission and power signals, Journal of Materials Processing Technology, 147, 65 – 71, 2004

[9] Karpushewski B., Wehmeier M., Inasaki I., Grinding monitoring system based on power and acoustic emission sensors, Annals of the CIRP, 49, 235 – 240, 2000

[10] Govekar, E., Baus, A., Gradišek, J., Klocke, F., & Grabec, I., A new method for chatter detection in grinding. CIRP Annals-Manufacturing Technology, 51(1), 267-270, 2002

[11] Gradišek, J., Baus, A., Govekar, E., Klocke, F., & Grabec, I., Automatic chatter detection in grinding. International Journal of Machine Tools and Manufacture, 43(14), 1397-1403, 2003

[12] González-Brambila, O., Rubio, E., Jáuregui, J. C., & Herrera-Ruiz, G., Chattering detection in cylindrical grinding processes using the wavelet transform. International Journal of Machine Tools and Manufacture, 46(15), 1934-1938, 2006

[13] Hecker, R. L., & Liang, S. Y., Predictive modeling of surface roughness in grinding. International Journal of Machine Tools and Manufacture, 43(8), 755-761, 2003

[14] Inasaki, I., Karpuschewski, B., & Lee, H. S., Grinding chatter–origin and suppression. CIRP Annals-Manufacturing Technology, 50(2), 515-534, 2001

[15] Morgan M.N., Cai R., Guidotti A., Allanson D.R., Moruzzi J.L., Rowe W.B., Design and implementation of an intelligent grinding assistant system, International Journal of Abrasive Technology, 1(1), 106-135, 2007

[16] Cai R., Morgan M.N., Development of Intelligent grinding database, Key Engineeing Materials, 329, 21 – 26, 2007

[17] Altintas, Y., & Weck, M., Chatter stability of metal cutting and grinding. CIRP Annals-Manufacturing Technology, 53(2), 619-642, 2004

[18] Baylis R.J., Stone B.J., The Build Up and Decay of Vibrarion during Grinding, Annals of the CIRP, 32(1), 265-268, 1983

[19] Krishna, A. G., & Rao, K. M., Multi-objective optimisation of surface grinding operations using scatter search approach. The International Journal of Advanced Manufacturing Technology, 29(5), 475-480, 2006

[20] Pawar, P. J., Rao, R. V., & Davim, J. P., Multiobjective optimization of grinding process parameters using particle swarm optimization algorithm. Materials and Manufacturing Processes, 25(6), 424-431, 2010

[21] Barrenetxea, D., Marquinez, J. I., Bediaga, I., & Uriarte, L., Continuous workpiece speed variation (CWSV): Model based practical application to avoid chatter in grinding. CIRP Annals-Manufacturing Technology, 58(1), 319-322, 2009

[22] Alvarez, J., Barrenetxea, D., Marquínez, J. I., Bediaga, I., & Gallego, I. (2011). Effectiveness of continuous workpiece speed variation (CWSV) for chatter avoidance in throughfeed centerless grinding. International Journal of Machine Tools and Manufacture, 51(12), 911-917.

[23] Alvarez, J., Zatarain, M., Barrenetxea, D., Ortega, N., & Gallego, I. (2013). Semi-discretization for stability analysis of in-feed cylindrical grinding with continuous

workpiece speed variation. The International Journal of Advanced Manufacturing Technology, 1-8.
[24] Rao B. K. N., Handbook of Condition Monitoring, Elsevier Science Ltd, 1996
[25] Montgomery D. C., Introduction to Statistical Quality Control, John Wiley & Sons, 6th Ed, 2008
[26] Jolliffe I. T., Principal Component Analysis, 2nd Edition, Springer Series in Statistics, 2002
[27] Ye J., Janardan R., Li Q., GPCA: An Efficient Dimension Reduction Scheme for Image Compression and Retrieval, Proceedings of the 10th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 354 – 363, 2004
[28] Lu H., Konstantinos N., Venetsanopoulos A. N., MPCA: Multilinear Principal Component Analysis of Tensor Objects, IEEE Transactions on Neural Networks, 19:1, 18 – 39, 2008
[29] Lu H., Konstantinos N., Venetsanopoulos A. N., Uncorrelated Multilinear Principal Component Analysis for Unsupervised Multilinear Subspace Learning, IEEE Transactions on Neural Networks, 20:11, 1820 – 1836, 2009
[30] Paynabar K., Jin J., Pacella M., Analysis of Multichannel Nonlinear Profiles Using Uncorrelated Multilinear Principal Component Analysis with Applications in Fault Detection and Diagnosis, IEE Transactions, 45:11, 1235 – 1247, 2013
[31] Grasso M., Colosimo B.M., Pacella M., Profile Monitoring via Sensor Fusion: the Use of PCA Methods for Multi-Channel Data, submitted to the International Journal of Production Research
[32] Kiers H. A. L., Towards a Standardized Notation and Terminology in Multiway Analysis, Journal of Chemometrics, 14, 105 – 122, 2000
[33] Grasso M., Colosimo B.M., Moroni G., The Use of Adaptive PCA-based Condition Monitoring Methods in Machining Processes, Proceedings of the ASME 2012 11th Biennial Conference of Engineering Systems Design and Analysis, 4, 133-140, 2012
[34] Wold S., Cross-Validatory Estimation of the Number of Components in Factor and Principal Components Models, Technometrics, 20:4, 397-405, 1978
[35] Valle S., Li W., Qin S. J., Selection of the Number of Principal Components: the Variance of Reconstruction Error Criterion with a Comparison to Other Methods, Industrial & Engineering Chemistry Research, 38, 4389-4401, 1999
[36] Liu R. Y., Tang J., Control Charts for Dependent and Independent Measurements Based on Bootstrap Methods, Journal of the American Statistical Association, 91:436, 1694 – 1700, 1996

