

# Use of MEMS sensors for condition monitoring of devices: discussion about the accuracy of features for diagnosis

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**Abstract.** This paper analyses the effect of the variability of metrological characteristics of a set of low-cost Micro Electro-Mechanical Systems (MEMS) for the acceleration measurement, on the calculation of typical features used for condition monitoring (CM) of automatic production lines. The knowledge of the contribution of the variability of metrological characteristics to the final accuracy of features is an aspect of interest when networks of low-cost sensors are used, in particular in case the variability of their characteristics is high. In fact, due to a mass production, the calibration is not carried out sensor by sensor, but the characteristics are determined on a sample basis and assigned to the entire batch. Neglecting the variability between sensors can lead to effects on the results of data analysis, which are not easily predictable. In this paper, the real variability of the sensor's characteristics, experimentally evaluated through the calibration of a set of 25 low-cost MEMS accelerometers, has been taken into account. Digital sensitivity, signal-to-noise ratio and data rate variability of each device have been considered for the analysis. The analysis has been carried out with reference to two different test cases of industrial interest, by modifying the real outputs of high performance piezoelectric accelerometers used for CM, in order to simulate the effect of the metrological characteristics of MEMS sensors. The results show which features, among those typically used for CM, are more affected and which characteristics of MEMS are more influencing the features themselves, with reference to the specific considered applications.

**Keywords:** Condition monitoring / accuracy / sensor networks / MEMS accelerometers

## 1 Introduction

The most modern industrial realities are structured as systems of collaborating computational entities which are in intensive connection with each other and with the physical world. This kind of operations provides and uses, at the same time, large amount of data, with the aim at realizing totally or partially autonomous operations. If applications concerning improvement of energy efficiency, reliability and safety of assets are considered, autonomous tuning, diagnosis and prognosis of devices could be achieved [1–3].

In this kind of industrial contexts, sensors and sensor networks cover a relevant role, because they must provide accurate quantitative information about physical processes which, ultimately, allows people or smart devices to make suitable decisions.

In case condition-based maintenance and device CM are of interest, one of the most common technique for fault

diagnosis/prognosis in rotating machinery is the vibration analysis [4,5]. Traditionally, this type of analysis has been carried out using sensors with very good performance, like piezoelectric accelerometers. In the last years, however, thanks to the advance of MEMS technology, large-band low-noise MEMS accelerometer have been proposed on the market, and many MEMS-based solutions for vibration analysis are being proposed in literature [6–9]. Many advantages could be envisaged by using these accelerometers, like miniaturizing, embedding, networking of sensors for more powerful measuring capabilities; however, some typical metrological attributes of measuring instruments, such as traceability and accuracy, should be guaranteed, to supply reliable measurement data from which to extract correct information about the system condition [10,11]. Traditionally, these requirements are satisfied for high performance accelerometers according to well established procedures of management of the instrumentation systems, according to standards (ISO 10012:2003, Measurement management systems — Requirements for measurement processes and measuring equipment), which require single calibration of sensors and management of the whole

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measuring process, which are expensive and no more suitable. A large debate is in literature in order to realize the better trade-off between metrological requirements and cost, suggesting many possible solutions [12–14]. Anyway, even though solutions suitable for many new and low-cost sensors have been suggested, the requirement of set low the cost of services for low-cost sensors, as in case of MEMS, affects the final accuracy of sensors themselves.

The accuracy of a MEMS sensor is linked to the characteristics of all the elements that constitute the electronic device. In fact, typically, within a digital sensor all the elements of a measuring chain are included: sensing element, charge amplifier, A/D converter, timing generator. These elements are integrated on the chip and are, usually, inaccessible from the outside, so their behaviour is not entirely knowable and controllable. For example, it is known that the sampling times are subject to fluctuations, due to temperature drift or other internal processes in the sensor, so the samples points are not strictly equidistant [15]. This behaviour can, of course, affect the successive data processing, in particular the analysis based on Fourier-transform-methods, that are typical of CM approaches.

The topic of digital MEMS sensors is beginning to be treated by the metrological institutes from the point of view of calibration methodologies [15,16], but the effects that the metrological characteristics of these sensors may have on the results of CM have not yet been thoroughly investigated.

The problem has been addressed in some scientific papers. For example, in [17] a system able to emulate bearing failures is used, to prove that a kind of MEMS-based device can match the performance requirements needed to implement a reliable CM system.

Reference [18] describes some preliminary results of comparison of a cheap MEMS accelerometer and a good quality piezoelectric accelerometer in CM of internal combustion engines. The research proved that MEMS accelerometers can provide measurements of good quality, able to realize at a reduced cost CM of internal combustion engines, with the detection of some typical failures.

However, it must be considered that the metrological characteristics of MEMS sensors could be not homogeneous, and the features for CM could be differently affected from each other, depending on the characteristic influencing the feature itself [19]; these aspects should be investigated in order to fully evaluate the effect of the use of MEMS sensor networks in CM applications.

The features for CM, which synthesize condition information about the system, can be sensitive to the variability of static characteristics of sensors, some other to the variability of dynamic ones, which are also related to the specific technology of devices, which is varied and evolving.

According to the previous considerations, the aim of this paper is to analyse the effect of the variability of metrological characteristics of a set of MEMS-based devices, on the calculation of typical features used in CM. The set of sensors taken into account is composed of 25 3-axis low-power digital MEMS accelerometers.

In order to estimate in the practical case, the influence on CM of the characteristics of MEMS devices, their effect will be simulated by appropriately modifying the vibration signals acquired during the monitoring of real industrial systems. This type of analysis has already been faced in a previous work of the authors [19] in a preliminary form, with reference to a single test case. In the present work, the methodology is refined and it is applied to two cases of industrial interest, very different in amplitude and bandwidth of vibration signals, in order to get a more general idea about these effects.

Calibration data will be used to separate the different effects, like the influence of sensitivity or acquisition rate variability, according to the availability of accurate reference data.

The impact of these elements on the calculation of the main features used for CM will be evaluated, also in terms of variability among MEMS. In literature studies can be found showing the effectiveness of using single low cost accelerometer in CM applications [17] or comparison between high performance and cost piezoelectric accelerometers and low-cost ones [18]; quite new seems this approach, aiming at considering the further contribution to the uncertainty of features due to the variability of performances among MEMS of the same batch.

The awareness about these effects can help in comprehensively evaluating the uncertainty of features and in understanding the resolution of CM techniques.

Section 2 describes the materials and the methodology used to evaluate the effect of both static and dynamic characteristics of MEMS devices, on CM features.

Section 3 shows the results with reference to two real test cases; many different features are taken into account.

Conclusions and future work will end the paper.

## 2 Materials and methods

The digital MEMS accelerometer considered in this work is a commercial ultra-low-power digital MEMS accelerometer (STMicroelectronics, model LSM6DSR), connected to an external IC-board (STMicroelectronics, model 32F769IDISCOVERY) [20]. The LSM6DSR, to be precise, is a system-in-package featuring a digital accelerometer and a digital gyroscope, but only the functionality as an accelerometer has been considered in this work, being of interest in condition monitoring applications.

The output signals range  $\pm(2^{16}-1) = \pm 32768$  Decimal<sub>16-bit-signed</sub>, where the digit unit is a signed 16-bit sequence converted into a decimal number. Then, the sensitivity of the digital MEMS accelerometer is expressed in linear units of Decimal<sub>16bit-signed</sub>/(m s<sup>-2</sup>) [20,21].

The variability of metrological characteristics within units and between units has been evaluated with reference to a set of 25 MEMS accelerometers made available by the manufacturer for a characterization study.

Calibration of MEMS accelerometers has been carried out using two different test benches, an oscillating linear slide in the low frequency range (3–10 Hz) [19] and an electromagnetic shaker, for vibration frequencies up to

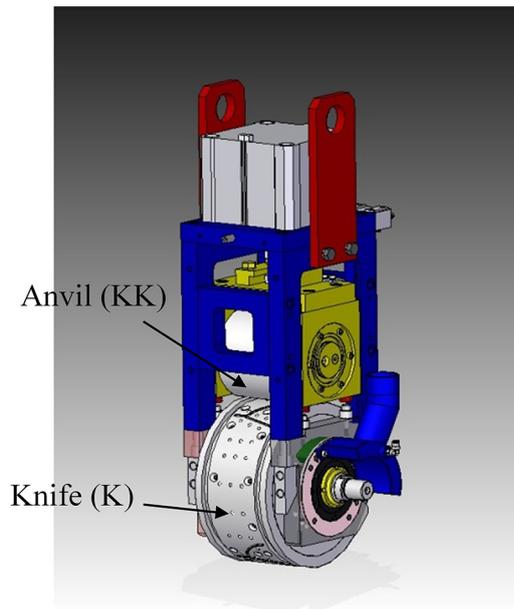


Fig. 1. 3D drawing of the first test case [19,22].

1000 Hz. It is to be pointed out that in the range of frequency 10–1000 Hz, sensitivity of MEMS can be considered nearly constant [21].

In order to estimate in the practical cases the influence of the metrological characteristics of MEMS-based devices on CM, the effect of these aspects will be evaluated with reference to two different real industrial applications:

- The first case (test case 1) is a high performance cutting stage for non-woven tissue (Fig. 1), described in [19,22]. The system includes a revolving cylinder with sharp profiles and a non-driven roller, supported in a lubricated cradle, that exerts an elastic force against the first element, by means of a pneumatic system. Piezoelectric accelerometers and other kind of sensors have been conveniently installed onto the cutting unit. In particular, the signal of an accelerometer positioned on a knife support, acquired in a CM campaign, has been considered in the present study. The aim of CM, in this application, is to recognize the actual working status of the machinery among 4 different conditions, corresponding to 4 different levels of the knife wear, called ‘0’, ‘1’, ‘2’, ‘3’. Condition ‘0’ corresponds to a new unit; the subsequent conditions correspond to increasing levels of wear.
- The second case (test case 2) is a mechatronic system in real scale (Fig. 2) [23] used for application of caps onto cans. The test bench is composed of one ball screw, two nuts and a spline shaft, and it is driven by a synchronous servomotor, able to realize a translation of the shaft. The system is monitored using a three-axis accelerometer, installed on the ball screw shaft. Experiments have been carried out, corresponding to different settings of the control system: in particular, tests for different values of the “jload” parameter have been carried out, that means changing the motor response to the inertia of the whole system. An incorrect setting can affect the accuracy of the motion.



Fig. 2. Picture of the second test case.

The aim of CM, in this application, is to recognize three different operation conditions, corresponding to three different setting of the “jload” parameter: 300, 550 and 800 kg cm<sup>2</sup>.

The methodology used in this work is according to the following steps, which will be described in detail in the next sections:

- evaluation of the metrological characteristics which are of interest for all the available MEMSs, connected to the external microcontroller;
- evaluation of the effect of the metrological characteristics of the MEMS-based devices, which in turn provides for the following operations:
  - modification of the real monitoring signals according to the metrological characteristic of interest, to simulate the effect of the characteristics of interest;
  - data processing of original and modified monitoring signals in order to evaluate features and their variability;
- analysis of variance (ANOVA) to statistically examine the effect on features of the metrological characteristics of MEMS sensors
- comparison among different features.

Classical features have been considered for the analysis [24,25], which have proved sensitive to changes in operating conditions, both in case 1 and in case 2:

- Root mean square (RMS): for a vector of  $n$  elements  $x_i$ ,

$$\text{RMS} = \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2}$$

- Kurtosis: is defined as  $k = \frac{E(x-\mu)^4}{\sigma^4}$  where  $\mu$  is the mean of the input vector,  $\sigma$  is the standard deviation, and  $E(t)$  represents the expected value of the quantity  $t$ .
- Crest factor: Peak-magnitude-to-RMS ratio.
- Mean of the peaks: average of the signal peaks.
- Signal-to-noise-and-distortion ratio (SINAD): signal to noise and distortion ratio in dBc. The SINAD is determined using a modified periodogram of the same length as the input signal. The modified periodogram uses a Kaiser window with  $\beta = 38$ .
- Shape factor: ratio between RMS and average of the absolute values of the input vector.

In addition, also features designed for the specific applications have been calculated, as, in particular, in the frequency domain:

- percentage ratio of the power spectrum content for harmonics multiple of the principal frequency of impact (in the first case) or of oscillation (in the second case) with respect to the frequency spectrum on the whole (called band);
- percentage ratio of the power spectrum content for harmonics multiple of the principal frequency, in specific ranges of frequencies. These ranges are different in the two considered cases, and are specifically selected because they are more sensitive to the conditions to be identified. In particular:
  - for case 1:
    - band1: [1400, 1800] Hz
    - band2: [2700, 3000] Hz
    - band3: [3200, 3700] Hz
  - for case 2:
    - band4: [0, 50] Hz
    - band5: (50, 100] Hz

## 2.1 Evaluation of characteristics of the MEMS-based devices

The following metrological characteristics have been evaluated: digital sensitivity, signal-to-noise ratio (SNR) and sampling rate. The methodology for the assessment of these characteristics is described in [19].

The results, used in this work, can be synthesized as follow:

1. Sampling rate:
  - Nominal sampling rate: 1660 Hz
  - Evaluated average sampling rate: 1602 Hz
  - Variability:
    - Variability calculated cycle by cycle for each accelerometer: 1.9%
    - Variability of the sampling rate among sensors: 0.93%
    - Overall variability: 2.1%
2. Sensitivity:
  - Nominal sensitivity:  $1671 \text{ Decimal}_{16\text{bit-signed}} / (\text{m s}^{-2})$ .
  - Variability among sensors:  $12 \text{ Decimal}_{16\text{bit-signed}} / (\text{m s}^{-2})$ .
3. Noise:

The SNR relative to the sinusoidal carrier has been evaluated, and the maximum standard deviation of the noise results to be  $0.066 \text{ m s}^{-2}$ .

## 2.2 Evaluation of the effect of the metrological characteristics of the MEMS-based devices

The modification of the original monitoring signals, according to the variability of the metrological characteristic of interest, has been realized as described in the following procedure:

- Evaluation of the sensitivity effect

The effect of using the nominal sensitivity instead of the real one has been estimated by multiplying the original signal by the ratio between measured sensitivity and nominal one:

$$\text{modified\_signal} = \text{original\_signal} \cdot \frac{S_{\text{meas}}}{S_{\text{nom}}} \quad (1)$$

where:

original\_signal: original accelerometer output;

modified\_signal: acceleration signal that, theoretically, we could obtain using a MEMS of the considered type with the nominal sensitivity provided by the manufacturer;

$S_{\text{nom}}$ : nominal sensitivity, set equal for all the MEMS sensors;

$S_{\text{meas}}$ : average measured sensitivity, obtained by calibration of the whole set of sensors.

- Evaluation of the noise effect

The standard deviation of the noise, evaluated by the signal-to-noise analysis of the data by the calibration, has been used to generate a normally distributed noise, which has been added to the original monitoring signal.

- Evaluation of the sampling rate effect

A different time array has been defined on the basis of the real sampling rate. The percentage variability of the sampling rate, estimated in the calibration phase, has been applied to the sampling period used in the real case ( $10^{-4}$  s in test case 1,  $10^{-3}$  s in test case 2). In particular, this variability value has been used as standard deviation of a normally distributed noise, that has been added to the time array. Then, the acceleration values corresponding to the new time array, have been calculated by interpolation.

Different interpolation methods have been considered: linear, spline, modified Akima cubic Hermite interpolation, piecewise cubic Hermite interpolating polynomial, cubic convolution, nearest neighbour interpolation [26]. Among all the interpolation methods, the nearest neighbour method has been considered, because it doesn't reduce the signal amplitude, unlike the others, and it keeps the bandwidth of the signal unchanged.

On the basis of data thus modified, the features have been calculated, and the differences with respect to those based on the original data have been estimated.

The evaluation of features has been carried out on data of 5 repeated tests, for each condition of the system, and the mean values have been considered.

**Table 1.** ANOVA test for the test case 1:  $p$ -values.

Condition	RMS	Kurtosis	Peaks average	Crestfactor	SINAD	Shape factor	Band	Band 1	Band 2	Band 3
Sensitivity effect										
0	0.0119	1	0.0015	1	1	1	1	1	1	1
1	0.4009	1	0.2918	1	1	1	1	1	1	1
2	0.0111	1	0.1142	1	1	1	1	1	1	1
3	0.0002	1	0.0086	1	1	1	1	1	1	1
Noise effect										
0	0.9972	0.9972	0.9974	0.9835	0.9968	0.9905	0.9981	0.9997	0.9991	0.9985
1	0.9954	0.9894	0.958	0.9945	0.9925	0.986	0.9977	0.9989	0.999	0.9977
2	0.9809	0.9819	0.9581	0.9965	0.9885	0.9802	0.9862	0.9958	0.9975	0.9951
3	0.9641	0.9885	0.9291	0.9951	0.9988	0.948	0.9959	0.9987	0.9953	0.9973
Sampling rate effect										
0	0.9519	0.9075	0	0.987	0	0.9652	0	0.0097	0	0
1	0.9964	0.9968	0.3436	0.9987	0.0002	0.9557	0.0054	0.5761	0	0.0008
2	0.9855	0.7492	0.9192	0.7457	0.021	0.9404	0	0.0424	0.0001	0
3	0.9613	0.8243	0.4154	0.9963	0	0.5184	0	0.3799	0	0

**Table 2.** ANOVA test for the test case 2:  $p$ -values.

jload	RMS	Kurtosis	Peaks average	Crestfactor	SINAD	Shapefactor	Band	Band 4	Band 5
Sensitivity effect									
300	0	1	0	1	1	1	1	1	1
550	0	1	0	1	1	1	1	1	1
800	0	1	0	1	1	1	1	1	1
Noise effect									
300	0.948	0.690	0.0311	0.956	0.528	0.464	0.966	0.954	0.949
550	0.986	0.543	0.188	0.826	0.531	0.262	0.789	0.757	0.960
800	0.929	0.436	0.472	0.134	0.435	0.456	0.866	0.757	0.960
Sampling rate effect									
300	0.929	0.944	0.0014	0.999	0.9865	0.983	0.906	0.976	0.749
550	0.978	0.890	0	1	0.9864	0.983	0.279	0.908	0.673
800	0.907	0.930	0.0204	0.611	0.9705	0.967	0.387	0.908	0.673

### 2.3 Analysis of variance

ANOVA tests [27] have been performed to statistically examine the effect on features of the metrological characteristics of MEMSs, evaluated as described in Section 2.2.

ANOVA has been carried out on the features before and after the addition of disturbances on sensitivity, signal-to-noise ratio and sampling frequency, both in test case 1 and test case 2. To determine whether the differences between features are statistically significant, the  $p$ -value [27] is compared to a significance level to assess the null hypothesis. The null hypothesis states that the population means are equal, then the characteristics of MEMS sensors doesn’t affect the features. A significance level  $\alpha = 0.05$

indicates a 5% risk of concluding that a difference exists when there is no actual difference: if  $p$ -value  $\leq \alpha$ , the differences between means are considered statistically significant.

The results, in terms of  $p$ -value, are reported in Tables 1 and 2, with reference to case 1 and 2, respectively; on the basis of these values, the following consideration can be made:

- *Sensitivity bias*: the results (Tabs. 1 and 2) show that, in both cases 1 and 2, the effect of the sensitivity bias is significant for RMS and peaks average. In fact, in the case of RMS and peaks average, the  $p$ -value is close to 0, which indicates a high probability (if  $p$ -value  $\leq 0.05$ , this probability is greater than 95%) that the populations of

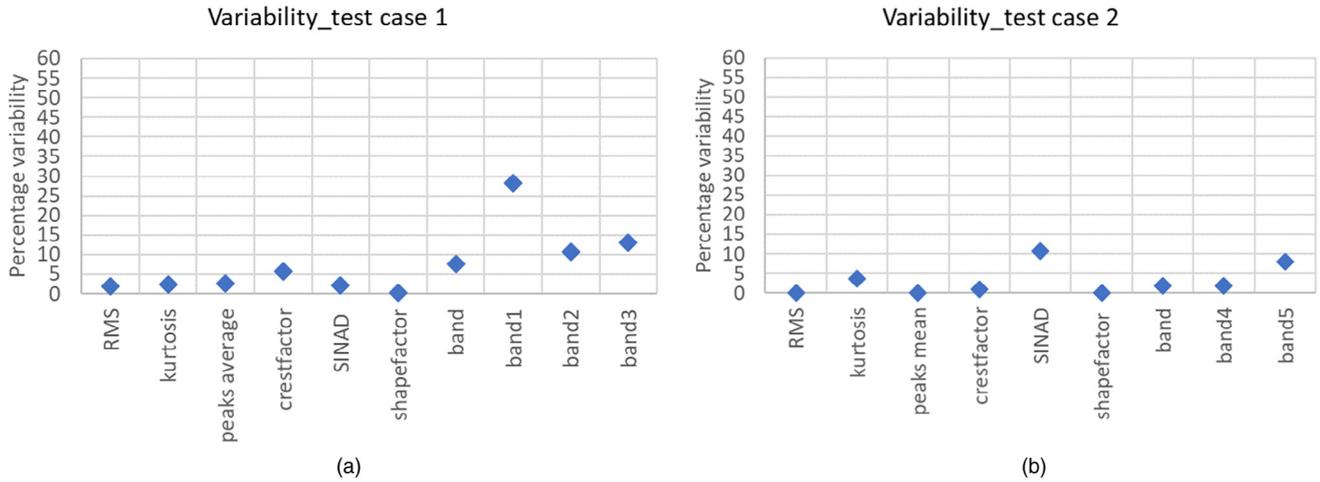


Fig. 3. Standard deviation of features for CM, in cases 1 (a) and 2 (b).

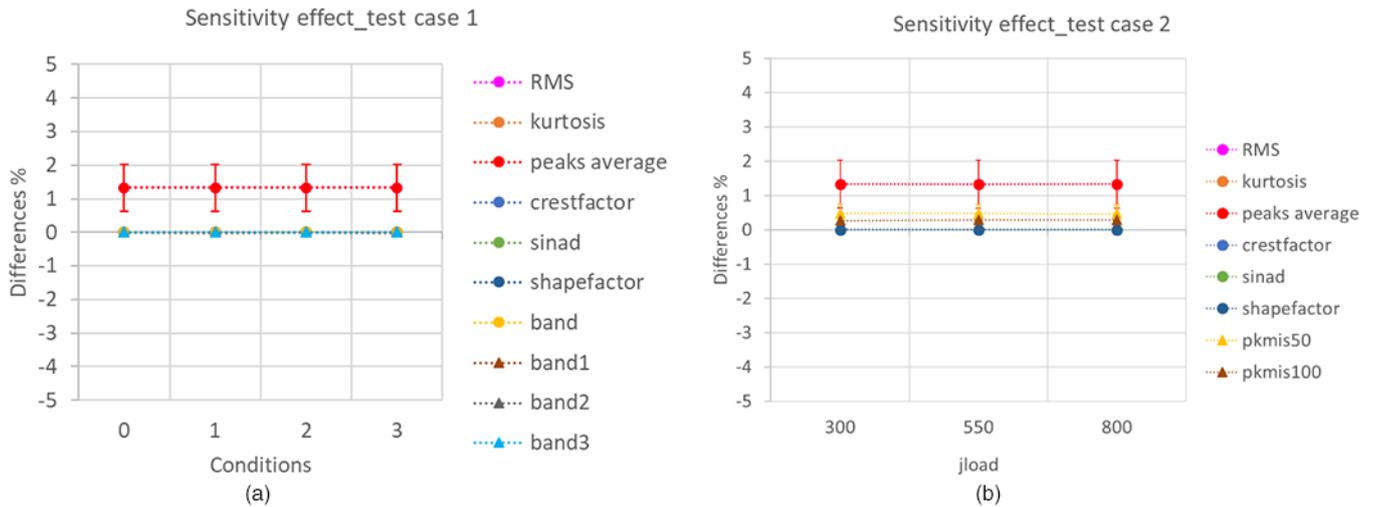


Fig. 4. Effect of the sensitivity on features for CM, in cases 1 (a) and 2 (b).

the values before and after the modification on the sensitivity, have different means, so that the effect can be considered significant. All the other features, on the contrary, being characterized by a  $p$ -value equal to 1, are not at all influenced by the disturbances that have been added.

- *Noise effect*: in both cases the addition of the MEMS noise to the real data doesn’t produce significant variations on the considered features, the  $p$ -value being near 1, as explained in the previous point. In case 2, the addition of noise produces greater effects (even if not significant at the 0.05 level) on peaks average, SINAD and shape factor, due to the lower amplitude of the original signal ( $100 \text{ m/s}^2$  in the first case,  $1.5 \text{ m/s}^2$  in the second case). In these cases, in fact,  $p\text{-value} \leq 0.5$ .
- *Sampling rate effect*: in the first case the bias of the nominal sampling rate with respect to the real one significantly affects, in particular, the calculation of the features in the frequency domain, based on the identification of the harmonics multiple of the cutting frequency, the so called “band” features. In these cases, in fact, the  $p$ -value is close to 0, or just equal to 0. Instead, in

the second case, this effect is not significant. In fact, the identification of peaks of the FFT, in the first case, is much more critical due to the presence of a higher level of noise ( $\text{SNR} \approx -17 \text{ dB}$  in case 1,  $\text{SNR} \approx 10 \text{ dB}$  in case 2), so that the shift in the sampling frequency can lead to the determination of wrong peaks, close to those of interest. In fact, the system analysed in case 1 is extremely more complex than the system in case 2: in case 2, a shaft translates according to a sinusoidal law; in case 1, two cylinders in contact, one of which with sharp profiles, rotate at high speed, and various effects produced by the rotation and impacts of the knife on the anvil, contribute to determine the harmonic content of the accelerometer signal.

### 3 Results and discussion

With reference to the two different CM applications, described in Section 2, the results have been represented in Figures 3–6, in order to highlight in a graphical way the extent of the effects produced on the features.

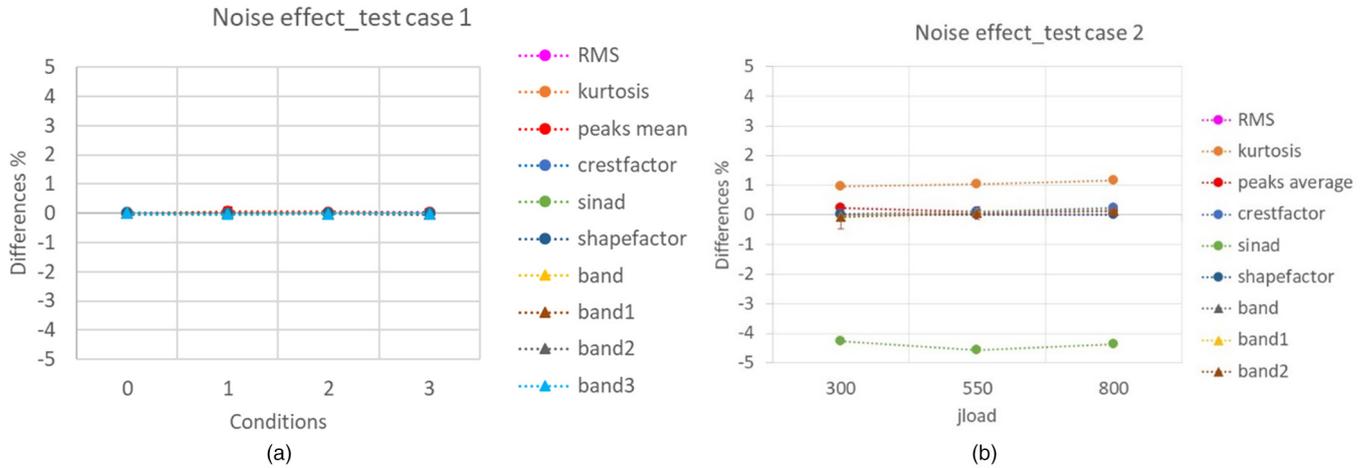


Fig. 5. Effect of the noise on features for CM, in cases 1 (a) and 2 (b).

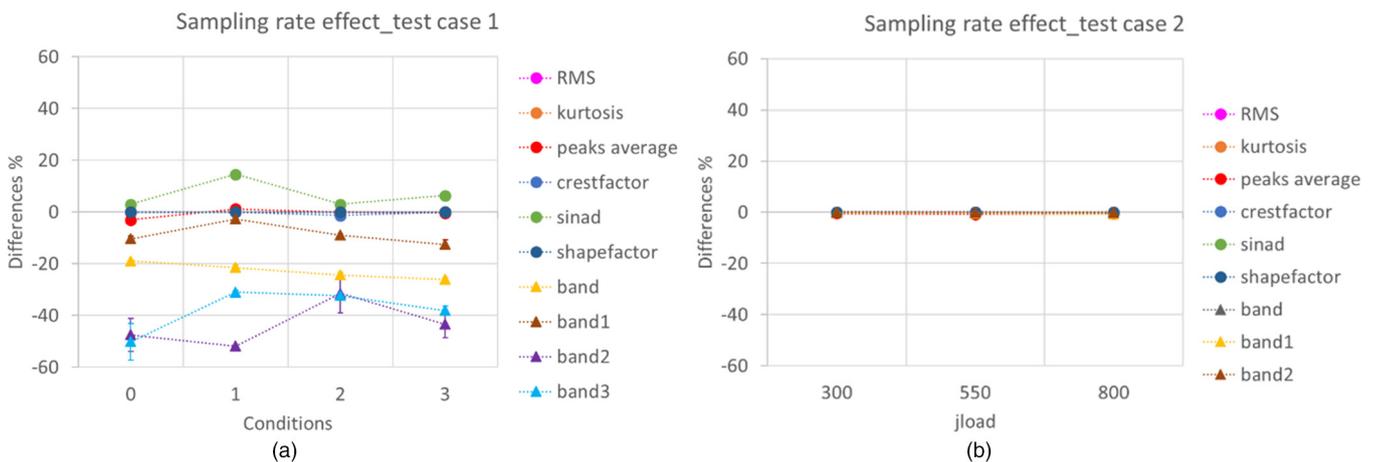


Fig. 6. Effect of the sampling rate on features for CM, in cases 1 (a) and 2 (b).

Figure 3a and b shows the variability of features for both test cases, based on the original data, acquired in 5 different trials carried out on different days. The most variable features are the ones related to the frequency spectra, mostly when the frequency band of interest is large (case 1); SINAD is also variable in case 2, due to a low level of noise in this application.

In Figures 4–6, the results are represented as percentage differences of features calculated on the basis of data modified for the effect of interest, with respect to those calculated on the basis of the original data. Error bars represent the standard deviation due to the variability among sensors of the considered characteristic.

Figure 4a and b shows the effect of considering the real sensitivity of each sensor, instead of the nominal one; being different the sensitivity of MEMS from each other, the variability of results is also represented.

Obviously, some features vary proportionally to the sensitivity variation (RMS, peaks average, ...), in the order of 1.3%, while, when the feature is according to a ratio of

measured values, it is unaffected by changes in sensitivity of sensors.

Figure 5a and b indicates the noise effect: in case 2, it is evident that the addition of noise produces greater effects, for example, on SINAD, as previously observed.

Figure 6a and b shows the sampling rate effect: in the first case, the bias of the nominal sampling rate with respect to the real one significantly affects the calculation of the so called “band” features; instead, in the second case, this effect doesn’t appear that significant.

As a rule of thumb, the effect of variable characteristics of a batch of MEMS does not increase the variability of many features of general use, like RMS, kurtosis...; furthermore, some of them are unaffected. Also bias effect is in most cases negligible, making reliable the use of MEMS for CM. Nevertheless, if more specific features are defined and used, with the aim at identifying more focused features to the particular applications, more care should be provided, being the effect of variable characteristic of MEMS difficult to be predicted.

## 4 Conclusions

This paper analyses the effect of the variability of metrological characteristics of a set of low-cost MEMS accelerometers, on the calculation of typical features used in CM of automatic production lines. The real variability of the sensors characteristics has been experimentally evaluated by means the calibration of 25 MEMS accelerometers. Digital sensitivity, signal-to-noise ratio and sampling rate variability of each sensor have been considered for the analysis.

In order to estimate the influence of the metrological characteristics of these MEMS-based devices on CM, the effect of these aspects has been evaluated with reference to two real industrial applications, that are very different in amplitude and bandwidth of signals, to cover a range of applications.

The results show that some characteristics of MEMS, in particular the difference between real and nominal sampling rate, could significantly affect the calculation of some features in the frequency domain, if the nominal value is used for data processing. This happens, in particular, for the features based on the identification of precise frequencies linked to hits, cuts, rotations, especially in signals with low SNR.

On the whole, it can be observed that using MEMS accelerometers in CM does not cause major problems, as long as the most appropriate features are chosen, depending on the applications.

The knowledge of the characteristics of the MEMS sensors is a further element for a comparative evaluation of the most suitable features. More care should be provided with reference to customized features, designed in order to highlight specific effect of the device under examination.

Furthermore, it should be emphasized that MEMS accelerometers appear to be usable in CM without major precautions when only their basic characteristics are considered. This means further studies are still needed to make corresponding statements when more complex uses, from a metrological point of view, are envisaged.

In the future work a more in-depth and systematic analysis will be carried out through a design of the experiments, to evaluate also the cross effects of the different aspects taken into account, and of other metrological characteristics of MEMS accelerometers, like stability and phase response.

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