Best Practices in Measurements for Asset Characterization in Complex Engineering Systems

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Abstract - *The evolution of systems based on the integration of Internet of Things (IoT) and Cloud computing technologies requires resolute and trustable management approaches, in order to let the industrial assets, thrive and avoid losses in efficiency and, thus, profitability. In this work, a methodology based on the evaluation of the measurement uncertainty is proposed, able to suggest possible improvement paths and reliable decisions. Its application in field, for the identification of the vibration and acoustic emission signatures of highly-performing machining tools, allowed directing future actions for increasing the potentiality of a proper management of the information provided by measurements. In a complex scenario, characterized by a large number of devices and instruments, the compliance with the procedures for measurement accuracy proved to be a useful support. A careful strategy in the reduction of uncertainty is useful in particular for classification of real damages allowing mitigating the intrinsic high variability of natural defects and threshold of defects detectability can be maintained low.*

Keywords: Measurement uncertainty, condition monitoring, centerless grinding.

1 Introduction

Exciting opportunities are arising from the evolution of the systems in the current industrial scenario. The integration of Internet of Things (IoT) [1] and Cloud computing technologies [2], leads us the Internet of Everything (IoE), a network of networks where billions of objects are connected, providing an informative base without precedent [3]. This trend is based on a large amount of data and returns the same uncountable quantity of data, which is called "big data" [4] [5]. Suitable information gathered by this huge mass of data is traditionally extracted by means of the use of data mining techniques [6], artificial intelligent tools [7], decision support systems and knowledge-based systems.

The impact on the manufacturing companies is remarkable.

In past years, the development of enterprise information systems (EIS) have allowed management to give rise to an informative base useful to decision-making [8]. The ability of an organization to take all input data and convert them into knowledge is referred as Business Intelligence (BI) [9]. On the other hand, the development of industrial automation, in rapid evolution, helped the industries to increase their productivity, setting up complex control and monitoring systems, aiming at a real-time management of the activities and achieving a real competitive advantage [10].

Nowadays, the possibility of applying new intelligent technologies, by integrating the informative content coming from disparate devices seems to make this goal possible, through the convergence of the physical world and the digital world into the so-called cyber-physical systems [11]. This new trend for industrial systems is known as "Industry 4.0" or "Industrie 4.0", in German [12] [13]. The adoption of the methods typically used in engineering tasks underline the possibility of merging them with "good" measurements.

In this context, the international reference standards offer a basic support to set corporate activities into a well-defined framework, in terms of the requirements for the implementation of integrated management systems. Quality [14], Environmental [15] Energy [16] and Asset [17] management systems are perhaps the most known international standards that companies adopt for benchmarking, marketing and self-organization purposes. Nevertheless, the quality of the achievable results and outcomes cannot be granted automatically and tacitly, since many aspects that could lead to variability may occur, due to the structure of these systems themselves. From the informative flow point of view, each node of the network requires specific procedures for assuring proper exchange of information.

Like and more than other branches of knowledge, measurement topics are stressed, in order to compete to the compliance of this requirement. This is primarily because, we have to measure to get experimental, objective and reliable information and because measurement results cannot be provided in a deterministic and univocal way.

Although a scheduled approach appears to be promising, such as that proposed by the international reference standards, the methods and tools provided seem to be not exhaustive and not-completely decisive, in the upcoming new era that we are called to manage, due to the following main reasons:

--High-connectivity and big data. Large scale and complex systems call for standardized and univocal methods for collecting, analyzing and interpret heterogeneous data provided by different devices and platforms, which inevitably cause chaos due to the increasing use of multi-purpose but poorly tested devices [1].

--Proactive methods and models. New perspectives in sensor and sensors technologies arise, e.g. those connected to

mechatronic smart components [18]. Furthermore, new supply chain management techniques (e.g. 6C framework to connect stakeholders [19]), new IT solutions and process mining techniques must be involved and harmonized all.
--Multi-disciplinary skills. In order to maximize the fluidity of these activities, transversal competences and skills are needed (e.g. those referred to mechanics and electronics, control systems and automation, informatics, software and telecommunication engineering [20], [21]), able to work together and coherently.
--Reliability of information. As a basic goal of the work, refined methods of diagnosis and control, able to support the accuracy of data and information appear essential for data management and analysis and for parallel processing and storage strategies, with reference to the large amounts of incoming data [9], [22].
Measurements play a key role as far as for the presence of sensors and devices, for data processing techniques, for the informative flow control and as a common factor of several fields of knowledge.
The variability of information turns into measurement uncertainty [23]. Treating with uncertainty is not just a formal requirement; previous work of the authors, concerning the production process of high complexity components for automotive industry [24], demonstrated that uncertainty can be used as an engineering and management tool. Further, merging methodologies are set, sharing actions of well-established improvement approaches like six sigma [24].
A methodology based on the evaluation of the measurement uncertainty is then discussed in this work, to explain this goal.
Three main guidelines are followed: the calibration as a guarantee given in advance, the uncertainty assessment of high-synthetic indicators and the adoption of an iterative approach during the process itself [25].
With reference to a condition monitoring (CM) application for a highly-performing centerless grinding machining tool, the preliminary calibration of the vibration and acoustic emission measurement chains and the reduction of the variability by improving the signal-to-noise ratio are used for the characterization of the asset state. Since the asset condition analysis is widely carried out using measurement data, attention to metrology concepts and in particular to calibration procedure will allow using the information provided by these data according to its own physical meaning. [24], [25], [26].
A condition monitoring application represents an important test-case for the methodology. In fact, both the identification of the machine signature is widely used in many applications, concerning for example bearing [27], or oil debris [28], and the operating scenario of interest is realized, in terms of the issues and challenges analyzed [29].
A careful strategy in the reduction of uncertainty will be demonstrated to be useful in particular for classification of real damages allowing to mitigate the intrinsic high variability of natural defects. It is expected to maintain low the threshold of defects detectability. In this application the sensors calibration is the concept particularly stressed.

This paper is organized as follows: in Section 2 the main steps of the methodology are briefly introduced and explained. Section 3 shows the application of the methodology to the test case selected. Short conclusions and future works end the paper.

2 Methodology

The methodology adopted is based on the measurement uncertainty evaluation and on its further reduction, in order to support actions for the improvement of decision's reliability. In this sense, the measurement uncertainty is seen as an efficacious engineering tool [25] [30].
In general terms, uncertainty is a measure of the 'goodness' of a result [31] and the approach considers the product and process conformity check [32].
The theoretical and experimental methodology is defined in 3 main steps, aiming at:
1) identifying the main uncertainty causes, taking into account real issues (STEP 1);
2) in field evaluating the uncertainty of measurement, merging all the most remarkable contributions (STEP 2);
3) defining improvement actions, able to reduce uncertainty and to recursively increase the reliability of decisions and provided solutions (STEP 3).
By iterating the afore-mentioned steps in a recursive manner over time, the methodology proposed is expected to provide an indication about the assessment of the performances to which it is referred, in line with the continuous improvement principle of many industrial management systems. In the following the above-mentioned steps for the methodology are briefly introduced.

2.1 STEP 1: Uncertainty causes identification

The first step of the methodology aims at the identification of issues connected to the validation of big amount of data. In facts, in order to start to use the measurement uncertainty, it is unavoidable to understand its causes. To this aim, some canonical techniques may be found in literature, such as those referred to the Procedure for Uncertainty Management (PUMA) [30]. In order to transfer the canonical techniques in field 4 main sub-steps have been identified, which are summarized as follows:

- 1.1 Characterization of the scenario,
- 1.2 Requirements and constraints,
- 1.3 Analysis's boundaries,
- 1.4 Materials,
  - 1.4.1 Literature survey,
  - 1.4.2 Test environment.

2.2 STEP 2: Uncertainty evaluation

The second step of the methodology aims at giving evidence to the measurement uncertainty in order to keep track of it, along all the informative flows in the process analyzed. Among the already existing methods that are usually followed for the measurement uncertainty assessment, some alternative techniques may be also found in literature (e.g. partial derivatives, numerical calculation and Monte Carlo method), though they still remain quite complex and elaborate, from the processing point of view. Furthermore, the simplification does increase the uncertainty, unless the physical meaning of the operations is adequately taken into account [24]. To this aim, two sub-steps are identified, with reference to the specific field of application and taking into account the priorities emerging in the previous step (STEP1):

2.1 Uncertainty budget and test plan,

2.2 Indicators for measurement uncertainty.

2.3 STEP 3: Uncertainty reduction

Goal of this sub-phase is keeping a low level of uncertainty in order to increase the reliability of future action plans. Even at this stage, the state of the art suggests some approaches to keep control of the measurement uncertainty, such as the metrological confirmation in [33], or the conformity assessment in [34]. Taking advantage from these approaches, the following sub-steps are highlighted:

3.1 Measurement uncertainty results,

3.2 Remarks,

thus allowing for providing further indications not available preliminarily and contributing to the system's knowledge.

3 Test case

In this application, the effects of quality of measurements in condition monitoring (CM) analysis are evaluated. The analysis focuses on the behavior of components of a high performance center-less grinding machine, for the detection and localization of the defects on the ball screw, using a self-implemented classification algorithm and other pattern recognition algorithms [35]. Vibration and acoustic emission measurements are the input data for the analysis. The preliminary calibration of the measurement chains and the reduction of the variability by improving the signal-to-noise ratio are the methodological approaches mainly stressed. In the following, the methodology introduced in Section 2 is applied and each sub-step described in further detail.

3.1 STEP 1: Uncertainty causes identification

3.1.1 Characterization of the scenario

The use of condition monitoring approaches is increased over the last decades. Description, issues and possible solutions to deal with sensor-based condition monitoring and diagnostics applications can be widely found in literature, such as [36], [37] [38]. On the other hand, metrology techniques and information coming from measurement data offer a useful contribution in facing engineering issues (e.g. 5 M – Machines, Materials, Methods, Measurements, Modelling approach and 5 S - Sensing, Storage, Synchronization, Synthesis and Service [39]), all suggesting us to include sensors and measurement aspects properly, in a big data environment.

3.1.2 Requirements and constraints

Condition monitoring applications represent a suitable example of application, where experts are called to tackle with a large amount of data. In this context, the requirements and constraints mainly refer to the need of having available optimized solutions for:

- the exploitation of data coming from disparate sensors;
- the application of suitable data mining and data processing techniques;
- the possibility of assuring the reliability of results, with reference to both measurements and algorithms.

In particular, as far as for the measurements' reliability, this is intended as the possibility of adopting preventive solutions (in terms of rigorous methods and operating procedures, able to avoid or minimize errors from the beginning

3.1.3 Test environment

With reference to Fig. 1, the focus of the analysis is set on: (a) the Machine, (b) the Method and (c) the Measurement. In particular, the system of interest is preliminarily analyzed, in its mechanical and dynamic functionalities on the one hand, and in its software system and control unit and architecture, on the other hand, in order to identify both the machine typical failure modes and the quantities of interest to be monitored, to the ultimate aim of associating the physical meaning of the obtained indications (i.e. measurements), to the phenomenon in exam (i.e. failure modes, faults and damages).

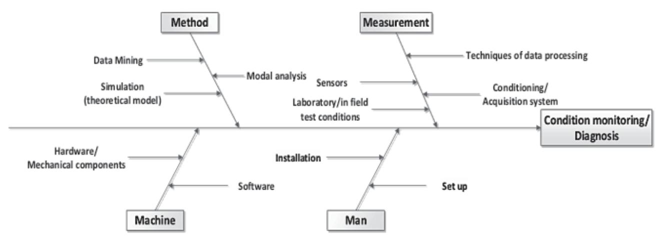

Fig. 1. Ishikawa diagram for a CM application

3.1.4 Test environment

The test environment refers to an axis test rig of a center-less grinding machine tool. It consists of a low-vibration granite machine bed and of a slide system [40]. A high-precision ball-screw system allows converting the rotary movement of the spindle drive into a linear movement of the unloading and infeed/recessing axes, which are rigidly connected to conveniently sized carriages sliding on the linear guidelines [41].

In this case, one of the most critical components, which cause machine breakdown, is the ball screw drive, since it determines the dimensional and surface precision of the work-pieces, depending on wear [35], [41].

The wear is due to the exchanged forces and solicitations, whose behavior is difficult to predict theoretically [42] [43] and for this reason the accuracy requirements satisfaction can be verified by means of an experimental monitoring [44].

Vibration and acoustic emission signals are used, in order to train the algorithms for machine learning developed in Matlab [26], [45].

3.2 STEP 2: Uncertainty evaluation

3.2.1 Uncertainty budget and test plan

Both real and artificial damages are taken into account, in order to apply and compare different machine learning techniques.
In order to guarantee the data accuracy, the following main aspects are taken into account:
- the most suitable positioning of sensors, in order to improve the signal-to- noise ratio of measurement data;
- the calibration of the vibration and acoustic emission (AE) measurement chains (absence of systematic error, repeatability and low level of noise). The analysis is carried out in laboratory and static conditions.
- the check of the quality of measurements when no remarkable damage is present on the system (reference conditions).

In facts, the willing of classifying also real damages requires a careful strategy in the reduction of the uncertainty, due to the intrinsic high variability of the characteristics of natural defects.

3.2.2 Indicators for measurement uncertainty

As far as for the **positioning of sensors**, several methods are studied, compared and selected in literature [46], [47] in order to assess the most suitable positions of the sensors on the machine. Here, sensor placement and frequency ranges to be examined for the condition monitoring application have been analyzed performing an experimental modal analysis, to identify the vibrations due to the resonances of the system and how the excited modal shapes look like [48], [49]. The results obtained in repeatability conditions are compared and qualitatively analyzed in terms of frequency and amplitude the Frequency Response Function (FRF) of each mode.
As far as for the **calibration** of the vibration measurement chain, the reference indicator to carry out the preliminary check of the vibration measurement chain is the sensitivity S expressed in V/g (where g is the acceleration due to gravity, g= 9,807 m/s2). The contribution of the measurement chain to the variability of the measurement data is assessed by means of mean value , and standard deviation s (Eq. 1, Eq. 2), calculated for each i-th estimated value of the sensitivity with i=1,…N (N=10 repeated tests) [51]

$$\bar{S} = \frac{\sum_{i=1}^{N} S_i}{N} \tag{1}$$

$$s = \sqrt{\frac{\sum_{i=1}^{N}(S_i\text{-}\bar{S}_i)^2}{N-1}} \tag{2}$$

As far as for the acoustic emission measurement chain, two acoustic emission sensors are mounted on the machine [35]. The positioning of the AE sensors may be optimized by means of preliminary analysis using FE models [51].
Repeated tests are carried out at a sampling frequency of 500 kHz. The RMS channels have been selected and used to acquire the signals and to check the absence of noise or of systematic error.
Finally, as far as for the **check of the quality of measurements in the reference conditions**, the variability bands ($low = \overline{RMS}\text{-}s_{RMS}$ and $up = \overline{RMS} + s_{RMS}$) for the sensors have been evaluated, when the machine realizes 5 different speeds (from 1000 mm/min up to 5000 mm/min), in steps of 1000 mm/min. The mean value of the Root Mean Square ($\overline{RMS}$) and standard deviation (s_{RMS}) of RMS values calculated on all the repeated tests, are evaluated according to the following equations (Eq. 3 and Eq. 4):

$$\overline{RMS} = \sqrt{\frac{1}{k}\sum_{j=1}^{k} v_{t_{RMS\,j}}} \tag{3}$$

$$s_{RMS} = \sqrt{\frac{\sum_{j=1}^{k}(v_{t_{RMS\,j}}\text{-}\overline{RMS})}{(k-1)}} \tag{4}$$

where $v_{t_{RMS}}$ stands for the RMS value of the measured signal v_t (Eq. 5):

$$v_{t_{RMS}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {v_{t_i}}^2} \tag{5}$$

3.3 STEP 3: Uncertainty reduction

3.3.1 Measurement uncertainty results

With reference to the positioning of the sensors, the qualitative and pragmatic modal analysis allowed selecting the front wall of the guide system as one of the suitable position for the accelerometer. The positioning of the AE sensors is selected, being on the support of the ball nut of the ball screw system, where a high signal-to-noise ratio is assumable.
The sensitivity S obtained for the three measuring axes (x, y and z) of the accelerometer in the laboratory conditions described above, confirmed the calibration certificate indications. Since negligible changes in the sensitivity can be detected, the accelerometer measurement chain is positively verified, in terms of absence of systematic error and low level of noise, and it can be suitably used in field. To assess the functionality of the acoustic emission measurement chain, two AE sensors are mounted on the external sides of the ball screw nut by means of a magnetic support. The AE resulting level in static conditions of the machine results in the order of 0.0020 ± 0.0005 V, (with reference to a voltage full scale of 4V), being the noise really negligible.
The accelerometer is placed on the front wall of the guide, with x positive to the right, y positive upwards, and z parallel to the plane of movement of the slide. The variability bands of the indicator associated to each monitored speed for each

measuring axis (x, y, z) in positive (+) and negative (-) directions are evaluated. Figure 3 and 4 show the variability bands for the $\overline{RMS}$ attesting that that the vibrational signature is defined with very a low dispersion.

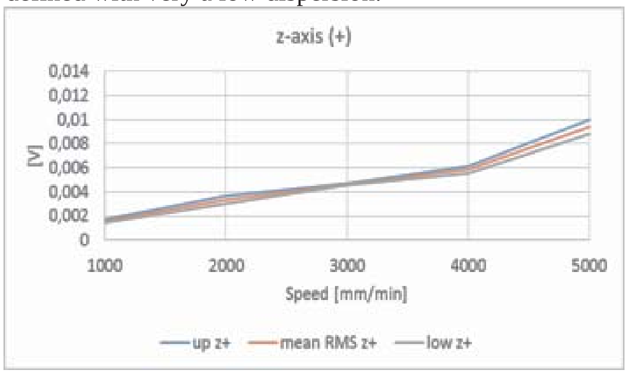

Fig. 3. Variability bands for mean RMS: z-axis measuring in positive (+) direction

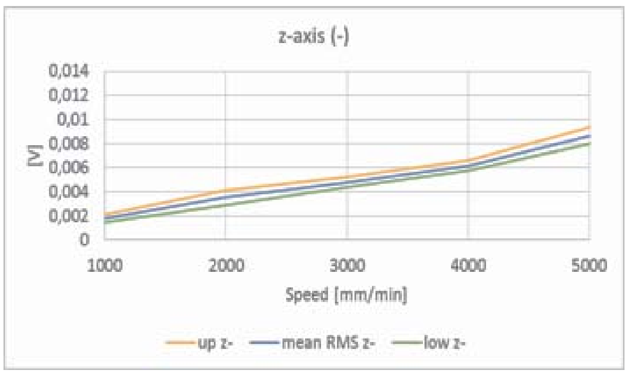

Fig. 4. Variability bands for mean RMS: z-axis measuring in negative (-) direction

Similarly, the trend of the same indicator associated to the different examined speeds together with their estimated variability bands are showed in Fig. 5 and 6, confirming that the AE measurement chains work properly also in working conditions and they can support the numerical procedures for defects classification.

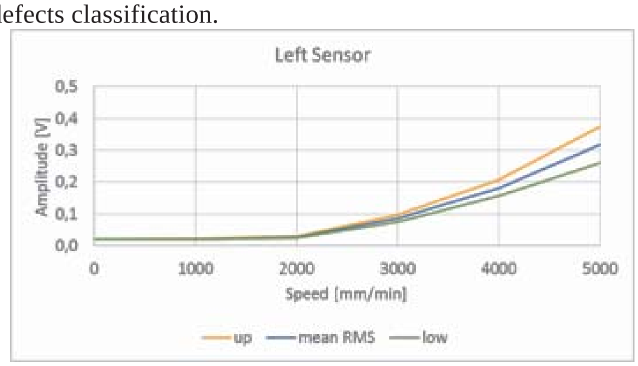

Fig. 5. Variability bands for mean RMS: left AE sensor

The obtained results show that the sensitivity threshold of the measurements to be intended as the maximum value of the indicator variability in correspondence of 0-2000 mm/min velocity range, is very satisfactory.

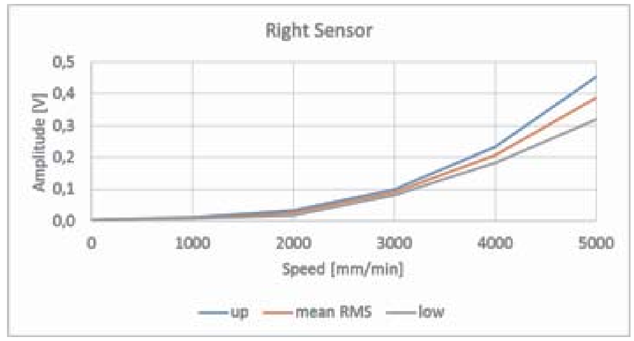

Fig. 6. Variability bands for mean RMS: right AE sensor

3.3.2 Remarks

The accuracy of measurement data is a pre-requisite to be assured as a priori condition, in order to support the success and the reliability of the condition monitoring analysis. In facts, the signature of the system, working in no damage conditions (i.e. the reference conditions), has been defined with a tiny uncertainty range, allowing identifying the occurrence of tiny variations of the working conditions with respect to the arise of defects

4 Conclusions

In this work, as a pre-requisite to be assured, particular attention has been paid to the preliminary calibration of the measurement chains and to the issues connected to the sensor positioning, allowing to define, with a very low level of variability, the working reference conditions for the system in exam.

The methodological approach adopted here is based on the validation analysis performed in advance, with respect to the further analysis for condition monitoring and diagnosis purposes (in terms of action taken for fault recognition, fault localization and identification of causes [52]) based on the evaluation of the measurement uncertainty (in terms of repeatability).

This solution appears suitable, in order to reduce the propagation of errors so that the threshold of defect detectability can be maintained low. This appears useful if defects have to be detected also at an early stage. Further, in order to detect incipient natural defects in complex systems, having a very low detectability threshold appears to be a mandatory requirement.

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