Predictive Maintenance using Incipient Fault Detection

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ABSTRACT

One focus of the Industry 4.0 paradigm is to enable Smart Factories with improved productivity and reduced down-times. In this context, Predictive Maintenance (PM) is a proactive approach to industrial services that optimises maintenance actions based on the system's health. In order to monitor and understand the system's status, effective PM requires dedicated tools capable of managing a large amount of data and discern the right data set required for analysis. As an aid for engineers, the software called MADe can be used. MADe is a model-based platform that can optimise maintenance actions following the information provided by the software itself, concerning sensor selection and functional models. In particular, among many others, MADe incorporates functionalities for incipient fault detection, which may be extremely useful when monitoring systems comprising fatigue or aging sensitive components. In fact, early fault detection enables scheduling of maintenance that will minimise the impact on production outputs. Owing to these considerations, this paper describes a technique for detection of incipient faults components affected by fatigue using an Equivalent Damage Index (EDI). This technique is tested on data taken from the literature in order to verify its potentials.

Keywords: Anomaly Detection, Incipient Fault, Residual Life Estimation, Maintenance-Aware Engineering tool

1. INTRODUCTION

The goals of the Industry 4.0 paradigm are to improve the flexibility, reliability, quality, and safety of production plants, while minimizing inefficiencies due, for instance, to machine downtime (McKinsey, 2015). Therefore, an ever-increasing importance is devoted to the selection of maintenance actions. In this context, Predictive Maintenance (PM) may be defined as a strategy based on monitoring the health condition of systems and components, in order to take appropriate action in an improved timing. The effectiveness of this type of maintenance depends on when a change in the behaviour of the system is detected, since early detection allows the scheduling of actions that minimises the impact on the production output. PM requires an in-depth system analysis for identifying possible failures and then select/position a sensor set, with consequent considerable expenses in terms of personnel training during both the plant design stage and its operating lifetime. Nonetheless, the reduction in downtime expenses and the possibility of managing the related failures in an improved manner makes this technique suitable for an increasing number of sectors and production areas. A possible PM conceptual workflow is depicted in Figure 1 and includes, in the preliminary phase, a functional model that provide insight about all the possible failures (thus, allowing an improved sensor positioning) and, in the operational phase, the collection of sensor data (and subsequent data) processing to perform system diagnosis and prognosis in order to study the best maintenance strategy. In particular, during the plant design (or redesign) phase a functional system model can be used to generate a failure diagram, namely a diagram for each component clearly summarizing all the main failure possibly involved in the component. As for this latter task, the Software *MADe - Maintenance Aware Design environment*, developed by PHM Technology, is perfectly suited for the purpose (Lindsey, Alimardani, & Gallo, 2020). This tool indeed provides several modules that allow users to create functional models, identify critical components, perform risk assessment, compare different maintenance strategies and carry out a sensor analysis to ensure sufficient coverage of failures. Every item engineered to provide a function, can also potentially fail, so it is necessary to assign a failure diagram for every component and sub-system. A failure diagram defines any fault that can lead to functional failure outlining possible causes and failure

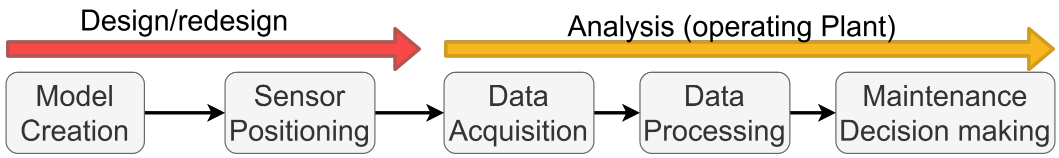

Figure 1. PM possible workflow in the different stages of a plant life cycle (i.e. design stage or operating plant)(Jardine et al., 2006)

mechanisms. A very simple example concerning a component possibly subjected to fatigue is shown in Figure 2. After a model has been created, MADe automatically provides a sensor position analysis driven by the model itself. The tool also include a customized library that contains different types of sensors, each characterized by technical features as well as dimensional and economical characteristics. The technical characteristics of a sensor are linked to the Probability of Detection of the true positives with respect to all the anomalies, and to the specificity, that is the percentage of true positives detected with respect to all the warnings. A sensor can be applied on a system variable (e.g. measuring angular velocity) or on a failure symptom (e.g. monitoring vibration on a rotating component). The software produces all the logical diagnostic rules to identify a fault based on the available sensor set. Finally, MADe provides a specific tool that allows the users to compare different maintenance strategies, such as scheduled maintenance or Condition Based Maintenance, through a Maintenance Cost Estimation. Within all the general-purpose MADe capabilities, whose in-depth description can be found in e.g. (Hess, Stecki, & Clark, 2008), this paper focuses on the detection of incipient fault for components subject to fatigue through the identification of the so-called Equivalent Damage Index.

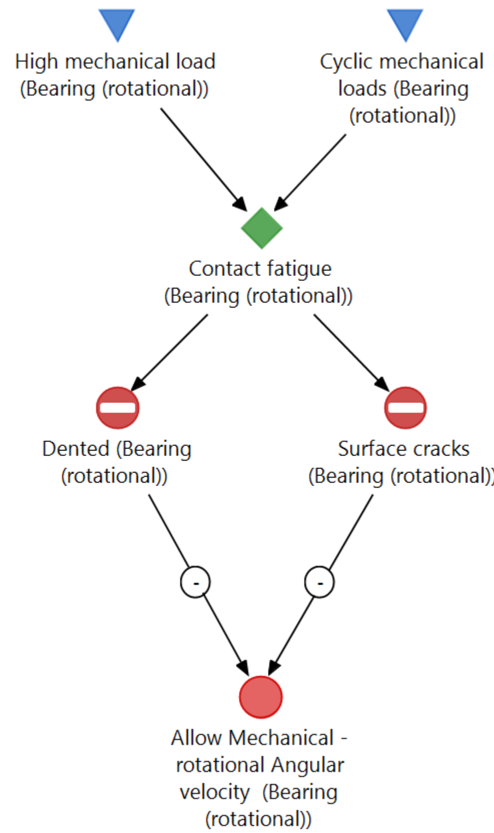

Figure 2. Example of failure diagram for contact fatigue mechanism

2. BASIC BACKGROUND

As known, fatigue is a destructive process that develops in all materials subject to time-dependent states of tension, generally simplified as the sum of various cyclic states of stress. Fatigue phenomena, causing approximately 90% of all mechanical service failures (Campbell, 2008) are generally distinguished in: i) **High Cycle Fatigue (HCF)**, when the deformation is small enough to allow the description of the phenomenon in purely elastic terms, usually is valid for more than 1000 cycles; ii) **Low Cycle Fatigue (LCF)**, when the plastic component of the deformation in certain critical areas of the material represents a significant proportion of the total one. As for HCF, it is a long term failure that develops through three phases: i) **Crack Nucleation**, namely the longest phase whose duration depends on geometrical factors (e.g. roughness or notches) and physical factors (e.g. surface hardness); ii) **Crack Propagation**, when the crack grows due to edge sharpening and, thus, localised tension increase; iii) **Final Failure**, when a brittle fracture occurs because the resisting section is too small to support the applied load. As for the second phase, the crack proceeds and stops, depending on the state of tension, producing the typical beach marks on the breaking surface. In practice, it is possible to identify the symptoms of this fault because the section is reduced so eventual vibration data slightly changes. The appearance of the fracture surface appears very different from a classic brittle fracture by presenting two different areas as shown in Figure 3: the first is a smooth area characterized by beach marks representing the propagation of the crack in the second phase; the second area shows a rough and bright appearance due to the brittle fracture in the third phase. As previously recalled, this paper deals with a method, based on Residual Life Estimation, which consists of an analysis of the complete history of the component subject to HCF to predict failure.

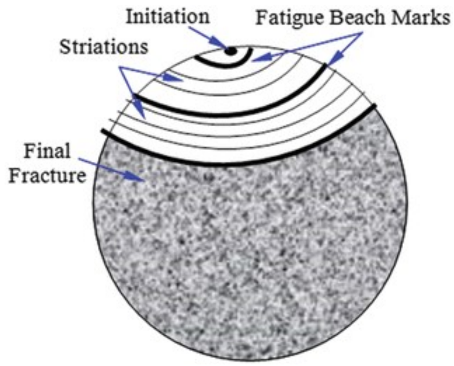

Figure 3. Schematic fatigue fracture surface (Perez, 2016)

3. DATA PROCESSING

Let one suppose that a time history of experimental measurements concerning a component that may fail due to HCF are available (data collection phase in Figure 1. In this phase, Data Processing is essential to create any diagnostic tool. Data Processing algorithms manipulate a batch of data to reduce the complexity of information and organize a data-set for the diagnostic tool. In particular, two data processing methods have been tested for incipient fault detection namely STatistical Analog Monitor (STAM) (Decker, 1979) and Rainflow method (Matsuichi & Endo, 1968). The latter has been finally chosen as it is best suited for fatigue analysis and provides quality resolutions. In practice, the Rainflow method (Matsuichi & Endo, 1968), also known as pagoda roof method, is a counting algorithm used for fatigue analysis. This data processing technique consists in filtering the signal by obtaining a series of periodic waves characterized by the number of cycles, the average and the wave amplitude. In fatigue analysis, these cycles represent hysteresis cycles of the material. Starting from the hypothesis of a significant random signal, which is a portion of the signal that can represent the behavior of the component, the algorithm selects peaks and valleys that will represent the extremes of the half cycles performed by the component; then it counts all the complete cycles, or eventually the half cycles, generating a list similar to the example shown in the Table 1 from raw signal data presented in Figure 4(a). Usually, for the real signals, the mean range and amplitude range are divided into regions to assimilate all the cycles within the regions. This procedure allows to build a histogram as in Figure 5 and simplifies the further step by standardising the cycles in given regions (Nieslony, 2010). The Rainflow method is an approach based on cycles which provides quality resolutions, even on very small amplitude oscillations but loses any information on constant stress states. For this reason it is widely used for fatigue analysis and for vibration sensors where the necessary information concerns the cycles.

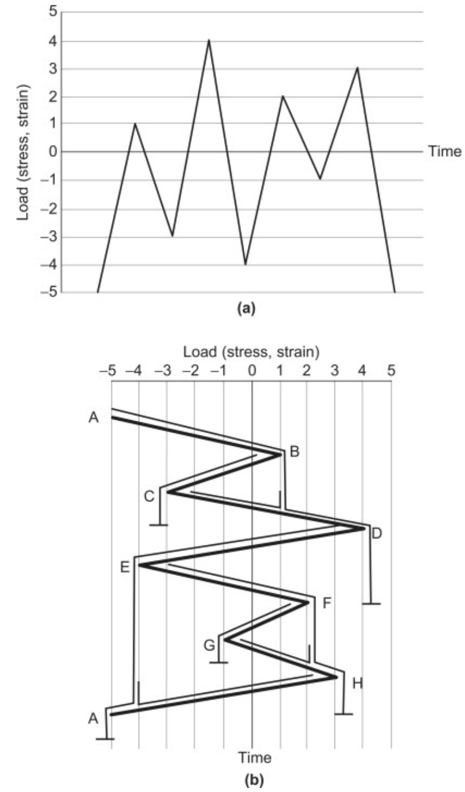

Figure 4. (a) Example of raw data for Rainflow method (b) Illustration of the rainflow counting technique.(Lee & Tjhung, 2012)

Table 1. Example of simple Rainflow processed data (Lee & Tjhung, 2012)

amplitude	mean	number of cycles
9	-0.5	1
4	-1	1
7	-0.5	1
3	0.5	1

4. RESIDUAL LIFE ESTIMATION

Residual Life Estimation is an analysis technique that allows to forecast a failure in a component subject to fatigue and it aims at building a Cumulative Damage Index (CDI), namely a parameter that describes the usage of the component. The CDI may vary between 0 and 1, where 0 indicates a new component and 1 should represent the failure occurrence. This method is typically used with data from load sensors, although more common and simpler sensors, like vibration sensor, can be used to make an indirect measurement and then correlate the measurement with the corresponding load. In any case, the method is powerful but requires the knowledge of several details about the component, hence being difficult to use for general purpose on-field monitoring.

The procedure to develop an estimation is composed of several steps. First of all, it is necessary to characterize the com-

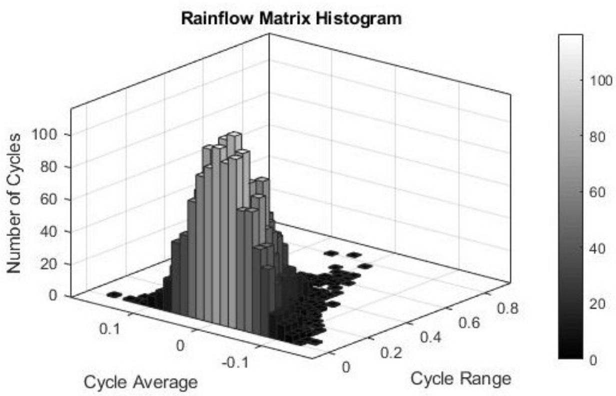

Figure 5. Example of histogram for Rainflow method

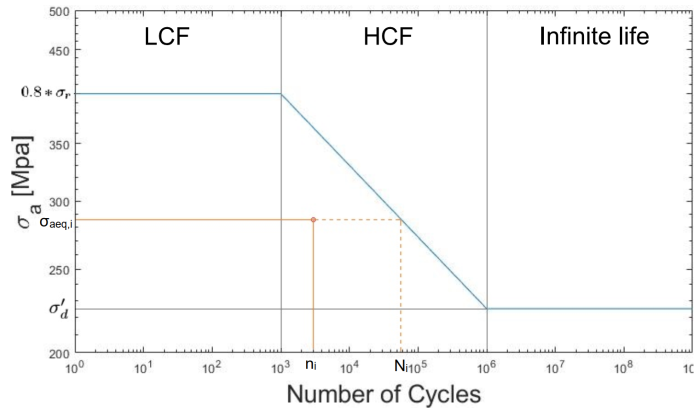

Figure 6. Wöhler curve

ponent in order to build a Wöhler curve, namely a logarithmic curve that identifies three distinct zones as shown in Figure 6. The first zone, almost flat, concerns LCF that occurs with large plastic deformations, which should be avoided during the design phase; the third zone, also almost flat, concerns infinite fatigue life design; the second area, the one of interest for this discussion, concerns HCF. The Wöhler curve for a generic component can be built, and then correctly employed, by knowing:

- **Employed Material**. The values of tensile, σ_r, and fatigue, σ_D, strengths are required.
- **Type of stress and configuration**. It is necessary to know the type of stress involved and the constrain configuration in order to correlate deformation signal and actual load. Also, the knowledge about the type of load allows to use correlation between actual stress and testing load.
- **Additional component information**. In a generic component, there are three parameters that reduce the fatigue strength, $sigma_D$ of the material, i.e. notch factor, size factor, surface factor. The following equations holds:

$$\sigma'_D = \frac{K_S\, K_D}{K_F}\, \sigma_D \tag{1}$$

where:
- σ'_D = corrected fatigue strength ($\sigma'_D < \sigma_D$);
- K_F = Notch Factor;
- K_D = Size Factor;
- K_S = Surface Factor.

The values of σ_r and σ'_D can be used to retrieve the Wöhler curve of the component, as shown in Figure 6. Subsequently, after the mentioned data processing and (possibly) a deformation signal being converted in stress data, it is necessary to compute an equivalent stress amplitude, as follows:

$$\sigma_{aeq} = \frac{\sigma_a}{(1 - \frac{\sigma_m}{\sigma_r})} \tag{2}$$

where:
- σ_{aeq} = equivalent stress amplitude;
- σ_a = stress amplitude;
- σ_m = mean stress;
- σ_r = tensile strength.

Finally, the Palmgren-Miner Rule (Juvinall & Marshek, 1999) is used to sum up the effects of all periodic signal packets counted by the Rainflow method, in order to finally compute the CDI as follows:

$$CDI = \sum_{i=1}^{k} \frac{n_i}{N_i} \tag{3}$$

where:
- k = No. of batches;
- n_i = No. of cycles of the i^{th} batch;
- N= No. of cycles to failure of the i^{th} batch according to the Wöhler curve.

As it may be evident, given the large amount of information required, it is rather difficult to retrieve a reliable CDI value without spending a lot of resources. Therefore, a comparative method may be preferable, namely the Incipient fault Identification technique described hereafter, that analyzes different behaviors of the same component avoiding all the above mentioned hypotheses.

5. INCIPIENT FAULT IDENTIFICATION

This section describes a technique for the detection of incipient fault in fatigue sensitive components. A feature of the signal called Equivalent Damage Index (EDI) is used to compare different working behaviours to identify incipient fault or anomaly. This method is very similar to the previous one but, being focused on the comparison between different duty cycles, it does not need all the information and assumptions foreseen for the Residual Life Estimation method.

5.1. Data Set

The method developed has been applied on a test rig in which the fatigue behaviour of ball bearings is analyzed. This data set has been generated by the IMS center for Intelligent Maintenance Systems (Qiu, Lee, Lin, & Yu, 2006) and concerns bearing run-to-failure experiments performed under normal load conditions on a specially designed test rig. As shown in Figure 7, the test rig consists of four bearings, each equipped with 2 High Sensitivity accelerometers, placed on a shaft moved at a constant speed of 2000 RPM by an AC motor coupled by belt. A radial load of 6000 lbs is applied to the shaft by the two central bearings with a spring mechanism. Data acquisition is performed by a DAQCard-6062E with 4 channels, one for each bearing, using a sampling rate of 20 kHz for 20480 points every 10 minutes until failure. The data-sets are composed of 984 batches of 1 second every 10 minutes allowing to record the entire life of the bearings that lasts around a week.

5.2. Build-up of Equivalent Damage Index

The process to be implemented to obtain an Equivalent Damage Index starts from the use of the Rainflow method. Then it is required to build a logarithmic curve with the same concept as the Wöhler curve whose characteristic points are r instead of σ_r, and d instead of σ'_D. Numerical values for r and d have been empirically chosen so as to allow the analysis to be performed with satisfactory results. Nonetheless, the dependence of the final outcome on such parameters is included in paragraph 5.3; these are the values chosen for r and d respectively in terms of amplitude and number of cycles.:

$$r = \{100; 10^3\}$$

$$d = \{10; 10^6\}$$

Similarly to Eq. 2, the equivalent amplitude, a_{eq}, for each set of data obtained via the Rainflow method has been found as follows:

$$a_{eq} = \frac{a}{1 - \frac{m}{r_a}} \tag{4}$$

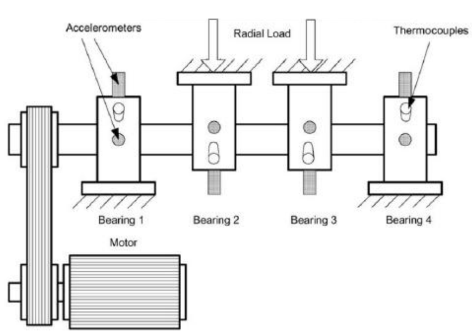

Figure 7. Bearing test rig and sensor positioning (Qiu et al., 2006)

where:
- a_{eq} = equivalent amplitude;
- a = amplitude of the periodic wave;
- m = mean value of the periodic wave;
- r_a = amplitude value of point r, set to 10.

By using a logarithmic plot (similarly to the Wöhler curve) and the equivalent amplitude value, a_{eq}, the maximum number of cycles N_i at failure can be found and employed withinthe Palmgren-Miner rule (as in Eq. 3. Finally, the computed EDI value is normalized on the first 100 batches, in order to obtain comparable and noise-free results.

5.3. Results

The proposed results are obtained by analysing the x-axis of the first channel, i.e. the one referring to a faulty bearing. The outcome will be compared with the available results through a simple collection of maximum values for each batch. The calculation time needed to carry out the EDI analysis is 33% longer but it is still reasonable considering that 984 batches, corresponding to 7 days, were analyzed in just over two minutes. The graphs containing the results do not show the first 400 batches to zoom in on the incipient fault. The first comparison concerns the first bearing, the faulty one. The data analysed by the maximum value method is shown in Figure 8, where it is possible to notice the incipient fault barely starting from batch 700 and the failure starting around batch 900. As for the EDI method, results are shown in Figure 9, where three behaviors are clearly highlighted:

- **Normal behavior** characterized by EDI close to 1;
- **Incipient fault** around batch 533 the EDI grows in two batches by 50% and reaches values around 20 from batch 700;
- **Failure** from batch 900 in this phase the EDI reaches 1900.

Another important detail is described in Figure 10, where it can be noted in channel four, referring to a healthy bearing, the effect of the incipient fault found in channel one. This can be useful, since the anomaly detected in channel four can validate the measurements made by the sensor placed on channel one, hence avoiding false positives and greatly improving the

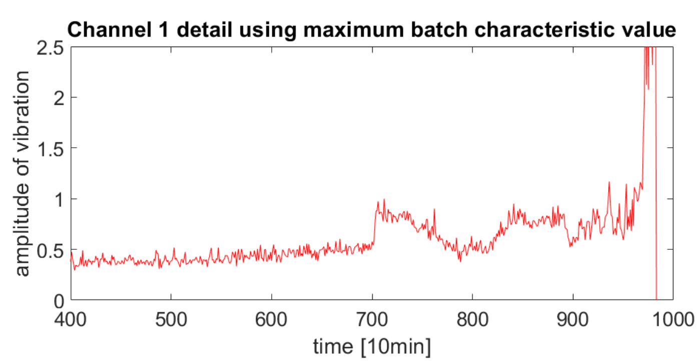

Figure 8. Plot of maximum value for first channel

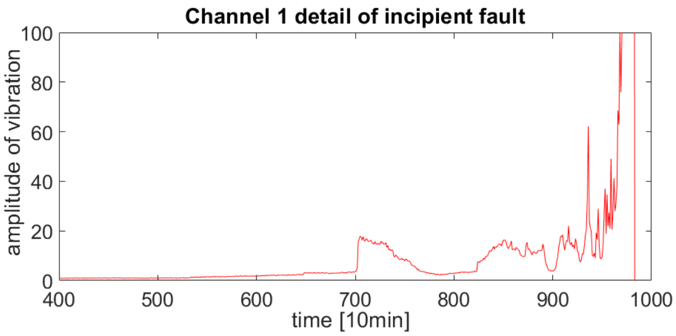

Figure 9. Plot of EDI of first channel

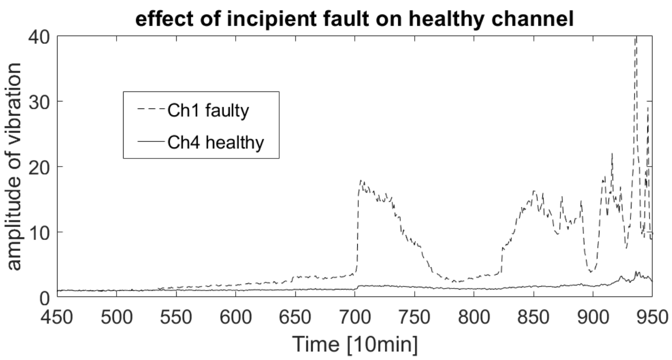

Figure 10. Close-up to effect of incipient fault on healthy channel

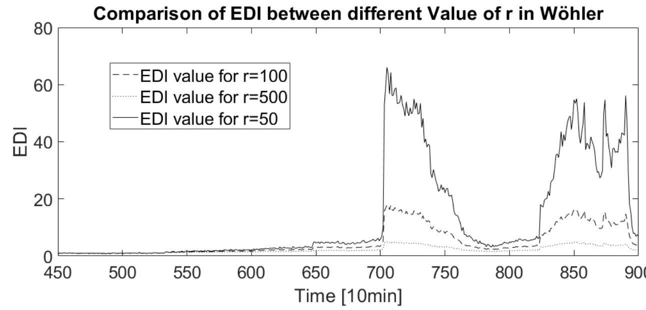

Figure 11. Sensitivity of the method to the parameter r

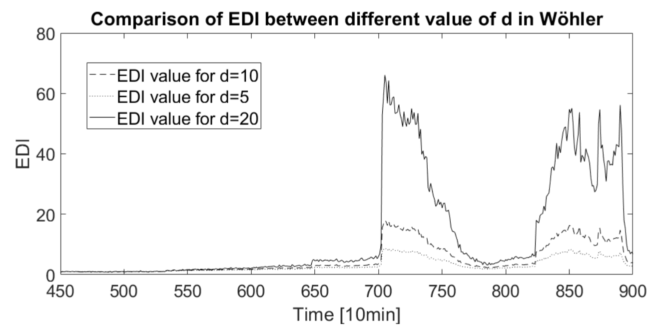

Figure 12. Sensitivity of the method to the parameter d

reliability of the sensors.
Since this method is comparative, some parameters have been chosen arbitrarily. Therefore, the sensitivity of the method is analyzed with respect to the following parameters:

- value r_a used in Eq. 4;
- amplitude values of r and d in the EDI-related Wöhler Curve.

As for the sensitivity analysis on r_a, values 10, 50, 100 have tested. Table 2 shows the results concerning the percentage of difference of the EDI values: totals and subtotals in the Incipient fault and Failure sectors. Results indicate almost no sensitivity in the incipient fault section and higher sensitivity in the failure section, while maintaining an acceptable value.
The second sensitivity analysis regards the amplitude of value r. This analysis highlights a strong influence of the r value on the EDI calculation with a percentage difference around 50%, However, as shown in Figure 11, the use of one of the three parameters does not affect the effectiveness of the method allowing to detect the incipient fault around the batch 533. It is important to note that reducing the r value increases the EDI value at the expense of increased noise.
The third sensitivity analysis regards the amplitude value of d; similarly to the previous analysis, the EDI value highly depends on the d parameter as shown in Figure 12. It can be seen that, even in this case, increasing the d parameter too much leads to an excessive increase in noise.

Table 2. Sensitivity of the method to the parameter r_a; mean percentage difference

r_a **value**	**total**	**incipient**	**failure**
50	0.16	1.26	0.17
100	0.19	1.41	0.20

6. CONCLUSION

Incipient fault identification has been tested by comparing results produced by an "Equivalent Damage Index (EDI)" with the ones produced by a second statistical method, i.e. the highest value, confirming that an EDI-based investigation allows to identify an incipient fault well before the mentioned statistical feature. In addition, the method has proved to be negligibly sensitive, at least in terms of functionality, to the parameters set a priori. Despite its functionality is actually maintained, there are dependencies of the EDI value and the associated noise with respect to the parameters that define the logarithmic curve. By employing an EDI and comparing signals coming from parallel sensors in systems comprising redundant components, it is possible to validate the fault signal, to check for the presence of repercussions, and thus to increase the sensor reliability. This method, included in the MADe tool, could be tested on other data sets to further validate its effectiveness.

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BIOGRAPHIES

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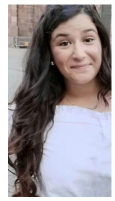

Cecilia Gattino she received the Bachelor degree in Mechanical Engineering from the University of Genova, and the Master degree in Mechanical Engineering Design and Production from the University of Genova in 2017 and 2020, respectively. She was an International student in Institut National des Sciences Appliquées de Strasbourg (INSA) Strasbourg.

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