Measurement uncertainty of contact and non-contact techniques on condition monitoring of complex industrial components

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Abstract. The paper discusses the effect of changing the sensor’s configuration and the data processing procedure on the results of Neural Networks (NN) algorithms. They are used for both classification and prediction in Condition Monitoring (CM) applications of real cutting machines of industrial automated production lines.

In particular, a comparison between non-contact techniques (laser displacement sensors) and contact ones (tri-axial accelerometers) is carried out. The robustness of results is studied, depending on the type of sensor and of the feature for monitoring, on the position and orientation of the sensors themselves. The physical meaning of choosing is taken into account throughout the procedure, in order to define optimized practical configurations based on the uncertainty evaluation.

Experimental results show the possibility of validating a configuration of good compromise based on a mixing of different types of sensors, for the benefit of the monitoring strategy itself and of the consequent preventive and condition-based maintenance actions.

1. Introduction

Condition monitoring (CM) of assets and the subsequent maintenance actions can help to increase the lifetime of assets and to reduce the costs due to the damage of items and the lack of production [1]. For this reason it is becoming more and more interesting for companies, seeking the operational continuity of industrial processes.

In condition monitoring, different approaches are possible:

- Data-driven analysis methods, based on experimental data. They are limited because cannot accurately predict scenarios outside the training dataset.
- Physics-based approaches, based on models that describe the behavior of assets, allowing us to generate data corresponding to different degradation stages of the machine.
- A hybrid approach, that combines physics-based and data-driven modeling, that can overcome these limitations, augmenting experimental datasets with the addition of data generated by models describing the behavior of assets [2].

These CM techniques are typically based on vibration analysis and include the following steps: physics-based modeling, data acquisition, signal processing and features extraction, and, finally, fault identification/prediction.
The identification of faults and the subsequent prediction, are mostly made by neural network or machine learning algorithms. Merging physics-based and experimental data and extracting synthetic features to train intelligent algorithms for diagnosis and prognosis purposes, is not a trivial task [3].

Many aspects have to be taken into account to guarantee the efficaciousness of the analysis [4]:

- sensors type, number of sensors, to be installed,
- positioning of sensors,
- choice of the most significant features for state identification.

About the typology of sensors and the number to be installed, new low-cost sensor technologies allow embedding of many sensor directly on the application, asking for reliable procedures of sensor fusion management [5]. Data fusion techniques combine data from multiple different sensors to achieve improved accuracies and greater robustness, compared to what can be achieved by the use of a single sensor typology. This is an opportunity, but it also makes more complex data management and processing [6], [7] and requires specific solutions to extract synthetic features from a large amount of different raw data.

Optimal positioning of tri-axial accelerometers, in particular in complex mechanical structures, generally requires a pre-test study, either by Finite Element Method (FEM) simulation or by experimental analysis. In literature, criteria of positioning according the mass weighting and modal vibration energy criteria can be found [8], [9], but these solutions are optimized especially for modal analysis of structures and they do not appear completely exhaustive for other applications, like CM [10].

For this reason, as well as for economic reasons, the goal is to create compact kits for condition monitoring, using the minimum number of sensors and indicators, useful for obtaining the required accuracy of the results.

Based on the above considerations, the goal of the paper is evaluating the effects of the choice among different sensors on the results of Neural Networks algorithms, which are used for both classification and prediction in a real condition monitoring application. The paper discusses the effects of type, position and orientation of sensors and of features, in order to define optimized practical configurations, reducing as much as possible the computing effort for CM.

In particular, a comparison between non-contact techniques (laser displacement sensors) and contact ones (tri-axial accelerometers and force sensors) will be carried out, with the aim of merging quite different measuring characteristics.

2. Materials and methods

A high performance cutting stage for non-woven tissue will be considered as test-case.

The test bench includes a revolving knife and an anvil, where the former is constituted by a cylinder with sharp profiles, and the latter consists of a non-driven roller supported in a lubricated cradle that exerts an elastic force against the cutting unit by a pneumatic system (Figure 1).

With the aim of monitoring its operating conditions, different kind of sensors have been installed onto the cutting unit:

- A laser displacement sensor
- A quartz force sensor
- Piezoelectric cube and ring accelerometers.

Positioning of all these kind of sensors is according to the literature indications, in order to optimize signal to noise ratio [12].

Two different NN algorithms are studied with the purpose of diagnosis and prognosis:
• a classification NN, able to recognize the actual working status of the machinery among 4 different conditions, corresponding to different levels of the knife wear;
• a fitting NN, able to identify the operating time of the machine starting from a reference one.

Figure 1. 3D drawing of the system, composed of a knife (indicated by K) and an anvil (indicated by KK) [11].

The NN will act in the training and testing phases by using synthetic features, calculated on the base of sensors raw data.

The features, in both the time and frequency domain, have to be sensitive to the periodic cutting action, and to the effect of the wear of the sharp profile on the cutting.

A preliminary study, based on the physical behaviour of the machine, allowed to identify the most significant features for this specific application:

1. in the time domain:
   – RMS
   – Kurtosis
   – Mean value of the amplitude peaks
   – Median value of the amplitude peaks
   – Standard deviation of the amplitude peaks
2. in the frequency domain:
   – Band acceleration content
   – Power content of the main harmonics of interest.

In a first analysis, as a reference case, all the cited features and accelerometers sensors have been considered for NN processing.

Figure 2 shows, as an example, the results for the classification NN among four operating conditions. They are very satisfying: the net is able to recognize correctly all the conditions of interest. The output of NN is 1 in correspondence to the addressed condition, and 0 in correspondence to the all other conditions. That means right classification.

In the same condition also the fitting NN has been studied, with reference to its capability of individuating the length of the utilization period: the net correctly detect the usage time of the machine, with a satisfactory error, being less than 2% of the whole-time interval of testing.
Figure 2. Outputs of the classification NN (reference case):
(a) Condition 1, (b) Condition 2, (c) Condition 3, (d) Condition 4.

In order to reduce the computing effort and, in perspective, to transfer on-line the data processing, the minimum number of features should be considered.

Taking into account this need, the analysis was carried out only considering:

- Kurtosis as a feature
- other types of sensors in addition to the accelerometers, that is:
  - a force sensor
  - a laser displacement sensor.

Comparison is now carried on, with respect to the following aspects:

- Typology of sensors.
- Orientation of sensors (x, y, z directions).
- Position of sensors (positioning on K or KK).
- Sensors fusion solutions.

As key performance indicators for the fitting and the classification NNs, the following parameters will be taken into account:

- for fitting, based on n tests, the Mean Squared Error (MSE) whit respect to the target values $t_i$:
  \[
  \text{MSE} = \frac{\sum_{i=1}^{n}(x_i - t_i)^2}{n}
  \]
- for classification, based on N tests, the Average cross-entropy (CE)
\[ CE = \left| \frac{\sum_{i=1}^{N} c_{e_i}}{N} \right| \]

where, for each pair of output-target \((x_i \text{ and } t_i, \text{ respectively})\):

\[ c_{e_i} = -t_i \cdot \log(x_i) \]

3. Results

In figure 3, 4 and 5, the performance of the NNs is represented, in correspondence to different configurations for typology, orientation, position of sensors. Variability of results is also represented by means of error bars.

In each figure, the following nomenclature has been used, to indicate the specific configurations considered:

- A: stands for accelerometer
- FS: stands for force transducer
- LDS: stands for laser displacement sensor
- c: stands for cube typology accelerometer
- r: stands for ring typology accelerometer
- K: stands for positioning on the knife support
- KK: stands for positioning on the anvil support
- B: stands for positioning on the basement
- x: stands for x-axis
- y: stands for y-axis

Axis specification means that the cut is in the direction of the axis and only data from that axis are considered.

No axis specification indicates that data from all the three axes have been used.

For instance AcB means: data from a tri-axial accelerometer, of cube type, mounted onto the basement of the cutting machine.

Figure 3 shows that, for the fitting NN, results are generally better, also in terms of variability, if all the three axes of the accelerometers are considered. Positioning on the basement, far from the cutting point, provides worse results than others. That appears quite obvious, even though it can be assumed as a confirmation of the used feature.

Figure 4 refers again to the fitting NN; in particular, a comparison is shown, using the data of single measuring components in the cutting direction of different sensors. Results corresponding to the LDS are better with respect to some accelerometers, depending on their positioning. Furthermore, if the same number of sensors is used, using a group of different types of sensors is better than a group of accelerometers.

Figure 5 describes the effects of limiting the number of features on classification capability of NN.

For the classification NN, the level of cross entropy is, on average, unsatisfactory; furthermore, no significant effect of type of sensor and of position is detected.

It must be observed that in classification, for good results, an increased number of features is requested.
Figure 3. Fitting algorithm: effects of the number of axes of the accelerometers.

Figure 4. Fitting algorithm: effects of typology and positioning of transducers.

Figure 5. Classification algorithm: effects of typology and positioning of transducers.
4. Conclusions
The paper discusses the effect of type, positioning and orientation of sensors used for condition monitoring and the definition of suitable features, on the results of NN algorithms, which have been implemented for both classification and prediction of the wear of a cutting unit for non-woven tissue. A reference situation including all the available sensors and the selected features has been set, showing that very satisfactory results could be achieved for NNs used in both classification and prediction for CM purposes.

With the aim of reducing the efforts in terms of number and cost of sensors and of testing and computation effort, reduced packages have been also considered, including only a part of sensors and features. In particular, a comparison among contact and non-contact techniques and an analysis of single feature selection have been carried out.

The main results can be summarized according to the following indications:

- for fitting, a configuration based on a mixing of different types of sensors is a convenient solution for the monitoring strategy and that allows to use the Kurtosis as a single feature.
- for classification, an increased number of features is requested, if satisfactory results want to be reached.

The way to harmonize the approach for both fitting and classification will be studied in the future, in order to realize one simple configuration for both purposes.

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