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Hybrid approach and sensor fusion for reliable condition monitoring of a mechatronic apparatus

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***Abstract* – In this paper the results are presented of a methodology for identification of the best setting of a mechatronic device at its set-up and/or of fault occurrence in working conditions. The condition monitoring approach merges the information deriving from experimental data of sensors and from a simulation model. The methodology is used to identify the most suitable quantities to be measured, independently on location for sensors. The hybrid information suggests a synthetic set of features, able to identify specific statuses of the mechatronic system, different as for initial setting and/or for the occurrence of faults, to be processed by advanced algorithms like Artificial Neural Networks. The tests show that the methodology is able to realize a resolute and reliable condition monitoring of a mechatronic system in real scale, with reference to both the parameters of setting and to the occurrence of wear and lubrication problems in the kinematic linkage. Finally, the information content of data deriving from internal sensors to the controller is maximized, so reducing the need of external ones for reliable condition monitoring applications.**

Keywords – Sensor fusion, Measurement accuracy, Repeatability, Condition monitoring, Diagnostics, Simulation.

I. INTRODUCTION

Condition Monitoring (CM) of assets, in particular automated production lines, is a topic involving more and more interest in modern industrial scenarios, due to many advantages, which can be reached. To only cite the most important aspects, the following results are possible:

- the optimization of set-up and working conditions;
- the improvement of maintenance strategies;
- the increase of the reliability of operations.

Nevertheless, many aspects should be considered and approached if effective, accurate, reliable methods have to be provided in the field of real industrial applications, which are also able to be of general validity.

The main topics to be solved can be summarized as follows:

- purely data driven methods are often expensive from the computation and experimentation point of view [1]; the use of advanced analytics and algorithms, like Artificial Neural Networks (ANN) makes possible achieving interesting results, even though they have to be optimized for the specific application [2];
- simulation and modelling, merged to experiments of mechatronic systems can improve the monitoring and prognostic capability, in particular when reliability considerations are of concern; nevertheless, the so-called hybrid approach should be simple to implement and of general validity [3];
- networking of sensors is more and more feasible, due to the increased possibility of miniaturizing and interconnecting them, even though trade-off between amount of data and the load in terms of time and computation resources has to be considered. Furthermore, the possibility of using internal sensors at the controllers, which are already present for automation purposes, is often preferable to the installation of external sensors for monitoring purposes;
- features for status description should be synthetic, reliable, accurate, and, above all, meaningful, in order to make easy to the post processing algorithms, the acknowledgement of statuses, which are only slightly different. Features' behaviour depends on many factors, like the physical quantity, the sensor type, the position and so on. Many attempts to select the most suitable features according to general rules have been made, which are able to work for features' selection and/or ranking [4], [5], [6], in an automatic [7 - 8] or unsupervised way [9]; how much these methods are general is still an open discussion.

In this paper, the Authors aim at presenting the generalization of a methodology, which has been already discussed in [10] and [11], with reference to a preliminary application, which is both "hybrid" and based on sensor fusion.

The main steps of the methodology are described in the following.

Features in the time and frequency domain, which are both typical and/or specifically defined for CM applications [12-15], are evaluated by merging experimental data and computations by a simulation model of the mechatronic system, concerning its kinematic and dynamic behaviour. The model is not used for a preliminary design of the system [16], neither to optimize the positioning accuracy of a manipulator [17]; its main usefulness, is to allow us to indirectly evaluate quantities of interest for CM, also at different positions with respect to the ones the sensors are installed on. Features of interest also refer to differences between measured and estimated values of the same quantities, "fusing" the whole information. The model, by a sensitivity analysis with reference to the effects of interest, indicates also the time windows of experimental and theoretical data, which are more physically related to the phenomenon of interest, improving the physical meaning of the feature.

Based on these considerations, in this paper a set of features will be identified, to be post-processed by ANN, for optimum setting recognition and/or the occurrence of a fault in the kinematic chain.

In Section II, the experimental test case is described, which is a mechatronic system in real scale, together with the steps of the data flow, able to make possible the evaluation of many features in both time and frequency domain.

In Section III, the main results will be presented, concerning the behaviour of the different features, when operating conditions are varied, changing the *jload* setting, or when the friction characteristics are modified by wear or changing the status of lubrication. In particular, the most suitable features will be identified, to selectively detect the different statuses. This will allow us to also reduce the size of the feature's data set, according to metrological and physical criteria, keeping a reliable and resolute procedure.

Conclusions end the paper, indicating also possible developments of the approach, based on the indications the present work makes available.

II. MATERIALS AND METHODS

The mechatronic apparatus under study is depicted in Fig. 1; it realizes a packaging action by an alternate linear and rotating motion.

The scheme of Fig. 2 shows the measurement apparatuses, with reference to both internal sensors to the controller, i.e. angular position and motor currents, and to the external ones, Laser Doppler Vibrometer (LDV) and Micro Electro-Mechanical System (MEMS) tri-axis accelerometer.

The methodology is based on the following main steps:

- Realization of a kinematic and dynamic model of the system, whose outputs are: angular position at the motor, angular velocity at the motor, linear acceleration at the ball screw shaft and current at the motor.
- Realization of experiments, corresponding to different settings, different *jload* parameter, or different operating conditions, varying the lubrication conditions of the ball screw shaft.
- Multiple runs of the model, considering as the input one quantity among the measured ones:
  - Angular position from the encoder, *Mpos*,
  - Angular velocity from the motor controller, *Mvela*,
  - Electric current at the driving servomotor, *Mcur*,
  - Linear acceleration from the accelerometer, *Maccl*,
  - Linear velocity from the LDV, *Mvell*,
- Definition, calculation and selection of the most suitable features for the system status identification. The calculation of the features is carried out on the basis of the comparison between outputs of the model and data deriving from measurements. In addition, some more features are obtained by processing Tracking Deviation (TD) data, supplied by the PLC, and related to the difference between the actual and the theoretical angular position of the motor axis.
- Post-processing of features by ANN, in order to experimentally optimize the whole procedure for CM.

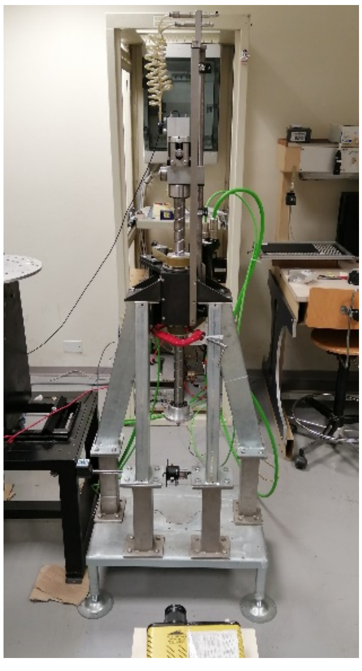

Fig. 1. Picture of the mechatronic device

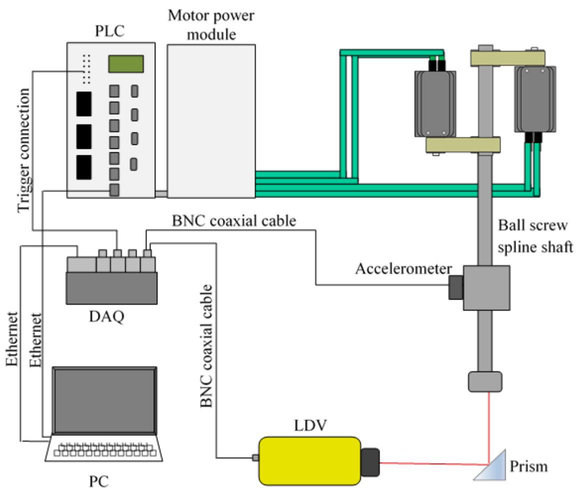

Fig. 2. Scheme of the measurement and data acquisition apparatus

III. RESULTS AND DISCUSSIONS

The tests have been realized varying the *jload* setting in the range 3 to 9 kg cm^2 at three different lubrication conditions:

- *NOG,* corresponding to uncontrolled status of lubrication
- *G1*, corresponding to a only few grease quantity applied on the ball screw
- *G2*, corresponding to the right amount of grease applied on the ball screw.

The sinusoidal motion frequency is 3 Hz, which is a challenging operating situation. The acquisition data rate is 1 kHz, for all the measured quantities.

Although simple and only coarsely validated, the model shows a satisfactory agreement with experimental data, as illustrated in Fig. 3. The comparison is between experimental data of current, *Mcur*, and simulation ones, based on accelerometer measurements, *Scur-Maccl*.

It has to be pointed out that model is used mainly to achieve the following results:

- Evaluation of quantities, even though measured at different points of the system or by other transducers;
- Sensitivity analysis to the specific effects;
- Identification of time windows during the operating cycle, where the effects of a phenomenon of interest are more remarkable.

All these actions are envisaged to improve the physical meaning of the features.

As an example, Fig.4 shows the effect of varying the friction coefficient in the ball screw assembly, with reference to the motor current.

Preliminary analysis has been also carried out with reference to the definition of the set of features to be proposed for analysis by ANN.

More than 90 features have been defined and evaluated in both the time and frequency domain and referred to both measured and simulated quantities: they will be selected, in order to identify a set of accurate and reliable features, of very limited number, to be processed by ANN.

The selection procedure considers metrological aspects, like repeatability and uncertainty of data, and physical likelihood, related to the suggestions by the simulation model. With respect to the ranking and selection proposals, which are available in literature, this approach could be classified as a supervised method; it predicts the feature relevance by physical considerations, without measuring previously the feature correlation with the class label [18].

As an example, the data of Fig. 5 and Fig. 6 show differences of amplitude 98th percentile (*PRC98*) of measured and simulated values of linear acceleration of ball screw and motor current, respectively, when the setting of the system, *jload*, is changed. The values are normalized with respect to the ones obtained when the *jload* is set to 5.5 kg cm^2 and the lubrication condition is *NOG*.

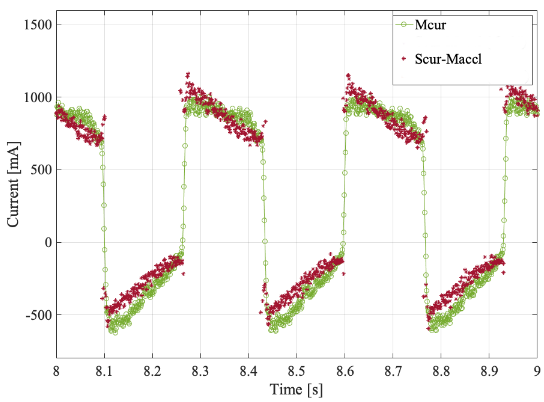

Fig. 3. Model (red) and measured (green) time series

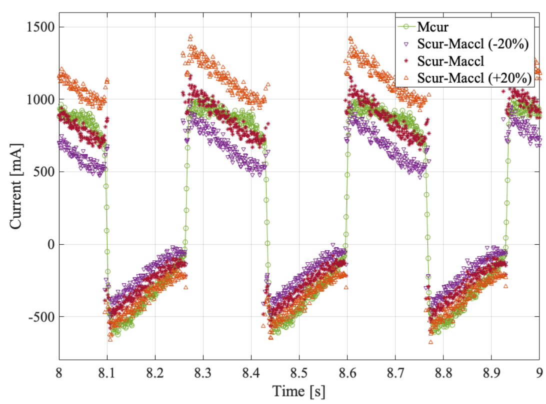

Fig. 4. Sensitivity analysis

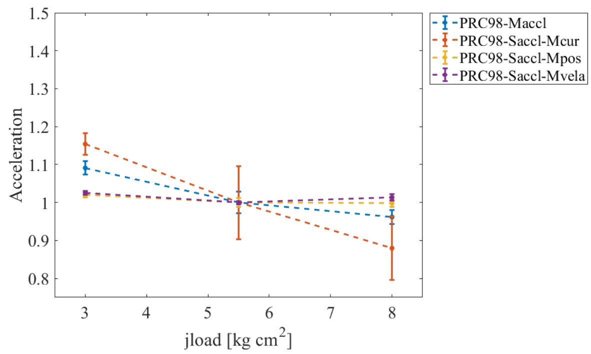

Fig. 5. 98th percentile, linear acceleration, NOG. The values are normalized.

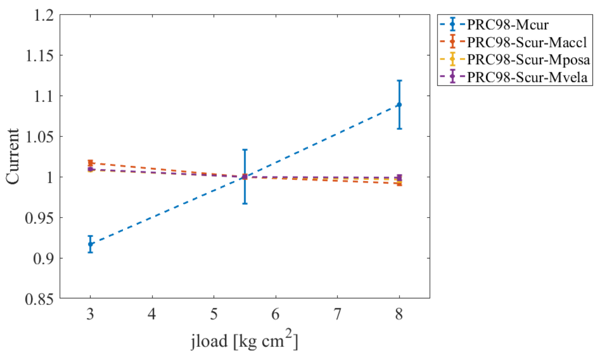

Fig. 6. 98th percentile of measured and simulated currents vs jload, NOG. The values are normalized.

It is quite evident that differences among operating conditions with different settings are remarkable only when linear accelerations or currents are considered, both measured and simulated by the model, (i.e. *PRC98-Saccl-Mcur* and *PRC98-Mcur*).

The temporal trends of TD and motor current in Fig. 7 and Fig. 8, show that differences arise, at the same *jload*, when the lubrication condition changes; in particular, TD seems the most sensitive parameter with respect to variations in the lubrication state. That is confirmed also by features calculated with reference to TD, as the 98th percentile level shows (Fig. 9). It can be seen that the three different lubrication conditions are clearly distinguished, if their variability is considered. The repeatability of data is represented as error bars.

The lubrication effects are shown also by features based on measured current (Fig. 10 and Fig. 11 in comparison with Fig. 5 and Fig. 6), with reduced gap with respect to TD.

The calculated features have been used to train a classification ANN, built to distinguish among the following 9 classes, obtained by combining the different *jload* and lubrication conditions:

1. *jload 3 – NOG*
2. *jload 3 – G1*
3. *jload 3 – G2*
4. *jload 5.5 – NOG*
5. *jload 5.5 – G1*
6. *jload 5.5 – G2*
7. *jload 8 – NOG*
8. *jload 8 – G1*
9. *jload 8 – G2*

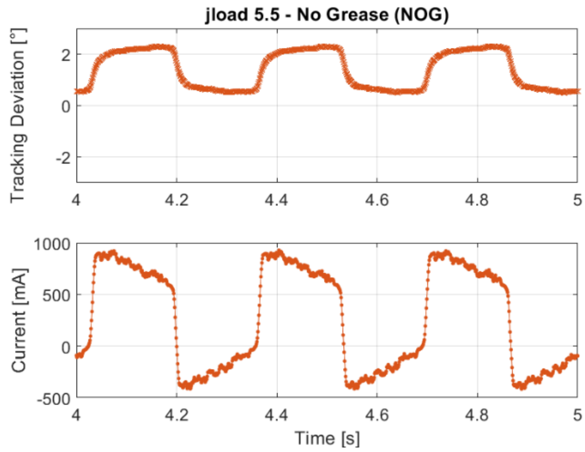

Fig. 7. Temporal trend of TD and current, for the NOG lubrication condition.

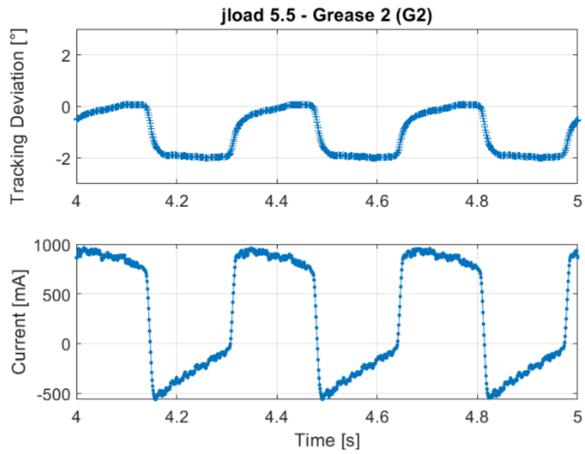

Fig. 8. Temporal trend of TD and current, for the G2 lubrication condition.

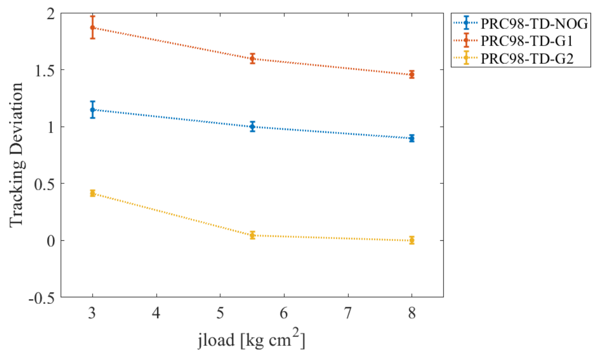

Fig. 9. TD 98th percentile vs jload, for different lubrication conditions. The values are normalized.

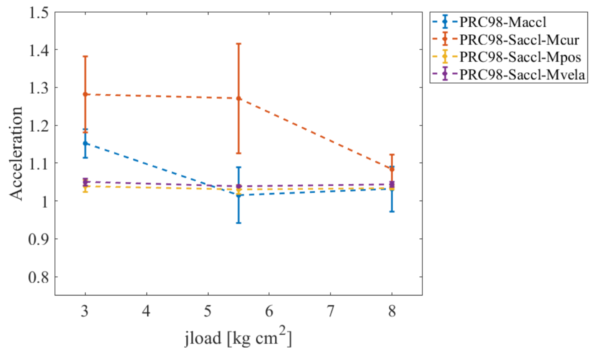

Fig. 10. 98th percentile of measured and simulated accelerations vs jload, for the G2 lubrication condition. The values are normalized.

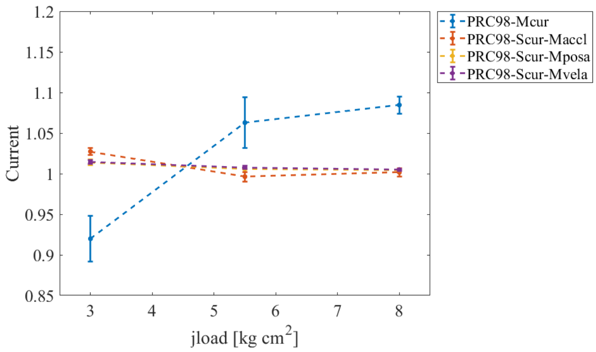

Fig. 11. 98th percentile of measured and simulated currents vs jload, for the G2 lubrication condition. The values are normalized.

The ANN results are summarized in Fig. 12 and Fig. 13, comparing the case when the whole set of features is used for training the ANN, and that related to a selected and optimized group of features, respectively. Fig. 12 shows that some classes are correctly recognized, when the output of the ANN is close to 1; some others are not recognized or are identified with a low output value.

The results clearly improve, as shown in Fig. 13, when the limited set of features is considered, based on TD or measured current and on a mixing of measured and simulated values of current.

The good performance of the classification algorithm is assessed by low values of the Cross-Entropy (CE), that is a performance index for classification ANNs [19]. The CE is reduced down to 0.007, when the selected group of features is used for training.

IV. CONCLUSIONS AND OUTLOOK

In this paper, the results are described of the application of a CM methodology for mechatronic systems, which is based on the parallel use of a kinematic and dynamic model of an automated device and experimental data.

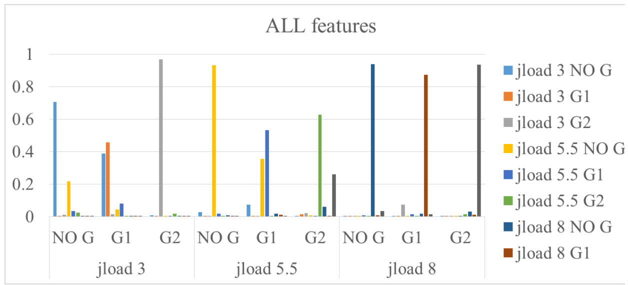

Fig. 12. Classification results, when the neural net is trained using all features.

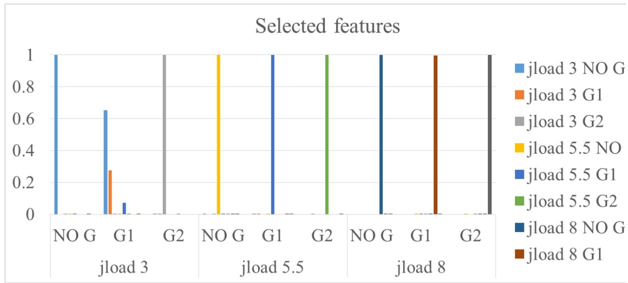

Fig. 13. Classification results, when the neural net is trained using only selected features.

The hybrid approach allowed us to define many features in the time and frequency domain, which are based also on statistics. Selection criteria of features have been applied, based on metrological and physical considerations, in order to supervise the automatic process of identification of the condition of interest. In particular, repeatability was considered as a good criterion for selectivity, together with aspects connected to the mechanical behaviour of the system.

The features mostly able to recognize differences between different *jload* settings and lubrication conditions, appear to be those related to the motor current and the TD.

Based on these consideration, a limited set of features has been identified and proposed, to be automatically processed by ANN, showing a better detection capability for status identification with respect to the whole set.

The obtained results confirmed experimentally the capability of this CM methodology to resolve even little changes of the operating status of the device, due both to settings and lubrication conditions.

Future work will be devoted to apply this methodology to the identification of defects occurrence and propagation in more complex mechatronic systems. This aim will require further improvement of selectivity of the method, proving its accuracy and robustness.

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