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IFAC PapersOnLine 56-2 (2023) 1282–1287

Norm-based data labelling in supervised learning for fault detection and diagnostics of rotating elements towards maintenance servitisation

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Abstract: In the current industrial context, the wide availability of data from the shopfloor is enabling companies to develop condition-based maintenance (CBM) and predictive maintenance (PdM) solutions towards production performance improvements. However, the path is not straightforward and several technological and managerial challenges have to be faced. Specifically, the current challenge is to mix the high-performance, yet difficult-to-interpret results, of AI (Artificial Intelligence) algorithms with the vast available domain knowledge provided by scientific literature and norms. It is the goal of this work to propose a norm-based data labelling to implement a supervised model which leverages on time-domain features to guarantee the interpretability of results for maintenance operators and technicians for FDD (Fault Detection and Diagnostics). The proposed approach is tested and a complete CBM solution is deployed in a case of an OEM (Original Equipment Manufacturer) of rotating elements. Through it, the company could move towards a fully-fledged maintenance service offering, already integrating norm-related knowledge.

Keywords: condition-based maintenance, predictive maintenance, fault detection and diagnostics, FDD

1. INTRODUCTION

In the current industrial context, the wide availability of data from the shopfloor is enabling companies to develop condition-based maintenance (CBM) and predictive maintenance (PdM) solutions towards production performance improvements (Tortorella et al., 2022). However, the implementation of such solutions is not straightforward as there are several challenges to be overcome along the way (Zonta et al., 2020). Challenges have to be intended not only on the technological side, which is anyhow relevant and manifold (Compare et al., 2020), but also on the managerial side (Selcuk, 2017). Recently, what has been put at the stack as a major challenge is the capability of AI (Artificial Intelligence) algorithms to outperform traditional statistical approaches while being barely interpretable and explainable to maintenance operators, technicians and managers (Brito et al., 2022).

On one side, maintenance decision-makers cannot directly use the outputs of AI due to their missing explanation (Hong et al., 2020). A trend towards XAI (Explainable AI) is evident, even though it is at its early stage, especially considering its application in the industry (Ahmed et al., 2022).

On the other side, there exists a huge body of knowledge that companies could reuse for CBM and PdM purposes (both internal for production machines or external for maintenance servitization), especially related to FDD (fault detection and diagnostics) of rotating components, which are the most critical elements in industrial machines (Lee et al., 2014). Indeed, not only vast scientific knowledge is available, e.g., tutorials on the bearing diagnostics (Randall & Antoni, 2011), but also ISO/IEC families of standards, e.g., the ISO 13373 and 13374 on condition monitoring and diagnostics of machines. Additionally, those companies, which are OEM (Original Equipment Manufacturers), that could rely on internal knowledge of the machines can improve their maintenance service offering, in the so-called PSS (Product-Service System) (Sala et al., 2021).

It is therefore advisable that the entire stack of knowledge coming from scientific literature, international standards and company experience could be reused also by AI algorithms to improve the interpretability of their results.

1.1 Research question, objective and scope

Given the premises above, this work stems from a research question that could be enucleated as follows: how to reuse the body of knowledge from norm to improve FDD of rotating elements in case of missing a priori historical data?

Indeed, the novelty of the research resides in the introduction of the severity chart, adopted from an international norm, to

10.1016/j.ifacol.2023.10.1761

automatically label the health state in supervised learning for FDD. The project is confined to the rotating elements realised by RULMECA company (see subsection 4.1). The long-term goal is to improve maintenance service offering also in those cases in which no a priori data are available.

The paper is so structured: Section 2 describes the adopted research methodology; Section 3 clears out the proposed approach for norm-based data labelling, later implemented and tested in Section 4. Finally, conclusions and future works are drawn in Section 5.

2. RESEARCH METHODOLOGY

The adopted research methodology stems from the PHM (Prognostics and Health Management) process described in ISO 13374-1. Specifically, for FDD, the required steps to be performed are, in order (Sikorska et al., 2011): data acquisition, data manipulation, fault detection, and diagnostics. Beforehand, FMECA and HAZOP analyses are necessary to start the development of such CBM solutions as they provide the knowledge background required to understand the physical entities under analysis and how they behave (Cattaneo et al., 2021). The research methodology is thus depicted in Fig. 1, where the blue box points out the novelty this research claims, that is, the use of norm-based data labelling in fault detection and fault diagnostics to enable the use of supervised learning algorithms.

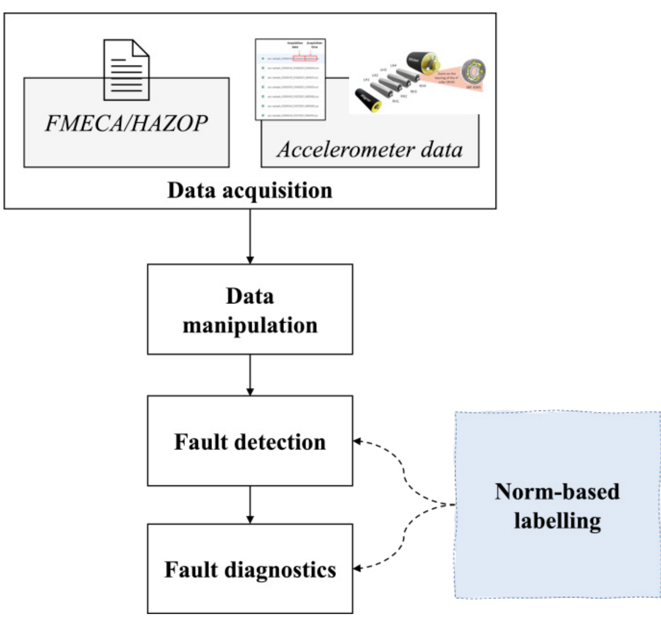

Fig. 1. Adopted research methodology for norm-based data labelling for FDD.

Such methodology has been followed throughout the entire project and interactions with the company happened multiple times to act as checkpoints as well as information exchange opportunities (especially for FMECA and HAZOP). Before describing the application of the methodology to the industrial case, it is worth detailing the novelty this work brings about, i.e., the proposed approach for norm-based data labelling, which allows for answering the research question.

3. PROPOSED APPROACH FOR NORM-BASED DATA LABELLING

This research work proposes a norm-based data labelling for FDD so to take advantage of and reuse extant available knowledge from international standards.

Indeed, historical data, when available, does represent the healthy state of the machines, or, in case a fault is registered, not much information could be easily retrieved (Jardine et al., 2006). Therefore, many times, available data to start developing CBM and PdM solutions are unlabelled, leading mainly to the use of unsupervised learning approaches (Zschech et al., 2019).

Nonetheless, there are numerous international standards and norms that can be used to deepen the analysis of the signals to extract information useful for fault diagnostics. The ISO 13373 family of standards proposes a wide set of predefined analyses that allows the development of FDD solutions for rotating elements.

In Fig. 2, the proposed approach for norm-based data labelling is graphically depicted.

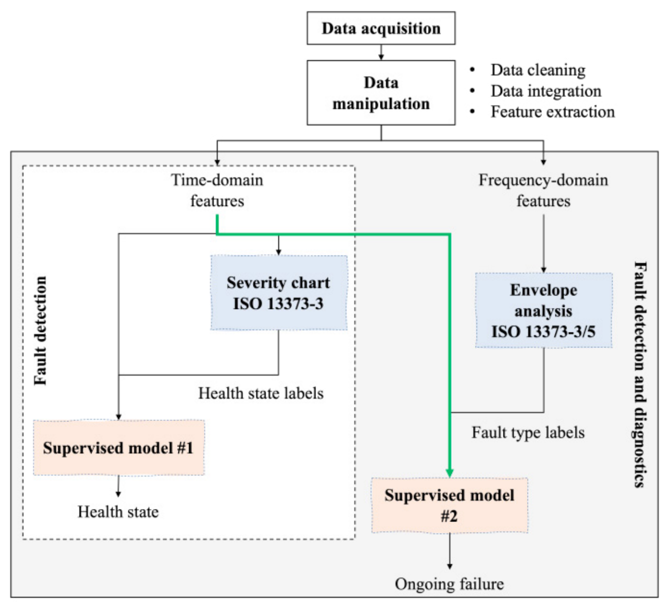

Fig. 2. Proposed approach for norm-based data labelling for FDD.

The proposal is mainly composed of three blocks, in accordance with the general FDD approach already presented in Fig. 1:

- Data manipulation (top-most block) takes care of the data cleaning and integration activities as well as feature extraction in time, frequency, and time-frequency domains.
- Fault detection (left-hand block) considers time-domain features that are the inputs to the supervised models (called #1) and the ISO 13373-3, which includes the severity chart, to provide the labels of the

different health states, classifying them as healthy, alerting, or alarm.

- Fault detection and diagnostics (right-hand block) is the core of the proposal. This block leverages first on the envelope analysis described in the ISO 13373-3/5 so as to be able to label the data, i.e., identify the fault types. Then, time-domain features are given as inputs to a supervised model (called #2) together with the fault types from the envelope analysis.

In Fig. 2, the block named "Fault detection" could have its own outputs as it may be the goal of the CBM solution to inform about the health state of the entity under analysis. Then, if necessary, the diagnostic capability could be introduced by leveraging frequency-domain features. Please note that there could be time-frequency domain features that, depending on the specific application, may be useful for FDD. In this work, such features are not considered.

The goal of the norm-based data labelling as well as the proposed approach for FDD is to provide useful information to the maintenance operator about the health state of the machine as well as the diagnosis of possible occurring failures in a way that he/she could interpret. Indeed, according to the authors' experience, time-domain features are usually easier to be understood and trusted as they are closer to the physical phenomena people experience day by day on the shop floor. For example, RMS (Root Mean Square) is a measure of the dissipated energy due to the rotation and maintenance operators could easily link the information provided by the CBM solution with his/her knowledge and experience and, consequently, trust it.

The proposed norm-based approach for FDD has been tested and implemented in an industrial application, as later presented in Section 4. The research work was carried out during a project together with RULMECA, which is researching how to improve their CBM/PdM solutions for their products in a maintenance servitization scenario.

4. INDUSTRIAL APPLICATION

The application of the proposed approach has been realised in a controlled environment of a testing line owned by RULMECA in their research centre. In subsection 4.1, the test bench is described in detail, while in subsections 4.2, 4.3 and 4.4 the application of the CBM solution for FDD is described, starting from the data manipulation, through fault detection, to fault diagnostics, respectively. For the sake of brevity, the FMECA and HAZOP analyses are not shown here.

4.1 Test bench for rotating elements

The industrial application is supported by RULMECA group (https://www.rulmeca.com/en/), which is a leading manufacturer and supplier of rollers, motorized pulleys, components and solutions for the global materials handling industry, looking for fully-fledged maintenance service offering. Therefore, to assess the proposed solution for the norm-based labelling for FDD, their test bench has been used so to have an industry-like, yet controlled, environment.

In the test bench, four rollers are mounted, and accelerometers are installed on both sides of the roller. In synthesis, the test bench is composed as follows:

- The motor allows the belt to run at constant speed.
- The belt connects all the components in the system and it makes the rollers rotate at 463 rpm.
- The belt is kept on track with guide rollers, located close to the motorized pulley.
- The four rollers rotate thanks to the belt; rollers are identified by means of consecutive numbers, namely 1, 2, 3, and 4 as IDs.
- Inside each roller, there are two 6305 bearings: one on the left side, identified by means of LH, and one on the right side, identified as RH. The nomenclature is then combined with the IDs of the bearings so as to univocally identify the interesting part of the roller by referring to it as RH4 (right side of roller 4) or LH3 (left side of roller 3), and so on and so forth.

In Fig. 3 and Fig. 4 the components and the real systems are depicted, respectively. Also, in Fig. 4, details for RH4 are shown.

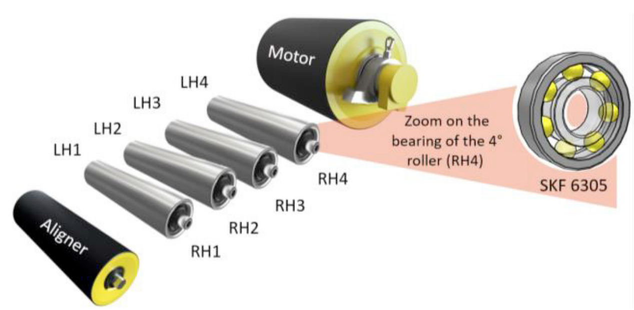

Fig. 3. The components of the test bench.

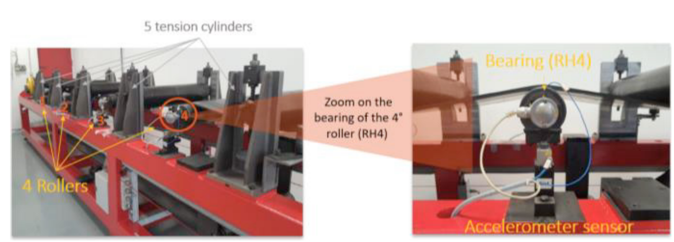

Fig. 4. The test bench and details on RH4.

To test if the FDD solution works, in all bearings a fault has been induced. Bearings mounted on the same roller have the same induced fault, e.g., inner race defect. This enables a step-by-step verification of the results obtained along the project.

4.2 Acceleration data acquisition and manipulation

The dataset is made of 4 months of data acquisition (from June 2021 to September 2021), and accelerations are gathered 3 times per day. Each sample is 2.3 seconds long with a sampling frequency of 20 kHz. Overall, 337 .csv files are generated, each containing almost 46,000 samples.

Data cleaning is then performed by:

- Coping with missing data: in the specific dataset, due to external factors, from 11 to 14 June 2021 no recordings are available.
- Coping with outliers: in the dataset, two complementary approaches to outlier detection are carried out, after the normality test that is verified:
    - A first global outlier detection aiming at identifying all data points exceeding $\mu \pm 3\sigma$ (where μ is the average and σ is the standard deviation of the signal); the identified points are replaced through the linear interpolation method. Overall, 0.008% of the available points were substituted.
    - A second local outlier detection is carried out through a moving window approach based on the median, with a size equal to 10 and a step equal to 3. Spline interpolation is used as it shows better results with respect to linear interpolation. Overall, 0.95% of the data points are modified.

Then, linear correlation analysis is performed so to extract possible additional information from the datasets. Given the set-up of the test bench, what is expected is that bearings on the same roller behave in the same way, as they are subjected to the same induced failure. The only exception to this is roller 4, whose signals are not linearly correlated as shown in the scatterplot in Fig. 5, where on the x-axis there is the acceleration in [g] of LH3 and on the y-axis is the acceleration in [g] of RH3.

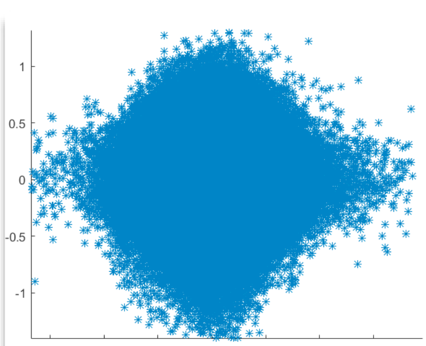

Fig. 5. Scatterplot of acceleration in [g] of LH3 (x-axis) and RH3 (y-axis).

Further investigations are carried out that certify that the two signals were highly linearly correlated but shifted in time. This is verified by applying Dynamic Time Warping, which seeks for temporal alignment that minimises Euclidean distance between series. Therefore, there must have been an incorrect installation of the two faulty bearings.

After having guaranteed the quality of the data, several features are extracted in the time domain, namely: mean, median, standard deviation, RMS, Kurtosis, crest factor, minimum, and maximum. Out of the eight extraction features, six were kept as they are highly representative.

4.3 Fault detection

Within fault detection, the aim is to identify in which health state the element, namely the bearing, is by looking at the monitored features. To do so, fault detection is separated into two steps. The first one deal with the use of an unsupervised learning algorithm so to identify homogenous clusters of data points that constitute the health state of the bearing. Then, the second step is to label each state by means of the severity chart, as a diagnostic analysis described in ISO 13373-3. Three clusters are identified by means of the density-based clustering algorithm k-means as graphically represented in Fig. 6 with an average of 0.8 for the silhouette.

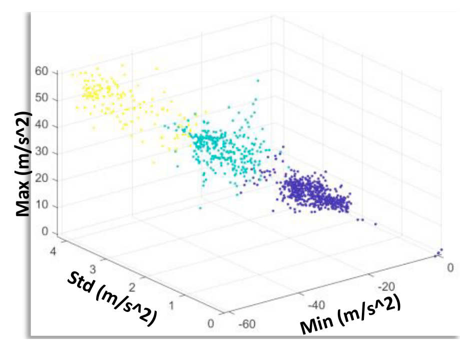

Fig. 6. K-means application results in three clusters.

Then, to label each cluster, i.e., bearing health state, the severity chart is used. The severity chart is double-logarithmic plot with the RMS on the x-axis and the maximum peak on the y-axis. The norm predefines some boundaries that allow to separate the states. Fig. 7 reports the application of the severity chart to the second month of the dataset.

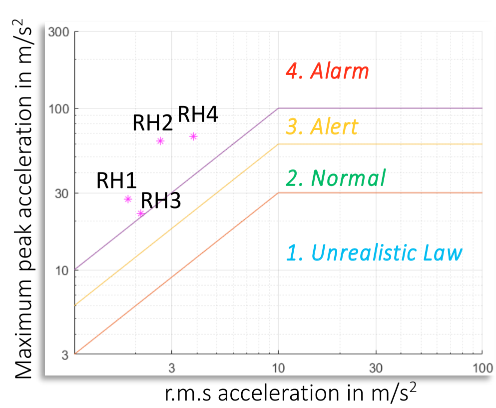

Fig. 7. Severity charts for RH1, RH2, RH3 and RH4.

The severity charts over the four months return that RH1, RH2 and RH4 could be classified as in the "Alarm" zone, while RH3 could be labelled as within the "Alert" zone. In turn, this serves to set the health states of the bearings as faulty (RH1, RH2 and RH4) and abnormal (RH3).

Finally, a neural network (NN) is developed to automatically classify the health state, and the NN resulted in 99,6% accuracy. This is the first important result as the interested company could stop with an already significant capability, that is the possibility to automatically identify the health state of the bearings by means of six time-domain features. The very next step is to use the same features to diagnose which failure is occurring.

4.4 Fault diagnostics

According to the approach presented in Fig. 2, the first step towards a complete FDD solution is the use of frequency-domain features to identify the failure occurring. To this aim, ISO 13373-3/5 is used, which suggests the adoption of the envelope analysis to extrapolate information on which amplitude in the envelope spectrum is deviating with respect to a normal, healthy condition. The analysis consists firstly in the evaluation of bearing elements frequencies: ballpass frequency outer race (BPFO), ballpass frequency inner race (BPFI), fundamental train frequency (FTF), and ball (roller) spin frequency (BSF). All the parameters are recovered from the SKF catalogue for model 6305, while rotational speed is provided by RULMECA.

The results for RH2 are reported in Fig. 8, where the BPFO and BPFI are drawn (vertical lines), as long as the FR, which represents the frequency of the shaft that is considered as a reference. FTF is shown in another graph to ease the visualisation (not reported here for the sake of conciseness).

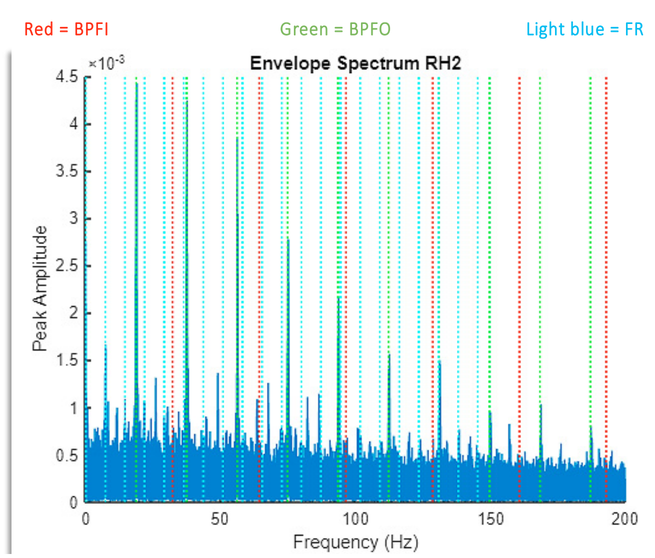

Fig. 8. Envelope spectrum for RH2, showing that the amplitude of BPFO suggests a failure on the outer race.

Overall, the results are confirmed by the RULMECA technicians:

- RH4: inner ring fault and cage deterioration.
- RH3: looseness and rolling element fault.
- RH2: outer ring fault and cage deterioration.
- RH1: outer ring fault and cage deterioration.

As confirmed by the experts, both outer ring and inner ring failure result also in cage deterioration. Hence, it is possible to identify three possible outcomes for the fault diagnostics, which are: inner ring fault and cage deterioration (RH4), outer ring fault and cage deterioration (RH1, RH2) and looseness and rolling element fault (RH3). These results are compliant with the output of the fault detection block (subsection 4.4) as RH3 was in an abnormal state while all the other ones in faulty.

Finally, an unsupervised model is used, whose inputs are the six features and the output the three possible identified failures. The model is a cubic support vector machine which resulted in a 96.7% of accuracy.

5. CONCLUSIONS

This research work aims at proposing a norm-based data labelling to implement CBM solutions also in cases where extant failure knowledge and related data are not available. Specifically, the proposed solution is also thought to support the interpretability of the results as AI models are fed with time-domain features that, according to the authors' experience, are easily understood and interpreted by maintenance operators and technicians and, consequently, more trusted.

The proposed approach extensively relies on norms to enable data labelling. Specifically, ISO 13373 is taken as reference: i) the severity chart is firstly used to label the health states identified by means of an unsupervised learning algorithm and ii) the envelope analysis is then adopted to diagnose which is the failure currently occurring to the bearing.

The first implementation of the proposed approach provides interesting results as the developed supervised model, namely a cubic support vector machine, is able to reach high accuracy. This enables prompt action of maintenance operators who are informed by the algorithms about the failure occurring and, also, on the specific values of features such as RMS to also support maintenance operators in their understanding of the physical phenomena.

Nonetheless, some limitations currently affect the proposed solution from scientific and application viewpoints. On the scientific research side, firstly, in this research work interpretability has been addressed namely in the feature engineering step of PHM; indeed, interpretability does include many other aspects worth to be considered to tackle "interpretative AI". Secondly, another limitation refers to the inclusion of norms-related knowledge only, in relation to both the PHM process and the related analyses and outputs obtained.

On the side of the application, firstly, the application is under controlled and stationary conditions not affected by noise from the surrounding environment. Secondly, there are no completely new bearings; hence no healthy state can be modelled in the FDD solution. Finally, each roller is affected by the same failure on both sides, therefore it is not taken into consideration cases where the two extremes of the rollers are subjected to different failures and their possible relative disturbances affecting model performance.

Stemming from the results obtained in the specific context of RULMECA, it is possible to envision an extension to other enterprises, as the realised FDD solution can be introduced in a wider CBM solution offering to improve maintenance as a service in the so-called Product Service Systems (PSS) business model. A standalone solution based on norms that could run on the premises of the customer without requiring connection with the OEM could be a viable option in all cases in which privacy concerns are of utmost importance. Also, even though the solution is based on AI for an automatic suggestion of health states and possible occurring failures, the use of time-domain features may induce a wider acceptance with respect to a complete black-box approach in which features are unknown or derived by transformation as PCA (Principal Component Analysis).

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