Predicting RUL of Bearings in the Pumps of a Critical Industrial Air Treatment System

H. Beirami[1], D. Calzà[1], A. Cimatti[1], M. Islam[1], M. Roveri[2], P. Svaizer[1]
[1] *Fondazione Bruno Kessler, Trento, Italy*
{*hbeirami,calza,cimatti,mislam,svaizer*}*@fbk.eu*
[2] *University of Trento, Trento, Italy*
marco.roveri@unitn.it

Abstract

Predictive maintenance is emerging as a promising technique to overcome the limitations of periodic maintenance. It integrates automatic condition monitoring to evaluate the health status of a system or device, with the estimation of Remaining Useful Life (RUL) of its components, in order to schedule maintenance only when really needed, minimizing the downtime of a plant.

In this paper, we report our results in evaluating the health conditions of the rotating ball bearings of a critical air pump which is part of the Clean Room industrial facility operating in the Micro-Technologies Laboratory of Fondazione Bruno Kessler. We instrumented such component with vibration and acoustic sensors with the aim of identifying a model of the evolving degradation and estimating the RUL of the bearings. The current dataset covers a period of one month before bearing replacement and about six months after the replacement. The first models, based on regression and particle filter processing of critical spectral components extracted from the sensors, indicate an estimated RUL of about 12 months that is in agreement with the average lifetime based on scheduled maintenance. Subsequent model evolutions have been observed in conjunction with scheduled greasing and periods of lower stress, which resulted in remarkable deviations from the initial degradation trends and in a consequent notable increase of the estimated RUL.

Results achieved so far are promising and could be used to extend the temporal distance among periodic maintenance interventions according to the estimated RUL.

1. Introduction

Gears and rotating elements are among the most critical components of industrial equipments. They are subject to mechanical wear which in turn leads to progressive deterioration, expensive long downtime, and production stops to repair and/or substitute them. The common practice to mitigate this problem consists in subjecting the critical components to regular periodic maintenance, despite still being in reasonably good conditions. This results in an increase of costs and in a waste of components, which might have a longer lifetime.

Prognostics and system Health Management (PHM) aims to overcome the limitations of periodic maintenance through i) an automatic condition monitoring intended to evaluate the health status of the observed unit by analyzing proper sensing information; ii) an estimation of the Remaining Useful Lifetime (RUL) of the components, to further schedule their maintenance only when really needed and in a way to minimize the impact on the associated production. Nowadays, PHM has received considerable attention: it guarantees reliability, overall performance and productivity of a system while reducing the costs of the maintenance (Gouriveau, Medjaher, & Zerhouni, 2016). Therefore, PHM has found wide range of usage in different industrial application such as predictive maintenance of compressors (Engelberth, Krawczyk, & Verl, 2018), chillers (Ke, Mulumba, Shen, & Afshin, 2014), wind turbines (Hossain, Abu-Siada, & Muyeen, 2018), or vehicles (P. Li & Goodall, 2004) to mention a few.

PHM includes two main procedures, namely diagnostics and prognostics. Diagnostics consists in detection, isolation, and identification of a fault, while prognostics, based on the current state of a system, aims at predicting the future evolution of the state and at estimating the RUL (Lei, 2016).

Among the manifold applications of PHM, maintenance of the bearings is of the highest importance, since they are one of the most frequently failing components in industrial rotating machines. If deterioration is not timely detected and properly predicted, faults in bearings can cause costly breakdown of operations (Kim et al., 2016) and even human casualties. Thus, prognostics of bearings is a key issue in any maintenance strategy. It requires early fault detection and a constantly updated RUL estimation which can only be attained by analyzing sensing information collected during machinery operation (Jardine, Lin, & Banjevic, 2006).

In this paper, we make the following contributions. First, we report our results in evaluating the health conditions and predicting the RUL of a critical component of the Clean Room industrial production facility of the Micro-Technologies Laboratory at Fondazione Bruno Kessler. This facility, devoted to production of small and expensive lots, demands for an accurate control to stabilize the temperature and pressure, achieved by a complex air-conditioning and pressurization plant. Such plant is equipped with a large number of critical air pumps whose main components consist of electrical motors with shafts rotating on ball bearings. These units incur in progressive wearing and require periodical replacement of the bearings with typical life-cycle from 12 to 18 months. Maintenance is currently performed on the basis of a predefined schedule and of periodical checking by expert technicians who evaluate the conditions of the devices. We instrumented one of such critical motors with vibration and acoustic sensors with the purpose of identifying a model for the evolving degradation and estimating the RUL of the bearings. The current dataset covers a period of one month at the end of the life-cycle (worn bearing before replacement) and a period of about 6 months following the bearing replacement. The observed and analyzed period includes the occurrence of several contingencies (e.g. stops, periodic maintenance) that may affect the analysis, but make the dataset significant since it reflects a typical use of the machinery under test.

We remark that publications and related datasets targeting the prediction of the RUL, in the context of a real industrial environment operated in real working conditions, are quite infrequent. For example, in (Nixon, Springer, Hoeprich, & Clouse, 2013) the authors provided a comparison of bearing life test results and predictive analysis methods for various tapered roller bearings operating under debris-contaminated conditions. However, the document is not accompanied by experimental data nor by details on how the analysis was carried out. The majority of the literature concentrate on dataset obtained from test-benches or controlled conditions. Noticeable examples are the PRONOSTIA (Nectoux et al., 2012) platform used to create the FEMTO IEEE PHM 2012 Prognostic Challenge[1] or the NASA Ames Bearing Data Set (Lee, Qiu, Yu, & Lin, 2007).

Second, we provide a thorough analysis of the relevance of several features extracted from the measured vibration signals, based on the typical time- and spectral-domain analysis for machinery diagnostics (Jardine et al., 2006). Such features were tested in order to identify their suitability for developing models able to represent the evolving conditions of the bearings. We identified the popular Short-Time Fourier Transform (STFT) and Wavelet Transform (WT) as the most promising analysis techniques from which to select the critical frequency bands that are most relevant to highlight trends associated with bearing conditions. The corresponding features were then processed by means of a Particle Filter (PF) and linear regression in order to extract an evolution model of the conditions of the bearing under analysis and to perform RUL estimation.

Finally, we observed evolving trends during the analyzed period. While the results observed during the first months of operation show trends that appeared to be quite stationary, leading to an initial RUL estimation of about 12 months. The results in the following months, due to several contingencies, show important changes in the monitored trends. Specifically, within the observation period, the analyzed bearing was greased according to a periodic maintenance program; Besides, subjecting the facility to stop due to the periodic holidays (Christmas) affected the maintenance activities of the monitored device. All these contingencies (typical of a normal use of an industrial machine in an industrial context) produced remarkable deviations from the initially modeled degradation trend, leading to noteworthy updating of the estimated RUL values. This clearly shows the need of a continuous (or periodic) update of the models, in order to include contextual information about the real usage of the component under test.

Analysis and observations are still in progress to complete the acquisition of a full life-cycle of the device and to further refine the identified prediction models. The plan is to use the computed models to support decision-making related to the periodic maintenance in the next years.

This paper is structured as follows. In Sect. 2 we analyze the related works. In Sect. 3 analysis of the use case and adopted setup are presented. Sect. 4 discusses the approach we followed, and presents a critical analysis of the results achieved so far.[2] Finally, in Sect. 5 we draw conclusions and outline future work.

2. RELATED WORKS

PHM of bearings have received considerable attention in the literature. Here we analyze the most relevant works tackling diagnostics and prognostics of bearings. We consider methods leveraging model based, data driven and hybrid approaches. Moreover, since feature extraction is one of the key aspects in different phases of PHM, we consider methods relying on features extracted from time, frequency, and time-frequency domain analyses (Nguyen et al., 2018).

In (Kim et al., 2016) an entropy-based feature calculated from a narrow-band signal in the spectral domain has been proposed. To demonstrate the superiority of the proposed solution, authors made a comparison with traditional time-domain

[1] `https://ti.arc.nasa.gov/c/18/` accessed in June 2020.

[2] A sample of data and of the code used to present the results discussed in this paper are available for download at the following URL: `https://tinyurl.com/y7k222n5`. The full dataset is available on request.

features such as kurtosis, root-mean-square, and envelope using a publicly available vibration dataset. As bearing monitoring signals are highly non-stationary, spectral components in the Hilbert-Huang Transform (HHT) have been found suitable as features to reveal the evolving trend of a fault (Nguyen et al., 2018). Moreover, the combination of HHT-features and Support Vector Regression (SVR) and other Machine Learning (ML) solutions have been successfully proposed for diagnostics and prognostics of a bearing (Soualhi, Medjaher, & Zerhouni, 2014).

The key role of fault diagnosis is to investigate the status of internal components by observing related external information. It has been proved that vibration analysis can contribute to detect anomalies of rotating machinery (Lei, 2016). Different ML techniques can be used to differentiate between normal and abnormal behaviors. To detect and classify bearing faults from vibration signals (Janssens et al., 2016) proposed a feature learning model for condition monitoring and the use of a Random Forest (RF) classifier. The use of deep learning techniques, Convolutional Neural Networks (CNNs), provided higher accuracy in detecting different types of faults and different levels of lubricant degradation. A procedure of fault detection by considering electrical current and vibration as suitable indicators of the degradation trend has been discussed in (Rações, Ferreira, Pires, & Damásio, 2019). Here various ML techniques such as Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), RF with extreme gradient boosting have been analyzed. Fault detection is achieved using Hilbert transform and statistical analysis of vibrations, and Parks Vector Modulus analysis of electrical current, checking deviation from a perfect sinusoid.

In order to detect bearing faults at an early stage of degradation, it is important to mitigate the background noise affecting the signals. To this end, complete ensemble empirical mode decomposition with adaptive noise and improved multivariate multi-scale sample entropy techniques have been shown effective in (Lv, Yuan, Wang, Li, & Song, 2018).

RUL estimation is generally a more challenging problem than fault detection. Also for RUL estimation the possible approaches are classified as either model-based, data-driven, or hybrid. Model-based methods describe degradation processes of a system using mathematical or physical models, and adjust model parameters using measured data (Lei, 2016; Yoo & Baek, 2018). In (Liu et al., 2018), physical model based approaches are presented, including Paris Crack Growth Model, Damage Mechanics-based Model, Spall Progression-based Model, and Stress-based Fatigue Model. Generally, model-based methods are quite reliable, provided that the adopted model is accurate enough to encode the underlying system. However, in real scenarios, assigning a precise mathematical or physical model to a complex system is often too hard (Jardine et al., 2006).

Data-driven methods for RUL estimation aim at capturing degradation processes of machinery directly from measurement signals. These methods can be classified as statistical or ML-oriented. There is a vast literature about statistical models, including linear regression, process models, Bayesian filtering, covariate-based hazard, and Markov models (Jin, Que, Sun, Guo, & Qiao, 2019). (Zhang & Li, 2014) used accelerated degradation testing to determine the health condition and RUL of bearings, making use of linear Wiener process models to perform reliability analysis under different stress levels, while (Zhao, Tang, & Tan, 2016) proposed a regression-based solution after the application of Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) on a time-frequency representation of vibration signals.

ANNs, LDA, SVMs, decision trees and deep learning are often used for RUL estimation (Jin et al., 2019). In (Porotsky & Bluvband, 2012) Adaptive Neuro-Fuzzy Inference System, ANNs, and the similarity-based prognostics approach are compared using FEMTO-ST bearing data. In (Wang, Yu, & Guo, 2020) the RUL of bearings is predicted in online manner by means of a back propagation neural network using kurtosis and other statistical features, and PCA sampling to reduce the size of the input.

In (Sutrisno, Oh, Vasan, & Pecht, 2012) three RUL estimation algorithms used in the IEEE 2012 PHM Data Challenge Competition are compared. The first method is based on a moving average spectral kurtosis feature extraction process and Bayesian Monte Carlo simulation. The second one uses a soft computing techniques based on least-squares SVR method, while the third algorithm is based on vibration frequency signature analysis and survival time ratio.

Recently Yoo and Baek applied deep learning based on a signal-to-image-based feature extraction process and CNNs for RUL estimation on the PRONOSTIA dataset. A continuous WT converts signals into images which are fed to a CNN for feature extraction. In (Ren, Sun, Wang, & Zhang, 2018) eigenvectors computed from raw vibration signals are used as inputs of a CNN, obtaining better results than with SVR and multi-layer perceptron. Deep learning solutions are also proposed in (Gugulothu et al., 2017) and (Hinchi & Tkiouat, 2018), where long-term dependencies in the input data are captured by means of long short-term memory recurrent neural networks.

Hybrid approaches attempt to integrate the strengths of both the data-driven and the model-based methods to build a more reliable RUL prediction (Lei, 2016). The works described in (Zio & Peloni, 2011; Qiu, Li, Jiang, & Zhu, 2018) combines a spectral analysis-based health index and particle filtering, while (Wu, Li, & Qiu, 2017) integrates the generalized Weibull failure rate function in a radial basis function neural network, introducing power on the sensitive frequency band as a suitable indicator of the bearing degradation.

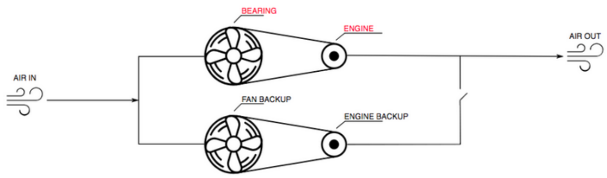


Figure 1. Schema of the air recirculation system.

Vulnerability to noise, presumption of Gaussian distribution, or need for considerable amount of data are frequent limitation of the data-driven approaches and, to some extent, hybrid approaches. Recently, Kalman filter is gaining momentum as an effective method to predict RUL estimation of bearings that contributes positively to overcome aforementioned limitations (Qiu et al., 2018; Cui, Wang, Xu, Jiang, & Zhou, 2019; Lim & Mba, 2015). (Singleton, Strangas, & Aviyente, 2013) suggested to extract measures that quantify the complexity of the time-frequency surfaces computed from vibration signals. These features are tracked through the lifetime of a bearing using curve fitting and Extended Kalman Filtering algorithms. Authors proposed Switching Kalman Filters (SKF) both for fault detection and RUL estimation. As SKF uses multiple dynamic models to demonstrate different degradation phases, it was mentioned that SKF can outperform the methods that allocate pre-defined thresholds (Lim & Mba, 2015). Recently Cui et al. applied a new version of SKF called Switching Unscented Kalman Filter. The proposed method attempts to estimate RUL when degradation speed is negative (i.e., early fault occurrence) (Cui et al., 2019).

3. THE CLEAN ROOM ENVIRONMENT

The Clean Room is a 700 square meters silicon production factory located in the Micro-Technologies Laboratory at Fondazione Bruno Kessler. It is an industrial production environment with an extremely low level of particulates, necessary to produce small lots of specialized microchips and hi-tech electronic devices, such as radiation detectors from silicon wafers. In this context, any stop due to a failure of a machinery results in loss of money. For the purpose of guaranteeing such a cleanliness level, the Clean Room is equipped with an extremely complex air treatment system, which provides controlled conditions and includes humidity and temperature stabilization, air recirculation and particle filtering. Poor air quality might lead to a bad adhesion of the photoresists to the surface in the photo-lithography process, leading to an overall inappropriate design and, consequently, a compromised final device. In order to avoid a similar situation, the infrastructure must guarantee continuity of service and preserve the air quality without any downtime, which might lead to a significant increase of production costs.

The air recirculation system consists of several pumps (see Fig. 1), which include electrical motors with shafts rotating on ball bearings. Such bearings are characterized by an important progressive wearing and so require an accurate and frequent inspection by technicians. The installed bearings are the "SKF 6206-2RS/C3" model with 9 balls, an inner diameter of 30 mm, an outer diameter of 62 mm and a ball width of 16 mm. Maintenance of the pumps is performed periodically by experts, and consists in the lubrication of the rotating bearings during their lifetime, prior to their replacement, besides scheduled status checks. The bearings' substitution operation occurs in a time window which ranges from 12 to 18 months of activity. In order to follow the working hours of the facility, with the aim of avoiding a waste of energy, the air recirculation plant operates in two different regimes: i) from 07:40 AM to 07:00 PM, during working days, the pumps run at 1270 rpm; ii) in the remaining time and on weekends the system works at a lower regime, operating at 700 rpm. In this paper we will provide information gathered from an accelerometer attached directly to the chassis of the pump engine, and from a microphone placed nearby in an enclosure.

3.1. Our setup

The adopted data collection setup (depicted in Fig. 2) relies on usage of open source software. An industrial PC mounting Ubuntu 18.04.4 LTS provides a robust solution for data collection from sensors. On the mentioned device runs a multi-threaded Python 3 script making use of the PyAudio library for signal acquisition at 16 kHz sampling rate. Data is then serialized into protocol buffers (protobuf) and sent via MQTT to the central internal server; this particular combination is widely used for message sending in Industrial IoT. The central server is continuously listening to the MQTT broker (Mosquitto), applying DSP techniques to received messages and saving both raw and processed data locally. Files are stored using the Parquet format provided by Apache, which provides a strong compression of data. A lower amount of data intended for visualization purposes is then stored in a real-time InfluxDB database, which provides temporal analytics to Grafana, an open source tool for dashboards enabling real-time analytics and alerting. Data analysis is achieved by means of the popular data science oriented libraries NumPy, Pandas and Matplotlib.

4. BEARING RUL ESTIMATION

In this section we describe the methodology we adopted and the techniques we used for the estimation of the RUL of the considered bearing.

Feature extraction and selection are important steps in capturing the bearing health status in operation (Nguyen et al., 2018; Kim et al., 2016; Soualhi et al., 2014; Rações et al., 2019; Lv et al., 2018; Zhang & Li, 2014; Zhao et al., 2016). Various feature extraction methods, that typically consist of time- and spectral-domain analysis of bearing vibration sig-

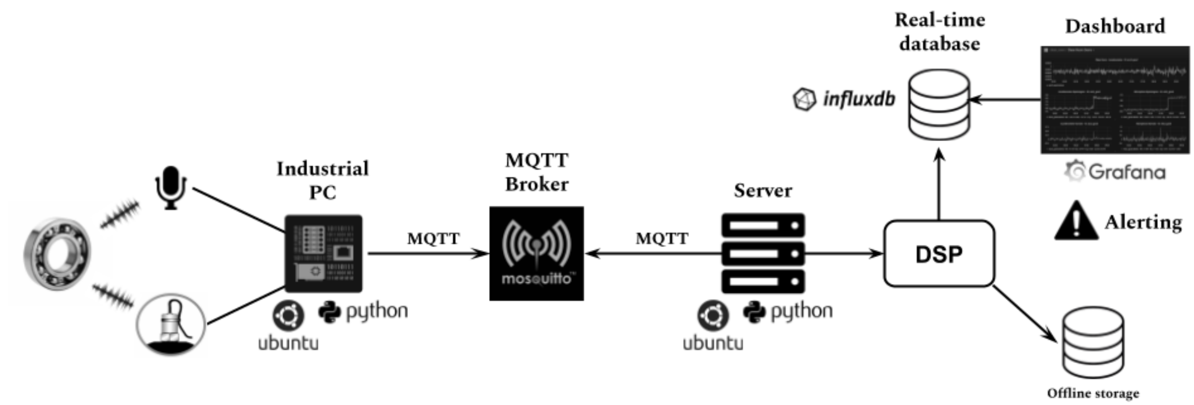


Figure 2. The adopted Clean Room PHM Infrastructure for data acquisition, processing, visualization and decision-making.

nals, have been investigated by researchers (Jardine et al., 2006; Nguyen et al., 2018). We analyzed almost all of them, and we identified the STFT and WT (Jardine et al., 2006) as the most promising ones. Both STFT and WT allow us to decompose a time-series signal into precise time-versus-frequency components in compare with traditional Fourier transform. Therefore, we select critical frequency bands with maximum energy criteria for STFT and WT. Logarithms of these energy values are selected as features and named Spectral Energy (SE) for STFT analysis and Wavelet Spectral Energy (WSE) for WT analysis. SE and WSE provide an effective model that we combined with linear regression and PF methods respectively for RUL estimation (Qiu et al., 2018).

First, in Sect. 4.1 we describe the approach based on a SE linear regression model which, for simplicity, assumes a constant degradation trend in the evolution toward the degraded condition. Second, in Sect 4.2 we describe a more elaborated approach based on PF for RUL estimation and show the extracted models. Finally, in Sec. 4.3 we provide a critical analysis of the extracted models.

4.1. Spectral Energy Regression based RUL Estimation

A plot of the spectrum of the vibration signal, averaged during an observation period, provides a concise representation of the vibration energy distribution over the different frequency bands. By comparing the spectrum measured before and after the degraded bearing replacement (see Fig. 3), we can perceive the effect of the bearing degradation on the friction of the rotating shaft. From the plots in Fig. 3, it is clear how bearing degradation is mainly reflected on the range from 1500 to 5500 Hz and partially also in the highest range close to the Nyquist frequency (8 kHz).

We made the following simplifying assumptions: a) the degradation of the rotation smoothness and the corresponding increase of vibration energy over time is due entirely to the wear of the bearing; b) the wear follows a progressive evolution without abrupt discontinuities due to unexpected deterioration or breaks of the bearing parts; c) the bearing deterioration is comparable between different life-cycles, i.e. after each replacement. We remark that, these simplifying assumptions reflects the experience gained by the engaged maintenance team in several years of operation.

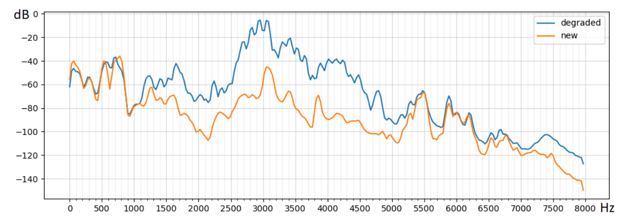


Figure 3. Average spectrum at 1270 rpm speed before (degraded, plotted in blue) and after (new, plotted in orange) bearing replacement.

The average spectrum is computed day by day, and its evolution at each frequency bin (a total of 257 bins from 0 Hz to the Nyquist frequency, providing a frequency resolution of about 30 Hz) is analyzed to detect the presence of consolidated trends. Data were analyzed over a period of 3 months after bearing replacement (see spectrogram in Fig. 4). Some frequency bins demonstrated a vibration energy increasing with time while other bins showed a stationary or decreasing trend.

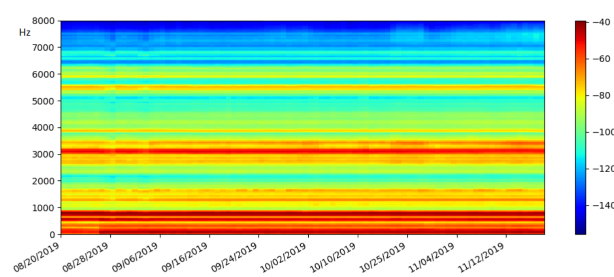


Figure 4. Spectrogram of the vibration signal (at 1270 rpm) during the first 3 months after bearing replacement.

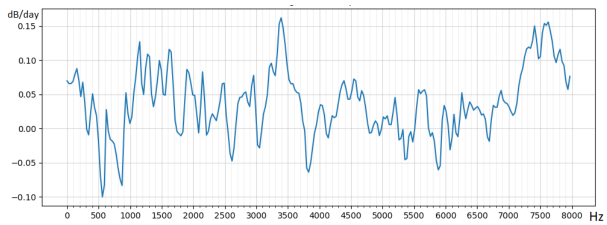


Figure 5. Slope of linear regression of energy over time as a function of frequency. Observation interval is of 3 months after bearing replacement.

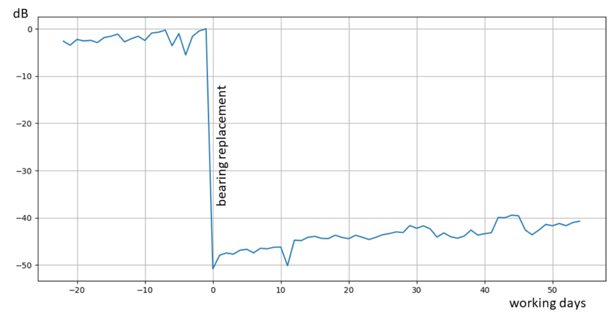


Figure 6. Progression of vibration energy level at 3400 Hz before and after bearing replacement. Time axis is the number of working days (operation at 1270 rpm). Note the jump in correspondence of the bearing replacement.

A linear regression over time was applied at each frequency bin. Since energy is expressed in dB, this corresponds to an exponential progression of energy amount with time.

Fig. 5 shows the resulting slope as a function of frequency. It is evident that the highest slope (the fastest increasing energy level) occurs at 3400 Hz. The peak indicates that energy at this frequency provides a significant feature for monitoring the condition of the bearing.

Based on this observation, we analyzed in detail the progression of the energy level of the bins around the peak. A first analysis was conducted over a period of one month before and three months after the replacement of the bearing. We detected a steady trend both at the beginning and at the end of the life-cycle, with an almost constant progression in time (see Fig. 6) at a rate of about 10 dB in three months. Considering the hypothesis of constant rate of degradation over the life-cycle would lead to estimate a RUL of about 12 months (in November 2019). In practice one month corresponds to about 20 working days, during which the pump operates at a rotational speed of 1270 rpm, while during the weekend it operates at a lower speed.

However, analysis over a longer period (see Fig. 7) evidenced that in the following months the operating conditions changed (lower load for the motor, lubrication of the bearing) and we observed a counter-trend toward the end of November 2019. This implied an extension of the estimated RUL which, according to a linear regression, amounted in December 2019 to about 20 months. Subsequently, after a month of downtime due to holidays and maintenance interventions, a period of two months with no definite trend follows. As a result, the estimated RUL is further extended and reaches a value of about 21 months in February 2020.

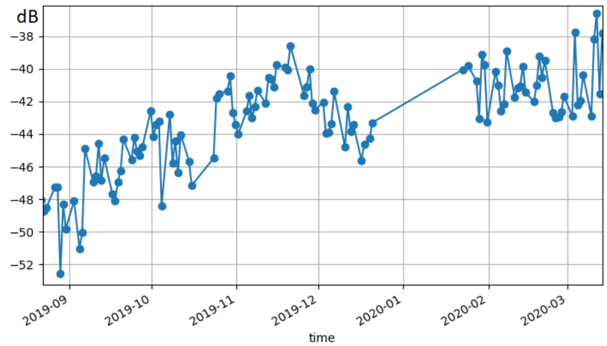


Figure 7. Vibration energy level at 3400 Hz (operation at 1270 rpm) over the full observation period after bearing replacement (on August 21, 2019).

The same sequence of trends is also confirmed by the analysis of a spectral distance measured with respect to the spectrum when the bearing was in degraded condition. Such distance measure was defined as the integral of the absolute difference between the current spectral curve and the curve associated to the degraded device, as depicted in Fig. 3. The evolution of this distance measure was depicted in Fig. 8, normalized with respect to its value on the first day after bearing replacement. Ideally, the curve would reach zero as soon as it returns to the initial degraded condition (supposing that exactly the same degradation occurs). The curve suggests that after the first three months, during which we can extrapolate a quite steady value for RUL, a change of trend develops and causes a jump in the normalized spectral distance, implying a higher RUL estimation. Finally, the constant phase at the end of the observation period gives rise to an updated RUL estimate which increases with time, given an almost constant spectral distance.

4.2. Particle Filter based RUL Estimation

We considered a second RUL estimation algorithm which is based on PF and consists in the following steps: i) calculate WSE in the narrow-band of a WT of the vibration signal; ii) apply a PF to estimate the WSE trend according to an exponential model of degradation.

The purpose of WSE calculation is to find a spectrum band where the vibration energy is mostly concentrated. Following (Antoni, 2007), we thus apply a 5-level wavelet decomposition to the vibration signal to iteratively decompose it into sub-bands as shown in Fig. 9. Spectral energy is then computed for each sub-band and the maximum energy of the sub-

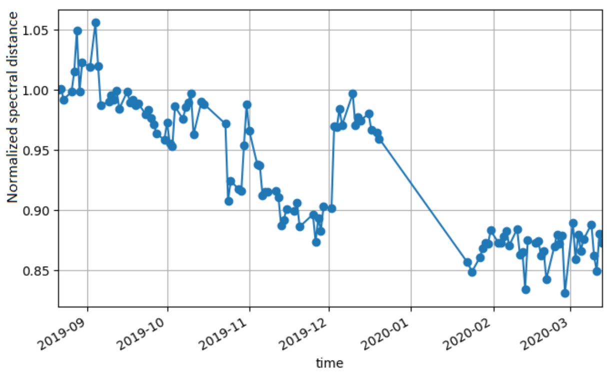


Figure 8. Normalized spectral distance between the curve of spectral energy distribution and the corresponding curve just before bearing replacement.

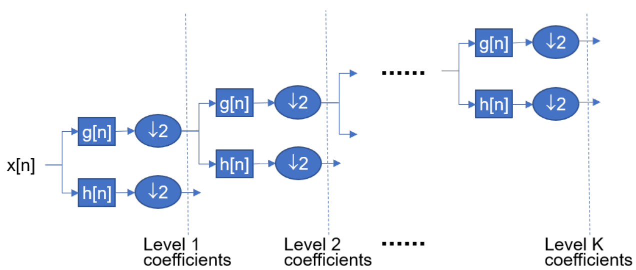


Figure 9. A K-level wavelet transform. g[n] and h[n] indicate low-pass and high-pass filter respectively.

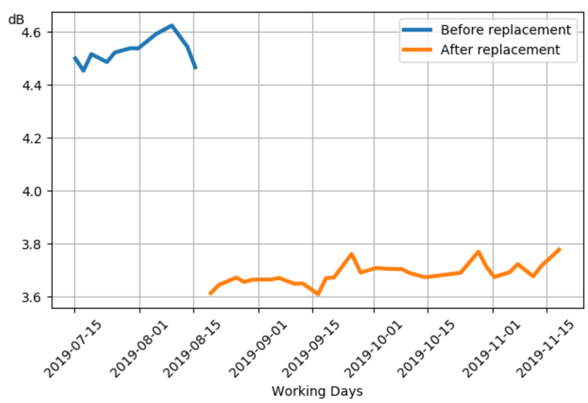


Figure 10. Wavelet spectral energy at 1270 rpm speed before and after bearing replacement.

bands is selected as WSE. The calculation of WSE is dynamic in nature since the sub-band with maximal energy is not defined a priori. WSE of the vibration signal is illustrated in Fig. 10 in a day-by-day manner over a period of one month before and three months after the bearing replacement. According to the plot, there is a trend of increasing WSE which denotes a progressive bearing degradation both before and after the replacement. Note that WSE, in the first three months after replacement, increases toward the value it had in the bad condition, and the difference with respect to it decreases of about 20%.

When a bearing starts to deteriorate, the degradation trend is expressed by an exponential model (N. Li, Lei, Lin, & Ding, 2015). Thus, we assume that the WSE value λ evolves over time as $\lambda = \alpha \exp(\beta t)$, where α and β are model parameters, t is time. For simplicity, we impose $\alpha = 1$, and thus we normalize the WSE values within the range 0 and 1, where 1 represents the maximum WSE value before replacement (degraded condition). In this paper, a particle filter is applied to estimate unknown parameter.

In PF, an update process is performed in a Sequential Monte Carlo manner with a set of particles representing probabilistically the unknown parameters (Jouin, Gouriveau, Hissel, Péra, & Zerhouni, 2016). When a new measurement is available, the posterior probability at previous step is used as prior information at the current step, and the parameters are updated by multiplication with the likelihood.

Once the parameters of the model have been estimated, the RUL is obtained as the time interval required by λ to reach a predefined threshold. The principle of the PF-based RUL estimation technique is depicted in Fig. 11.

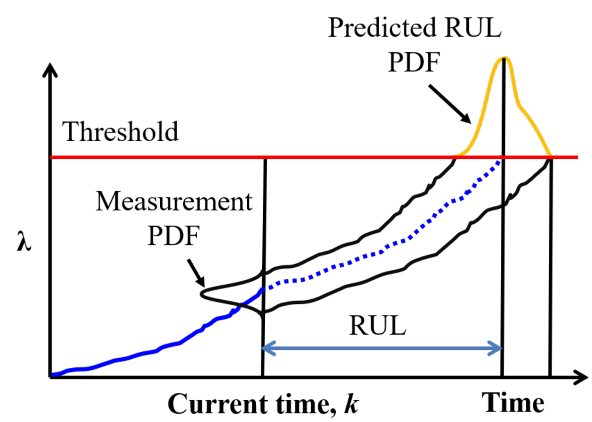


Figure 11. Procedure to predict the RUL using particle filtering technique.

We tested the proposed PF-based RUL estimation algorithm using a set of 4500 particles.[3] The results provided by the PF algorithm on the basis of the measurements during the first three months (till November 2019) is provided in Fig. 12. The peak of the predicted RUL distribution (see detail in Fig. 13) indicates the most likely RUL which is 289 working days (and corresponds to about 14.5 months, since the pump operates at high speed for about 20 days per month).

After the first three months, there were maintenance interventions (lubrication) and periods of lower stress which changed

[3]This value is in the typical range used in related literature (Zio & Peloni, 2011; Qiu et al., 2018), and represents a tradeoff between complexity and achieved accuracy.

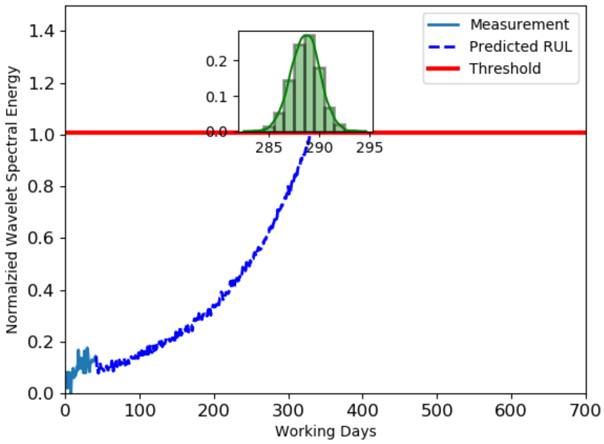


Figure 12. A visualization of predicted RUL trend at November 2019.

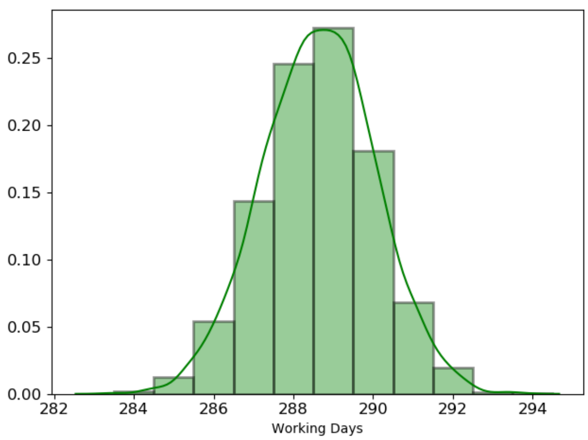


Figure 13. Distribution of the predicted RUL at November 2019. The predicted RUL is 289 working days (i.e. about 14.5 working months).

the operating conditions. These changes reflected also in the WSE trend(Fig. 14). Another contingency that caused a jump in the WSE trend was due to holidays and maintenance interventions. This also confirms the results obtained through spectrum analysis in Sect. 4.1. Considering these contingencies, we applied the RUL estimation algorithm again in December 2019 and February 2020.

The RUL predicted at December, reported in Fig. 15 and Fig. 16, turns out to be increased with respect to the previous estimate and amounts to 418 working days (e.g., about 21 working months). In February (Figs. 15 and 16) we found again a further increase instead of a decrease. These results confirmed the trends observed with the spectral energy regression discussed in Sect. 4.1. According to the distribution of the predicted value, the RUL amounted in Febraury 2020 to

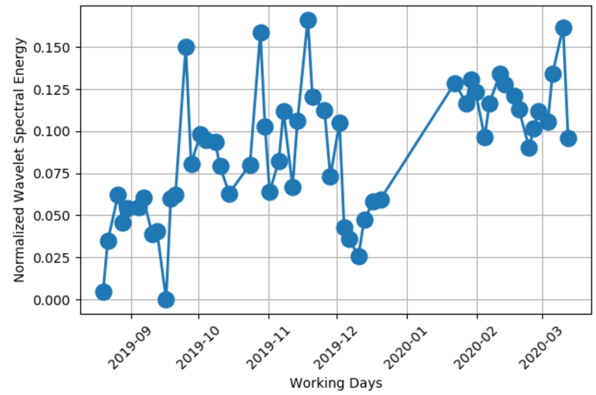


Figure 14. WSE trend over the full observation period after bearing replacement in August 2019.

443 working days (e.g., about 22 working months). Although the estimated RUL values are slightly different from the ones obtained in Sect. 4.1, the observed trend is in accordance with those estimates.

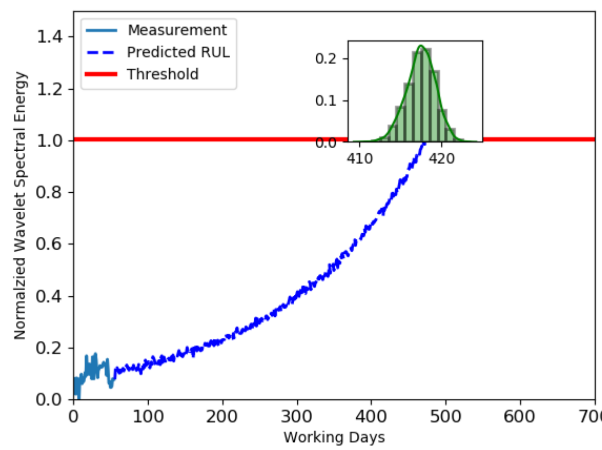


Figure 15. A visualization of predicted RUL trend at December 2019.

4.3. Critical analysis of the results

The two proposed RUL estimation methods, leveraging respectively on spectral regression and particle filtering, provide slightly different but comparable results. In particular, we identified three different phases in the evolution of the spectral data, leading to models with correspondingly distinct degradation rates and consequent increasing RUL estimated values (from about 12 months to almost 2 years).

The obtained RUL estimates are characterized by a quite high uncertainty and variability, due to the influence of many boundary contingent conditions that, in the real operative setup, change with time. This clearly shows the need of a con-

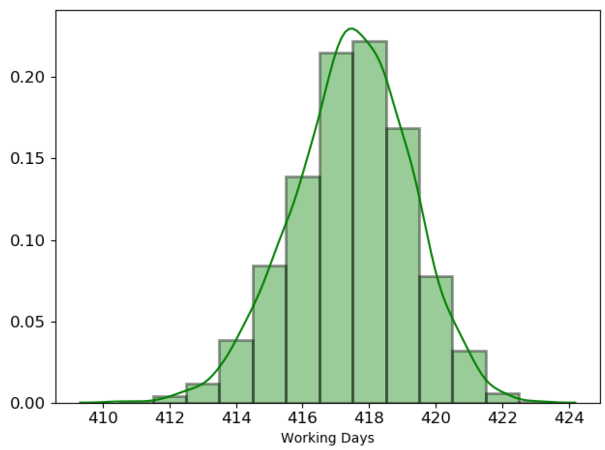


Figure 16. Distribution of the predicted RUL at December 2019. The predicted RUL is 418 working days (i.e. about 21 working months).

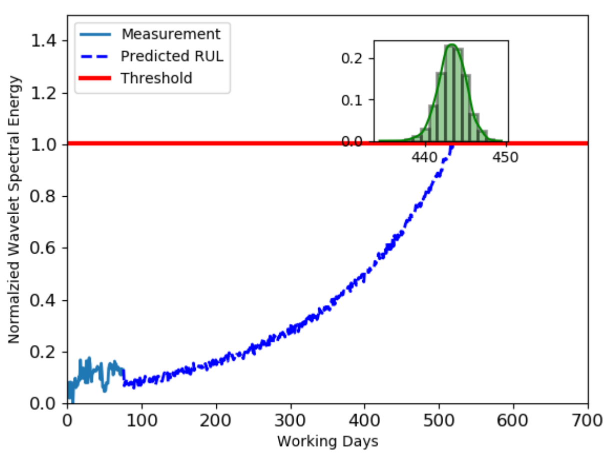


Figure 17. A visualization of predicted RUL trend at February 2020.

tinuous (or periodic) update of the models, in order to include contextual information about the real usage of the component under test in the online running condition monitoring.

Another source of uncertainty is due to the physical constraint in the placement of the sensor on the operating device. As a matter of fact, the accelerometer is not directly mounted on the bearing frame but on the motor chassis close to the bearing. Vibration of the bearing, which is indeed the most rapidly wearing component, is therefore acquired only indirectly (after passing through a mechanical filtering with unknown transfer function) and is mingled among other signal components due to vibrations of the overall pump system.

Data collection and analysis are still in progress. Given the long observation time required by the real case of the air-

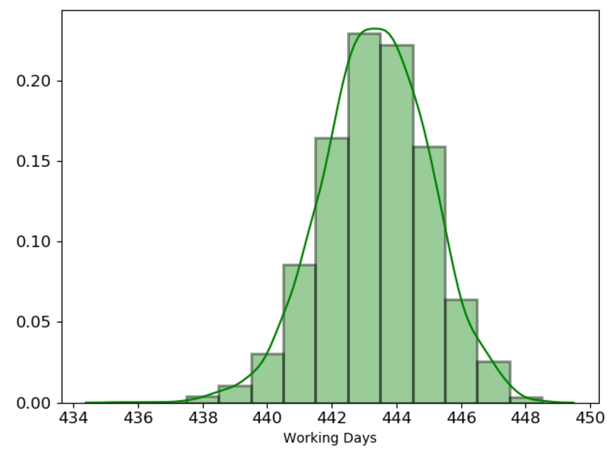


Figure 18. Distribution of the predicted RUL at February 2020. The predicted RUL is 443 working days (i.e. about 22 working months).

recirculation pump operating in a running plant, the dataset currently includes only one partial life-cycle of a single device. We are aware that under such circumstances the data we collected and the analysis we performed are still incomplete and, being very specific for the case under study, can hardly be generalized to a more generic scenario. However, we are confident that the overall approach to RUL estimation we followed, i.e. isolating meaningful trends within a time-frequency representation, keeps its validity in a very wide range of analogous situations.

5. CONCLUSIONS AND FUTURE WORKS

Past studies on predictive maintenance related to critical rotating machines health monitoring are mostly confined to artificial or simulated test-bed dataset. In this paper, we continuously recorded vibration data of rotating bearings of a critical air pump of an industrial plant. To predict the RUL of the system under test, we applied state-of-the-arts signal processing techniques namely STFT and WT to extract informative features that correspond to bearing degradation trends. These degradation models are further employed with linear regression and particle filter respectively for RUL estimation. The preliminary results indicate that estimated RUL mostly complies with provided RUL of the bearing. Moreover, analysis over a reasonably long period of real usage in an industrial setting (e.g., around 6.5 months after replacement) evidenced that operating conditions such as motor load, rotational speed, and periodic lubrication of the bearing have a non-negligible impact on the life of the component and thus on the respective RUL prediction. These cases have been vastly ignored in the past research, and demand for techniques that will allow to properly integrate the contextual information to improve the confidence and accuracy of the predictions.

We are continuously monitoring the air pump, updating the predictive models to consider the occurring contingencies. We work together with the maintenance experts of the clean room facility to support them in future maintenance activities to possibly reduce periodic maintenance costs.

In the future, we plan to further investigate the relations between the estimated RUL and the true RUL from run-to-failure bearing dataset obtained from industrial environment subject to work load variability and periodic maintenance integrating contextual reasoning. To this extent, we envisage the identification of hybrid approaches combining model based techniques (e.g. finite state machines) with statistical reasoning and digital signal processing. The model based techniques seems very promising to allow to reason on contextual information. Finally, reliability and robustness analysis of the evolving prediction models will also be conducted to meet industry standard.

REFERENCES

Antoni, J. (2007). Fast computation of the kurtogram for the detection of transient faults. *Mechanical Systems and Signal Processing*, *21*(1), 108 - 124.

Cui, L., Wang, X., Xu, Y., Jiang, H., & Zhou, J. (2019). A novel switching unscented kalman filter method for remaining useful life prediction of rolling bearing. *Measurement*, *135*, 678–684.

Engelberth, T., Krawczyk, D., & Verl, A. (2018). Model-based method for condition monitoring and diagnosis of compressors. *Procedia CIRP*, *72*, 1321–1326.

Gouriveau, R., Medjaher, K., & Zerhouni, N. (2016). *From prognostics and health systems management to predictive maintenance 1: Monitoring and prognostics*. John Wiley & Sons.

Gugulothu, N., TV, V., Malhotra, P., Vig, L., Agarwal, P., & Shroff, G. (2017). Predicting remaining useful life using time series embeddings based on recurrent neural networks. *arXiv preprint arXiv:1709.01073*.

Hinchi, A. Z., & Tkiouat, M. (2018). Rolling element bearing remaining useful life estimation based on a convolutional long-short-term memory network. *Procedia Computer Science*, *127*, 123–132.

Hossain, M. L., Abu-Siada, A., & Muyeen, S. (2018). Methods for advanced wind turbine condition monitoring and early diagnosis: A literature review. *Energies*, *11*(5), 1309.

Janssens, O., Slavkovikj, V., Vervisch, B., Stockman, K., Loccufier, M., Verstockt, S., … Van Hoecke, S. (2016). Convolutional neural network based fault detection for rotating machinery. *Journal of Sound and Vibration*, *377*, 331–345.

Jardine, A. K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical systems and signal processing*, *20*(7), 1483–1510.

Jin, X., Que, Z., Sun, Y., Guo, Y., & Qiao, W. (2019). A data-driven approach for bearing fault prognostics. *IEEE Transactions on Industry Applications*, *55*(4), 3394–3401.

Jouin, M., Gouriveau, R., Hissel, D., Péra, M.-C., & Zerhouni, N. (2016). Particle filter-based prognostics: Review, discussion and perspectives. *Mechanical Systems and Signal Processing*, *72*, 2–31.

Ke, Y., Mulumba, T., Shen, W., & Afshin, A. (2014). Model-based predictive maintenance of chillers. In *Proceedings of the 7th Asian Conference on Refrigeration and Air Conditioning.*

Kim, S., Park, S., Kim, J.-W., Han, J., An, D., Kim, N. H., & Choi, J.-H. (2016). A new prognostics approach for bearing based on entropy decrease and comparison with existing methods. In *Annual Conference of the Prognostics and Health management Society.*

Lee, J., Qiu, H., Yu, G., & Lin, J. (2007). *Bearing Data Set: NASA Ames Prognostics Data Repository* (Tech. Rep.). Moffett Field, CA, USA: Rexnord Technical Services (2007), IMS, University of Cincinnati, NASA Ames Research Center. (`http://ti.arc.nasa.gov/project/prognostic-data-repository`)

Lei, Y. (2016). *Intelligent fault diagnosis and remaining useful life prediction of rotating machinery*. Butterworth-Heinemann.

Li, N., Lei, Y., Lin, J., & Ding, S. X. (2015). An improved exponential model for predicting remaining useful life of rolling element bearings. *IEEE Transactions on Industrial Electronics*, *62*, 7762–7773.

Li, P., & Goodall, R. (2004). Model-based condition monitoring for railway vehicle systems. *Control 2004*.

Lim, R., & Mba, D. (2015). Fault detection and remaining useful life estimation using switching kalman filters. In *Engineering asset management-systems, professional practices and certification* (pp. 53–64). Springer.

Liu, H., Mo, Z., Zhang, H., Zeng, X., Wang, J., & Miao, Q. (2018). Investigation on rolling bearing remaining useful life prediction: A review. In *2018 Prognostics and System Health Management Conference (PHM-Chongqing)* (pp. 979–984).

Lv, Y., Yuan, R., Wang, T., Li, H., & Song, G. (2018). Health degradation monitoring and early fault diagnosis of a rolling bearing based on ceemdan and improved mmse. *Materials*, *11*(6), 1009.

Nectoux, P., Gouriveau, R., Medjaher, K., Ramasso, E., Chebel-Morello, B., Zerhouni, N., & Varnier, C. (2012, June). PRONOSTIA : An experimental platform for bearings accelerated degradation tests. In *IEEE International Conference on Prognostics and Health Management, PHM'12.* (Vol. sur CD ROM, p. 1-8). Denver, Colorado, United States: IEEE Catalog Number : CPF12PHM-CDR.

Nguyen, T. P. K., Khlaief, A., Medjaher, K., Picot, A., Maussion, P., Tobon, D., . . . Cheron, R. (2018). Analysis and comparison of multiple features for fault detection and prognostic in ball bearings..

Nixon, H., Springer, T., Hoeprich, M., & Clouse, D. (2013). *Experimental And Analytical Methods For Assessing Bearing Performance: Under Debris Contaminated Lubrication Conditions* (Tech. Rep.). The Timken Company.

Porotsky, S., & Bluvband, Z. (2012). Remaining useful life estimation for systems with non-trendability behaviour. In *2012 IEEE conference on prognostics and health management* (pp. 1–6).

Qiu, M., Li, W., Jiang, F., & Zhu, Z. (2018). Remaining useful life estimation for rolling bearing with sios-based indicator and particle filtering. *IEEE Access*, *6*, 24521–24532.

Rações, H. D., Ferreira, F. J., Pires, J. M., & Damásio, C. V. (2019). Application of different machine learning strategies for current-and vibration-based motor bearing fault detection in induction motors. In *IECON 2019-45th Annual Conference of the IEEE Industrial Electronics Society* (Vol. 1, pp. 68–73).

Ren, L., Sun, Y., Wang, H., & Zhang, L. (2018). Prediction of bearing remaining useful life with deep convolution neural network. *IEEE Access*, *6*, 13041–13049.

Singleton, R. K., Strangas, E. G., & Aviyente, S. (2013). Time-frequency complexity based remaining useful life (rul) estimation for bearing faults. In *2013 9th IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives (SDEMPED)* (pp. 600–606).

Soualhi, A., Medjaher, K., & Zerhouni, N. (2014). Bearing health monitoring based on hilbert–huang transform, support vector machine, and regression. *IEEE Transactions on Instrumentation and Measurement*, *64*(1), 52–62.

Sutrisno, E., Oh, H., Vasan, A. S. S., & Pecht, M. (2012). Estimation of remaining useful life of ball bearings using data driven methodologies. In *2012 IEEE Conference on Prognostics and Health Management* (pp. 1–7).

Wang, H., Yu, Z., & Guo, L. (2020). Real-time online prediction of data driven bearing residual life. In *Journal of physics: Conference series* (Vol. 1437, p. 012025).

Wu, B., Li, W., & Qiu, M.-q. (2017). Remaining useful life prediction of bearing with vibration signals based on a novel indicator. *Shock and Vibration*, *2017*.

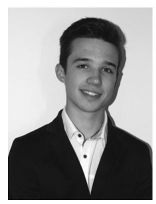
Yoo, Y., & Baek, J.-G. (2018). A novel image feature for the remaining useful lifetime prediction of bearings based on continuous wavelet transform and convolutional neural network. *Applied Sciences*, *8*(7), 1102.

Zhang, X., & Li, X. (2014). Degradation and acceleration modeling for ball bearings based on kurtosis of vibration data. *Vibroengineering PROCEDIA*, *4*, 259–264.

Zhao, M., Tang, B., & Tan, Q. (2016). Bearing remaining useful life estimation based on time–frequency representation and supervised dimensionality reduction. *Measurement*, *86*, 41–55.

Zio, E., & Peloni, G. (2011). Particle filtering prognostic estimation of the remaining useful life of nonlinear components. *Reliab. Eng. Syst. Saf.*, *96*(3), 403–409.

Hani Beirami received his masters degree from the University of Tehran, Iran. He is currently enrolled as a Ph.D. student in the Information Engineering and Computer Science Department of the University of Trento funded by a grant by Fondazione Bruno Kessler, Italy. His research interests include formal methods and machine learning. The focus of his Ph.D. at the University of Trento is on improving the functionality of predictive maintenance.



Davide Calzà is Bachelor's student at the Information Engineering and Computer Science Department of the University of Trento, Italy. He received his High School diploma from the I.T.T. G.Marconi of Rovereto, Italy. He is part of the Embedded System Unit of the Fondazione Bruno Kessler in Trento, Italy, as junior research assistant since 2019. His interests focus on predictive maintenance in the field of rotating machinery analysis, diagnosis and prognosis.

Alessandro Cimatti is a senior researcher at Fondazione Bruno Kessler, Trento, Italy, where he coordinates the activities on Digital Industry and leads the research unit in Embedded Systems. His research interests concern formal verification of industrial critical systems, methodologies for design and verification of hardware/software systems, decision procedures and their application, safety analysis, diagnosis and diagnosability. He has published more than two hundred conference and journal papers in the fields of Formal Methods and Artificial Intelligence, and has co-chaired the FMCAD, SAT, DX and SEFM conferences.

Manjurul Islam received a Ph.D. degree in Computer Engineering from the University of Ulsan, South Korea in 2019. He is now working as a postdoctoral researcher in the Embedded Systems Unit of Fondazione Bruno Kessler in Trento, Italy. His research interests include multimedia signal processing, statistical modeling, and predictive maintenance in the field of industrial machine analysis, diagnosis and prognosis.

Marco Roveri received a Ph.D. degree in Computer Science from the University of Milano, Italy in 2002. He is an Associate Professor in the Information Engineering and Computer Science Department of the University of Trento, Italy. He was Senior Researcher in the Embedded Systems Unit of Fondazione Bruno Kessler in Trento, and before a researcher in the Automated Reasoning Division of the Istituto Trentino di Cultura, Trento, Italy, in 1998, first as a consultant, and in 2002 as a full time researcher. In 2008 he was appointed as a senior researcher in the Embedded Systems Unit of the Fondazione Bruno Kessler, Trento, Italy, and in 2020 he was appointed as Associate Professor in the University of Trento. His research interests include automated formal verification of hardware and software systems, formal requirements validation of embedded systems, model based predictive maintenance, and automated model based planning, and application of such techniques in industrial settings.

Piergiorgio Svaizer received his degree in Electronic Engineering from the University of Padua, Italy, in 1989. From 1989 to 1990, he was a consultant at the National Council for Research, Padua, where he worked on multi-band image processing and pattern recognition. In 1991 he joined the Interactive Sensory System Division at ITC-IRST, Trento. He is a now a senior researcher at the Center for Information and Communication Technology, Fondazione Bruno Kessler, Trento, Italy. Since 2001 he collaborates in teaching activities for digital signal processing with the University of Trento. His main research interests include digital signal processing, statistical modeling and time-frequency analysis of multichannel signals, microphone arrays for acoustic scene analysis and spatial selectivity, speech analysis, enhancement and separation, DSP for condition monitoring of industrial equipment.