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Review

A review on data-driven fault severity assessment in rolling bearings

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ABSTRACT

Health condition monitoring of rotating machinery is a crucial task to guarantee reliability in industrial processes. In particular, bearings are mechanical components used in most rotating devices and they represent the main source of faults in such equipments; reason for which research activities on detecting and diagnosing their faults have increased. Fault detection aims at identifying whether the device is or not in a fault condition, and diagnosis is commonly oriented towards identifying the fault mode of the device, after detection. An important step after fault detection and diagnosis is the analysis of the magnitude or the degradation level of the fault, because this represents a support to the decision-making process in condition based-maintenance. However, no extensive works are devoted to analyse this problem, or some works tackle it from the fault diagnosis point of view. In a rough manner, fault severity is associated with the magnitude of the fault. In bearings, fault severity can be related to the physical size of fault or a general degradation of the component. Due to literature regarding the severity assessment of bearing damages is limited, this paper aims at discussing the recent methods and techniques used to achieve the fault severity evaluation in the main components of the rolling bearings, such as inner race, outer race, and ball. The review is mainly focused on data-driven approaches such as signal processing for extracting the proper fault signatures associated with the damage degradation, and learning approaches that are used to identify degradation patterns with regards to health conditions. Finally, new challenges are highlighted in order to develop new contributions in this field.

Contents

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1. Introduction

Health condition monitoring (HCM) of rotating machinery is a crucial task to guarantee reliability in industrial processes. It is oriented towards detecting the presence of fault situations such as the identification of healthy and faulty state, and diagnosis of the type of faults, using available models and signals, such as vibration and acoustic emissions [1–4]. Bearings are mechanical components used frequently in most rotating devices and they represent the main source of faults in such equipment; bearing faults can constitute the 44% of the total number of faults in some devices [5]. In a rough manner, a rolling bearing, also known as rolling-element bearing, has four main components: (i) the ball, also called roller or rolling element, (ii) the inner race, (iii) the outer race, and (iv) the cage, which provides equal spacing between balls for preventing internal strikes; damages or faults can appear on these components, as illustrated in Fig. 1, or even appear as a generalized damage of the whole device. There are also other standardized forms of roller elements such as cylindrical rollers, tapered rollers, needles, and barrel rollers, but they are not within the scope of the present study. The selected papers in this review tackle the fault severity assessment mainly for the inner race, outer race, and ball.

Basically, bearing faults are classified as (i) single point defect, (ii) multiple point defect, and (iii) generalized roughness; also called "distributed faults". The single point defect is defined as a single, localized defect on a relatively intact bearing surface. A single point defect will cause certain characteristic fault frequencies which appear in the vibration, current, sound, or acoustic emission signals. These frequencies are predictable and depend on the surface of the bearing containing the fault point, i.e., inner race, outer race, ball, and cage [6]; therefore, there is one characteristic fault frequency associated with each of the four components of the bearing. A detailed analysis of the single inner race defect is given in [7]. Examples of single point defects are cracks, pits or holes, and spalls. Cracks and holes, on the inner and outer race, occur if the bearings are used for a long time. These faults are severe and many research papers have discussed the single point defect. As claimed in [8], cracks on inner and outer races are the most frequent faults, with 90% of all faults in rolling bearings, while cracks in balls or cages represent 10%. Spalling or pitting is the main manifestation of fault development in a bearing during the earlier stages [9].

In spite of the name, a bearing can possess multiple single-point defects, which consist of several, perhaps overlapping, single point defects. In such a case, the spectra of the vibration signal differ from those expected from the single point defect. For instance, spectral lines can occur at the same frequencies expected for single point defects, but the relative amplitudes of the components may change considerably, and perhaps, their harmonics are not necessarily the largest components. A detailed description of these type of faults is given in [10].

Fig. 1. A physical bearing and related damages.

Finally, the generalized roughness faults are due to deterioration of the bearing, over a large area of the bearing's surface, which becomes rough, irregular, or deformed. There is no localized defect to be identified as the fault. A common example is the overall surface roughness produced by contamination, lack or loss of lubricant, shaft currents, misalignment, or by the progression of localized faults [6]. This type of fault is gradual and generates complex vibration patterns with no specific corresponding characteristic vibration frequencies; then, this type of fault is difficult to predict [11]. In this sense, most literature is devoted to the analysis of suitable techniques for detection and diagnosis of single point defects. This review deals mainly with the severity assessment of single point defects under controlled experiments, and generalized roughness due to run-to-failure tests.

Fault detection and diagnosis in bearings have been widely studied for several years by using signal processing approaches [12,13], and more recently by using machine learning methods [14–16]. Fault detection is limited by the result of knowing whether the device is in a different condition from the normal or nominal state, i.e., the device is or not in fault. After fault detection, assessment of the damage is needed. Usually, the diagnosis is limited by the result of knowing the fault mode in which the device is working, but the magnitude of the fault is not analysed. In a rough manner, fault severity is associated with such magnitude of the fault. It can be related to the physical size of the fault, e.g. the size of holes in bearing races, or a general degradation of the component. In the first case, more complex signal processing techniques are required to analyse the dynamical behaviour in cases such as the entrance and exit events when the ball passes over the races' damaged area; in the second one, the objective is to create a degradation assessment indicator based, in some cases, on the knowledge of degradation models [17]; this is a necessary step when predicting health condition of bearings [18].

The vibration signal coming from a ball bearing system can reveal the location of a fault and its severity. An appropriate signal processing technique is required to extract relevant information from such vibration signal. In bearing degradation assessment, the bearing characteristics frequencies (BCF) are typically indications of the defect's severity, and the presence of harmonics of such BCF is also an indicator of degradation and spall formation [19]. A fault severity indicator can be defined to determine the level of bearing failure at each monitored interval; this indicator allows one to observe if the considered faulty bearing's component gets worse or it remains stable. For instance, Prudhom et al. [20] stated that many alternative fault indicators may be defined based on the results of the time-frequency transforms. Particularly, a simple fault severity indicator using information from the Short Time Fourier Transform (STFT) is proposed; this indicator relates the energy of the time-frequency region containing the fault component with the energy of the time-frequency region containing the main vibration component. The idea when defining this indicator is to observe how the fault degrades over time. Liu [21] proposed another simple indicator, called fault severity degree evaluation factor; this factor is based on the ratio between the fault characteristic frequency component and the current sampled vibration signal. The fault's characteristic frequency component is identified by applying Wavelet Packet Decomposition to the raw signal and the Hilbert transform in order to calculate the instantaneous frequency and instantaneous amplitude of the high- and low-frequency narrow-band signals. Yang and Court [22] proposed the use of classical statistical parameters extracted from the vibration signal as fault severity indicators; they analysed the behaviour of Normalized Information Entropy, J-Divergence, Kurtosis and Composite criterion, for several fault size severities in ball, inner and outer race.

In general, vibration signal monitoring reveals early signs of abnormality, even several months prior to any permanent damage, due to their high reactivity to the failure's development. However, other signals such as acoustic emission (AE), current and voltage, in case of electrical devices, can be analysed in order to estimate the fault's severity [23]. Muetze and Strangas [24] presented a brief summary with tools and methods for the reliable estimation of bearings maintenance schedules for electrical devices, through fault severity estimation and Remaining Useful Life (RUL). In case of monitoring low-speed large-sized bearings, AE is well established as a proper signal rather than the vibration signal [25]. However, vibration-based monitoring leads over the acoustic emission technique, due to its low sensor cost and ease in measurement, resulting in the most widely used technique.

The assessment of bearings' health using vibration data has been a research topic of interest in recent years, and several works have been devoted to signal processing methods and the development of learning-based algorithms. For instance, the estimation of the fault's size, from the vibration signal is still a challenge and a subject of interest for several researchers. Estimating the bearing's health at various stages of degradation is important for predicting of the RUL and making maintenance decisions. Appropriate acquisition and understanding of data related to the bearing's working state enable identification of potential failures, reducing the likelihood of machine downtime and guaranteeing high productivity. There are several review papers addressing the problem of fault detection and diagnosis in rotating machinery as the previous step of fault severity assessment, see [2,26–31]. Some reviews have covered the problem of degradation models, predictive health monitoring and prognosis [17,18,32,33]; however, to the authors' knowledge, the literature regarding the severity assessment of bearing damages is not exhaustive, and has been more limited to the case of gears as shown in [34].

This paper presents an updated and comprehensive review of techniques and methods for fault severity evaluation in bearings, due to its important role in the reliability analysis of rotating machinery, and decision making in maintenance activities. Two approaches for fault severity evaluation are discussed: (i) signal processing and (ii) learning. The first applies techniques on raw signals to extract features revealing clearly the fault pattern on time, frequency or time-frequency domains, by constructing proper and de-noised fault signatures. The latter is used to identify or recognize fault patterns associated with a certain type of fault and its severity levels, by creating machine learning based models through the automatic analysis of a dataset. Basically, the dataset is composed of instances of fault patterns described by a vector of features, also called "attributes", and a learning process is applied on the dataset to build a model which reveals or discovers the fault patterns. In the presence of a new instance, with a certain vector of features, the learned model is able to give some information about the fault pattern and its characteristics, if they are considered into the model. Usually, the features are obtained from classical statistical metrics calculated over the raw signal, or they can be extracted by using specialized signal processing techniques [35]. In both approaches, the objective of fault severity assessment is the construction of a defect severity index to measure the size of the damage. This review provides a detailed description of each presented technique or method, emphasizing on the features extraction and feature selection as key procedures in data-driven based techniques. Particularly, the review shows that bearing damages on ball, inner and outer race, such as pitting damages such as holes, as illustrated in Fig. 1, are widely reported. In this case, the severity evaluation is addressed in two ways: (i) the estimation of the fault size, by identifying the entry and exit events from the vibration signal, and (ii) the classification of the vibrations pattern in different levels of severity such as healthy, low, medium, and high. Other damages such as bearing wear are also reported; in this case, the fault's severity is addressed by analysing the trends in time of certain vibration features. Different thresholds for the feature magnitude are established to alert about low, medium and high severity levels.

The paper is organizing as follows. Section 2 briefly presents the problem of fault severity assessment in bearings from the point of view of the size of the physical damage; illustrated with damages in the outer or inner race, and as a generalized degradation damage which can occur on any surface of the rolling bearing. Section 3 describes the methodological framework used to accomplish the search in the most common academic databases and some quantitative analysis about the number of works in the field. Sections 4 and 5 present the most important results devoted to the main signal processing based approaches and learning based approaches, respectively. Finally, Section 6 gives some conclusions and states new challenges for fault severity assessment in bearings.

2. Fault severity in bearings

As mentioned previously, some research works in bearing faults are regarded to the fault detection in order to identify the status of the bearing, between good and faulty state, and then, the fault diagnosis in order to indicate the defective components of the bearings (ball, inner and outer race, mainly). Randall [36] presented a comparative study of various diagnostic methods for rolling element bearings in the form of a tutorial; basically, these methods aim at identifying the fundamental frequencies and their harmonics in the spectrum on the vibration signal. When there is a local fault on one raceway of a ball bearing, passing roller elements (balls) over the local fault create pulses at one of the fundamental fault frequencies, Ballpass frequency in outer race (BPFO) or Ballpass frequency in inner race (BPFI). Additionally, if there is a local fault on the rolling elements (balls), the local fault creates impacts on both inner and outer raceways. Therefore, a frequency close to 2BSF (Ball Spin Frequency) appears in the spectrum. In many cases, this frequency is modulated with BPFO or BPFI [37].

Other works have been oriented towards estimating the size of the damage, which is a complex problem to solve. A simple view of this type of research could be related to the magnitude value of the vibration signal, as studied in the early 1970s. In the case of bearings, two events are identified from the vibration signal when a ball or roller is in contact with a damaged area on the inner or outer race: the first event is due to the entry of the rolling element into the spall-like area, and the second event is the exit from the fault region. Entry and exit events generate a double impulse of vibration signal as illustrated in Fig. 2. This "Double-impulse structure" that produces the called "mode mixing problem" in vibration signals is a typical symptom of mechanical faults.

A simple way to estimate the defect's size on bearing races is by measuring the impulse of vibration. Shock Pulse Method (SPM) generates a maximum normalized shock value (dB) that gives an indication of the bearing's condition, and that value can discriminate among healthy condition, weak, or heavy fault. The use of SPM instrument and shock pulse sensor can provide useful information for detecting impulses within the frequency spectrum of the vibration signal [38]. This method can be improved by combining the SPM with demodulation method for estimating bearing running state as proposed in [39]. A more complex way to do so, is from knowledge of the time interval between the entry and exit events from the vibration signal, as illustrated in Fig. 2 [40]. The defect size can be estimated by using a proper equation that uses information about the spinning speed of the ball, the shaft rotational speed, the pitch diameter of the bearing, the ball diameter, the contact angle, and the duration between the entry and impact pulse [41]. Recently, a work using band-pass and high-pass filters to detect the entry and exit frequencies to determine the duration between the entry and impact pulse in a rolling element bearing was presented in [42]. A systematic study of ball passing frequencies based on dynamic modelling of ball bearings with localized surface defects, that serve to illustrate the event of entering and exiting from a defect surface, was presented in [43,44].

An extensive review of vibration modelling of rolling-element bearings with localized and extended defects was performed by Singh et al. [45]; they focused on the study of diagnostic signatures of different type of damages. Dobrica and Fillon [46] analysed in detail the degradation process in scratched journal bearings, based on numerical simulations of a mathematical model; in order to evaluate the bearing performance degradation, several operating parameters such as: minimum film thickness,average oil temperature, and maximum hydrodynamic pressure are computed. An extensive review on models and simulated results for the wear process in bearings was presented by El-Thalji and Jantunen [47]. These authors then illustrated the evolution of the fault features with respect to the wear evolution process in rolling bearings through a dynamic model [48]; mainly, the effect of several types of fault sizes on the spectral response by using FFT was analysed in order to detect the different degradation stages, as illustrated in Fig. 3, due to the evolution of the surface topology, i.e., the characteristic of the surface, such as defect shape or size, under continuous deformations. For this type of degradation assessment, the researches aim at proposing a degradation index that has a time behaviour as in Fig. 4.

There are another types of damages such as the presented by Skrimpas et al. [50], where the bearing creep fault detection of bearing creep and its severity assessment in wind turbine generators is analysed; however, there is very limited literature in regards to this class of damage. In induction motors, air gap eccentricity fault can produce bearing damage, but in this case, the fault severity analysis is oriented towards determining the failure evolution of the air gap eccentricity as it was presented by Maruthi and Hedge [51].

Fault size estimation or degradation assessment is usually based on the analysis of the fault signature. A fault signature is a vector of symptoms for each fault, that can be related to the extraction of specific features from the analysed signals, such as vibration, AE, current or voltages. These features might be direct measurements, model residuals, or other transformations of measurement values by using signal processing techniques. Vibration signals often contain complex, non-stationary and

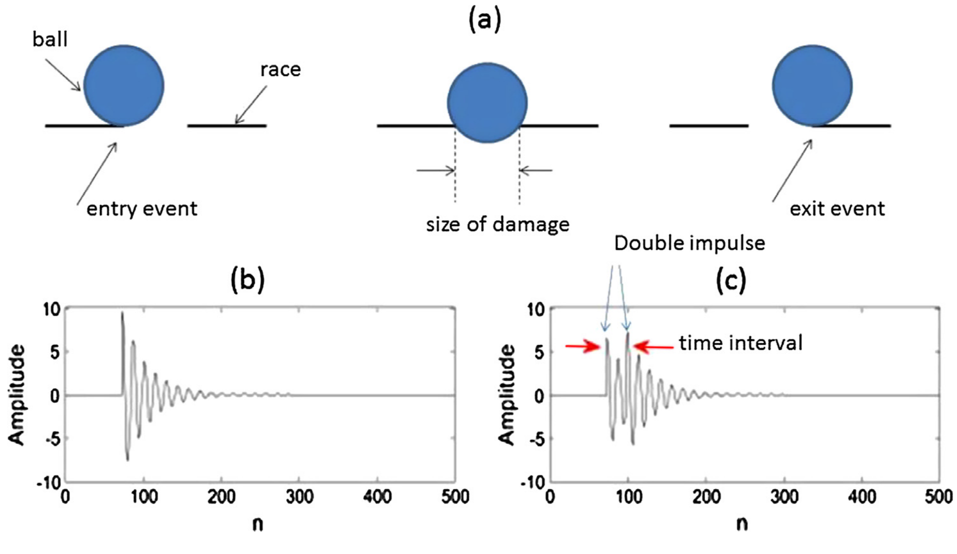

Fig. 2. (a) Entry-exit events due to damages on inner or outer races. (b) Dynamic impact on the vibration signal on a single point (no fault). (c) Dynamic impact due to double-impulse structure.

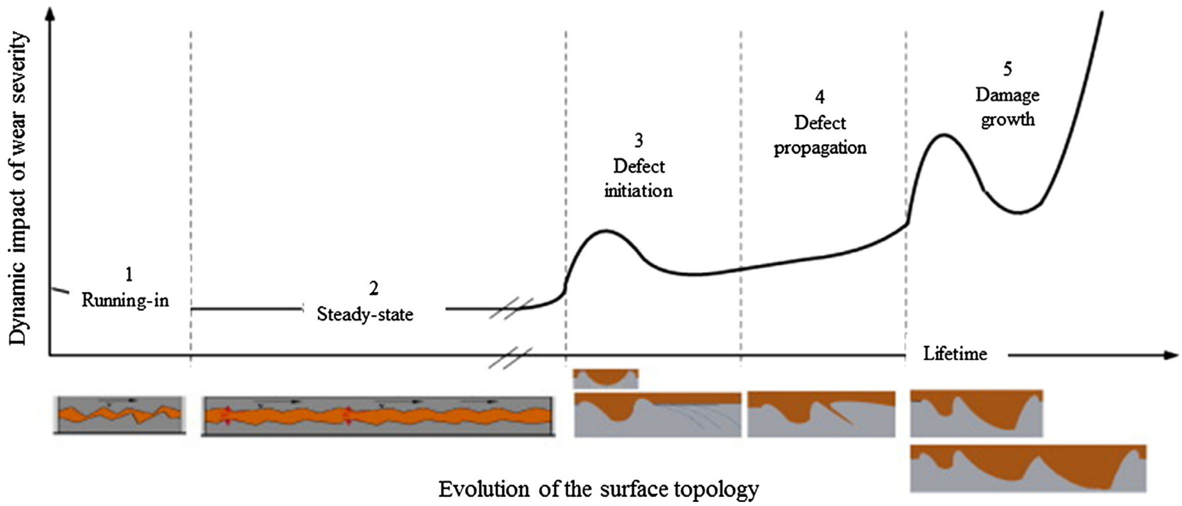

Fig. 3. Dynamic impact of the wear severity in bearings [48].

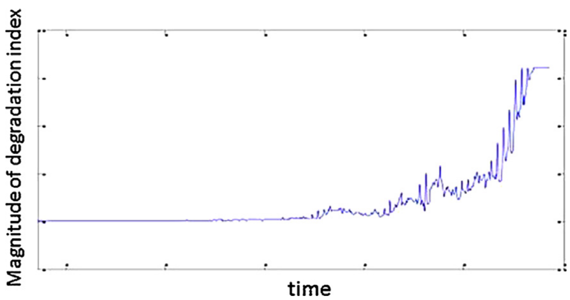

Fig. 4. Monotonic degradation assessment [49].

non-linear characteristics, in this sense, the extraction of a degradation index is not a trivial task; an analysis of the complexity in the performance of the degradation process in rolling element bearings was presented by Pan and Chen [52], based on correlation and approximate entropy. Additionally, an analysis about the optimal time to apply condition based monitoring to detect proper degradations trends in bearings was discussed by Yang and Court [53]. Finally, a fault signature pattern can be associated with a particular failure mode and severity; it is a classification problem that is usually solved through statistical or machine learning approaches.

3. Methodological framework

A global search on the most important academic data bases has been performed by searching documents related to several keywords such as "fault severity", "fault assessment", "fault size", and "fault quantitative diagnosis" in bearings, on title, abstract and keywords, from 2010 until 2016. Some techniques, methods and case studies on fault severity assessment are analysed in some works on fault diagnosis; however, works directly related to the fault diagnosis do not contain at all results on fault severity assessment. This is why our search is guided strictly by the keywords that are more close to the problem of fault severity assessment in order to have a better filter regarding our domain of interest. The search was performed over the most important academic databases such as ScienceDirect, IEEE Xplore and Scopus; works from conference proceedings and journals were equally considered. Of course, with our proposed search criteria on title, keyword an abstract, a large quantity of papers on "fault diagnosis" have appeared, but some of them were discarded as they have no results properly related to the focus of our review.

Taking into account that the works in ScienceDirect and IEEE Xplore are usually included in Scopus, this database is selected to show the trend of the number of available works in the last decade (2006–2016). Regarding the works in the last decade, in Fig. 5 we can see a growing trend in recent years, particularly over the time period of our exhaustive search 2010–2016. The main works show that fault severity techniques can be grouped in signal processing-based techniques and learning-based techniques. The next section discusses the most important results in this review.

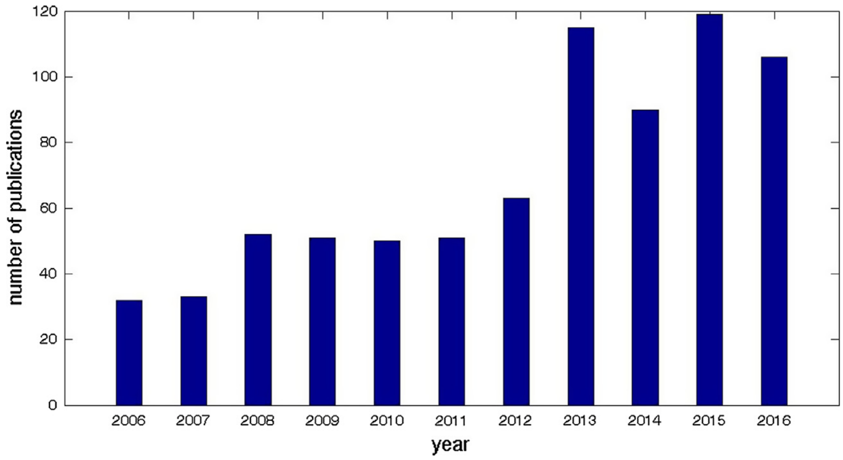

Fig. 5. Trending in number of publications on bearing fault severity analysis from 2006 to 2016.

4. Signal processing-based approaches

Signal processing methods are required to extract features related to fault size estimation and the wear process in bearings, from vibrations, AE, or electrical signals such as current and voltage, and how to track their evolution. Basically, this features extraction aims at constructing a fault signature. Due to the background noise in acquired signals, it is not always possible to identify probable faults from raw signatures, then, the de-noising process is one of the most essential steps in the field of Condition Monitoring (CM) and fault detection. Several signal processing methods oriented to de-noising are commonly applied in experimental and real tests.

Table 1 shows some relevant works published from 2010. These techniques are divided according to the aim of the analysis, such as fault size estimation (FSE) or fault degradation estimation (FDE), the analysed signals, such as Vibration (VIB), Acoustic Emission (AE), Current (CUR), Voltage (VOLT), and the used techniques. The most common damages analysed in these works are spall-like fault on the outer race, shape on the outer race, deep groove of the outer race, crack zones on flat ring, accelerated wear of small rolling bearings in run-to failure-tests, outer race with scratch damage in increasing levels and, in general, different severity levels in diameter and depth at inner race, outer race and rolling element.

Table 1
Relevant works in fault severity assessment by using signal processing approaches, from 2010 to 2016.

Aim	Signal	Methods and/or techniques
FSE	VIB	Matching pursuit method [54,55], Approximate entropy method and Empirical mode decomposition [9], Discrete wavelet transform [41,56,57], Fourier transform, Band pass filter, Hilbert transform [58], Continuous wavelet transform, Cepstrum analysis and Minimum entropy deconvolution [59], Shift-invariant dictionary learning and Markov models [40]
FSE	AE	Information entropy, Signal shape factor, Envelope analysis, Spectrum analysis, Pronys energy method, Eigen analysis and Auto regressive models [60–62], Discrete wavelet transform, Envelope analysis and Low pass filtering [63], Averaged energy and Maximum amplitude values [64], Wavelet packet decomposition, Shannon entropy and Envelope analysis [65], Continuous wavelet transform, Squared Hilbert transform and Autocorrelation function [66]
FDE	VIB	Empirical mode decomposition, Teager energy operator, Mahalanobis distance and confidence value [67], Cyclic coherence analysis [68], Improved empirical mode decomposition, AM-FM demodulation algorithm, Maximum correlated kurtosis deconvolution [69], Approximate entropy method and Cross correlation functions [70], Improved morphology filtering, Lempel Ziv complexity algorithm, Kolmogorov measure, Artificial immune optimization [71], Optimal local mean decomposition [72], Singular value decomposition and Henkel matrix [37,73], Hilbert transform and Envelope analysis [74], Spline wavelets, Correlation coefficient and Mutual entropy [75], Wavelet packet decomposition, Auto regressive filter, Minimum entropy deconvolution filter, Kurtosis feature, Empirical mode decomposition [76], Comblet filtering, Exponentially weighted moving average [77], Recurrence quantification analysis and phase space of time series [78], Spectral analysis and Statistical analysis [79], Weibull proportional reliability function and Proportional hazards model [80], Kolmogorov-Smirnov test and Auto-regressive model [81], Kernel locality preserving projection, Statistical features from time domain, frequency domain, and Wavelet packet decomposition [82], Jensen-Rényi divergence, Ensamble empirical mode decomposition, Pearson correlation [83], Empirical mode decomposition and Variance regression approach [84]
FDE	CUR and VOLT	Instantaneous power spectrum [85], Filtering and Spectral analysis [86,87], Spectral analysis, Phase modulation and Bessel function [88], Hilbert-Huang transform and Thermal analysis [89], Volterra time series model and Quantum particle swarm optimization [90]

4.1. Fault size estimation

As mentioned, the quantitative diagnosis for fault size estimation can be reached if the entry-exit event times are accurately calculated. Vibration and acoustic emission signals are analysed to identify the mentioned events. However, just a few works are devoted to research on this topic. Next sections present recent results by using both signals.

4.1.1. Vibration based analysis

Cui et al. [55] used a Matching Pursuit (MP) method to measure the fault size. Step-like response is associated with the entry event while impulse-like response is associated with the exit event. Then, the method proposes a step-impulse dictionary for developing a theoretical model to extract signal features with different fault sizes. In this sense, a quantitative MP algorithm is proposed on a new dictionary model and by taking into account the time interval between the two actions of entering to and exiting from the spall-like fault. Additionally, the authors proposed an atomic selection mechanism to estimate the bearing fault size with adequate accuracy; the detailed model of the nonlinear vibration used in this work was fully developed in [54].

Zhao et al. [9] used Empirical Mode Decomposition (EMD) and Approximate Entropy (ApEn) methods to estimate the size of the spall-like faults in order to clearly separate the entry-exit events. The raw vibration signal is decomposed by EMD to obtain intrinsic mode function (IMF) components which have valuable information for entry and exit events. ApEn method is used to increase the precision of EMD without an extensive knowledge about the level of noise and fault signal features. In this sense, the concept of IMF-ApEn is introduced to overcome the mode mixing problem when noise and intermittence produce significant distortions in the IMF.

Khanam et al. [41] applied the Discrete Wavelet Transform (DWT) to identify the entry-exit events. In particular, "symlet" wavelet is used because of its linear phase nature which maintains sharpness in the vibration signal, even when sudden changes occur; as a consequence, "symlet" wavelet can be used to assess the bearing fault quantitatively. The decomposed signal splits the peak corresponding to the ball entry into and exit from the fault region, then, the estimation of the defect size is achieved. The authors used a proper equation that quantifies the fault size according to the time between the entry and impact pulse. Time is calculated from the appropriate level of wavelet decomposition that identifies the two successive impulses. A similar analysis using "symlet" decomposition to measure defect size was presented in [56,57]. At first step, the signal amplitude is multiplied by its own absolute value in order to deal with the problem of weak burst detection in the normal vibration signal while the sign of the original signal is retained. Next, "symlet5" wavelet decomposition is applied to get a signal that is able to show entry-exit events associated with the size of seeded defect in outer groove race. As proposed in [41], the outer groove race defect width can be calculated from the vibration burst duration by using a proper equation. Another work using successive signal processing techniques over the raw vibration signal, such as FFT, band pass filter, inverse FFT, Hilbert transform to obtain the envelope spectrum, was presented by Bujoreanu et al. [58]; in order to identify the entry-exit events, proper equations taking into account the average time T (samples) between the fault entry and exit are used to estimate the length of the damage in the inner race of the bearing.

Sawalhi and Randall [59] used the Cepstrum Analysis (CA) for estimating the time delay between double impulse from the vibration signals. This is accomplished through a simple three step algorithm to achieve an adequate signal showing the entry-exit events in case on spall faults. First, Spectral Kurtosis using autoregressive models are used for preprocesing the raw vibration signal. Second, multi-resolution analysis using Morlet wavelet transform is applied to identify the two successive events. Finally, squared enveloped signal processed using minimum entropy deconvolution serves as a source to estimate the time between events. An enhanced algorithm is also proposed for a separate treatment of the entry and exit events, from an enhanced version of the pre-processed signal using minimum entropy deconvolution as well. Each signal is treated with the described three step algorithm, and then the separated signals are assembled to produce a new enhanced signal where the estimation of the fault size is more clear. The CA is used for estimation of the time delay. The relationship between the width of the fault and the time to impact is given by a proper equation.

Zhou et al. [40] used an adaptive feature extraction technique based on shift-invariant dictionary learning (SIDL) for the double-impulse structure detection. Shift-invariance is very suitable to extract periodic impulses, then, the purpose is reconstructing an input signal using basis atoms in all possible time shifts. After learning the basic atoms, a set of latent components of the original signal are reconstructed and the kurtosis of envelope spectrum is used to select the optimal components. The double-impulse structure must be identified from the optimal component, and the space between the two peaks estimates the size of the defect. Classification capabilities are enhanced by including a Hidden Markov Model for analysing the latent components, in this case the features are extracted by calculating the energy of each latent component. Classification of fault types is out of the scope in this section.

4.1.2. Acoustic emission based analysis

The Acoustic Emission (AE) based analysis offers earlier fault detection and improved identification capabilities than vibration analysis; moreover, the AE also provides an indication of the defect size, allowing the user to monitor the rate of degradation on the bearing that could be not possible with vibration analysis. For instance, Al-Ghamd and Mba [25] applied the Acoustic Emission technique for identifying the presence and size of a defect on a radially loaded bearing. The size of a natural defect was accomplished by identifying the duration of the acoustic emission (AE) bursts that are accessioned with the bearing defect.

In [60–62], extensive analyses of the natural mechanical degradation measurements in slow speed bearings with AE were developed. Particularly, [60] concluded that sub-surface initiation and subsequent crack propagation can be detected using a range of data analysis techniques on acoustic emissions generated from natural degrading bearings over a wide time window, such as: information entropy, signal shape factor, enveloping, and spectrum analysis through FFT, Pronys Energy Method, Eigen-Analysis, auto-regressive models and continuous wavelet transforms. Statistical parameters such as root mean square, crest factor, kurtosis, shape factor and impulse factor have been also used because their values may come down according to the level of undamaged bearings when the damage is well advance. The size of a natural defect was accomplished by identifying the duration of the AE bursts by using proper equations.

Al-Dossary et al. [64], developed a work similar to [60], and analysed the effect on the AE signal of different incremental fault sizes in inner and outer races by observing the averaged energy and maximum amplitude values. Observations of burst duration in the acoustic signal for outer and inner race defects aim at estimating the size of the fault. In conclusion, an increase in a defect size resulted in an increase in levels of acoustic emission energy for outer and inner race seeded defects.

Hemmati et al. [65] performed a quantitative analysis by using the Squared Hilbert Transform (SHT) for estimating the defect size by studying the time duration between double spikes of AE signals. Particularly, the work aims at selecting the most appropriate mother wavelet through a quantitative measurement tool, for band selection. The mother wavelet that has produced the maximum kurtosis to Shannon entropy ratio in the wavelet coefficients is chosen as the best fitting wavelet. As a result, the band-passed signal associated with the optimal wavelet coefficient reveals clear impulses due to defective conditions in the roller bearing. The post-processing of the band-passed signal by using envelope analysis and multi-scale enveloping spectrum gives, as a final output, a three-dimensional scale-frequency color map that indicates the intensity and frequency of the defect, and the corresponding time can be estimated.

Sun et al. [63] studied the entry-exit events in the case of spall faults in bearing from AE and Hilbert based Envelope Analysis (HEA). First, the DWT with Daubechies mother wavelet is used to enhance the characteristic AE generated by the spalling, and then the HEA and FFT-based low pass filtering was utilized to extract the double impulses. AE and Squared Envelope Analysis (SEA) was also used by Ming et al. [66] for fault size estimation of the outer race. The interval between the entry-exit events and ball-passing frequency are estimated through the autocorrelation function of the envelope signal of the AE. Morlet band-pass filter is first applied around the resonance frequency of the AE transducer, and the SEA is then applied on the filtered signal.

4.2. Fault degradation estimation

The proposition of fault degradation indexes is the main focus of this kind of research, which has been done in order to provide monotonic functions reflecting the degradation process of machinery. Some signal analysis serve to estimate the fault degradation level from the amplitude evolution of certain indicators through appropriate signal processing techniques. Having a correct degradation indicator may produce accurate useful life prediction results. Vibration signal and electrical signals, such as stator current and voltage, have been studied for extracting such fault degradation indicator; on the contrary, AE signal has not been widely used for this purpose. An interesting contribution by using AE signal was recently presented by Liu et al. [91], where a feature called "AE compressive feature" is extracted from the AE signal by using compressive sensing technique; they propose considering this new feature as a degradation indicator. Next sections present a detailed review of the most relevant works on vibration-based and current-voltage-based indicators for fault degradation estimation.

4.2.1. Vibration based indicators

Some works in the literature propose the extraction of simple health indicators from vibration signals. For instance, Medjaher et al. [92] presented a very simple health indicator; it is based on the correlation between two vibration signals associated with a healthy bearing and a degraded one. A similar approach was used by Wang et al. [93], who used the Mahalanobis distance to fuse the input features into a new feature to reflect the degradation of the bearing more effectively, regarding a known healthy state. Another simple degradation index is the Relative Root Mean Square (R-RMS) computed over the raw vibration signal, which has a monotonic characteristic in most bearing defects, presented by Chen et al. [94], or the Average RMS (A-RMS) computed over a window of the specific defective frequency and its firsts significant harmonics, once the failure mode is diagnosed, presented by Ma et al. [95]. The RMS extracted from the narrowband interference cancellation signal can track the bearing degradation better than the RMS extracted from the original vibration signal, as proposed by Zhang et al. [96]. Wu [97] analysed proper features in the time domain that can effectively track the evolution of bearing faults. Besides such contributions, there are more complex signal processing approaches using the vibration signal, that are presented in Table 1 and they are described in detail, as follows.

A method using EMD, Teager Energy Operator (TEO) and Mahalanobis Distance (MD) was presented by Tang et al. [67] in order to propose a health assessment index for roller bearings. The proposed index is represented by a confidence value which is computed from the current MD between the test data and the normal condition data. If the confidence value is close to 0 the higher fault degradation is identified. Input features to calculate the MD are the energy values obtained by applying TEO on the most interesting IMF of the vibration signal EMD. Dong and Chen [68] proposed a Cyclic Energy Indicator (CEI) for the performance degradation assessment in bearings. This indicator is based on the second order cyclostationary signal analysis, specifically in the cyclic coherence function for a vibration signal. Experimental tests show that this CEI increases when a single point damage in the inner race is more severe. Zhang et al. [69] addressed a new improved EMD using an Amplitude-

Modulated and Frequency-Modulated (AM-FM) demodulation algorithm to solve the mode mixing problem of IMF. The IMFs unrelated to bearing fault will be deleted and a new signal can be reconstructed by using the remaining IMFs. Then, the Maximum Correlated Kurtosis Deconvolution (MCKD) is applied on the new signal to enhance the detection of a periodic impulse signal, and the correlated kurtosis is used as an indicator to track the bearing degradation.

Wang et al. [70] combined ApEn with the cross correlation function to propose an approach called "cross correlation approximate entropy" in order to provide a quantitative method for detecting the anomaly of running state of equipment without any previous knowledge. Basically, the cross-correlation theory is used to identify new patterns from signals, and then ApEn theory permits the analysis of similarity between two cross-correlation functions associated with different patterns. The approach is tested on a dataset with different severity damages in ball, inner and outer races; as a result, different magnitudes of entropy are found among different types of fault and the corresponding severity level. Jiang et al. [71] considered a quantitative method for assessment of fault severity of the rolling-element bearing, based on the complexity of the signal. First, the vibration signal is preprocessed by an improved morphology filtering to avoid ambiguity between severity fault and the pure random noise. Next, the signal is analysed by using the Lempel Ziv complexity algorithm and the Kolmogorov measure, to avoid the loss of weak impact signal. Particularly, the Lempel Ziv complexity value will be mostly affected by the bearing system; then, it may be adopted as a quantitative bearing fault diagnosis method. Artificial immune optimization algorithm with the target of impulse index of the signal is used to obtain optimal filtering signal.

Li et al. [72] used Optimal Local Mean Decomposition (LMD) to identify the natural defect propagation at early stages. Particularly, the method is useful to identify the healthy condition, weak, and severe degradation, during a wide operation interval by performing the spectrum analysis of the processed vibration signals. LMD is originally developed to decompose a multi-component AMFM signal into a sum of Product Functions (PF). PF are obtained from the product of an amplitude envelope signal and a frequency modulated signal. The optimal approach in this paper aims at selecting the optimal product function (OPF) from the rational Hermite interpolation. Periodic impulses associated with fault types can be discovered clearly from the OPF by performing the spectrum analysis, and degradation levels are estimated from the instantaneous amplitudes of the selected OPF.

Golafshan and Sanliturk [37] used a de-noise approach based on Singular Value Decomposition (SVD) and Henkel Matrix (HM) for diagnosing fault size in ball bearings. Small, medium and large sizes of fault defects in the outer race are analysed by applying the de-noise approach on time domain vibration signals and their spectrum, to improve the reliability of the fault detection process. The fact is that the defective bearings generate high Singular Values (SV) and this is used to assess the condition of the corresponding bearing. Particularly, the kurtosis ratio of the output de-noised signals to input raw signal in time domain is obtained as a function of the number of SV, and the magnitude of this ratio clearly identifies the size of the defect. Tabaszewski and Cempel [73] presented the analysis of the time evolution of the SV as degradation indicators; this analysis is conducted on a experimental test of accelerated wear of small rolling bearings, as a result the magnitude of some SV can be highly affect from some observation time in which a jump in the magnitude evolution is observed.

Siegel et al. [74] proposed a novel tachometer-less synchronously averaged envelope (TLSAE) signal processing and feature extraction technique for rolling-element bearing, in order to effectively estimate the bearing health state. TLSAE method uses a narrow band pass filter around the bearing fault frequency of interest, next Hilbert Transform is applied to this band signal and the derivative of the phase is calculated to generate a synthesized tachometer signal. This signal is representative of the impact due to a bearing defect and it is combined with the high frequency envelope method to perform synchronous averaging on the envelope signal. As a result, a defect synchronous envelope spectrum is obtained, in which the frequency content is in terms of the fault frequency orders. The reduction in noise is the potential advantage offered by the TLSAE method, then, the peak magnitude at the bearing fault frequencies are key indicators for assessing the health state. The proposed method is able to distinguish all three levels of damage on the outer race.

Wavelet-based filters (WF) are also reported as appropriate techniques for fault assessment. Paliwal et al. [75] proposed two fault assessment indicators. The first one, by applying spline wavelets for finding the existence of defective performances; the best spline wavelet applied to the raw vibration signal is calculated, by identifying the suitable wavelet parameters from visual similarity, correlation coefficient and maximum mutual entropy. The second indicator is defined from classical time-domain parameters of the raw signal such as RMS, Crest Factor, Impulse Factor and standard deviation; they are properly arranged in a scalar indicator for quantifying the severity of defect from initial stage of degradation. Gu et al. [76] proposed a feature-based degradation assessment index, which combines WF with other signal processing techniques such as Auto Regressive (AR) and Minimum Entropy Deconvolution (MED) filters, and EMD. Basically, the kurtosis feature is extracted from the signal obtained after applying Wavelet Packet Decomposition (WPD) up to certain level, and then AR and MED filters, successively, to remove discrete frequency and enhance impulsive fault signal, respectively. Finally, EMD is applied on the kurtosis signal and the residual component describes the trend behaviour on time. The approach is tested on a run-to-failure dataset. Miao et al. [77] used a new wavelet called "comblet for filtering the vibration signal to propose a new health indicator for bearings; after applying the comblet filtering, the obtained signal is treated with a spectrum analysis by absolute value of the Fourier transform amplitude, and its spectrum energy is calculated over the whole signal. Finally, an Exponentially Weighted Moving Average (EWMA) is used to define the health indicator based on the energy value at each time t. This new health indicator is validated on a run-to-failure dataset.

Qian et al. [78] presented a new application of Recurrence Quantification Analysis (RQA) for damage severity assessment of mechanical systems. Four quantitative measures such as Recurrence Rate (RR), determinism (DET), laminarity (LAM), and entropy (ENTR), are investigated as quantitative indicators. These quantitative measures are obtained from recurrence plot

(RP) in order to quantitatively characterize the changing dynamics of a given system in the reconstructed phase space. The phase space is obtained by applying a time-delayed coordinates approach to the sequence of raw vibrations measured data, based on the Takens embedding theorem. Four severity levels such as healthy, light, medium and severe defects on inner raceway of test bearings. After several experimental analysis, authors conclude that ENTR and LAM are effective quantitative indicators. In general, the value of RR, LAM and ENTR for defective bearings are larger than that for healthy bearings.

The evolution of the fault severity in the inner race was characterized by Gerber et al. [79], by using three automatically-generated frequency-domain health indicators: the number of harmonics, the energy, and the fundamental frequency. Basically, the authors propose a method to automatically generate system health indicators without any a priori information about the monitored system or the acquired signals, and by considering the time evolution of the fault. Basically, the approach is accomplished in two steps: the first one is performing spectral analysis on the vibration signal for peak identification of each successive signal acquired at different timestamps, in order to detect and characterize the different spectral structures such as harmonic series and the modulation sidebands. The second step is tracking the spectral structures through the different timestamps to create spectral structure trajectories to extract the mentioned health indicators. Particularly, the tracking process is driven on spectral peaks, harmonic series and the modulation sidebands. Experimental test on wear phenomena from healthy to full degradation validates the proposed approach.

Ding and Re [80] estimated the bearing degradation trend by using the Weibull proportional reliability function as degradation index. Particularly, the proportional hazards model are included in the Weibull function, and kurtosis and crest factor of the raw vibration signal are proposed as the covariates in the hazards model. The proportional hazards model is widely accepted for analysing failures with covariate. The approach is validated on a dataset with different levels of bearing severity in ball, inner and outer races; as a result, a curve that reflects magnitude and trend of the damaged severity is obtained. Cong et al. [81] proposed an approach based on probability distribution; the Kolmogorov-Smirnov Test (K-S-T) is used to assess the performance degradation of rolling-element bearings. The method can detect incipient weak defects and reflects the performance degradation process appropriately. The similar probability value $p(D)$ is calculated over the distance D between the target and the reference cumulative distribution functions of vibration signals; hence, if two vibration signals are similar, then, $p(D)$ tends to 1, else, it tends to 0. Before applying K-S-T, and AR model based filter is used for pre-whitening the vibration signal. The approach is tested on a run-to-failure dataset of a rolling-element bearing.

Sun et al. [82] proposed a novel method based on Kernel Locality Preserving Projection (K-LPP) to generate a non-linear subspace from the nominal bearing data. The test data measured from an unknown condition are projected onto the subspace to obtain an index for assessing bearing degradation degrees given by the angle between the test data and the nominal one. In this sense, the degradation index, that is expressed in the form of the inner product, indicates similarity of the nominal data and the test data. A set of features, in time, frequency, and time-frequency domains using WPD, are extracted from several vibration signals in the nominal state, in order to form the feature matrix used to compute the mentioned subspace. The proposed index is validated over a run-to-failure dataset that is obtained from a simulated degradation process of bearings.

Singh et al. [83] proposed a standardized index for on-line bearing degradation assessment, based on the sensitive IMFs associated with the Ensamble EMD (EEMD) applied to the vibration signal. Basically, the Jensen-Rnyi Divergence is used as degradation parameter to monitor the overall condition of bearings, and its calculation is based on the probability distributions of the IMF energies generated by EEMD, regarding the healthy condition (base probability) and the new condition data measured. The selection procedure of sensitive IMFs is based on the Pearson coefficient, which is used to measure the correlation between the original signal and the individual IMFs. The relative change in the normalized coefficients is used to select the IMF threshold criteria for partitioning the IMFs in sensitive and not-so-sensitive groups. The cluster of sensitive IMFs is used to evaluate the probability distribution to ascertain bearing damage. A multiscale signature based on EMD was proposed by He et al. [84] as an index to evaluate different health statuses in defective rolling bearings. The proposed signature is based on the logarithmic variance of the IMF that displays different linear regression slope. In brief, the method selects the localized defect-induced IMF by using a variance regression approach, the multiscale signature is estimated from the regression line fitted over logarithmic variances of the IMFs excluding the defect IMF. The effectiveness of the approach is verified with real vibration signals associated with different defect sizes in the outer race, inner race and balls of rolling bearings.

4.2.2. Current-voltage based indicators

Fault signature for bearing damages in induction motors can be also extracted from current and voltage signals; fault-related frequency components are reflected as sidebands of the current and voltage time harmonics. Irfan et al. [85] analysed the magnitude of the instantaneous power spectrum for detecting the bearing damage, in the outer race and its severity levels, by comparing the instantaneous power spectrum for the healthy case with respect to the damage case. Results show that in case of damage, a peak clearly appears in the power spectrum at a specific frequency. Then, some fault degradation indicators can be defined from the mentioned signals.

Kompella et al. [86] defined a threshold limit from the current signature in order to alert about the severity of the faults in induction motor's bearings due to generalized roughness. The non bearing related fault components in a stator are considered as noise, then, the bearing fault components are estimated by canceling the noises in a stator current signature by using a Wiener filter. As a result, the current spectrum isolates clearly the frequencies where the bearing damages are occurring, and the level of the damages is analysed with regard to the magnitude of the noise floor.

Wu et al. [88] analysed the stator current through phase modulation. Particularly, bearing damages are reflected in the stator current when torque vibration is produced due to the bearing damages at a single point. Then, characteristic frequencies appear in the stator current through the form of phase modulation. The authors propose a modulation index that is the amplitude of the angle variation in the stator reference coordinate which helps detecting bearing faults and determining their possible severity. The analysis is enhanced with the study of the sideband frequencies of the stator current.

Skrimpas et al. [87] developed also electric signature analysis for fault severity assessment in bearing outer race defect related to the mechanical condition of the power production units. Particularly, they focus the attention on the energy content between the fundamental, 5th and 7th harmonics in current and voltage frequency spectrum, called "residual value", as condition indicator. The time evolution of the RMS residual value is compared to three predefined limit associated with the severity level of the fault, named as inspection level, maintenance level and critical level. The approach is only tested with data from the simulation model of a multipole permanent magnet generator.

Picazo-Rodenas et al. [89] highlighted the difficulty of the classical current-based method fault analysis when diagnosing some faults under certain operating conditions (pulsating load torques, unloaded machines, among others). Then, the authors propose using time-frequency techniques (TFT) for tracking the frequency components evolution in time. Particularly, the use the Hilbert-Huang Transform (HHT) aims at building time-frequency maps, where some quantitative indicators, such as the energy of the map's boxes, can be used for fault severity evaluation. After obtaining a possible false positive through TFT, they also propose the use of infra-red radiation measurement to obtain temperature measurement related to fault damages. The approach was tested on a run-to-failure dataset for general damages in bearings.

Xu et al. [90] presented an interesting model-based approach for analysing fault severity in induction motor bearings. They propose using the Volterra time series model in order to describe the relation between the power grid voltage (input) and the stator current (output) of the motor. The Volterra kernel function is identified by using an algorithm based on quantum particle swarm optimization; such identified kernels have significant information about fault severity. The approach is tested over real data with different levels of fault severities in the outer race, and a surface plot of the kernels shows significant differences according to the severity level.

4.3. Advantages and limitations of the signal processing based approach

As mentioned previously, the de-noising and filtering processes are essential capabilities to be exhibited by the techniques for signal processing in the field of condition monitoring to fault assessment. This is why most of the presented works aim at combining different de-noising and filtering techniques to get significant information from the signal treated, e.g. vibration, AE, current, or voltage, through the proper extraction of the fault signature. Then, more than analysing the advantages and limitations of each technique discussed in the previous sections, Tables 2 and 3 present the advantages and limitations of the signals commonly used by the signal processing techniques oriented to FSE or FDE, respectively. In this sense, researchers have to take into account these items to decide the use, or the improvement, of the existing techniques. On the other hand, a wide knowledge about the physical phenomenon of the bearing faults and its influence on the analysed signal is highly required to understand the results of the signal processing techniques, and it could be considered as a limitation to the researchers.

Table 2
Advantages and limitations of the use of VIB and AE signals in signal processing based FSE.

Signal	Advantages	Limitations
VIB	There is a wide knowledge about the physical relation between the fault size, in inner and outer races, and the burst phenomenon due to the entry-exit events in the fault area. Dynamic ball bearing models have been developed to study this effect on the vibration behaviour The effectiveness of the use of vibration signal is verified in most of real practical cases to measure different defect sizes in the outer race and inner race	The burst duration in vibration signal might not be indicative of the defect size with a high precision, as the decaying of burst highly depends on the damping in the system The signal processing techniques must be able to perform a high de-noising and filtering over the raw signal to identify properly the time of the entry-exit events If the signal-to-noise ratio is small, then the fault size estimation could not be accomplished in early stages
AE	The AE parameters related to the fault size are less sensitive to the variation of load conditions on the bearing It is an alternative informative diagnostic signal because of its inherent high signal-to-noise-ratio. In this case, signal processing is able to de-noising and filtering as much as possible without loss of information to identify the entry-exit events AE is more sensitive to the internal or superficial energy related to the faults in early stages, it gives to the AE an indisputable diagnosis advantage regarding the vibration analysis AE signature is less sensitive to the typical mechanical noise, because the informative spectrum is in another frequency band; in this sense, this kind of noises, derived from the parts of bearing and other rotating parts of the machine, is naturally eliminated	The AE parameters are more sensitive to the varying rotating speed, under most running conditions of the bearings There is no wide knowledge about the behaviour of the AE in rotating system analysis, then, there are no standard protocols of analysis in such case, as in case of non-rotating systems Success in the use of AE depends on the high sampling capability, and the ability to deal with large amount of sampled data

Table 3
Advantages and limitations of the use of VIB, CUR and VOLT signals in signal processing based FDE.

Signal	Advantages	Limitations
VIB	The trend of some classical statistical features, such as RMS, kurtosis and correlation measures between healthy and faulty state, can be used as a degradation indicator in most of cases of bearing faults Once the characteristic frequency is identified, the size of the peak magnitude of the signal in the frequency domain can serve as degradation indicator The vibration signal can provide robust indicators for bearing defects after a suitable de-noising and filtering processing	Vibration signals from bearings might be highly noisy due to mechanical interferences or other faults in the equipment. Then, signal processing techniques must have a high performance in de-noising and filtering Environmental conditions such as temperature can affect the magnitude of the vibration signal. Then, the degradation indicator can offer informative values that are not appropriate Vibration-based indicators might not be sensitive to failures in early stages, then, the proposed indicators might not provide informative trending in this case
CUR and VOLT	The use of current and/or voltage signals ideally are a non-invasive method to acquire information about mechanical faults, regarding the use of accelerometers, which must be located into the rotating machine. Usually, current and/or voltage in the motor stator are signals measured in most of industrial cases	The real magnitude of the mechanical fault could be not properly transmitted to the current or voltage signals, since the physical linkage between the mechanical part and the motor is used to damp mechanical vibrations Current and voltage signals are sensitive to faults in the electrical device, such faults can overlap the mechanical faults under study The current components related to mechanical faults are buried in noise, and thus, they could be very difficult to extract significant information without a dedicated de-noising processing

5. Learning-based approaches

In these approaches the objective is to learn the signal pattern associated with a certain type and severity level of fault and to associate it to a fault indicator. This indicator can be discrete, then, the result is a multi-classification model in the sense of the supervised learning, where the whole knowledge about the faulty patterns must be known. Most of the recent works are addressed in this sense. On the other hand, some works analyse fault severities in different location on the bearing, but they group the data with the same severity in a class, so, the problem is also treated as a simple classification problem [98,99].

Another kind of research aim at proposing a continuous indicator related to the severity level or damage degradation, including the estimation of the damage size. This indicator can be learned under supervised approaches, as proposed in a simple way by Rao and Ratnam [100]; in this case, load, Revolutions Per Minute (RPM) and vibration RMS velocity are inputs to a classical neural network to predict the size of the damage in a rolling-element bearing. Unsupervised approaches aim at learning the estimated healthy pattern and then propose a fault indicator based on distance for measuring the damage level. In general, the objective of proposing a continuous fault indicator is to determine whether the fault is in slight, medium, and serious (or severe) state. Works within this field are mainly focused on the assessment of faults in ball, inner and outer races with one point defect of different diameters; the wear process is also studied. The Bearing Data Center of Case Western Reserve University is the most common database used for testing the approaches, and recently some works use PRONOSTIA for testing health indicator construction on bearing degradation datasets [101].

Cococcioni et al. [102] presented a general overview on the use of some learning-based classifiers; statistical classifiers such as neural networks are used for identifying several levels of damages in bearings. The work develops linear discriminant, quadratic discriminant classifiers, and multilayer perceptron and radial basis function neural networks under a strategy of ensemble of classifiers, if it is required, for the improvement of the classification accuracy. Each frequency sample is considered as a feature. Several types of faults are considered: indentation on the rolling element, indentation on the inner raceway, unbalanced cage, and sandblasting of the inner raceway. Particularly, severity levels in the indentation on the rolling element are analysed. At the time when this paper was published in 2013, authors claimed that the issue of recognizing different severities of the same fault, as belonging to the same class, had not been tackled and solved in literature.

Learning-based approaches need to extract features from time, frequency, and time-frequency domains, such as RMS, kurtosis, crest factor, standard deviation, energy operator of coefficients from WPD or IMF from EMD, and signal energy after applying Hilbert-Huang transform, among other specialized features. However, new methods for feature extraction have been recently proposed, for instance, the Symbolic Aggregate Approximation reported in [99]. In fact, most of works are focused on extracting special features that can be treated easily for classical classifiers, such as log energy entropy and sure entropy as good indicators of variation in fault severity [103]. Another issue to reach adequate classification based bearing severity assessment, is the selection of the proper features to accomplish better separation between classes, as shown by Yaqub et al. [104]; they aim at developing a specialized classifier using classical features.

Next tables show some relevant works published from 2010. These works are discussed according to the aim of the analysis such as classification in Table 4, or damage degradation in Table 5, and the used techniques. The most common damages are related to one point defect in inner race, outer race and ball elements, with different depths and diameters, and fault degradation in inner and outer races in run-to-failure tests.

According to Table 4, the most reported technique is Support Vector Machine (SVM) including some extensions such as Hyper-sphere-structured multi-class Support Vector Machine (HSSMC-SVM) and Support Vector Machine-based Binary Tree

Table 4
Relevant works in classification-based fault severity assessment by using learning approaches, from 2010 to 2016.

Technique	Feature extraction and other used techniques
ANN	Singular values decomposition [105], Empirical mode decomposition [106–108], Nearest-class-mean rule, Detrended-fluctuation analysis, Hurst rescaled-range analysis and Principal component analysis [109]
DBN	Wavelet packet decomposition [110]
SON	Curvilinear component analysis and Statistical analysis on time domain [111]
SVM	Swarm particle optimization, Empirical mode decomposition and Kernel principal component analysis [112], Inter-cluster distance, Empirical mode decomposition, Permutation entropy [113], Wavelet leaders multifractal features and Wavelet packet decomposition [114], Higher order statistics and bi-spectrum analysis [115], Synchrosqueezed wavelet transforms, Entropy distribution [116], Moving average, Pearson correlation and Principal component analysis [117]
HSSMC-SVM	Empirical mode decomposition [118]
SVM-BT	Local mean decomposition, Optimum product function, Improved multi-scale fuzzy entropy, Laplacian score [119], Hierarchical fuzzy entropy and Laplacian score [120]
NNC	Linear singular spectrum analysis and Auto-regressive model [121], Principal component analysis, Gaussian detector, Empirical mode decomposition, Hilbert transform [5], Timefrequency distribution and Manifold learning [122], Wavelet packet energy and Manifold learning [123], Locally preserving projection [124], Rough sets, K-Nearest neighbour, Random forest, Decision trees [125]
KMC-MD	Multifractal detrended fluctuation analysis [126], Local characteristic scale decomposition, Intrinsic scale components, Teager energy operator, Principal component analysis and Generalized Hurst exponent [127]
HMM, CHMM, MGHMM	Filtering and Monitoring index vector [128], Neighbourhood component analysis, Wavelet packet decomposition and Envelope analysis [129], Wavelet packet decomposition [130]
ANFIS	Multi-scale entropy algorithm [131], Discrete wavelet packet decomposition, Fast Fourier transform, Spectrum peak ratio [132]
Fuzzy-ARTMAP-BBM	Moment estimates of power, Frequency weighted by power, Wavelet grey moment and Auto-regression model parameters [98]
LDA	Fast Fourier transform and Short time Fourier transform [133], Fast Fourier transform and Envelope analysis [134,135]

Table 5
Relevant works in degradation estimation based fault severity assessment by using learning approaches, from 2010 to 2016.

Technique	Feature extraction and other used techniques
NN-SOM	Gaussian mixture models, K-means, Negative log likelihood probability [136], Wavelet packet and empirical mode decomposition [137], Wavelet Neural Networks and Gaussian Process Regression [138], Multifractal spectrum and MahalanobisTaguchi system [139–141], Minimum quantization error, Statistical parameters on time domain and Envelope analysis on frequency domain [142], Minimum quantization error, Empirical mode decomposition, Principal component analysis[143], Minimum quantization error, neighborhood preserving embedding [144], Weighted minimum quantization error, Spearman coefficient, correlation clustering [145]
SVM	Classical statistical parameters [146], Wavelet Packet Decomposition [147], Classical statistical parameters, Principal component analysis, Genetic algorithm and Particle swarm optimization [148], Classical statistical parameters, Wavelet packet decomposition, Empirical mode decomposition, Principal component analysis, and Particle swarm optimization [149], Improved assemble empirical model decomposition, Singular value decomposition, Locally linear embedding, classical statistical features [150]
RVM	Classical statistical parameters, Principal component analysis, Survival probability and KaplanMeier estimator [151], Kurtosis and Logistic regression [152]
SVR	Classical statistical features [153]
SVDD	Bispectrum based signal processing, statistical features [154]
RSVDD	Classical statistical features, incremental learning [155]
FSVDD	Classical statistical features, fuzzy degradation index [49]
GMM	Kernel principal component analysis and Exponentially weighted moving average [156], Locally preserving projection, Envelope analysis, Wavelet packet decomposition [157]
FL	Improved artificial neural networks, classical features from frequency domain [158], Spectral content and Gaussian distribution [159], Wavelet filtering and Differential evolution [19], Gaussian mixture models, Principal component analysis [160], Particle filtering, features from frequency domain [161]
CHMM	Neighbouring singular value ratio [162], Zero crossing features [163], Locally preserved projection [164], Nuisance Attribute Projection [165]
PM	Particle filtering [166], Stochastic filtering [167], Probabilistic model [168], Statistical model and Exponential weighted moving average [169], Recursive Bayesian inference based probability [170–172], Extended Kalman filter, Time variance analysis and Time-frequency entropy analysis [173], Switched Kalman filter [174], Stochastic degradation model, maximum likelihood estimation, Kalman particle filtering, Brownian motion [175], Stochastic exponential degradation model, expectation maximization algorithm [176], Kalman filter, Wiener process, Chapman-Kolmogorov equation, Mahalanobis distance [177]
Other approaches	Negative selection algorithm, Wavelet packet decomposition and Principal component analysis [178], Auto-regressive model and Recurrence quantification analysis [179], Fuzzy c-Means based clustering and Lifting wavelet packet decomposition [180], Clustering, Mahalanobis distance, Fisher discriminant analysis, Wavelet packet decomposition [181]

(SVM-BT). The next reported technique is the clustering-based approach such as Nearest Neighbour Clustering (NNC) and K-means Clustering combined with Mahalanobis Distance (KMC-MD). Network-based models such as classical Artificial Neural Networks (ANN), Self Organizing Networks (SON), and Deep Belief Networks (DBN) are also widely used. Approaches based on classical Hidden Markov Model (HMM) and some variation such as Coupled Hidden Markov Model (CHMM) and Mixture of Gaussian Hidden Markov Model (MGHMM) are other reported techniques, followed by fuzzy and statistical approaches, such as Adaptive Neuro-Fuzzy Inference System (ANFIS), Fuzzy Adaptive Resonance Theory Map with Bayesian Belief Method (Fuzzy-ARTMAP-BBM), Linear Discriminant Analysis (LDA), respectively.

Table 5 shows that approaches using Neural Network-based Self-Organization Mapping (NN-SOM), Support Vector Machine (SVM), and those ones based on Probabilistic Models (PM) are widely used, followed by Fuzzy Logic (FL) based approaches. Contributions using Continuous Hidden Markov Models (CHMM) and Gaussian Mixture Model (GMM) are also reported, and some works as extensions of SVM, such as Relevance Vector Machine (RVM), Support Vector Regression (SVR), Support Vector Data Description (SVDD), Rough Support Vector Data Description (RSVDD) and Fuzzy Support Vector Data Description (FSVDD), have been found in the search. Finally, other approaches by combining known techniques are included in this review.

5.1. Fault severity classification

Artificial Neural Networks (ANN) and Support Vector Machines (SVM) have been reported as the most popular techniques used as multi-classifiers, but clustering, Markov Models (MM), fuzzy approaches, and statistical classifiers such as Linear Discriminant Analysis (LDA) are also reported. New results rely on the extraction of specialized features combined with these classical classification models.

5.1.1. Artificial Neural Networks-based classifiers

Muruganatham et al. [105] used SVD and feed-forward Back Propagation Neural Networks (BPNN) to estimate different fault categories with different sizes. The appropriate SV are selected as input features to the BPNN with a single hidden layer architecture. SV are analysed through singular spectrum plots under healthy and faulty conditions with different fault sizes in order to select the most representatives SV, according to the relationship between load and fault size. A similar framework was presented by Ali et al. [106], where an BPNN with two hidden layers is used for fault classification between normal, degraded and severe failure stages of roller element, inner and outer race. Input features are extracted from time domain through EMD and the best IMF are selected. More detailed analysis for feature selection was firstly discussed in [107]. In a similar manner, Lei et al. [108] used Wavelet Neural Networks (WNN) as the severity classifier, the input features are obtained by selecting the most sensitive IMF from the ensemble EMD. Sensitive criteria is stated, based on the mean and standard deviation of kurtosis values of data samples for each IMF. Another work using BPNN for fault severity classification was developed by de Moura et al. [109]; in this case, input features are obtained by Detrended-fluctuation analysis (DFA) and Hurst rescaled-range analysis (RSA). Additionally, they propose another classification model by applying the nearest-class-mean rule for clustering after applying PCA to the obtained features from DFA and RSA.

Gan et al. [110] presented another Neural Network-based architecture for fault diagnosis and fault severity ranking. They propose a Hierarchical Diagnosis Network (HDN) based on a collection of Deep Belief Networks (DBN) that are constructed from multiple layers of Restricted Boltzmann Machines (RBM). The proposed HDN can provide not only an accurate fault classification, but its hierarchical structure is able to further judging the severity ranking. Basically, the HDN architecture is composed of two successive layers with one DBN for fault identification and a set of DBNs for further severity classification. Input features are composed by the normalized energy calculated from the coefficients of the WPD. Delgado et al. [111] used the HDN with a kind of self-organizing neural network called Curvilinear Component Analysis (CCA). Several features from time-domain are proposed and then selected through Linear Discriminant Analysis (LDA), to compose a set of features for classifying different types of fault (healthy, inner race, outer race and ball) and three different severities for each type of fault. Then, each set of features is used as input to each CCA model. The notion of hierarchy relies on the fact of identifying at first the type of fault, and then the severity level.

5.1.2. Support Vector Machine based classifiers

Zhang et al. [112] used a Support Vector Machine (SVM) as a model for identifying different stages of fault degradation, like a classification problem; Swarm Particle Optimization is used in the optimization process for adjusting the SVM model. The input vector to the SVM model is obtained after applying the Kernel Principal Component Analysis on the original features to reduce the feature dimension. Classical original features are extracted from time domain and frequency domain, but also the normalized SV, that are associated with the best IMF from the EMD, are included. As a result, the SVM is able to diagnose the fault location and its degree of severity. Wang et al. [118] developed a similar work using SVM as classifier; the authors use hyper-sphere-structured multi-class SVM in order to construct one hyper-sphere to each class. SVD of the obtained IMF from EMD are used as input features. Then, a SVM model is adjusted for each faulty class associated with single point faults in the inner race and outer race with different diameter size. Zhang et al. [113] used SVM optimized by inter-cluster distance (ICD) in the feature space (ICD-SVM) to classify the fault type and its severity. Inputs Features to the ICD-SVM are composed of the Permutation Entropy values of IMF (IMF-PE) decomposed by ensemble EMD.

Du et al. [114] also used SVMs as classification models, but their contribution is about the features extraction. The authors propose the use of wavelet leaders multifractal features for classifying different fault locations and three different fault degrees. Additionally, they analyse the performance of the classification by extending the input features with the energy of the signals from WPD. Classical SVMs using one-vs-all and all-vs-all strategies for fault severity classification were presented by Saidi et al. [115]; feature extraction is performed by using higher order statistics from the bi-spectrum analysis of the vibration signal. More recently, a classic multi classifier based on SVMs was used by Wen et al. [116]; input features are extracted by using a new method called Synchrosqueezed wavelet transform (SWT). SWT decomposes the original vibration signals into several intrinsic mode type functions, and then SWT energy distribution for each component is obtained as the feature. The approach is tested on experimental dataset related to different level of severities in inner and outer races. Liu et al. [117] used another classical application of SVMs to classify several degradation stages; the features are extracted by applying the moving average method to obtain several data points from the raw vibration signal. Pearson correlation and PCA are applied for feature selection and reduction, respectively. Samples composed of the input features are associated with different fault degradation clusters by applying fuzzy C-means in order to label the samples obtained from a run to failure dataset.

Li et al. [119] used an Improved Support Vector Machine-based Binary Tree (ISVM-BT) in order to classify different fault categories in slight, medium, and severe. ISVM-BT takes the advantage of both the efficient computation of the tree architecture and the high reorganization accuracy of SVM. The main challenge in ISVM-BT is the definition of the optimal hierarchy of SVM classifiers. For feature extraction, Local Mean Decomposition (LMD) was used by Li et al. [72] to obtain the optimum product function (OPF) that composes the original raw vibration signal. The Improved MultiScale Fuzzy Entropy is used to calculate the selected OPF in different scales. For selecting the best scales, the Laplacian Score (LS) algorithm is used. Finally, the first five scale factors with least LS values are the new input feature vector to the ISVM-BT classifier model. A similar approach using ISVM-BT is presented in [120] where Hierarchical Fuzzy Entropy and LS are applied to extract and select features, respectively.

5.1.3. Clustering based classifiers

Al-Bugharbee and Trendafilova [121] used a Nearest Neighbour (NN) in a two-stage classification approach. In the first stage the type of fault is classified in healthy, ball, inner, or outer race; in the second stage the corresponding severity is classified as small, medium, or large. In order to obtain the input features, a data pre-processing is applied by using Singular spectrum analysis which is performed in two stages: decomposition, and reconstruction of the time vibration signal. Then, a stationarization technique is applied in order to use a Linear Auto Regressive (LAR) modelling for the representation of each available signal. Finally, the coefficients of the LAR models compose the input features to the NN classifier. He [123] reported another approach using nearest mean (NM) classifier and NN classifier in order to classify ten classes associated with several defect sizes in the outer race, inner race, and ball of the rolling bearing. The point of interest in this work is the definition of a new feature obtained from Wavelet Packet Energy (WPE), by using the manifold learning technique through the algorithms Locally Linear Embedding (LLE). Basically, he focuses on the discovery of the non-linear structure (manifold) from the WPE flow map of vibration signals; then, a new feature called "WPE manifold" is proposed. Similarly, Ding et al. [124] proposed a new set of features, that has the most sensitive discriminatory capability as this new set improves the between-class and within-class scatters between classes to perform a NM based classifier. This is based on a new two-step fusion feature extraction scheme, by using the Locality Preserving Projection (LPP).

Georgoulas et al. [5] also used a NN combined with other classifiers. Particularly, the work exploits a hybrid approach that involves an ensemble of anomaly detectors trained on different representations of the hypothesis space, that are combined by using a simple majority voting scheme. The anomaly detectors are based on the one-class classification approach, that is, the anomaly detection algorithm learns a discriminative boundary around the normal instances using a one-class classification algorithm. Three anomaly detectors are used: Gaussian, Nearest Neighbour (NN), and Principal Component Analysis. Input features to the mentioned detectors are extracted by performing, on the raw vibration signal, successive procedures as segmentation over a fixed time window, normalization over mean and deviation, and EMD. The first few IMF from the EMD are selected, and their instantaneous frequency as well as their spread were selected as input features. This selection was made based on the observation of their associate Hilbert spectrum and kurtosis value.

He [122] performed fault diagnosis and fault severity evaluation through a simple clustering using specialized features. The author proposes a novel time-frequency manifold (TFM) technique to combine time-frequency distribution (TFD) and manifold learning to deal with the problem of feature extraction from vibration signals. The technique aims at learning a non-linear manifold on the TFD to produce good time-frequency signature that allows revealing the underlying manifold structure in the sampling signals. Different health conditions display TFM with different patterns. TFM features in the form of a signal samples are extracted from TFM signatures that could be used for health diagnosis or severity evaluation from a simple clustering. The approach is able to distinguish different levels of severity in the outer-race defect condition of the rolling-element bearing.

Lin and Chen [126] presented clustering and Mahalanobis distance criterion to identify different types and severity of bearing faults. The authors use the multifractal detrended fluctuation analysis to obtain the multifractal spectrum of the vibration signal. Next, a set of parameters describing multifractality of time series are selected as sensible features to characterize different fault types and severities. Liu et al. [127] used clustering and Multifractal detrended fluctuation analysis as feature extraction technique, fault identification and severity evaluation. Previously, the raw signal is preprocessed with Local Characteristic Scale Decomposition to obtain the Intrinsic Scale Components (ISC). Next, the Teager Energy operator is used to compute the instantaneous amplitude and the instantaneous frequency of each ISC. Finally, generalized Hurst exponent for each ISC is obtained as the multi-fractal characteristic and PCA is applied to the set of generalized Hurst exponent for dimensionality reduction. Basically, fault identification and severity evaluation is carried out by visual inspection of the performance of the Hurst exponents for each ISC, or by analysing the clustering results from the scatter plot of the obtained principal components.

Pacheco et al. [125] proved several classifiers based on K-Nearest Neighbour, Random Forest, Decision Trees, and SVM, to classify different severity levels in bearings. Particularly, the work analyses a dataset with different size in the diameter of damages on the inner and outer race, and the roller element. Mainly, the work is oriented towards selecting the best classical statistical features extracted from the vibration signal in time, frequency, and time-frequency domains through WPD, by using rough set theory and clustering.

5.1.4. Markov Models based classifiers

The use of MM for classification has been mentioned in Section 4 as a part of the work by Zhou et al. [40]. MM in the discrete form is developed also in [128] for fault severity assessment as classification problem. The information input is a monitoring index vector (MIV) that is selected based on its sensitivity to allow performance changes of the monitored system. The size of the MIV matches the number of parallel filters previously applied to the vibration signal. The list of the input symbols to the HMM is obtained by comparing the current monitoring index vectors to the reference vectors by using the K-means clustering method. Then, symbols are assigned to the given observations. Finally, the optimal HMM must be adjusted to find the best state sequence given a sequence of observations. In case of fault severity evaluation, each state of the HMM are defined as normal, low, medium, high and severe.

Zhou et al. [129] showed the use of Coupled Hidden Markov Models (C-HMM) to fuse data from multi-channels, such in the case of fault diagnosis. A C-HMM, with Gaussian mixed models to describe the probability distribution, is proposed to classify fault severities in bearings such as healthy stage, early fault stage, degraded stage and failure stage. Then, one C-HMM is proposed for each state and the maximum value of the log-likelihood of each C-HMM determines the actual state. Features are extracted by calculating the energy from the WPD and envelope analysis. Neighbourhood component analysis is used to dimensional reduction of the feature space.

Tobon-Mejia et al. [130] proposed a Mixture of Gaussian Hidden Markov Models (MoG-HMM) to fit the degradation phenomenon in bearings. Input features are extracted from the WPD coefficients in a particular level. The advantage of using MoG-HMM is due to the duration in each healthy state can be estimated and then the Remaining Useful Life can be predicted. Several behavioural MoG-HMM corresponding to different initial states and operating conditions of the component are learned. In the on-line phase, the best MoG-HMM that fits the current input features is selected through a likelihood calculation, and finally the current state into the model is estimated by identifying the shortest and longest path. The longest path is the optimal scenario and the shortest path is the pessimistic one. The approach was tested on a run to failure dataset of bearings damages under eleven operational scenarios and three degradation levels were defined for the eleven MoG-HMM.

5.1.5. Fuzzy Logic based classifiers

Fuzzy approaches are also used for fault severity classification. Zhang et al. [131] used a classical Adaptive Neuro-Fuzzy Inference System (ANFIS) as classifier; feature extraction is performed by using the sample multi-scale entropy algorithm applied to the raw vibration signal and feature vector is composed by the sample entropy from twenty scales. Different levels of severity in ball and inner and outer races are analysed; the output is the class number. ANFIS system is also used by Attoui et al. [132] for one step head predictions of the faults in ball, inner race and outer race according to the fault location and severity. Discrete Wavelet Packet Decomposition (DWPD) is applied to obtain the signal in the low pass band at the last level. Then, the Fast Fourier Transform (FFT) is applied to identify the amplitude of the fundamental bearing defect frequencies in the vibration signal at time t. Spectrum Peak Ratio (SPR) and the sum of the all frequency amplitudes are used as features to the ANFIS classifier.

Jin et al. [98] used an ensemble Fuzzy ARTMAP for classifying different severity levels in ball, inner and outer races. The best ARTMAP is selected through a decision fusion process based on improved the Bayesian belief method. Input features are calculated using estimated moments of power, estimated moments of frequency weighted by power, wavelet grey moment and auto-regression (AR) model parameters.

5.1.6. Linear Discriminant Analysis based classifiers

Haddad et al. [133] used the machine stator current signals, instead of the conventional vibration signals, to detect and estimate the severity of an outer race bearing fault such as healthy case, medium, and severe bearing fault. Motor current signature analysis is performed during the steady state and start up using Fast Fourier Transform and Short Time Fourier Transform; Linear Discriminant Analysis (LDA) is used later for classification with the amplitude of the grid harmonics as input features. Another work using LDA as classifier was developed by Harmouche et al. [134,135], with spectral input features. Particularly, the feature vector is formed with the absolute amplitude of spectral lines at the ball pass frequencies that are automatically extracted after applying the FFT on the spectrum of the envelope vibration signal, corresponding to each fault case, by selecting the dominant frequency components. Experimental tests aim at classifying different sizes of faults in balls, inner and outer race, and it is verified that LDA is better than PCA for identifying severity levels.

5.2. Fault degradation estimation

The main objective is to define quantitative indicators for degradation stages. As in the previous section, ANN and SVM have been reported useful techniques, but Gaussian Mixture Models (GMM) have been also used as techniques for this purpose.

5.2.1. Artificial Neural Networks based approaches

Neural network based self-organization mapping (SOM) is reported as a technique for providing health indicators for the condition assessment of the performance degradation.

Yu [136] proposed a SOM-based degradation assessment; a hybrid feature selection scheme integrating Gaussian Mixture Model and K-means algorithms is developed to sort and select effective features from a candidate feature set. Log likelihood probability (LLP) combined with reduced kernel density estimator algorithm is proposed for quantifying bearing health states, where LLP indicates how the input vector follow the probability distribution of the trained SOM by normal dataset. In general, as a modification of LLP negative LLP (NLLP) is used as the quantization indication for machine health state. To improve the sensitivity and reliability of the NLLP to the slight degradation of bearing health, EWMA statistic based on the NLLP is applied as an improved quantification indication.

Hong et al. [137] proposed a confidence value (CV) as a health indicator which is obtained from a SOM. A higher CV represents a normal state, whereas a lower CV indicates a failure state. Four stages are classified as normal, slight degradation, severe degradation, and failure. For this purpose, Wavelet packetempirical mode decomposition (WP-EMD) is used for feature extraction. Particularly, the energy and the entropy of each sub-band from the proper wavelet decomposition is calculated, and the entropy sequences are analysed by using EMD until obtaining n-empirical modes. These empirical modes are the input features to the SOM. First, the SOM is trained by the feature vectors under the normal condition. Then, as the bearing operates, the feature vectors obtained by the vibration signal are calculated for further training. For an input vector, the Best Matching Unit (BMU) of the SOM is used to calculate the minimum quantization error used in the CV equation.

The work in [138] is an extension of the previous work in [137]. The change rate of the CV value is used to identify in which degradation stage the bearing is currently operating. Once the degradation stage is determined, a more accurate prediction model for estimating the CV values is learned. Wavelet Neural Networks and Gaussian Process Regression are used to estimate slight and severe degradations stages. Another work using SOM for fault degradation estimation was presented by Hu et al. [139,141]. Feature parameters such as multifractal spectrum entropy are calculated and optimized by an statistical method called Mahalanobis-Taguchi system. After training the SOM, different BMU areas are able to represent clusters of the same degradation states of bearings. Mappings of different degradation levels that are obtained by the SOM help differentiating each degradation stage and describe a degradation trajectory of the run-to-failure operation. More detailed analysis about the behaviour of the Mahalanobis distance as degradation indicator for failure assessment is presented by the authors in [140].

Siegel et al. [142] and Lu et al. [143] also used a SOM to obtain the minimum quantization error (MQE) as a distance metric regarding the healthy baseline. The MQE is calculated by using the best BMU that matches the current sample. In [142], multiple feature inputs extracted from time domain, and envelope analysis in frequency domain are fused by the SOM to produce a single health indicator. The approach is tested on a run-to-failure experimental data with corrosion damages in the inner race of two bearings. In [143], input features are extracted by using EMD and PCA is used to reduce the dimensionality of the feature vector composed by the energy of the IMFs. The result of performance degradation assessment from the MQE is quantitatively indicated by a confidence value (CV) ranged from 0 to 1, to indicate unacceptable and normal performance, respectively over time.

Zhang and Li [144] presented a work using MQE. The objective is to test the capability of the unsupervised algorithm called "Neighborhood Preserving Embedding" (NPE) for feature extraction in cases of varying running conditions. A similar health indicator named "Weighted Minimum Quantization Error" (WMQE) was presented by Lei et al. [145], for the assessment of the fault degradation process. The Spearman coefficient is used to evaluate the trendability and the monotonicity of the features. A correlation clustering algorithm is implemented to identify the redundant features, and the feature which has the highest trendability is selected from each cluster. The selected features in healthy condition are used to train a SOM, and the distance between the BMU in the SOM and certain unknown input feature vector measures the deviation of the unidentified condition from the normal operation stage. Finally, the WMQE indicator is proposed based on the normalized trendability of the selected features, the sensitivity of the feature to the degradation process and the weight of the corresponding BMU. The performance of the proposed WMQE indicator is tested by using features extracted from vibration signals which are measured on an accelerated degradation experiment of rolling-element bearings.

5.2.2. Support Vector Machines based approaches

Kim et al. [146] used a Support Vector Machine (SVM) as a tool for estimating the health state probability of the machine degradation process to provide long term prediction. The simple idea is using the probabilities of each health state from the SVM multi-classification result to obtain the probability distribution of each health state. Input features candidates to the SVM model are collected from the classical statistic parameters in time and frequency domain; effective features were selected by using certain distance evaluation criteria between all attributes in an specific health state.

Yaqub et al. [147] proposed an adaptive severity estimation model using SVM for severity estimation; SVM is trained with a set of data from lower and upper severity levels, and the model parameters are optimized such that the out probability of the SVM is 0.5 for the data with intermediate severity level. Input features are adaptively selected from the RMS of the wavelet coefficients associated with the raw vibration signal, until certain level. Adaptive process is included in the SVM adjustment by optimizing also the ratio between the sum of the best RMS nodes regarding the sum of the total RMS nodes. The approach is tested in real data of faulty inner race with different levels of severity.

Kang et al. [150] proposed a novel state assessment method based on the relative compensation distance of multiple-domain features, for assessing the state of a rolling bearing. A SVM is used to calculate the compensation distance of each fault state of the rolling bearing, and the unified assessment model is obtained by the distance between different fault locations, and the relative distance between different degrees of performance degradation regarding the normal-state optimal classification surface. The input features are extracted by applying Locally Linear Embedding on the feature vector to reduce its dimensionality. This feature vector is composed of multiple-domain features: the SV obtained by SVD on the sensitive IMF matrix, which is obtained by improved EEMD applied on the raw vibration signal, features in time domain and frequency domain of sensitive IMFs, features in time domain and frequency domain of raw vibration signal. The monotonicity and consistency of the performance degradation index and fault degree are well verified with actual vibration data for a bearing.

Dong and Luo [148] used a Least Square Support Vector Machine (LS-SVM) multi-step prediction model to estimate different degradation stages. Original features from time, frequency, and time-frequency domains of the vibration signals are extracted, and then PCA is used to merge the original features for producing a reduced input vector to the LS-SVM model. Genetic Algorithm and Particle Swarm Optimization (PSO) are used for tuning the prediction model. Another work using LS-SVM based predictive model was developed by Lu et al. [149] to estimate the slewing bearing degradation trend with small sample data. Classical statistical parameters such as root mean square, kurtosis, wavelet energy entropy, and IMF energy are fused by using PCA, and the first component is stated as the degradation index. In this sense, LS-SVM is used to predict the time series describing such index. PSO is used to the fit the parameters of the LS-SVM.

Widolo and Yang [151] also presented SVM for machine degradation assessment; Relevance Vector Machine (RVM) and survival probability are used. RVM is a Bayesian form of a generalized linear model in identical functional form of support vector machine (SVM), but it provides a probabilistic interpretation of its outputs. In this manner, the target objective of degraded condition data is associated with the survival probability of mechanical components. Survival analysis is performed by using KaplanMeier (KM) and probability density function (PDF) estimators. Features from time domain signals such as peak, kurtosis and entropy estimation were computed, and PCA was used for dimensionality reduction. Although the work aims at predicting the life time of machine components, the predicted probability can be used as degradation indicator. A similar work was presented by Caesarendra et al. [152], which combines probability theory and a data-driven approach using RVM and logistic regression (LR). The kurtosis is used as input feature to RVM, and the failure probabilities estimated by LR are stated as the target vectors. After a training process, RVM is employed to predict the failure probability of a individual unit of bearing sample, and hence this probability is a fault assessment index. An extension of SVM models is the Support Vector Regression (SVR) that have been also used to propose quantitative indicator of fault severity in bearing. Shen et al. [153] used a SVR model to estimate a fault size in a quantitative manner. Some classical statistical parameters on time domain are used as input features and, as a result, the size of damages in the outer race are estimated.

Wang and Chen [154] used another SVM based classification: the Support Vector Data Description (SVDD), a single value classification method, which is used in order to overcome the problem of lack of samples in the degradation process of the rolling bearing. Bispectrum-based signal processing is applied on the vibration signal and proper statistical features are extracted from the healthy vibration data; bispectrum seems to be an adequate signal processing technique as it could reveal non-linearities and non-stationary characteristic due to its higher computation efficiency. Finally, a SVDD model fitting a tight hypersphere is trained with these data. The generalized distance of test data to this hypersphere is used as the degradation index. The method is validated on a rolling bearing accelerated life dataset. A similar work using another version of SVDD was presented by Zhu et al. [155], where a bearing performance degradation assessment based on Incremental Rough SVDD (IRSVDD) is proposed. The assessment indicator is defined by considering the distance information and spatial position information during the degradation process, regarding the two hyperspheres obtained by the RSVDD and IRSVDD models, respectively. Shen et al. [49] proposed a monotonic degradation assessment index of rolling bearings using Fuzzy Support Vector Data Description (FSVDD) to construct a fuzzy-monitoring coefficient which describes the accelerating relationships between the damages and running time. FSVDD is trained for the normal condition, and the fuzzy-monitoring coefficient is defined by considering the radius of the trained hypersphere and the distance of a new testing sample to the hypersphere center. Such coefficient is sensitive to the initial defect and stably increases as faults develop. The stability features, such as RMS, square-root amplitude (SRA) and absolute average values (AAV), and the sensitive feature as kurtosis factor are selected as input features to FSVDD. The running time is introduced to form a monotonic index, namely damage severity index. The approach is tested on a run-to-failure dataset.

5.2.3. Gaussian Mixture Model based approaches

An integrated approach using Gaussian Mixture Model (GMM) with Kernel Principal Component Analysis (KPCA) and EWMA was presented by Aye et al. [156] in order to propose a quantification index, called Degradation Assessment Index (DAI), from acoustic emission (AE). This index is used as an indicator of the degradation of the slow speed bearing. Each DAI on the time series may be plotted for the whole life of each bearing, to form a monitoring chart for the slight bearing degradation. First, normalised relevant features as kurtosis, RMS, peak-to-peak, crest factor and skewness are computed from the AE; next, the polynomial kernel by using KPCA are extracted and used as inputs to the GMM analysis in order to describe the multimodal data distribution. GMM provides the unconditional probability density which indicates how the input follows the probability distribution of the GMM trained by a healthy database. Finally, EWMA model is used to improve the sensitivity and dependability of the Negative Log-Likelihood (NLL) of the GMM.

Yu [157] evaluated a similar approach, based on Gaussian mixture model (GMM)-based negative log likelihood probability, for bearing defect and severity classification. GMM is developed to provide a comprehensible health assessment indication for quantifying bearing performance degradation in a similar manner as proposed in [156]. The input features to the

GMM are obtained from the vibration signal by using a novel linear dimensionality reduction and feature extraction algorithm, called Locally Preserving Projection (LPP). LPP is applied to the original features from time domain (such as RMS, kurtosis, among others), signal energy from the WPD, and magnitudes of characteristic frequency of envelope signals.

5.2.4. Fuzzy Logic based approaches

A health degree (HD) indicator for rolling bearings based on the fuzzy set theory was proposed by Yang et al. [158], which ranges from 0 to 1 to mean from severe fault condition to health status, respectively. Health set, sub-health set, and fault set are defined as three fuzzy sets, and the membership degrees are calculated by an improved ANN with an structure based on the idea of Kalman prediction. HD is defined as the linear combination of the membership degrees obtained for each fuzzy set. Sensitive condition parameters on frequency domain are selected as input features to the improved ANN; the sensitivity between a set of candidate condition parameters are measured through a difference index which is defined by considering the mean and the standard deviation of the condition parameters.

Amar et al. [159] constructed a fuzzy-logic inspired process for estimating the severity of bearing faults. Gaussian distributions associated with the spectral content of vibration signals across frequency bins are identified, and they are used to define characteristic membership functions for each severity level. The approach is tested on different severity levels in the inner race.

An approach for early detection of faults in fan bearings and severity assessment was proposed by He et al. [19] by using a WF. The Sum of the Amplitudes of Bearing Characteristic Frequencies (SABCF) and their harmonics is used as an index to capture the bearing degradation trend. A fuzzy rule is introduced in order to match the wavelet filter that maximizes the amplitudes of the SABCF, which are an indicator of bearing faults. Basically, the SABCF are defined in a fuzzy way by using Gaussian membership functions that are described in terms of the theoretical BCF; the fuzzy membership function indicates that the closer the frequency to the theoretical BCF, the higher confidence that the frequency is related to a bearing fault. The optimization problem for adjusting the wavelet parameter maximizing the fuzzy amplitude is solved by using differential evolution. The performance of the proposed SABCF index is quantified by three measures such as monotonicity, prognosability, and trendability.

Liu et al. [160] used a fuzzy regression model to describe the degradation path related to the degradation indexes which are acquired by using GMM at each operating condition. WF is used to eliminate the environmental noise in the raw vibration signal; next, the features in time, frequency, time-frequency and information domains are calculated; PCA is used to reduce the dimensionality of the feature vector. GMM are adjusted with the Expectation Maximization algorithm, and the obtained GMM for each health state are used to compute the proposed degradation index by evaluating the overlap rate between the baseline features (healthy condition) with the on-line features. Finally, a fuzzy regression model is adjusted to model the behaviour of the degradation index under new data.

Chen et al. [161] used a neuro-fuzzy system (NFS) as a one step ahead prognostic model to forecast the evolution over time of the machine fault state, in order to improve the degree of belief in the forecasting estimations; an updating scheme using Bayesian estimation algorithms, solved with the particle filtering method, is integrated to the NFS by taking into account the probability density function of residuals between the real (on-line measurements) and predicted condition data by the NFS. Basically, this approach creates a fault grow model of certain condition monitoring index. The model is validated in two case studies, one of them related to the health monitoring of a helicopter oil cooler bearing with unknown fault mode, where the sum of weighted frequency components related to harmonics of the frequency of interest is used as the monitoring index to be predicted.

5.2.5. Continuous Hidden Markov Model based approaches

Jiang et al. [162] used a Continuous Hidden Markov Model (CHMM) to perform the automatic classification and performance assessment based on the concept of neighbouring singular value ratio (NSVR). Basically, the NSVR is the ratio between one SV and its successive one. Both vectors of SV and NSVR are proposed as input features to the CHMM. In case of the performance assessment, one CHMM is trained using sample data from the bearing under normal condition. Then, when the testing bearing is degraded, the output of CHMM is decreased and the output probability of CHMM can be treated as the performance index to assess the bearing performance. A methodology based on the Zero Crossing (ZC) features and a Coupled Hidden Markov Model (CoHMM) was introduced in Liu et al. [163], for estimating bearing performance degradation. Basically, there are different types of ZC features and here the authors select the exceeding threshold measurement over a specified time window. CoHMM has powerful potential for multichannel fusion, then in case of performance degradation, the multichannel statistical features are analysed by the multiple chains of the CoHMM. CoHMM is estimated using a normal condition dataset, and the LLP of testing data is used as degradation indicator.

Another work using CHMM-based Negative LLP (CHMM-NLLP) was presented by Zhang et al. [164], to obtain a sensitive bearing degradation indicator with significant trend. Specifically, NLLP is used as the degradation indicator by computing the probability of the observation sequence given a CHMM. Classical statistical features are extracted from the vibration signal in the healthy condition, and LPP are used for feature reduction. CHMM is trained with this data, by considering a certain number of artificial states. The value of the NLLP is a health indicator when an on-line sequence of data observations is processed by the CHMM, as the current sequence can deviate from the healthy condition. A similar work was also performed recently by Jiang et al. [165] to perform the degradation assessment in bearings. Effective features are extracted by using Nuisance Attribute Projection (NAP) and they are used as input features to the HMM. The new feature space projected by NAP is more sensitive to the bearing health changes occurring in operation condition. Input feature vectors of normal condition are used to train a nominal HMM, and the BaumWelch algorithm is used to estimate the parameters of the HMM. Given an input feature vector obtained from an unknown bearing condition, the likelihood probability is used as index of the bearing degradation. The likelihood probability indicates how well the new feature vector matches the probability distribution of the nominal HMM.

5.2.6. Probabilistic model based approaches

One important task in prognosis is the assessment of fault severity or fault degradation in order to estimate the remaining useful life. For this purpose, probabilistic models are interesting frameworks for estimating futures stages of the damages. Recent results in this field that use particle filtering were reviewed by Jouin et al. [166], when signals are under non-Gaussian additive noise; particularly, the work refers to the use of particle filtering on vibration feature data from a fatigue-driven fault in a critical aircraft component [182]. Stochastic filtering was applied by Myotyri et al. [167] for estimating an stochastic degradation process and uncertain condition monitoring measurements; the approach is validated with a simplified fatigue crack growth process, which can be used to model certain rotating machinery faults.

Gobbato et al. [170] used a recursive Bayesian updating scheme to assess the current state of fatigue damages like cracks. Bayesian inference-based probability was also developed by Yu [171] as a quantification indicator of machine health degradation by analysing vibration signals. A high-order Markov process is used to predict the evolution of the machine health in the form of a probability density function. Another gamma-prior Bayesian updating approach for modelling a degradation model was presented by Li et al. [172]. From the available degradation dataset, an stochastic exponential degradation model considering a Brownian motion process is adjusted; with help of the Bayesian approach, the prior model is updated by considering the new data. A feature such as the peak-to-peak value of vibration signals is selected to describe the degradation process of bearings in the validation case study.

A probabilistic model was proposed by Lorton et al. [168] to estimate the conditional distribution of the system state with respect to the specific information available about this system. A variation of the approach in [157] is presented in [169]; he uses a statistical model instead of GMM for defining a quantification index Q, through combination of T^2 and squared prediction error (SPE) statistics from the nominal data. Q index is treated with EWMA to provide an improved bearing performance assessment model.

Singleton et al. [173] used an Extended Kalman Filter (EKM) to fit the trending function in time of the variance in time domain and the entropy in time-frequency domain that are obtained from the raw vibration signal. Then, variance and entropy are stated as degradation indexes of bearing damages. The state vector, of each EKM for the variance and the entropy, contains the equation for the curve fit and the unknown parameters. As a result, a dynamic model describing the trend of the fault degradation is obtained. The approach was tested on a run-to-failure dataset for bearing damages. The switched Kalman filter was proposed by Lim and Mba [174] to infer the most probable degradation model, from the condition monitoring data, by using Bayesian estimation. In this analysis, it is assumed that the bearing degradation is monotonically increasing and it evolves from serviceable to stable wear and then accelerated wear. The dynamics of zero, first, and second order Kalman filters are analysed to track good and accelerated wear. In this case, an appropriate monotonic feature must be used to train the models. Instead of relying on the absolute value of the condition monitoring feature, it uses the dynamic behaviour between the current and past measurement to infer the degradation state, as a probability measure.

Lei et al. [175] proposed a probabilistic model based degradation process assessment, by taking into account four variability sources, such as: the temporal variability, the unit-to-unit variability, the nonlinear variability, and the measurement variability. Basically, the model is an stochastic one, considering the Brownian motion to describe the degradation process. In order to adjust the model parameters, a set of difference equations are derived and extended to a state-space model, and Kalman Particle Filtering (KPF) is used for the adaptive adjustment. The model parameters are initialized using the Maximum Likelihood Estimation (MLE) algorithm. A similar work was presented by Li et al. [176], where the degradation model is given by an exponential model also considering the Brownian motion, and expectation maximization algorithm is used to adjust parameters. One advantage of these model-based degradation assessment approaches is that they also serve as prediction models for calculating the Remaining Useful Life. Another stochastic degradation model expressed as a linear state-space model was developed by Wang et al. [177], based on a Wiener process and the standard Brownian motion; the Chapman-Kolmogorov equation was used to recursively calculate the probabilistic distribution function of the mean and variance associated with the model state. Finally, a Kalman filter is used to recursively adjust the state-space model. Before start running the degradation model, the Mahalanobis distance using statistical time domain features is monitored to identify the beginning of the degradation process. The platform PRONOSTIA is used for validating this model.

5.2.7. Other approaches

Li et al. [178] introduced an "abnormal degree" as a quantitative indicator of fault severity, based on negative selection that is able to detect different fault types with the same fault degree, and the same fault type with different fault degrees in ball bearings. Negative selection algorithm is a bio-inspired technique that works as one-classification algorithm; in this case the concept of "abnormal degree" is used to describe the degree in which a non-self sample (faulty condition) deviates from the self space (healthy condition). An abnormal degree function is established, i.e. mapping the state-space and the abnormal degree space. The values of abnormal degree space vary from 0 to 1. Raw time series data from vibration signals are analysed by the wavelet "db16" and the high-frequency wavelet coefficient energy of certain layers are selected as features, and finally reduced with PCA. The final result is that the adequate identification of the abnormal degree distribution of ball fault with different fault degrees.

As an extension of the work in [78], an AR model was used by Qian et al. [179] to predict the value of the RP entropy (ENTR), which is defined as the Shannon entropy based on the diagonal structure of the recurrence plot obtained from the RQA. As mentioned in [78], the RP entropy can be used as an effective indicator for bearing degradation monitoring.

Pan et al. [180] proposed fuzzy c-Means based clustering for bearing performance degradation assessment. The energy of the nodes computed from the Lifting Wavelet Packet Decomposition (LWPD) are used as feature vector, normal and final failure data are used as training samples, and an assessment model with two clusters is built by using fuzzy c-means. The subjection of tested data to the normal state is defined as a degradation indicator in the range from 0 to 1. The subjection as degradation indicator has excellent explanation related to degradation degree. Its effectiveness has been validated by using an accelerated bearing life test, and a robust strategy is proposed to improve its robustness to outliers in the training set. Another work based on clustering for degradation assessment was presented by Tao et al. [181], by using the Mahalanobis distance between the new measured data and the cluster previously identified as the healthy condition. Features for building the proper cluster are obtained by calculating the energy coefficient of the WPD applied on the raw vibration signal, and Fisher Discriminant Analysis (FDA) to decrease the dimensionality of the feature vector. A normalized confidence value (CV) is applied on such distance to obtain values between 0 and 1, where a higher CV closer to 1 indicates a performance state closer to normal, and a lower CV closer to 0 is closer to a condition of failure.

5.3. Advantages and limitations of the learning-based approach

As presented in the previous sections, this approach is oriented towards to two objectives: Fault Severity Classification (FSC) and Fault Degradation Estimation (FDE). Machine Learning (ML) models are used to accomplish these aims, and it is well-known that the results from these models depend highly on the quality of the dataset, i.e., proper number of samples and proper features. Particularly, the feature extraction and selection, as steps before developing the ML models, can affect the performance of such models. This requirement can be considered as a limitation of the use of techniques to the learning based approach, and most of the presented works are different to each other because they use different signal processing techniques to extract features.

Opposite to the signal processing based approach, where a wide knowledge about the mechanical phenomenon related to the bearing faults and its influence on the signal is required, it is not required in the learning-based approach since it is assumed that the quality of the dataset extracted from the available signals is high. This is why the learning based approach has the property to extract knowledge from data; this is considered as an advantage. Additionally, some ML models are used to extract artificial features which can be used to FSC or FDE. This is also an advantage.

More than analysing the advantages and limitations of each technique discussed in the previous sections, Table 6 shows more detailed aspects about the use of the learning based approach that the researchers might take into account when performing FSC and FDE, through this approach.

How a result of previews studies in rotative machines, prior knowledge (structural, configuration setup, etc.) has been obtained. However, most of available classical machine learning models have a no clear methodology for including it. Then is necessary the combination with other approaches i.e,bayessian and/or fuzzy, with the corresponding increasing in the complexity of the model.

Table 6
Advantages and limitations of the learning based approach to FSC and FDE.

Aim	Advantages	Limitations
FSC	A wide set ML models are available as classifiers under proper feature selection Some recent ML models are able to give good classification results, even under non proper feature selection Interpretability of the fault severity indicator, in the sense that it is defined as a binary value regarding the class membership of the new sample	A training dataset composed of labeled samples regarding the fault sizes (classes) must be available, as the classification model is developed under supervised learning A large amount of samples for each fault class might be needed, according to the used ML model
FDE	A dataset related to the healthy state is only needed for training the ML model, in some approaches Several metrics are available to measure the distance between the dataset related to the healthy state and other dataset (probably associated with faulty states) A wide set of ML models are available as regression models, to propose fault degradation indicators Probabilistic models describing the phenomenon of fault degradation are available, and can be adjusted, by learning, to a dataset for a case of study	Proper distances between the dataset related to the healthy state and other states must be clearly defined Most of available models are weak to including the new knowledge about the fault trending, e.g. new classes and/or clusters, or new features, from a new set of unlabelled samples

6. Conclusions and new challenges

This up-to-date and comprehensive review is focused on a detailed description of the most relevant techniques and methods for fault severity assessment, from 2010 to 2016. The selected works report adequate and novel results regarding the underlying techniques, and they show the problem of fault severity assessment, analysed from two main points of view: (i) fault size estimation from the identification of the double impulse structure in vibration or acoustic emission signal, due to one single point defect, and (ii) fault degradation estimation, that is commonly associated with wear processes and can be divided into incipient, moderate, severe, and failure states. The first view has been treated with signal processing approaches to identify the entry and exit events from the time domain of the analysed signal, and the second one with both signal processing and learning approaches to propose some degradation index or health index to quantify the damage.

Based on the contributions by using signal processing approaches presented in Table 1, the topic of fault severity estimation using vibration signals is more reported than the fault size estimation. The use of current and voltage signals is limited in this topic. Fault size estimation is a very important topic in fault severity assessment; however, based on our review, no large number of contributions has been devoted to this topic, and a similar number of contributions consider the use of vibration signals and acoustic emissions.

According to the contribution in Table 4, learning-based approaches have reported less contributions than signal processing approaches in the fault severity assessment based on classification. Learning-based approaches are very popular in fault detection and diagnosis to classify the fault condition in bearings, however, the fault severity assessment is not included in most of works using classification. Despite this result, under learning approaches the most used method in this review is the development of classification models, that requires the knowledge of all the fault patterns; i.e., the classes associated with the severity level. Obviously, this is a very strong requirement. Besides, the recent results show that learning approaches are focused towards three directions: (i) proposing the extraction of proper features to reach adequate results in classification by using classical classifiers, (ii) proposing new classifiers, and (iii) defining health index to measure the degradation stages. Support Vector Machine and Nearest Neighbour clustering are the most reported techniques in classification based models.

Table 5 shows that the fault degradation estimation topic has been widely analysed with learning-based techniques. Neural Network based-Self Organizing Mapping, Support Vector Machines, and probabilistic approaches are the most used techniques. On the other hand, the vibration signal is the most commonly used signal in learning approaches. Current, voltage and acoustic emission were found not as widely analysed signals.

Regarding the practical significance of the presented data-driven techniques, learning-based approaches are very popular in industrial applications, due to their ability of learning from data without a wide expertise about the process knowledge associated with the analysed data. On the contrary, signal processing based approaches require the knowledge of certain parameters of the device such as geometrical parameters, rotation speed of the motor shaft, among others; then, they might not be suitable in some industrial applications. The relative performance in both approaches depends on data quality.

On the other hand, the use of audio or sound signals for fault severity assessment is out of this review. The fault signature is hard to recover from these kinds of signals, as it is usually immersed in noise, then, complex signal processing is required. This is why no extensive works are devoted to analyse this signal, and mainly in case of bearings, as discussed in the work [183] which is devoted to analyse this signal to the fault diagnosis problem.

Based on the previous discussion about the main results found in this review, the problem of fault severity evaluation might be still waiting to be widely studied in several ways, that represent new challenges in fault severity evaluation:

- The application of intelligent learning approaches to detect the occurrence of entry and exit events for fault size estimation. According to our review, this topic is studied by using mainly signal processing approaches, hence, new approaches using learning-based techniques could be exploited.
- The combination of fault signature extraction in wear process by using signal processing with learning approaches to propose new health indexes. The signal processing approaches in this review show new contributions for proposing new features as health indexes, but learning approaches could be applied to combine classical health indexes to propose new ones, with the desired monotonic characteristic expected for this kind of indexes.
- The development of health indexes with partial information of the healthy condition. In this case, the use of techniques for knowledge discovery is required.
- The application of unsupervised intelligent learning approaches to discovering new patterns, i.e., classes, of fault degradation conditions.
- The extensive analysis of audio and current signals. The use of this kind of signals can be an important contribution in industrial environments where the coupling of vibration sensors is difficult. In case of the audio signal, de-noising techniques must carefully researched.

Finally, the information provided from voltage, current and acoustic emission signals could be exploited in new researches for the development of new health indexes. The use of signal processing or learning approaches separately is still a valid challenge to deal with this kind of signals.

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References

[1] K.A. Loparo, M.L. Adams, W. Lin, M.F. Abdel-Magied, N. Afshari, Fault detection and diagnosis of rotating machinery, IEEE Trans. Ind. Electron. 47 (5) (2000) 1005–1014.
[2] A.K. Jardine, D. Lin, D. Banjevic, A review on machinery diagnostics and prognostics implementing condition-based maintenance, Mech. Syst. Sign. Process. 20 (7) (2006) 1483–1510.
[3] R.B. Randall, Vibration-Based Condition Monitoring, Wiley, West Sussex, United Kingdom, 2011.
[4] R. Li, Rotating Machine Fault Diagnostics using Vibration and Acoustic Emission Sensors Ph.D. thesis, University of Illinois, Chicago, 2012.
[5] G. Georgoulas, T. Loutas, C.D. Stylios, V. Kostopoulos, Bearing fault detection based on hybrid ensemble detector and empirical mode decomposition, Mech. Syst. Sign. Process. 41 (12) (2013) 510–525.
[6] J.R. Stack, T.G. Habetler, R.G. Harley, Fault classification and fault signature production for rolling element bearings in electric machines, IEEE Trans. Ind. Appl. 40 (3) (2004) 735–739.
[7] P. McFadden, J. Smith, Model for the vibration produced by a single point defect in a rolling element bearing, J. Sound Vib. 96 (1) (1984) 69–82.
[8] D. Kateris, D. Moshou, X.-E. Pantazi, I. Gravalos, N. Sawalhi, S. Loutridis, A machine learning approach for the condition monitoring of rotating machinery, J. Mech. Sci. Technol. 28 (1) (2014) 61–71.
[9] S.F. Zhao, L. Liang, G.H. Xu, J. Wang, W.M. Zhang, Quantitative diagnosis of a spall-like fault of a rolling element bearing by empirical mode decomposition and the approximate entropy method, Mech. Syst. Sign. Process. 40 (1) (2013) 154–177.
[10] P. McFadden, J. Smith, The vibration produced by multiple point defects in a rolling element bearing, J. Sound Vib. 98 (2) (1985) 263–273.
[11] B. Dolenc, P. Boškoski, ani Juričić, Distributed bearing fault diagnosis based on vibration analysis, Mech. Syst. Sign. Process. 6667 (2016) 521–532.
[12] C. Li, V. Sanchez, G. Zurita, M.C. Lozada, D. Cabrera, Rolling element bearing defect detection using the generalized synchrosqueezing transform guided by timefrequency ridge enhancement, {ISA} Trans. 60 (2016) 274–284.
[13] C. Li, D. Cabrera, J.V. de Oliveira, R.-V. Sanchez, M. Cerrada, G. Zurita, Extracting repetitive transients for rotating machinery diagnosis using multiscale clustered grey infogram, Mech. Syst. Sign. Process. 7677 (2016) 157–173.
[14] C. Li, J.V. de Oliveira, M. Cerrada, F. Pacheco, D. Cabrera, V. Sanchez, G. Zurita, Observer-biased bearing condition monitoring: from fault detection to multi-fault classification, Eng. Appl. Artif. Intell. 50 (2016) 287–301.
[15] C. Li, J.V. de Oliveira, R.-V. Sánchez, M. Cerrada-Lozada, G. Zurita, D. Cabrera, Fuzzy determination of informative frequency band for bearing fault detection, J. Intell. Fuzzy Syst 30 (2016) 3513–3525.
[16] C. Li, R.-V. Sánchez, G. Zurita, M. Cerrada, D. Cabrera, Fault diagnosis for rotating machinery using vibration measurement deep statistical feature learning, Sensors 16 (6).
[17] N. Gorjian, L. Ma, M. Mittinty, P. Yarlagadda, Y. Sun, Engineering Asset Lifecycle Management, Springer, 2010, pp. 369–384 (Chapter A review on degradation models in reliability analysis).
[18] I. El-Thalji, E. Jantunen, A summary of fault modelling and predictive health monitoring of rolling element bearings, Mech. Syst. Sign. Process. 6061 (2015) 252–272.
[19] W. He, Q. Miao, M. Azarian, M. Pecht, Health monitoring of cooling fan bearings based on wavelet filter, Mech. Syst. Sign. Process. 6465 (2015) 149–161.
[20] A. Prudhom, J. Antonino-Daviu, H. Razik, V. Climente-Alarcon, Time-frequency vibration analysis for the detection of motor damages caused by bearing currents, Mech. Syst. Sign. Process. 84 (Part A) (2017) 747–762.
[21] Y. Liu, Fault diagnosis based on {SWPT} and hilbert transform, Proc. Eng. 15 (2011) 3881–3885.
[22] W. Yang, R. Court, Experimental study on the optimum time for conducting bearing maintenance, Measurement 46 (8) (2013) 2781–2791.
[23] F. Immovilli, A. Bellini, R. Rubini, C. Tassoni, Diagnosis of bearing faults in induction machines by vibration or current signals: a critical comparison, IEEE Trans. Ind. Appl. 46 (4) (2010) 1350–1359.
[24] A. Muetze, E. Strangas, On inverter induced bearing currents, bearing maintenance scheduling, and prognosis, in: 2014 International Conference on Electrical Machines, IEEE, 2014, pp. 1915–1921.
[25] A.M. Al-Ghamd, D. Mba, A comparative experimental study on the use of acoustic emission and vibration analysis for bearing defect identification and estimation of defect size, Mech. Syst. Sign. Process. 20 (7) (2006) 1537–1571.
[26] N. Tandon, A. Choudhury, A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings, Tribol. Int. 32 (8) (1999) 469–480.
[27] P. Kankar, S.C. Sharma, S. Harsha, Fault diagnosis of ball bearings using machine learning methods, Expert Syst. Appl. 38 (3) (2011) 1876–1886.
[28] Y. Lei, J. Lin, Z. He, M.J. Zuo, A review on empirical mode decomposition in fault diagnosis of rotating machinery, Mech. Syst. Sign. Process. 35 (12) (2013) 108–126.
[29] R. Yan, R.X. Gao, X. Chen, Wavelets for fault diagnosis of rotary machines: a review with applications, Sign. Process. 96 (Part A) (2014) 1–15 (Time-frequency methods for condition based maintenance and modal analysis).
[30] A. Rai, S. Upadhyay, A review on signal processing techniques utilized in the fault diagnosis of rolling element bearings, Tribol. Int. 96 (2016) 289–306.
[31] S. Devendiran, K. Manivannan, Vibration based condition monitoring and fault diagnosis technologies for bearing and gear components – a review, Int. J. Appl. Eng. Res. 11 (6) (2016) 3966–3975.
[32] A. Heng, S. Zhang, A.C. Tan, J. Mathew, Rotating machinery prognostics: state of the art, challenges and opportunities, Mech. Syst. Sign. Process. 23 (3) (2009) 724–739.
[33] J. Lee, F. Wu, W. Zhao, M. Ghaffari, L. Liao, D. Siegel, Prognostics and health management design for rotary machinery systems – reviews, methodology and applications, Mech. Syst. Sign. Process. 42 (12) (2014) 314–334.
[34] M. Cerrada, C. Li, R.-V. Snchez, F. Pacheco, D. Cabrera, J.V. de Oliveira, A fuzzy transition based approach for fault severity prediction in helical gearboxes, Fuzzy Sets Syst. http://dx.doi.org/10.1016/j.fss.2016.12.017. URL <http://www.sciencedirect.com/science/article/pii/S0165011416304584>.
[35] C.M. Bishop, Pattern Recognition and Machine Learning, Springer, New York, USA, 2007.
[36] R.B. Randall, J. Antoni, Rolling element bearing diagnosticsa tutorial, Mech. Syst. Sign. Process. 25 (2) (2011) 485–520.
[37] R. Golafshan, K.Y. Sanliturk, {SVD} and Hankel matrix based de-noising approach for ball bearing fault detection and its assessment using artificial faults, Mech. Syst. Sign. Process. 7071 (2016) 36–50.
[38] R. Yang, J.K. adn Jinsong Zhao, J. Li, H. Li, Case study of bearing condition monitoring using SPM, in: 2014 Prognostics and System Health Management Conference, IEEE, 2014, pp. 695–698.
[39] L. Zhen, H. Zhengjia, Z. Yanyang, C. Xuefeng, Bearing condition monitoring based on shock pulse method and improved redundant lifting scheme, Math. Comput. Simulat. 79 (3) (2008) 318–338.

[40] H. Zhou, J. Chen, G. Dong, R. Wang, Detection and diagnosis of bearing faults using shift-invariant dictionary learning and hidden markov model, Mech. Syst. Sign. Process. 7273 (2016) 65–79.
[41] S. Khanam, N. Tandon, J. Dutt, Fault size estimation in the outer race of ball bearing using discrete wavelet transform of the vibration signal, Proc. Technol. 14 (2014) 12–19 (2nd International Conference on Innovations in Automation and Mechatronics Engineering, {ICIAME} 2014).
[42] G. Kogan, J. Bortman, R. Klein, Estimation of the spall size in a rolling element bearing, Insight: Non-Destr. Test. Cond. Monit. 57 (8) (2015) 448–451.
[43] X. Li, Y. Zhu, Z. Zhou, N. Wang, Fault diagnosis based on nonlinear dynamic modeling in rolling element bearing systems, in: 2013 IEEE International Symposium on Assembly and Manufacturing, IEEE, 2013, pp. 12–15.
[44] L. Niu, H. Cao, Z. He, Y. Li, A systematic study of ball passing frequencies based on dynamic modeling of rolling ball bearings with localized surface defects, J. Sound Vib. 357 (2015) 207–232.
[45] S. Singh, C.Q. Howard, C.H. Hansen, An extensive review of vibration modelling of rolling element bearings with localised and extended defects, J. Sound Vib. 357 (2015) 300–330.
[46] M. Dobrica, M. Fillon, Performance degradation in scratched journal bearings, Tribol. Int. 51 (2012) 1–10.
[47] I. El-Thalji, E. Jantunen, A descriptive model of wear evolution in rolling bearings, Eng. Fail. Anal. 45 (2014) 204–224.
[48] I. El-Thalji, E. Jantunen, Fault analysis of the wear fault development in rolling bearings, Eng. Fail. Anal. 57 (2015) 470–482.
[49] Z. Shen, Z. He, X. Chen, C. Sun, Z. Liu, A monotonic degradation assessment index of rolling bearings using fuzzy support vector data description and running time, Sensors 12 (8) (2012) 10109–10135.
[50] G. Skrimpas, I. Dragiev, R. Hilmisson, C. Sweeney, B. Jensen, N. Mijatovic, J. Holboll, Detection of generator bearing inner race creep by means of vibration and temperature analysis, in: 2015 IEEE 10th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives, IEEE, 2015, pp. 303–309.
[51] V. Maruthi, G.S. Hegde, Mathematical analysis of unbalanced magnetic pull and detection of mixed air gap eccentricity in induction motor by vibration analysis using MEMs accelerometer, in: 2013 IEEE 1st International Conference on Condition Assessment Techniques in Electrical Systems, IEEE, 2013, pp. 207–212.
[52] Y. Pan, J. Chen, The changes of complexity in the performance degradation process of rolling element bearing, J. Vib. Contr. 22 (2) (2016) 344–357.
[53] W. Yang, R. Court, Experimental study on the optimum time for conducting bearing maintenance, Measurement 46 (8) (2013) 2781–2791.
[54] L. Cui, Y. Zhang, F. Zhang, J. Zhang, S. Lee, Vibration response mechanism of faulty outer race rolling element bearings for quantitative analysis, J. Sound Vib. 364 (2016) 67–76.
[55] L. Cui, N. Wu, C. Ma, H. Wang, Quantitative fault analysis of roller bearings based on a novel matching pursuit method with a new step-impulse dictionary, Mech. Syst. Sign. Process. 6869 (2016) 34–43.
[56] R. Kumar, M. Singh, Outer race defect width measurement in taper roller bearing using discrete wavelet transform of vibration signal, Measurement 46 (1) (2013) 537–545.
[57] M. Singh, R. Kumar, Thrust bearing groove race defect measurement by wavelet decomposition of pre-processed vibration signal, Measurement 46 (9) (2013) 3508–3515.
[58] C. Bujoreanu, R. Monoranu, N.D. Olaru, Study on the defects size of ball bearings elements using vibration analysis, Appl. Mech. Mater. 658 (2014) 289–294.
[59] N. Sawalhi, R. Randall, Vibration response of spalled rolling element bearings: observations, simulations and signal processing techniques to track the spall size, Mech. Syst. Sign. Process. 25 (3) (2011) 846–870.
[60] M. Elforjani, D. Mba, Accelerated natural fault diagnosis in slow speed bearings with acoustic emission, Eng. Fract. Mech. 77 (1) (2010) 112–127.
[61] M. Elforjani, D. Mba, Detecting natural crack initiation and growth in slow speed shafts with the acoustic emission technology, Eng. Fail. Anal. 16 (7) (2009) 2121–2129.
[62] M. Elforjani, D. Mba, Natural mechanical degradation measurements in slow speed bearings, Eng. Fail. Anal. 16 (1) (2009) 521–532.
[63] S. Sun, Y. Guo, Y. Gao, Experimental investigation on double impulses phenomenon of outer race spalled rolling element bearings based on acoustic emission signals, in: 2015 IEEE International Conference on Information and Automation, IEEE, 2015, pp. 1931–1935.
[64] S. Al-Dossary, R.R. Hamzah, D. Mba, Observations of changes in acoustic emission waveform for varying seeded defect sizes in a rolling element bearing, Appl. Acoust. 70 (1) (2009) 58–81.
[65] F. Hemmati, W. Orfali, M.S. Gadala, Roller bearing acoustic signature extraction by wavelet packet transform, applications in fault detection and size estimation, Appl. Acoust. 104 (2016) 101–118.
[66] A. bo Ming, W. Zhang, Z. ye Qin, F. lei Chu, Dual-impulse response model for the acoustic emission produced by a spall and the size evaluation in rolling element bearings, IEEE Trans. Ind. Electron. 62 (10) (2015) 6606–6615.
[67] Y.N. Tang, C. Lu, J.M. Hu, Rolling bearing fault diagnosis and health assessment based on EMDTEO, Adv. Mater. Res. 998–999 (2014) 470–475.
[68] G. Dong, J. Chen, Study on cyclic energy indicator for degradation assessment of rolling element bearings, JVC/J. Vib. Contr. 17 (12) (2011) 1805–1816.
[69] X. Zhang, J. Kang, L. Hao, L. Cai, J. Zhao, Bearing fault diagnosis and degradation analysis based on improved empirical mode decomposition and maximum correlated kurtosis deconvolution, J. Vibroeng. 17 (1) (2015).
[70] T. Wang, W. Cheng, J. Li, W. Wen, H. Wang, Anomaly detection for equipment condition via cross-correlation approximate entropy, in: 2011 International Conference on Management Science and Industrial Engineering, IEEE, 2011, pp. 52–55.
[71] K. Jiang, G. Xu, L. Liang, G. Zhao, T. Tao, A quantitative diagnosis method for rolling element bearing using signal complexity and morphology filtering, J. Vibroeng. 14 (4) (2012) 1862–1875.
[72] Y. Li, M. Xu, Z. Haiyang, Y. Wei, W. Huang, A new rotating machinery fault diagnosis method based on improved local mean decomposition, Digit. Sign. Process. 46 (2015) 201–214.
[73] M. Tabaszewski, C. Cempel, Application of evolution of singular values in multisymptom diagnostics of machines, in: 2012 International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering, IEEE, 2012, pp. 555–560.
[74] D. Siegel, H. Al-Atat, V. Shauche, L. Liao, J. Snyder, J. Lee, Novel method for rolling element bearing health assessment tachometer-less synchronously averaged envelope feature extraction technique, Mech. Syst. Sign. Process. 29 (2012) 362–376.
[75] D. Paliwal, A. Choudhury, G. Tingarikar, Wavelet and scalar indicator based fault assessment approach for rolling element bearings, Proc. Mater. Sci. 5 (2014) 2347–2355 (International Conference on Advances in Manufacturing and Materials Engineering, {ICAMME} 2014).
[76] H. Gu, J. Zhao, X. Zhang, Hybrid methodology of degradation feature extraction for bearing prognostics, Maint. Reliab. 15 (2) (2013) 195–201.
[77] Q. Miao, C. Tang, W. Liang, M. Pecht, Health assessment of cooling fan bearings using wavelet-based filtering, Sensors 13 (1) (2012) 274–291.
[78] Y. Qian, R. Yan, M. Shan, Damage assessment of mechanical systems based on recurrence quantification analysis, in: 2012 IEEE Conference on Prognostics and System Health Management, IEEE, 2012, pp. 1–5.
[79] T. Gerber, N. Martin, C. Mailhes, Time-frequency tracking of spectral structures estimated by a data-driven method, IEEE Trans. Ind. Electron. 62 (2) (2015) 6616–6626.
[80] F. Ding, Z. Re, Formalization of reliability model for assessment and prognosis using proactive monitoring mechanism, in: Prognostics and Health Management Conference, IEEE, 2010, pp. 1–6.
[81] F. Cong, J. Chen, Y. Pan, Kolmogorov-Smirnov test for rolling bearing performance degradation assessment and prognosis, J. Vib. Contr. 17 (9) (2011) 1337–1347.
[82] C. Sun, Z. Zhang, Z. He, Z. Shen, B. Chen, W. Xiao, Novel method for bearing performance degradation assessment – a kernel locality preserving projection-based approach, Proc. Inst. Mech. Eng. Part C: J. Mech. Eng. Sci. 228 (3) (2014) 548–560.
[83] J. Singh, A. Darpe, S. Singh, Bearing damage assessment using Jensen-Rényi divergence based on {EEMD}, Mech. Syst. Sign. Process. 87 (Part A) (2017) 307–339.

[84] Q. He, P. Li, F. Kong, Rolling bearing localized defect evaluation by multiscale signature via empirical mode decomposition, J. Vib. Acoust. 134 (6) (2012) 061013.
[85] M. Irfan, N. Saad, R. Ibrahim, V. Asirvadam, N.T. Hung, Analysis of bearing outer race defects in induction motors, in: 2014 5th International Conference on Intelligent and Advanced Systems, IEEE, 2014, pp. 1–6.
[86] K. Kompella, M. Rao, R. Rao, R. Sreenivasu, Estimation of nascent stage bearing faults of induction motor by stator current signature using adaptive signal processing, in: 2013 Annual IEEE India Conference, IEEE, 2013, pp. 1–5.
[87] G. Skrimpas, K. Marhadi, B. Jensen, Automatic mechanical fault assessment of small wind energy systems in microgrids using electric signature analysis, in: 2013 4th IEEE/PES Innovative Smart Grid Technologies Europe, IEEE, 2013, pp. 1–5.
[88] X. Wu, C. Qiu, M. Xia, G. Cheng, Z. Xue, Research on the current feature of induction motor bearing fault based on phase modulation, in: 2014 Fifth International Conference on Intelligent Control and Information Processing, IEEE, 2014, pp. 181–186.
[89] M. Picazo-Rodenas, J. Antonino-Daviu, V. Climente-Alarcon, R. Royo-Pastor, A. Mota-Villar, Combination of non-invasive approaches for general assessment of induction motors, in: 2014 International Conference on Electrical Machines, IEEE, 2014, pp. 1496–1502.
[90] C. Xu, C. Qiu, M. Xia, G. Cheng, Z. Xue, The diagnosis method for induction motor bearing fault based on volterra series, in: Fifth International Conference on Intelligent Control and Information Processing, IEEE, 2014, pp. 319–325.
[91] C. Liu, X. Wu, J. Mao, X. Liu, Acoustic emission signal processing for rolling bearing running state assessment using compressive sensing, Mech. Syst. Sign. Process. 91 (2017) 395–406.
[92] K. Medjaher, N. Zerhouni, J. Baklouti, Data-driven prognostics based on health indicator construction: application to pronostias data, in: 2013 European Control Conference (ECC), 2013, pp. 1451–1456.
[93] Y. Wang, Y. Peng, Y. Zi, A two-stage data-driven-based prognostic approach for bearing degradation problem, IEEE Trans. Ind. Inform. 12 (3) (2016) 924–932.
[94] X. Chen, Z. Shen, Z. He, C. Sun, Z. Liu, Remaining life prognostics of rolling bearing based on relative features and multivariable support vector machine, Proc. Inst. Mech. Eng. Part C: J. Mech. Eng. Sci. 227 (12) (2013) 2849–2860.
[95] L. Ma, J.S. Kang, C.Y. Zhao, Research on condition monitoring of bearing health using vibration data, Appl. Mech. Mater. 226–228 (2012) 340–344.
[96] X. Zhang, J. Kang, E. Bechhoefer, H. Teng, Enhanced bearing fault detection and degradation analysis based on narrowband interference cancellation, Int. J. Syst. Assur. Eng. Manage. 5 (4) (2014) 645–650.
[97] Z. Wu, Rolling bearing fault evolution based on vibration time-domain parameters, Key Eng. Mater. 693 (2016) 1412–1418.
[98] M. Jin, R. Li, Z. Xu, X. Zhao, Reliable fault diagnosis method using ensemble fuzzy {ARTMAP} based on improved bayesian belief method, Neurocomputing 133 (2014) 309–316.
[99] G. Georgoulas, P. Karvelis, T. Loutas, C.D. Stylios, Rolling element bearings diagnostics using the symbolic aggregate approximation, Mech. Syst. Sign. Process. 6061 (2015) 229–242.
[100] V. Rao, C. Ratnam, Estimation of defect severity in rolling element bearings using vibration signals with artificial neural network, Jordan J. Mech. Ind. Eng. 9 (2) (2015) 113–120.
[101] P. Nectoux, R. Gouriveau, K. Medjaher, E. Ramasso, B. Chebel-Morello, N. Zerhouni, C. Varnier, Pronostia: an experimental platform for bearings accelerated degradation tests, in: IEEE International Conference on Prognostics and Health Management (PHM), 2012, pp. 1–8.
[102] M. Cococcioni, S. Lazzerini, B. Volpi, Robust diagnosis of rolling element bearings based on classification techniques, IEEE Trans. Ind. Inform. 9 (4) (2013) 2256–2263.
[103] A. Sharma, M. Amarnath, P. Kankar, Feature extraction and fault severity classification in ball bearings, J. Vib. Contr. 22 (1) (2014) 176–192.
[104] M.F. Yaqub, I. Gondal, J. Kamruzzaman, An adaptive self-configuration scheme for severity invariant machine fault diagnosis, IEEE Trans. Reliab. 62 (1) (2013) 160–170.
[105] B. Muruganatham, M. Sanjith, B. Krishnakumar, S.S. Murty, Roller element bearing fault diagnosis using singular spectrum analysis, Mech. Syst. Sign. Process. 35 (12) (2013) 150–166.
[106] J.B. Ali, N. Fnaiech, L. Saidi, B. Chebel-Morello, F. Fnaiech, Application of empirical mode decomposition and artificial neural network for automatic bearing fault diagnosis based on vibration signals, Appl. Acoust. 89 (2015) 16–27.
[107] J.B. Ali, L. Saidi, A. Mouelhi, B. Chebel-Morello, F. Fnaiech, Application of feature reduction techniques for automatic bearing degradation assessment, in: 2014 International Conference on Electrical Sciences and Technologies in Maghreb, IEEE, 2014, pp. 1–6.
[108] Y. Lei, Z. He, Y. Zi, {EEMD} method and {WNN} for fault diagnosis of locomotive roller bearings, Expert Syst. Appl. 38 (6) (2011) 7334–7341.
[109] E. de Moura, C. Souto, A. Silva, M. Irmo, Evaluation of principal component analysis and neural network performance for bearing fault diagnosis from vibration signal processed by {RS} and {DF} analyses, Mech. Syst. Sign. Process. 25 (5) (2011) 1765–1772.
[110] M. Gan, C. Wang, C. Zhu, Construction of hierarchical diagnosis network based on deep learning and its application in the fault pattern recognition of rolling element bearings, Mech. Syst. Sign. Process. 72 (2016) 92–104.
[111] M. Delgado, G. Cirrincione, A.G. Espinosa, J.A. Ortega, H. Henao, Dedicated hierarchy of neural networks applied to bearings degradation assessment, in: 2013 9th IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives, IEEE, 2013, pp. 544–551.
[112] Y. Zhang, H. Zuo, F. Bai, Classification of fault location and performance degradation of a roller bearing, Measurement 46 (3) (2013) 1178–1189.
[113] X. Zhang, Y. Liang, J. Zhou, Y. zang, A novel bearing fault diagnosis model integrated permutation entropy, ensemble empirical mode decomposition and optimized {SVM}, Measurement 69 (2015) 164–179.
[114] W. Du, J. Tao, Y. Li, C. Liu, Wavelet leaders multifractal features based fault diagnosis of rotating mechanism, Mech. Syst. Sign. Process. 43 (12) (2014) 57–75.
[115] L. Saidi, J.B. Ali, F. Fnaiech, Application of higher order spectral features and support vector machines for bearing faults classification, {ISA} Trans. 54 (2015) 193–206.
[116] J. Wen, H. Gao, S. Li, L. Zhang, X. He, W. Liu, Fault diagnosis of ball bearings using synchrosqueezed wavelet transforms and SVM, in: 2015 Prognostics and System Health Management Conference, IEEE, 2015, pp. 1–6.
[117] Z. Liu, M.J. Zuo, Y. Qin, Remaining useful life prediction of rolling element bearings based on health state assessment, Proc. Inst. Mech. Eng. Part C: J. Mech. Eng. Sci. 230 (2) (2016) 314–330.
[118] Y. Wang, S. Kang, Y. Jiang, G. Yang, L. Song, V. Mikulovich, Classification of fault location and the degree of performance degradation of a rolling bearing based on an improved hyper-sphere-structured multi-class support vector machine, Mech. Syst. Sign. Process. 29 (2012) 404–414.
[119] Y. Li, M. Xu, R. Wang, W. Huang, A fault diagnosis scheme for rolling bearing based on local mean decomposition and improved multiscale fuzzy entropy, J. Sound Vib. 360 (2016) 277–299.
[120] Y. Li, M. Xu, H. Zhao, W. Huang, Hierarchical fuzzy entropy and improved support vector machine based binary tree approach for rolling bearing fault diagnosis, Mech. Mach. Theory 98 (2016) 114–132.
[121] H. Al-Bugharbee, I. Trendafilova, A fault diagnosis methodology for rolling element bearings based on advanced signal pretreatment and autoregressive modelling, J. Sound Vib. 369 (2016) 246–265.
[122] Q. He, Timefrequency manifold for nonlinear feature extraction in machinery fault diagnosis, Mech. Syst. Sign. Process. 35 (12) (2013) 200–218.
[123] Q. He, Vibration signal classification by wavelet packet energy flow manifold learning, J. Sound Vib. 332 (7) (2013) 1881–1894.
[124] X. Ding, Q. He, N. Luo, A fusion feature and its improvement based on locality preserving projections for rolling element bearing fault classification, J. Sound Vib. 335 (2015) 367–383.
[125] F. Pacheco, M. Cerrada, R.-V. Snchez, D. Cabrera, C. Li, J.V. de Oliveira, Attribute clustering using rough set theory for feature selection in fault severity classification of rotating machinery, Expert Syst. Appl. 71 (2017) 69–86.
[126] J. Lin, Q. Chen, Fault diagnosis of rolling bearings based on multifractal detrended fluctuation analysis and mahalanobis distance criterion, Mech. Syst. Sign. Process. 38 (2) (2013) 515–533.

[127] H. Liu, X. Wang, C. Lu, Rolling bearing fault diagnosis based on LCD-TEO and multifractal detrended fluctuation analysis, Mech. Syst. Sign. Process. 6061 (2015) 273–288.
[128] T. Boutros, M. Liang, Detection and diagnosis of bearing and cutting tool faults using hidden markov models, Mech. Syst. Sign. Process. 25 (6) (2011) 2102–2124.
[129] H. Zhou, J. Chen, G. Dong, H. Wang, H. Yuan, Bearing fault recognition method based on neighbourhood component analysis and coupled hidden markov model, Mech. Syst. Sign. Process. 6667 (2016) 568–581.
[130] D. Tobon-Mejia, K. Medjaher, N. Zerhouni, G. Tripot, A data-driven failure prognostics method based on mixture of gaussians hidden markov models, IEEE Trans. Reliab. 61 (2) (2012) 491–503.
[131] L. Zhang, G. Xiong, H. Liu, H. Zou, W. Guo, Bearing fault diagnosis using multi-scale entropy and adaptive neuro-fuzzy inference, Expert Syst. Appl. 37 (8) (2010) 6077–6085.
[132] I. Attoui, N. Boutasseta, N. Fergani, B. Oudjani, A. Deliou, Vibration-based bearing fault diagnosis by an integrated DWT-FFT approach and an adaptive neuro-fuzzy inference system, in: 2015 3rd International Conference on Control, Engineering & Information Technology, IEEE, 2015, pp. 1–6.
[133] R.Z. Haddad, C.A. Lopez, J. Pons-Llinares, J. Antonino-Daviu, E.G. Strangas, Outer race bearing fault detection in induction machines using stator current signals, in: 2015 IEEE 13th International Conference on Industrial Informatics, IEEE, 2015, pp. 801–808.
[134] J. Harmouche, C. Delpha, D. Diallo, Linear discriminant analysis for the discrimination of faults in bearing balls by using spectral features, in: 2014 International Conference on Green Energy, IEEE, 2014, pp. 182–187.
[135] J. Harmouche, C. Delpha, D. Diallo, Improved fault diagnosis of ball bearings based on the global spectrum of vibration signals, IEEE Trans. Energy Convers. 30 (1) (2015) 376–383.
[136] J. Yu, A hybrid feature selection scheme and self-organizing map model for machine health assessment, Appl. Soft Comput. 11 (5) (2011) 4041–4054.
[137] S. Hong, Z. Zhou, E. Zio, K. Hong, Condition assessment for the performance degradation of bearing based on a combinatorial feature extraction method, Digit. Sign. Process. 27 (2014) 159–166.
[138] S. Hong, Z. Zhou, E. Zio, W. Wang, An adaptive method for health trend prediction of rotating bearings, Digit. Sign. Process. 35 (2014) 117–123.
[139] J. Hu, L. Zhang, W. Liang, Degradation assessment of bearing fault using SOM network, in: 2011 Seventh International Conference on Natural Computation, IEEE, 2011, pp. 561–565.
[140] J. Hu, L. Zhang, W. Liang, Incipient machine degradation assessment by MF-MTS system, in: 2012 International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering, IEEE, 2012, pp. 635–640.
[141] J. Hu, L. Zhang, W. Liang, Dynamic degradation observer for bearing fault by MTS-SOM system, Mech. Syst. Sign. Process. 36 (2) (2013) 385–400.
[142] D. Siegel, C. Ly, J. Lee, Methodology and framework for predicting helicopter rolling element bearing failure, IEEE Trans. Reliab. 61 (4) (2012) 846–857.
[143] C. Lu, H. Yuan, Y. Tang, Bearing performance degradation assessment and prediction based on EMD and PCA-SOM, J. Vibroeng. 16 (3) (2014).
[144] S. Zhang, W. Li, Bearing condition recognition and degradation assessment under varying running conditions using NPE and SOM, Math. Probl. Eng. 2014 (2014).
[145] Y. Lei, N. Li, S. Gontarz, J. Lin, S. Radkowski, J. Dybala, A model-based method for remaining useful life prediction of machinery, IEEE Trans. Reliab. 65 (3) (2016) 1314–1326.
[146] H.-E. Kim, A.C. Tan, J. Mathew, B.-K. Choi, Bearing fault prognosis based on health state probability estimation, Expert Syst. Appl. 39 (5) (2012) 5200–5213.
[147] M. Yaqub, I. Gondal, J. Kamruzzaman, Machine fault severity estimation based on adaptive wavelet nodes selection and svm, in: 2011 IEEE International Conference on Mechatronics and Automation, IEEE, 2011, pp. 1951–1956.
[148] S. Dong, T. Luo, Bearing degradation process prediction based on the {PCA} and optimized ls-svm model, Measurement 46 (9) (2013) 3143–3152.
[149] C. Lu, J. Chen, R. Hong, Y. Feng, Y. Li, Degradation trend estimation of slewing bearing based on {LSSVM} model, Mech. Syst. Sign. Process. 7677 (2016) 353–366.
[150] S. Kang, D. Ma, Y. Wang, C. Lan, Q. Chen, V. Mikulovich, Method of assessing the state of a rolling bearing based on the relative compensation distance of multiple-domain features and locally linear embedding, Mech. Syst. Sign. Process. 86 (Part A) (2017) 40–57.
[151] A. Widodo, B.-S. Yang, Application of relevance vector machine and survival probability to machine degradation assessment, Expert Syst. Appl. 38 (3) (2011) 2592–2599.
[152] W. Caesarendra, A. Widodo, H.T. Pham, B.-S. Yang, Machine degradation prognostic based on RVM and ARMA/GARCH model for bearing fault simulated data, in: Prognostics and Health Management Conference, 2010. PHM'10, 2010, pp. 1–6.
[153] C. Shen, F. Hu, F. Liu, A. Zhang, F. Kong, Quantitative recognition of rolling element bearing fault through an intelligent model based on support vector regression, in: 2013 Fourth International Conference on Intelligent Control and Information Processing, IEEE, 2013, pp. 842–847.
[154] H. Wang, J. Chen, Performance degradation assessment of rolling bearing based on bispectrum and support vector data description, J. Vib. Contr. 20 (13) (2014) 2032–2041.
[155] X. Zhu, Y. Zhang, Y. Zhu, Bearing performance degradation assessment based on the rough support vector data description, Mech. Syst. Sign. Process. 34 (1–2) (2013) 203–217.
[156] S.A. Aye, P.S. Heyns, C.J. Thiart, Fault detection of slow speed bearings using an integrated approach, IFAC-PapersOnLine 48 (3) (2015) 1779–1784 (15th {IFAC} Symposium on Information Control Problems in ManufacturingINCOM 2015).
[157] J. Yu, Bearing performance degradation assessment using locality preserving projections and gaussian mixture models, Mech. Syst. Sign. Process. 25 (7) (2011) 2573–2588.
[158] Y. Yang, L. Zhang, L. Zhang, X. Cai, S. Zhang, The health degree evaluation of rolling element bearings using an improved bp neural network, J. Inform. Comput. Sci. 9 (14) (2012) 4217–4227.
[159] M. Amar, I. Gondal, C. Wilson, Fuzzy logic inspired bearing fault-model membership estimation, in: 2013 IEEE Eighth International Conference on Intelligent Sensors, Sensor Networks and Information Processing, IEEE, 2013, pp. 420–425.
[160] L. Liu, X.-Y. Li, W. Zhang, T.-M. Jiang, Fuzzy reliability prediction of rotating machinery product with accelerated testing data, J. Vibroeng. 17 (8) (2015).
[161] C. Chen, B. Zhang, G. Vachtsevanos, Prediction of machine health condition using neuro-fuzzy and bayesian algorithms, IEEE Trans. Instrum. Meas. 61 (2) (2012) 297–306.
[162] H. Jiang, J. Chen, G. Dong, T. Liu, G. Chen, Study on Hankel matrix-based {SVD} and its application in rolling element bearing fault diagnosis, Mech. Syst. Sign. Process. 5253 (2015) 338–359.
[163] T. Liu, J. Chen, G. Dong, Zero crossing and coupled hidden Markov model for a rolling bearing performance degradation assessment, J. Vib. Contr. 20 (16) (2014) 2487–2500.
[164] S. Zhang, Y. Zhang, L. Li, J. Zhu, Rolling elements bearings degradation indicator based on continuous hidden Markov model, J. Fail. Anal. Prev. 15 (5) (2015) 691–696.
[165] H. Jiang, J. Chen, G. Dong, Hidden Markov model and nuisance attribute projection based bearing performance degradation assessment, Mech. Syst. Sign. Process. 72–73 (2016) 184–205.
[166] M. Jouin, R. Gouriveau, D. Hissel, M.-C. Pra, N. Zerhouni, Particle filter-based prognostics: review, discussion and perspectives, Mech. Syst. Sign. Process. 7273 (2016) 2–31.
[167] E. Myötyri, U. Pulkkinen, K. Simola, Application of stochastic filtering for lifetime prediction, Reliab. Eng. Syst. Saf. 91 (2) (2006) 200–208.
[168] A. Lorton, M. Fouladirad, A. Grall, A methodology for probabilistic model-based prognosis, Eur. J. Oper. Res. 225 (3) (2013) 443–454.
[169] J.-B. Yu, Bearing performance degradation assessment using locality preserving projections, Expert Syst. Appl. 38 (6) (2011) 7440–7450.
[170] M. Gobbato, J.B. Kosmatka, J.P. Conte, A recursive bayesian approach for fatigue damage prognosis: an experimental validation at the reliability component level, Mech. Syst. Sign. Process. 45 (2) (2014) 448–467.

[171] J. Yu, Machine health prognostics using the bayesian-inference-based probabilistic indication and high-order particle filtering framework, J. Sound Vib. 358 (2015) 97–110.
[172] B. Li, Z. Gao, Z. Shen, X. Chen, Z. He, A gamma Bayesian exponential model for computing and updating residual life distribution of bearings, Proc. Inst. Mech. Eng. Part C: J. Mech. Eng. Sci. 227 (11) (2013) 2620–2633.
[173] R. Singleton, E. Strangas, S. Aviyente, Extended Kalman filtering for remaining-useful-life estimation of bearings, IEEE Trans. Ind. Electron. 62 (3) (2015) 1781–1790.
[174] C.K.R. Lim, D. Mba, Switching Kalman filter for failure prognostic, Mech. Syst. Sign. Process. 5253 (2015) 426–435.
[175] Y. Lei, N. Li, J. Lin, A new method based on stochastic process models for machine remaining useful life prediction, IEEE Trans. Instrum. Meas. 65 (12) (2016) 2671.
[176] N. Li, Y. Lei, J. Lin, S.X. Ding, An improved exponential model for predicting remaining useful life of rolling element bearings, IEEE Trans. Ind. Electron. 62 (12) (2015) 7762–7773.
[177] Y. Wang, Y. Peng, Y. Zi, X. Jin, K.-L. Tsui, An integrated Bayesian approach to prognositics of the remaining useful life and its application on bearing degradation problem, in: Industrial Informatics (INDIN), 2015 IEEE 13th International Conference on, IEEE, 2015, pp. 1090–1095.
[178] D. Li, S. Liu, H. Zhang, Negative selection algorithm with constant detectors for anomaly detection, Appl. Soft Comput. 36 (2015) 618–632.
[179] Y. Qian, S. Hu, R. Yan, Bearing performance degradation evaluation using recurrence quantification analysis and auto-regression model, in: Instrumentation and Measurement Technology Conference (I2MTC), 2013 IEEE International, 2013, pp. 1713–1716.
[180] Y. Pan, J. Chen, X. Li, Bearing performance degradation assessment based on lifting wavelet packet decomposition and fuzzy c-means, Mech. Syst. Sign. Process. 24 (2) (2010) 559–566.
[181] X. Tao, C. Lu, C. Lu, Z. Wang, An approach to performance assessment and fault diagnosis for rotating machinery equipment, EURASIP J. Adv. Sign. Process. 1 (2013) 2013.
[182] M. Orchard, G. Kacprzynski, K.G. Ebel, B. Saha, G. Vachtsevanos, Advances in uncertainty representation and management for particle filtering applied to prognostics, in: International Conference on Prognostics and Health Management, IEEE, 2008, pp. 1–6.
[183] P. Henriquez, J.B. Alonso, M.A. Ferrer, C.M. Travieso, Review of automatic fault diagnosis systems using audio and vibration signals, IEEE Trans. Syst. Man Cybernet.: Syst. 44 (5) (2014) 642–652.