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Prognostics and Health Management: A Review of Vibration Based Bearing and Gear Health Indicators

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ABSTRACT Prognostics and health management is an emerging discipline to scientifically manage the health condition of engineering systems and their critical components. It mainly consists of three main aspects: construction of health indicators, remaining useful life prediction, and health management. Construction of health indicators aims to evaluate the system's current health condition and its critical components. Given the observations of a health indicator, prediction of the remaining useful life is used to infer the time when an engineering systems or a critical component will no longer perform its intended function. Health management involves planning the optimal maintenance schedule according to the system's current and future health condition, its critical components and the replacement costs. Construction of health indicators is the key to predicting the remaining useful life. Bearings and gears are the most common mechanical components in rotating machines, and their health conditions are of great concern in practice. Because it is difficult to measure and quantify the health conditions of bearings and gears in many cases, numerous vibration-based methods have been proposed to construct bearing and gear health indicators. This paper presents a thorough review of vibration-based bearing and gear health indicators constructed from mechanical signal processing, modeling, and machine learning. This review paper will be helpful for designing further advanced bearing and gear health indicators and provides a basis for predicting the remaining useful life of bearings and gears. Most of the bearing and gear health indicators reviewed in this paper are highly relevant to simulated and experimental run-to-failure data rather than artificially seeded bearing and gear fault data. Finally, some problems in the literature are highlighted and areas for future study are identified.

INDEX TERMS Ball bearings, condition monitoring, feature extraction, gears, prognostics and health management, signal processing algorithms, vibrations.

I. INTRODUCTION

Prognostics and health management [1], [2] is an emerging discipline to scientifically manage the health condition of engineering systems and their critical components, which has attracted much attention from engineers and scholars in recent years [3]–[7]. Prognostics and health management is mainly concerned with three aspects: construction of health indicators, remaining useful life (RUL) prediction and health management. Construction of health indicators aims to evaluate the current health condition of an engineering system and its critical components, which is then used to infer their remaining useful lifetime [8], [9]. Based on the first two aspects, the optimal health management schedule is planned to minimise costs and prevent unexpected accidents [10]–[12]. Construction of health indicators is the key to RUL prediction because it provides a health indicator for the prediction. For example, rolling element bearings are critical components commonly used in rotating machines [13], [14]. Once the rolling element bearings fail, they accelerate the failure of other adjacent components and machines. Therefore, predicting their health condition is necessary to prevent any unexpected accidents caused by bearing failures.

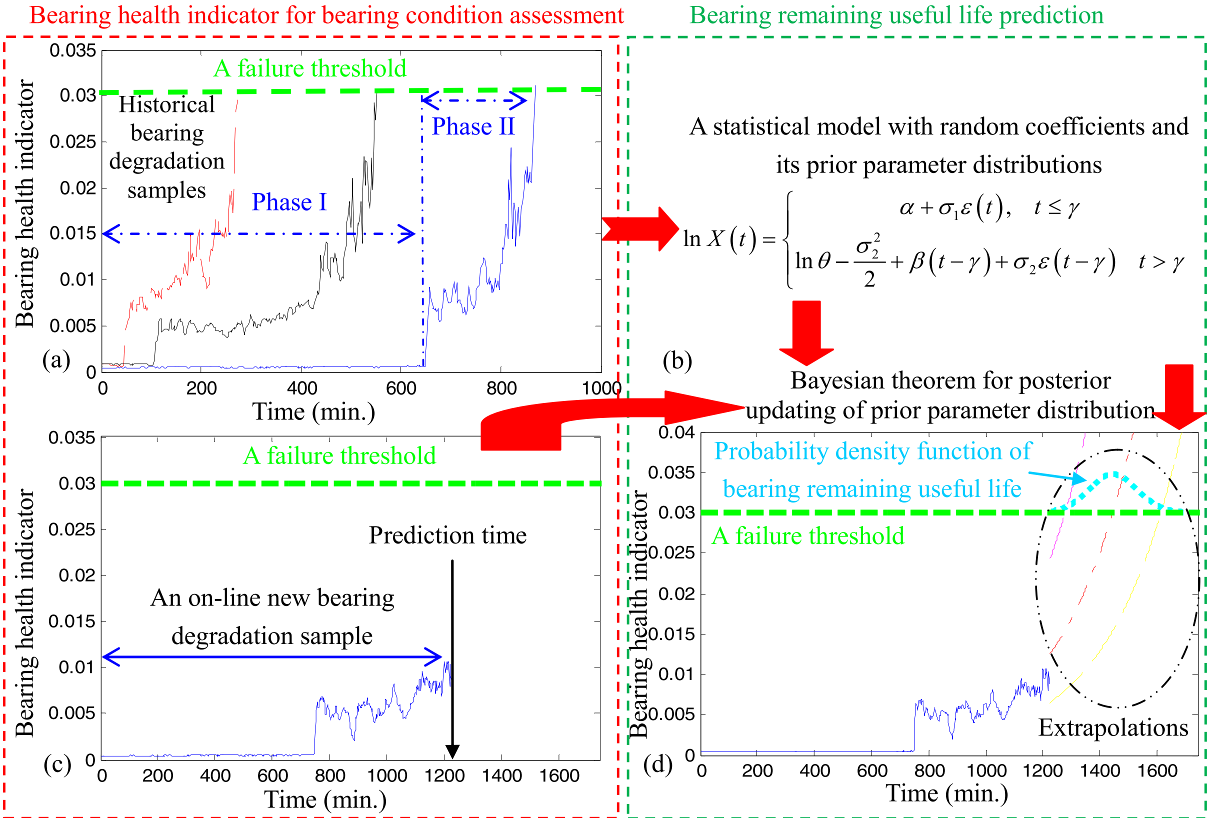

FIGURE 1. **Relationship between a bearing health indicator and bearing RUL prediction: (a) three historical samples of a bearing health indicator; each represents a specific type of bearing degradation; (b) determination of a statistical model with random coefficients and its prior distributions; (c) on-line monitoring observations of the bearing health indicator for a new bearing; (d) RUL prediction by extrapolation of a posteriorly updated statistical model to a predetermined failure threshold.**

Because temperature is only sensitive to severe bearing failures, it is preferable to use other signals, such as vibration signals collected by accelerometers and acoustic signals collected by acoustic emission sensors, for the fault diagnosis and prognostic analysis of rolling element bearings. Moreover, thanks to the concept of blind fault component separation [15], bearing fault signals can be well separated from loud heavy noises and other unwanted strong components. The quantification of bearing fault signals can generate a bearing health indicator for bearing condition degradation assessment. Fig. 1 (a) shows that a bearing health indicator consisting of the sum of bearing defect frequencies and their harmonics in a laboratory environment [16] has two distinct phases. In Phase I, the bearing health indicator stays stable, which shows that the bearing is in a normal health condition. After the first large change in the bearing health indicator, the bearing enters an abnormal health condition and degrades exponentially over time until the indicator reaches a user-predetermined failure threshold. As a result, three historical bearing degradation samples represent three bearing run-to-failure processes, respectively. Based on these observations, it is concluded that the bearing health indicator is the basis for bearing prognostics, especially RUL prediction. First, historical samples of the bearing health indicator in Fig. 1 (a) can be used to empirically establish a statistical model, such as the exponential model with random coefficients proposed by Gebraeel *et al.* [17], [18] or the piecewise statistical model with random coefficients proposed by Chen and Tsui [19] in Fig. 1 (b), and then to determine the prior parameter distributions of the statistical model. Second, once on-line monitoring observations of the bearing health indicator are available for a new bearing, as shown in Fig. 1 (c), they can be used to posteriorly update the prior parameter distributions of the statistical model. Extrapolations of the posterior statistical model to the failure threshold can be used to predict bearing RUL and its uncertainty, as shown in Fig. 1 (d). Consequently, in this example, the bearing health indicator provides the observations for the statistical model and the Bayesian inference on the parameters of the statistical model for predicting the bearing's RUL.

Several distinguished scholars have conducted reviews of RUL prediction [20]–[24]. Heng *et al.* [20] summarised conventional reliability models, condition-based prognostic models and their hybrid models. Ye and Xie [21] summarised a number of degradation models and comprehensively compared stochastic process models with general path models. Si *et al.* [22], [25] discussed various prognostic methods based on statistical modelling. Lee *et al.* [23] clarified the relationship between machine diagnostics and prognostics and then summarised many prognostic methods for predicting the RUL of critical components such as bearings and gears. Zhang and Lee [24] reviewed prognostic methods for rechargeable lithium-ion batteries, which are also potentially useful for predicting the RUL of machines, especially bearings and gears. The main difference between battery prognostics and bearing and gear prognostics is that the health status of rechargeable lithium-ion batteries can be quantified and described by the battery capacity, which is calculated by integrating the battery current over time in the process of discharging. However, for bearing and gear prognostics, it is rare to discover a simple and direct health indicator to track the current health condition. This paper presents a thorough review of vibration based bearing and gear health indicators constructed from mechanical signal processing, modelling and machine learning. The review is intended to be useful in the design of bearing and gear health indicators. Most of the reviewed health indicators are highly relevant to simulated and experimental run-to-failure data rather than artificially seeded bearing and gear data. The main advantage of simulated and experimental machine run-to-failure data is that they provide early bearing and gear fault detection and their condition assessment in a natural fault-propagation way.

The rest of this paper is outlined as follows. Section II provides a thorough review of bearing and gear health indicators. Section III discusses the methods and identifies some potential future works and Section IV provides some concluding remarks.

II. REVIEW OF VIBRATION BASED BEARING AND GEAR HEALTH INDICATORS

Bearing and gear health indicators are reviewed in three categories: mechanical signal processing–based, model-based and machine learning–based.

A. MECHANICAL SIGNAL PROCESSING–BASED BEARING AND GEAR HEALTH INDICATORS

Mechanical signal processing is extremely useful in detection of early defects, extraction of fault features and construction of bearing and gear health indicators because it is able to separate the components of interest from heavy noises and other unwanted strong vibration components [15], [26]. After pre-processing of the vibration signals, statistical parameters are directly used to characterise the frequency components of interest for construction of bearing and gear health indicators. Here, construction of a mechanical signal processing–based bearing health indicator is taken as an example. The simulated and experimental bearing run-to-failure data [27] were collected from an experimental platform installed in the Center for Intelligent Maintenance System at the University of Cincinnati and have been widely investigated by many engineers and scholars. The real photo and schematic diagram of the experimental platform are plotted in Figs. 2 (a) and (b), respectively. The bearing run-to-failure experiment was conducted at a constant speed and load. A vibration signal with a

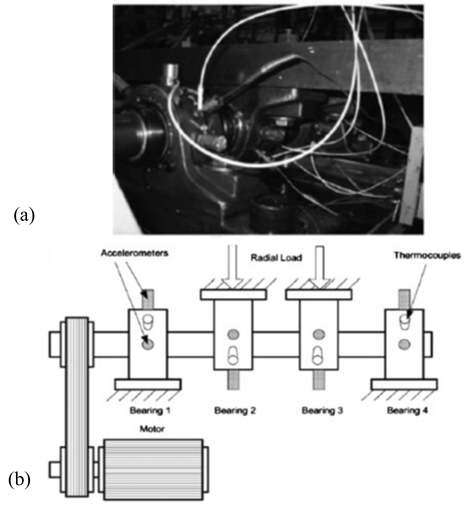

FIGURE 2. An experimental platform [27] for collection of bearing run-to-failure vibration data: (a) a real photo of the experimental platform; (b) a schematic diagram of the experimental platform.

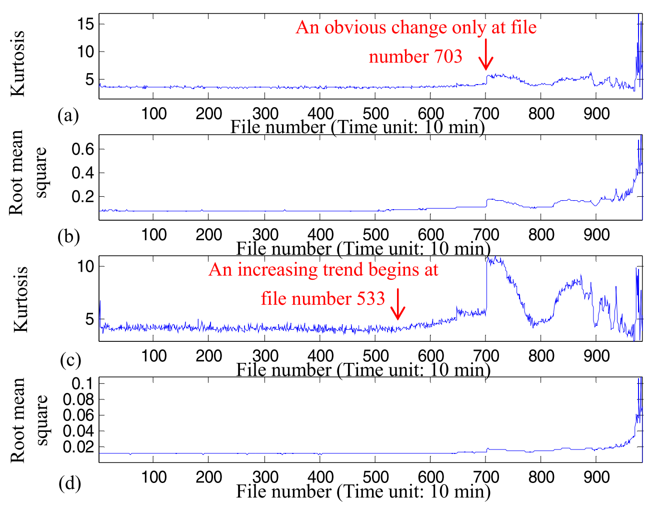

FIGURE 3. Bearing health indicators constructed from kurtosis and root mean square: (a) kurtosis without signal pre-processing; (b) root mean square without signal pre-processing; (c) kurtosis with signal pre-processing; (d) root mean square with signal pre-processing.

length of 20,480 samples was stored every 10 minutes and thus a total of 984 files were stored during the bearing's lifetime. Kurtosis and root mean square [28] are two of the most commonly used statistical parameters and are directly used to quantify the collected bearing run-to-failure vibration signals. The results are plotted in Figs. 3 (a) and (b), which show obvious increasing trends and changes after file number 703. Autoregressive filtering with an order of 50 and Gabor wavelet transform with a centre frequency of 4363 Hz and bandwidth of 4000 Hz, as determined by our analyses, are then used to pre-process all vibration signals before the same two statistical parameters are used to quantify the collected bearing vibration signals. The final results are plotted in Figs. 3 (c) and (d), in which an increasing trend can

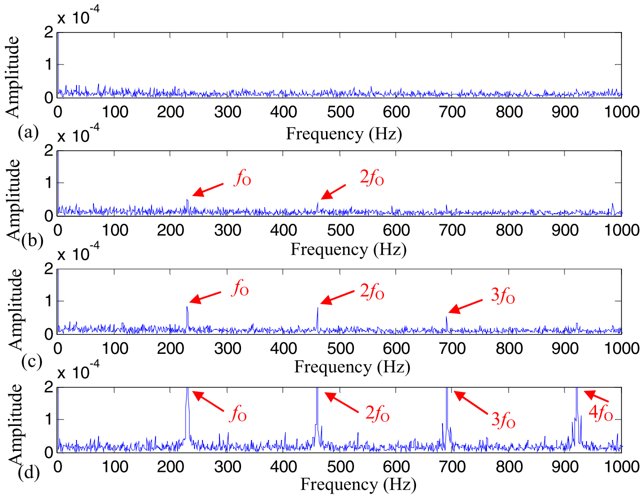

FIGURE 4. Squared envelope spectra with signal pre-processing at some selected file numbers: (a) at file number 532; (b) at file number 533; (c) at file number 540; (d) at file number 703.

be clearly observed after file number 533. To discover what the increasing trend indicates, a squared envelope spectrum analysis is performed after conducting the same signal pre-processing on some selected vibration signals. The squared envelope spectra of the filtered signals at some selected file numbers are plotted in Figs. 4 (a) to (d). In Fig. 4, a bearing defect frequency f_O and its several harmonics can be detected in file number 533, confirming that an early bearing outer race defect occurred at this point. From this case study, it is clear that mechanical signal processing is helpful for bearing health indicators and statistical parameters to detect early bearing defects and abnormal bearing health conditions.

The spectral kurtosis proposed by Antoni [29] is one of the most interesting and useful methods for construction of a bearing health indicator. The basic idea is to use a statistical parameter called kurtosis, which is the ratio of the fourth-order central moment to the squared second-order central moment, to characterise the amplitude distribution of a vibration signal filtered at specific frequency bands [30]. When a bearing has a defect on the surface of an inner or outer race, the impacts generated by the rollers striking the defect excite resonant frequency bands and cause transients over time. The underlying assumption of the spectral kurtosis is that higher kurtosis indicates a more informative frequency band. Here, the more informative frequency band is highly relevant to resonant frequency bands. Consequently, the spectral kurtosis indirectly finds the locations of resonant frequency bands for bearing condition degradation assessment. One benefit is that the lower bound of the kurtosis is 3 for real Gaussian noises and 2 for complex Gaussian noises [29]. The kurtosis for a bearing health indicator starts from 3 or 2. A recent study showed that the kurtosis is proportional to the squared sum of the squared envelope spectrum [31], which indicates that the kurtosis is highly relevant to spectral correlation analysis, which is closely related to squared envelope spectrum analysis [32]. Another benefit is that the kurtosis is dimensionless, which indicates that it is insensitive to varying operating loads and speeds. The kurtosis can be easily generalised to many other statistical parameters specified by considering central moments with different orders [33].

The problem with the spectral kurtosis method is that it is sensitive to outliers. Another classic statistical parameter is the smoothness index [34], which is defined as the ratio of the geometric mean to the arithmetic mean of the modulus of the wavelet coefficients. Bozchalooi and Liang [34] mathematically proved that the upper bound of the smoothness index is 0.8455 in the case of complex Gaussian noises and the modulus of wavelet coefficients follows the Rice distribution. The smoothness index for bearing condition degradation assessment is constrained to a range from 0 to 0.8455. With the assumption of cycloergodicity, Wang *et al.* [35] proved mathematically that the modulus of wavelet coefficients follows the non-central chi distribution and that the squared modulus of wavelet coefficients follows the non-central chi square distribution. Because squared envelope spectrum analysis is close to spectral correlation analysis [32], the squared modulus is preferable for bearing fault diagnosis and prognostics. Based on this motivation, the smoothness index was redefined as the ratio of the geometric mean to the arithmetic mean of the squared modulus of the wavelet coefficients, and its upper bound is 0.5614 for complex Gaussian noise [35]. The smoothness index for bearing condition degradation assessment is constrained to a range from 0 to 0.5614. With the assumption of cycloergodicity, Wang and Tsui [36] extended the smoothness index to a more general bearing health indicator, which is defined as the ratio of the generalised means with different orders of squared wavelet coefficients. For example, the smoothness index is the ratio of the generalised mean with the first order to the generalised mean with the zero order of the squared wavelet coefficients; and the sparsity measurement is the ratio of the generalised mean with the second order to the generalised mean with the first order of the squared wavelet coefficients [37]. More importantly, Wang and Tsui [36] mathematically provided the upper bound of the generalised bearing health indicator for complex Gaussian noise. It was experimentally shown that the indicator decreases in the presence of transients caused by bearing defects. In addition to the aforementioned statistical parameters, Shannon entropy [38] and its variants, such as approximate entropy [39], permutation entropy [40], Re'nyi entropy [33], and Lempel-Ziv complexity [41], [42], a synthesised health indicator [43], are much more attractive for construction of bearing health indicators.

Another key issue for construction of bearing health indicators is the proper design of a band-pass filter to retain one of the resonant frequency bands [44]. The design of band-pass filters has been extensively discussed in many review articles relevant to wavelet transform [45], multi-wavelet transform [46], spectral kurtosis and its variants [47], cyclostationary analysis [48], [49] and empirical mode decomposition and its variants [50]. Many interesting and useful methods have been proposed for construction of bearing health indicators based on different band-pass filters and statistical parameters. Qiu *et al.* [51] proposed a two-step process to optimise the parameters of a Morlet wavelet filter originally introduced by Lin and Qu [52] for the early detection of bearing defects in an accelerated bearing degradation process. Hong and Liang [41] evaluated bearing degradation based on Lempel-Ziv complexity and continuous wavelet transform. He *et al.* [53] optimised Morlet wavelet filtering and then used the sum of bearing defect frequencies as a bearing health indicator to evaluate the whole bearing life process of cooling fans. Miao *et al.* [54] constructed a bearing health indicator based on comblet filtering and an exponentially weighted moving average to analyse the same cooling fan bearing degradation data. Pan *et al.* [55] proposed spectral entropy to quantify accelerated bearing degradation signals. Dong and Chen [56] used cyclostationary analysis to pre-process accelerated bearing degradation data and considered the integration of the cyclic power spectrum as a bearing health indicator. Although cyclostationary analysis is powerful for analysing bearing fault signals, its calculation time is extensive. Wang and Shen [57] simplified the bearing health indicator proposed by Dong and Chen [56] and then constructed an equivalent indicator based on squared envelope spectrum analysis, which considerably reduced the calculation time. Furthermore, Borghesani *et al.* [31] discovered that kurtosis is proportional to the squared sum of the squared envelope spectrum and designed a more precise bearing health indicator based on the kurtosis. Zhang *et al.* [58] investigated the effectiveness of information exergy used in thermodynamics for evaluating bearing degradation. Lei *et al.* [59] used a Spearman coefficient to select some features exhibiting monotonic degradation trends and then used a correlation clustering algorithm to reduce the redundancy of the selected features. They then fused the final typical features into a bearing health indicator called the weighted minimum quantisation error to track bearing condition degradation. Tse and Wang [60] designed a new accelerated bearing experiment and used the root mean square of a signal filtered from a selected frequency band for bearing degradation assessment. The root mean square was also used by Lei *et al.* [61] to quantify accelerated bearing degradation data. Qian *et al.* [62], [63] and Yan *et al.* [64] used recurrence quantification analysis to extract a recurrence plot entropy feature for monitoring bearing degradation. Kosasih *et al.* [65] extracted the root mean square, skewness and kurtosis from vibration signals pre-processed by the combination of a low-pass filter and adaptive line enhancer to monitor low-speed slewing bearings. Further, Caesarendra *et al.* [66] proposed several features including circular-domain kurtosis and the largest Lyapunov exponent feature [67] to monitor low-speed slewing bearings. The results [68] showed that these new features were better able to reveal the degradation trends than traditional methods such as time-domain features extracted from wavelet packet transform and ensemble empirical mode decomposition.

Time synchronous averaging [69] is the most effective and useful technology to process gear vibration signals for construction of gear health indicators. An underlying assumption of time synchronous averaging is the use of a fixed gear rotation frequency. On the basis of the theoretical study of a residual acceleration error signal by Wang and McFadden [70], and Miller [71] proposed the concept of a Comblet, which consists of a linear superposition of several wavelets, to relieve the underlying assumption and applied it to decompose an acceleration error signal into a harmonic acceleration error signal and a residual acceleration error signal. The residual acceleration error signal was experimentally proven to be sensitive to gear faults and less dependent on varying loads. Miller [71] proposed a gear fault growth parameter based on the residual acceleration signal and the three-sigma rule. Following this work, Lin *et al.* [72] improved the gear fault growth parameter by adding weights to it. Moreover, they introduced incorporation of the gear fault growth parameter with proportional-hazards modelling. Because wavelet transform is able to detect the singularity of a signal, Miao *et al.* [73] proposed Lipschitz exponent–based kurtosis to track gear deterioration over time. Wang *et al.* [74] used discrete wavelet transform to quickly evaluate gear condition degradation over time and found that the energy of the signal filtered by discrete wavelet transform is insensitive to different wavelet decomposition levels and wavelet mother functions. Based on the previous works on the fault growth parameter, Wang *et al.* [75] used complex continuous Morlet wavelet transform to construct a gear health indicator that works at varying operating loads. Bartelmus and Zimroz [76] and Bartelmus [77] discovered that the abnormal health condition of a multistage gearbox is more susceptible to varying operating conditions and proposed a health indicator in the function of an instantaneous input speed to monitor its health condition. Moreover, they suggested that for such a complicated object, the interactions among different components of the multistage gearbox should be taken into consideration in the design of the health indicator [78]. A similar idea [79] was also applied to bearing condition degradation under varying operating conditions.

B. MODEL-BASED BEARING AND GEAR HEALTH INDICATORS

Model-based gear health indicators aim to use an autoregressive model residual to monitor gear deterioration over time. The autoregressive model established using healthy gear data exhibits a consistent prediction error if a gear is still in a normal health condition, but results in significant prediction errors if a gear departs from its normal health condition. The main reason the autoregressive model is only used for gear health indicator is that gear signals are purely periodic, whilst bearing fault signals are slightly random and cyclostationary [15], [80] and cannot be modelled by the autoregressive model. Another point that should be highlighted is that the order of the autoregressive model and its variants is the dominating factor for construction of model-based gear health indicators.

Zhan *et al.* [81] and Zhan and Makis [82] extended the idea of the autoregressive model residual initialised by Wang and Wong [83] to a noise-adaptive Kalman filter–based time-varying autoregressive model residual and then used the three-sigma rule to construct an autoregressive model-based gear state parameter for evaluating the evolution of gear health under varying load conditions. Zhan *et al.* [81] thoroughly analysed how to optimally choose the order of an autoregressive model working under varying load conditions and referred to the order selection procedure as compromised model fitting. Zhan and Jardine [84] used a noise-adaptive Kalman filter, an extended Kalman filter and a modified extended Kalman filter to estimate the parameters of a time-varying vector autoregressive model to investigate gear states under varying load conditions. Zhan and Mechefske [85], [86] used Kalman filter–based autoregressive filtering to model a residual acceleration error signal and then used the Kolmogorov-Smirnov goodness of fit test to check whether the autoregressive filtering residual is normally distributed for gear condition assessment under varying load conditions. Shao and Mechefske [87] proposed an extended Kalman filter–based autoregressive model to fit a residual acceleration error signal and obtain an autoregressive model residual. They then used several hypothesis tests to find the optimal order of an autoregressive model and constructed a gear health indicator working under varying load conditions. Yang and Makis [88] used the F-test to check the residual between a future residual acceleration error signal and the signal predicted by an autoregressive model with exogenous variables of a healthy residual acceleration error signal for monitoring gear deterioration under varying load conditions.

C. MACHINE LEARNING-BASED BEARING AND GEAR HEALTH INDICATORS

Machine learning–based bearing and gear health indicators require historical normal bearing or gear data to train a statistical and probabilistic model, and any deviation from the trained model can be regarded as a bearing or gear health indicator. The main idea of machine learning–based health indicators can be simply understood as anomaly detection/novelty detection/one-class classification/statistical process control [89], [90] over time. The construction of machine learning–based health indicators contains four main steps: signal pre-processing, feature extraction, dimensionality reduction and statistical and probabilistic modelling. Signal reprocessing and feature extraction methods are discussed and reviewed in Section II. A. In this section, the main focus is on reviewing the application of dimensionality reduction methods and statistical and probabilistic models to generate bearing and gear health indicators.

Numerous machine learning-based methods for construction of bearing health indicators have been proposed in the past few years. Qiu *et al.* [91] used Morlet wavelet filtering to de-noise bearing fault signals and then extracted the root mean square, kurtosis and crest factor from the de-noised signals to train a self-organising map. Any deviation from the trained self-organising map was regarded as an indicator of bearing condition degradation. By considering mutual information on multiple fault features, Huang *et al.* [92] used a self-organising map to derive the minimum quantisation error as a bearing health indicator. Ocak *et al.* [93] used wavelet packet transform to extract node energies from normal bearing fault signals and then used the node energies to train a hidden Markov model. Any deviation from the trained hidden Markov model was used as a bearing health indicator. Following the similar idea of Pan *et al.* used wavelet packet node energies to train support vector data description [94] and fuzzy c-means [95], respectively. Any deviation from the trained support vector data description or fuzzy c-means was used as a bearing health indicator. The mixture of support vector data description and fuzzy c-means was also developed by Pan *et al.* [96] to assess bearing condition degradation. Several authors have developed variants of wavelet packet transform and support vector data description-based bearing health indicators, including rough support vector [97], fuzzy support vector [98], a combination of wavelet packet symbolic entropy and support vector [99], a combination of bispectrum and support vector [100] and optimised support vector data description [101].

The aforementioned hidden Markov model and its variants, including the semi-hidden Markov model [102], [103], coupled hidden Markov model [104], [105], adaptive hidden Markov Model [106], mixture of hidden Markov models [107] and adaptive hidden semi-Markov model [108], are also attractive for construction of bearing health indicators because the hidden Markov model and support vector data description are two popular methods for anomaly detection [109]. Equivalently, the Gaussian mixture model has the same functionality. Hong *et al.* [110] used ensemble empirical mode decomposition to pre-process bearing degradation data and used a Gaussian mixture model to approximate the distribution of a low-dimensional feature space obtained by principle component analysis. Compared with principle component analysis, locality preserving projections are able to mine the local structure of the data manifold. Yu [111] therefore used them to reduce the dimensionality of a feature space and then proposed an exponential weighted moving average statistic for bearing condition assessment. Instead of the exponential weighted moving average, Yu [112] used a Gaussian mixture model to model the low-dimensional feature space obtained by locality-preserving projections. Following this idea, Sun *et al.* [113] proposed a kernel locality projection–based health indicator. Later, Yu [114] developed a more advanced strategy based on a hybrid feature selection scheme and self-organising map. The hybrid feature selection scheme consisted of Gaussian mixture models and K-means to form an unsupervised learning method for feature dimensionality reduction. Yu [115] proposed a generative topographic mapping and contribution analysis based bearing health indicator to evaluate bearing degradation over time. Instead of generative topographic mapping, Yu [116] considered the hidden Markov model, proposed a local and nonlocal preserving projection and experimentally demonstrated that the projection was more effective than principle component analysis for dimensionality reduction. Furthermore, Yu [117] proposed a joint global and local/nonlocal discriminant analysis to realise the same purpose. Lu *et al*. [118] used principle component analysis to fuse multiple feature vectors including root mean square, kurtosis, wavelet energy entropy and intrinsic mode function energy to form a bearing health indicator for slewing bearing degradation. Ma *et al.* [119] extracted statistical features from the sub-signals obtained by a second generation wavelet packet and then constructed a bearing health indicator based on locally linear embedding on a Grassmann manifold.

Guo *et al.* proposed [120] a recurrent neural network–based bearing health indicator to fuse several classic bearing fault features for bearing condition assessment. Ali *et al.* [121] used the Weibull distribution to fit the root mean square, kurtosis and root mean square entropy, respectively. The fitted features were then input to a fuzzy adaptive resonance theory map neural network to identify different degradation states over a bearing's lifetime. This method can avoid the fluctuations of some typical bearing health indicators and monotonically evaluate bearing degradation over time. Caesarendra *et al.* [122], [123] used logistic regression to map kurtosis to a failure probability and used kurtosis as an input to a Cox-proportional hazard model to assess bearing degradation.

The Mahalanobis distance [124], [125] is an alternative anomaly-detection method that can be used to construct a bearing health indicator from healthy bearing data. Wang *et al.* [126] used empirical mode decomposition and singular value decomposition to pre-process bearing fault signals and then used the Mahalanobis distance to construct a bearing health indicator. Wang *et al.* [127] extracted 14 time-domain features and then used the Mahalanobis distance calculated from healthy bearing data to fuse these time-domain features to form a bearing health indicator. Jin and Chow [128] used the Mahalanobis distance to evaluate the cooling fan bearing deterioration. Because the range of the Mahalanobis distance varies from zero to positive infinity, it is not easy to directly set a threshold to detect abnormal cooling fan bearings. Considering this point, Jin and Chow [128] used the Box-Cox transformation to make the Mahalanobis distance normally distributed. In their further work, Jin *et al.* [129] combined the Mahalanobis distance with fault features selected by minimum redundancy maximum relevance to track cooling fan bearing degradation.

For construction of gear health indicators, Miao and Makis [130] found that the modulus maxima distribution of a gear motion error signal can be used to characterise the health condition of a gear and used this feature to train and test hidden Markov models to monitor the health condition over the gear's lifetime. Miao *et al.* [131] used empirical mode decomposition to pre-process gearbox vibration signals and combined several intrinsic mode functions to form a combined-mode function covering the gear meshing frequency band and its several harmonics. The energy of the combined-mode function extracted from normal gearbox data was then used to train a hidden Markov model. Any deviation from the trained model was used as a gear health indicator. Based on the residual acceleration error signal, Wang *et al.* [132] found that different statistical parameters mainly belong to two categories. The statistical parameters located in the first category, such as residual acceleration error signal–based kurtosis, are sensitive to early gear faults but cannot be used for gear degradation trends because these statistical parameters fluctuate severely as gear fault levels increase. The parameters in the second category, such as the residual acceleration error signal–based root mean square, are insensitive to early gear faults but are useful in describing gear degradation trends over time. Based on this phenomenon, Wang *et al.* [132] suggested using two support vector data description models to fuse these parameters into two gear health indicators. In their successive work [133], they proposed a high-order complex comblet to obtain a residual acceleration error signal and then used a hidden Markov model to construct a gear health indicator. In this work [133], they used the envelope spectrum of the signal filtered by the high-order complex comblet to explain the first severe change in the gear health indicators caused by an early gear defect. Furthermore, they connected gear health indicators with RUL prediction using state space modelling and particle filtering.

III. DISCUSSION AND FUTURE WORKS

The various bearing and gear health indicators are summarised in Table 1. We discuss the findings of our literature review in this section.

First, as shown in Table 1, there are many more studies on health indicators for bearings than for gears, perhaps due to the availability of public bearing run-to-failure data provided by the prognostics Data Repository [27], [134]. Any scholar can download and use this bearing degradation data to verify their ideas. Moreover, according to the work by Antoni and Randall [80], bearing fault signals are not periodic but slightly random and cyclostationary, whilst gear signals are purely periodic. This phenomenon may cause scholars to prefer processing cyclostationary bearing fault signals. Nevertheless, only a few papers have explained why a sudden change was observed in a bearing or gear health indicator and provided sufficient evidence to support the occurrence of a bearing or gear defect.

Second, almost all bearing health indicators have been verified in a constant operating condition. So, more methods should be proposed and verified at varying operating conditions. It should be noted that because many bearing health indicators are not dimensionless, they are prone to be affected by varying operating conditions, which significantly influence the bearing RUL prediction. If a bearing

TABLE 1. Summary of vibration based bearing and gear health indicators.

Objects	References	Main ideas
Mechanical signal processing-based bearing and gear health indicators		
Bearings	Gebraeel et al., [16-18], Chen and Tsui [19]	sum of bearing defect frequencies and their harmonics
	Antoni and Randall [29, 30]	spectral kurtosis
	Borghesani et al. [31]	cyclic band kurtosis
	Bozchalooi and Liang [34], Wang et al.[35]	smoothness index and redefined smoothness index
	Wang et al.[36]	a generalised dimensionless bearing health indicator
	Tse and Wang [37]	sparsity measurement
	Antoni [38], Yan and Gao [39], Yan et al. [40], Tao et al. [33], Pan et al. [55], Zhang et al. [58], Qian et al. [62-64]	spectral entropy, approximate entropy, permutation entropy, Re´nyi entropy, information Exergy, recurrence plot entropy feature
	Hong and Liang [41], Yan and Gao [42]	Lempel-Ziv complexity
	Li et al. [43]	synthesised health indicator
	Qiu et al. [51], He et al. [53], Miao, et al.[54]	wavelet filter and wavelet filter-based comblet filter
	Dong and Chen [56], Wang and Shen [57]	cyclic energy indicator and its simplified indicator
	Lei et al. [59]	weighted minimum quantisation error
	Tse and Wang [60], Lei et al.[61]	root mean square
	Caesarendra et al. [66, 68]	circular domain features
	Caesarendra et al. [67]	largest Lyapunov exponent feature
	Kosasih et al. [65]	low-pass filter and adaptive line enhancer
	Zimroz et al. [79]	regression analysis
Gears	Miller[71], Lin et al. [72]	fault growth indicator, weighted fault growth indicator
	Miao et al. [73]	Lipschitz exponent
	Wang et al. [74], Wang et al. [75]	discrete wavelet transform, continuous wavelet transform
	Bartelmus et al. [76-78]	regression analysis
Model-based gear health indicators		
Objects	References	Main ideas
Gears	Zhan et al. [81, 82, 84-86], Shao and Mechefske [87], Yang and Makis [88]	compromised autoregressive models and hypothesis tests
Machine learning-based bearing and gear health indicators		
Objects	References	Main ideas
Bearings	Qiu et al. [91], Huang et al. [83], Yu [114]	wavelet filter and self-organising map, hybrid feature selection and self-organising map
	Ocak et al. [93], Dong and He [102, 103], Liu et al. [104], Xiao et al. [105], Yu [106, 116], Liu et al. [108], Medjaher et al. [107]	wavelet packet transform and hidden Markov model, hidden semi-Markov model, coupled hidden Markov model, adaptive hidden Markov model, adaptive hidden semi-Markov model
	Pan et al. [94], Zhu et al. [97], Shen et al. [98], Zhou et al. [99], Wang and Chen [100], Wang et al.[101]	wavelet packet transform and support vector data description, rough support vector data description, fuzzy support vector data description, bispectrum and support vector data description, modified support vector data description
	Pan et al. [95, 96]	wavelet packet transform and fuzzy c-means
	Hong et al. [110]	ensemble empirical mode decomposition and Gaussian mixture model
	Lu et al. [118], Yu [111, 112, 115-117], Sun et al. [113], Ma et al. [111]	principle component analysis, locality preserving projections and Gaussian mixture model, kernel locality preserving projection, global and local/nonlocal discriminant analysis, generative topographic mapping and contribution analysis, hidden Markov model and contribution analysis, locally linear embedding on Grassmann manifold
	Guo et al. [120]	recurrent neural network
	Ali et al. [121]	Weibull distribution and artificial neural network
	Caesarendra et al. [122, 123]	relevance vector machine and logistic regression
	Caesarendra et al.[141]	Cox-proportional hazard model
	Jin et al. [124, 128, 129], Shakya et al. [125], Wang et al. [127], Wang et al.[126]	Mahalanobis distance
Gears	Miao et al. [130, 131], Wang et al. [132, 133]	modulus maxima distribution and hidden Markov model, empirical mode decomposition, high-order complex comblet, support vector data description

health indicator only works in a constant operating condition, a statistical model working at varying operating conditions and its Bayesian parameter inferences become extremely complicated. However, if a bearing health indicator can work at and be insensitive to varying operating conditions, a well-known statistical model such as the exponential model with random coefficients proposed by Gebraeel *et al.* [17], [18] or the piecewise statistical model with random coefficients proposed by Chen and Tsui [19] in Fig. 1 (b), can directly predict bearing RUL. It is thus suggested that readers and scholars should design more accelerated bearing degradation data at varying operating conditions and propose more bearing health indicators working at varying operating conditions.

Third, as suggested by Bartelmus and Zimroz [76] and Bartelmus [77], component interactions should be taken into consideration in the machine degradation process. Consequently, more complicated machines rather than a simple gearbox and a simple bearing housing should be taken as objects of study and more accelerated run-to-failure experiments should be designed and conducted. In addition, according to the blind fault component separation method proposed by Antoni [15], more advanced signal processing methods should be used in the machine degradation process to separate bearing fault signals with gear signals and detect early bearing and gear faults. Here, we should further point out that sparse representation [135] and stochastic resonance [136] are two emerging technologies in the research community of machine fault diagnosis. These technologies should be used to detect natural degradation defects rather than artificially seeded defects to further verify their effectiveness in naturally early fault detection.

Fourth, for machine learning–based bearing health indicators, it is better to use bearing health indicators such as those obtained by the mechanical signal processing methods, instead of some traditional statistical parameters such as the root mean square and kurtosis [137], to train a normal statistical and probabilistic model. This will naturally improve the prediction accuracy of machine learning regardless of a statistical and probabilistic model. Moreover, the idea of deep learning [138]–[140] should be introduced in the machine degradation process to fuse the increasing amount of data collected from different sensors and locations and to mine more fault signatures for construction of bearing and gear health indicators.

Fifth, even though many gear and bearing health indicators have been proposed for a constant operating environment in the past few years, most gear and bearing health indicators do not have theoretical upper and lower bounds, hence theoretical baselines do not exist. More theoretical research should be conducted. Additionally, different performance metrics based on monotonicity, variance, trendability, prognosability, early fault detection, calculation time, etc., should be proposed and used to compare different gear and health indicators.

IV. CONCLUDING REMARKS

In this paper, we clarified the relationship between health indicators and RUL prediction in the framework of prognostics and health management and pointed out that health indicators are the key to RUL prediction. Based on the accelerated bearing and gear run-to-failure degradation data, we then reviewed the vibration based bearing and gear health indicators and discussed their existing problems. We then suggested some directions for future work to enrich the reviewed methods.

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