A Review on Prognosis of Rolling Element Bearings Operated Under Non-stationary Conditions

Leila L. Mbagaya, James K. Kimotho and Jackson G. Njiri

Abstract—Bearings constitute a majority of the components found in rotating machines. Though inexpensive, their failure can result in unnecessary downtime, losses in production and propagation of failure to other critical components leading to expensive maintenance actions. Most of these machinery are operated under adverse and varying conditions which result in difficulty in defining health indices from condition monitoring data. Therefore, techniques for condition monitoring of rotating machinery operated under non-stationary conditions are necessary. This paper aims at summarizing and reviewing the recent trends and developments in prognostics of rotating machines operating under non-stationary conditions with emphasis on rolling element bearings. Various techniques, methods, and models used in bearing prognosis are discussed. Moreover, the research gaps and possible future trends are addressed in the conclusion.

Keywords—Bearing Prognosis, Non-stationary Conditions, Remaining Useful Life (RUL),

I. INTRODUCTION

ROTATING machineries are the most common mechanical components in industrial application. Their main components are gear boxes, roller bearings and rotary shafts. Typically, these machines operate under adverse conditions of high load and high temperatures. These conditions may cause severe breakdowns and decrease in the equipment's performance resulting in reduced safety, availability and reliability, economic losses, and lower product quality [1]. A good maintenance strategy is crucial in preventing such catastrophic failures while maintaining machine safety and reliability as well as adding value to maintenance practices.

The simplest maintenance strategy employed in the industries is known as breakdown maintenance according to Heng et al [2]. This is where machines are run until they fail and when failure has occurred, reactive maintenance is carried out. This approach can be extremely costly due to long hours of machine downtime and may also lead to propagation of failure to other components. A slightly more effective time-based maintenance technique known as preventive maintenance involves periodical cleaning, servicing and inspection of machines in order to prevent abrupt failure. However, this method cannot guarantee the absence of any breakdown and the replacement of parts before their end lifetime.

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More efficient maintenance approaches such as condition-based maintenance (CBM) have been adopted to address the issue of machine reliability and reduction of maintenance related expenses. CBM is a maintenance strategy aimed at maximizing productivity and machine up time while lowering operating costs by carrying out maintenance when the need arises [3]. The actual conditions of a machine are monitored to obtain the health status of a system and if the indicators show signs of upcoming machine failure, maintenance is carried out. A CBM program consists of two important aspects known as diagnostics and prognostics.

Diagnostics is concerned with fault detection, isolation and identification when it occurs. Fault detection indicates when a failure has occurred; fault isolation locates the faulty component; and fault identification determines the nature of the fault when it is detected. Prognostics, unlike diagnostics, is a prior event analysis process that deals with failure prediction before it occurs. It is the ability to predict accurately and within acceptable error bandwidth the remaining useful life of a failing component or subsystem [4]. Prognostics is much more efficient than diagnostics in reducing machine downtime. However, diagnostics is still useful when failure prediction fails and a fault occurs.

Prognostic approaches can be classified into three main methods as shown in Fig. 1. Data-driven approach relies on observable past data and statistical models [6]–[8]. The models are derived from routinely monitored system operating data such as oil debris, vibration signals, temperature, and pressure.

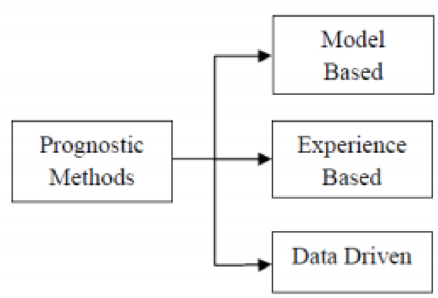

Fig. 1: Classification of Prognostic Methods [5].

Experience based approach is based on the use of simple reliability functions such as Weibull law and exponential law, rather than complex mathematical models [9]. Model-based approach however, uses models which make use of laws of physics [10]–[12]. This approach employs residuals as features by carrying out consistency checks between sensor measurements of a system and outputs of a mathematical model.

Most of the research that has been carried out in the field of prognostics has focused on machines operating under stationary conditions. Rotating machines have increased complexities and complex degradation processes due to non-stationarity. Satisfactory results can therefore not be produced when traditional techniques are applied to non-stationary conditions. With increasing complex machinery, there arises a need for CBM techniques that are able to operate on such machines operating under non-stationary conditions such as wind turbines and automobile drive trains. Thus the focus on this paper is to review the prognostics of rotating machines operated under non-sationary conditions. The key subject of this study is rolling element bearings because they have resulted in a majority of the failures in rotating machines [13] as depicted in Fig 2. Moreover, failure prediction of bearings can improve the safety and reliability of rotating machines while reducing maintenance costs.

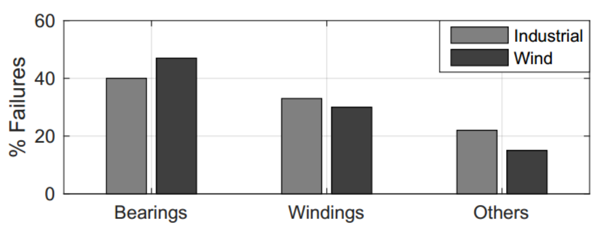

Fig. 2: Comparison of failures in rotating machines in industrial and wind turbine applications [14]

II. PROGNOSTIC APPROACHES

A. Model-based Approach

The model-based prognosis approach relies on a mathematical model of system under observation by assuming that a fault in the system will lead to deterministic changes in the model parameters. Input includes information on operating and environmental conditions. A comparison of model output to actual system outputs is done to generate a residual signal as depicted in Fig. 3. The ratio of output and input can be used as a health index to track degradation of the system. Based on that generated signal, useful information is extracted and potential fault conditions are identified.

A common model-based approach is crack growth modelling. Li et al [16] based their bearing prognostic methodology on the in process adaptation of defect propagation rate with vibration signal analysis. The defect size as predicted by

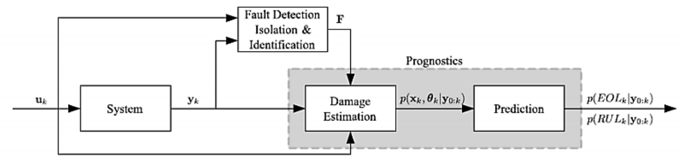

Fig. 3: Model-based prognostic approach [15].

a fatigue crack propagation model was compared to the estimation from a diagnostic model in the future to fine tune the propagation model parameters. However, the assumption that the defect size can directly be estimated from vibrations is faulty since the instantaneous defect size cannot be measured without interrupting machine operation.

Li et al [17] predicted spall progression of tapered roller bearings using an empirical method. The empirical constants need to be determined for all bearings and all operating conditions for which is used. Kotzalas and Harris [18] also presented a spall progression model by extending the Ionnades-Harris (I-H) fatigue life theory. The equations relating spall progression rate $\frac{dSp}{dN}$ to spall similitude W_{sp} are as follows;

$$\frac{dSp}{dN} = C(W_{sp})^m \tag{1}$$

$$W_{sp} = (\theta_{max} + \tau_{avg})\sqrt{\pi Sp} \tag{2}$$

where θ_{max} is maximum stress, τ_{avg} is average shearing stress, Sp is spall length, C and m are constants.

The research done by Kotzalas and Harris [18] showed that 3 to 20% of a particular bearings useful life remains after spall initiation. The study identified two spall progression regions as shown in Fig. 4; stable spall progression region characterized by gradual spall growth and minimum vibratory loading and unstable spall region characterized by increasing broadband vibration amplitudes. The boundary between the two regions was selected as the spall progression life. With their model, prediction of the life of a spall progression was achieved so long as bearing fracture does not occur.

Li and Lee [11] used an embedded gear dynamic model to predict the remaining useful life (RUL). The advantage of this model is that finite element analysis (FEA) enables stress calculation based on the gear geometry, speed, load, material properties and so on. However, this method is time consuming, needs expensive software to analyze the vibration data and calculate the stress value, and the results rely on the accuracy of the defect size.

Oppenheimer and Loparo [19] used Forman Law of linear elastic fracture mechanics to model rotor shaft crack growth. The assumption made from these crack growth models is that the defect size could be estimated directly from vibration data [2]. This assumption, however, is questionable

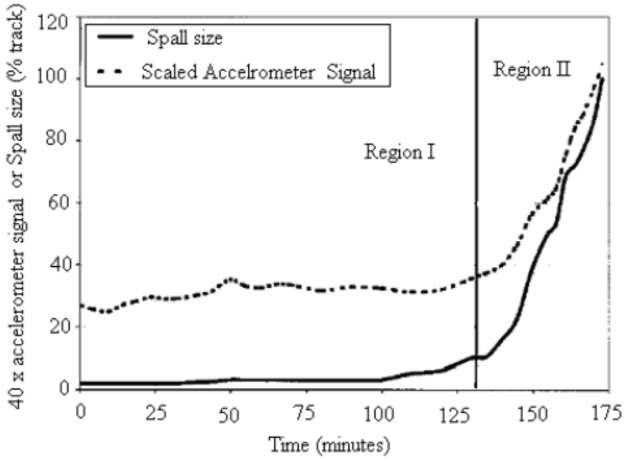

Fig. 4: Scaled accelerometer signal and spall size as a function of time

since instantaneous defect size cannot be measured without interrupting the operation of the machine thereby hindering the usefulness of this model.

Linkan Bian et al [20] investigated a method for modeling degradation signals from components functioning under dynamically-evolving environment conditions. In-situ sensor signals were utilized in real time to predict and update the distribution of a component's residual lifetime. The research showed that the Bayesian updating scheme provides reasonable lifetime prediction results, especially as information is progressively revealed over time. However, this is based on the simplified assumption that the current environmental or operational conditions affect the time-dependent rate at which a component's degradation signal increases.

Matej Gasperin and Juricic [21] modelled feature time series as an output of dynamic state model. The model was then used to determine the presence of a fault and predict the future behavior and remaining useful life of a system. The optimal model at the current state of failure is found by adopting an algorithm for on-line model estimation. The approach is validated using the experimental data on a single stage gearbox. The results showed that the model can be used to predict the evolution of the fault under variable operating conditions, if the future time profile of the load is known. Moreover, a linear relationship was assumed between operating conditions, fault dimension and vibration feature value.

The research done by Liao and Tian [22] was also based on simplified assumptions on the relationship between operating conditions and the rate of degradation. An enhanced Bayesian technique for predicting the RUL of a single unit under time-varying operating conditions was investigated. The approach integrates in situ degradation measurements of the interested unit as well as the operating conditions with a population-based Accelerated Degradation Testing (ADT) model. The results showed that the proposed approach is capable of achieving accurate RUL prediction under complex operating conditions that may involve stochastic components. However, more test units need to be considered and further investigation into the different failure modes needs to be done.

Zhao et al [23] developed an integrated prognostics approach to deal with time-varying operating condition, which integrates physical gear models and sensor data. The degradation model is built on the physics of damage progression, which takes the form of a function of environmental parameters. Any changes of these environmental parameters, such as load, temperature, and speed can be manifested immediately in the physical model. The assumption that future loading conditions are known may lead to difficulty in quantifying the remaining useful life. Moreover, validation of the proposed model with experimental investigations in a lab environment did not take place. Therefore this model may not represent the physical behavior of the target system.

B. *Experience-based Approach*

Experience-based prognostic approach is concerned with integrating reliability data into prognostics. It uses the data of the experience feedback gathered during a significant period of time (maintenance data, operating data, failure times, etc.) to adjust the parameters of some predefined reliability models. The obtained models are then used to predict the time to failure, or the RUL cite.

Goode et al [24] presented a relatively simple model that combines reliability data with condition monitoring measurements to predict the remaining useful life of pumps in a hot strip steel mill. The evolution of CM data was divided in stable and failure zone. Little information was provided by CM data in stable zone. Therefore reliability data was used to predict the point when machine enters failure zone. The results from the study indicated that the prediction model is dependent on the quality and accuracy of the condition-monitored measurements.

Proportional Hazard (PH) models have also been employed in prognostics by Jardine et al [25], [26] to predict the reliability of rolling element bearings and engines. PH models are a class of survival models in statistics where analysis deals with time duration until one or more events happen. These models assume that hazard changes proportionately with asset condition and that the proportionality constant is the same at all time.

Wang and Christer [27] modeled bearing residual life distribution based on stochastic filtering theory. The model developed in the paper was based upon the assumption that the measurement noises are non-Gaussian distributed, which is a natural requirement in condition monitoring modelling. However, as with all other cases employing condition monitoring (CM) and reliability data, threshold identification of defect initiation is required, which is challenging to determine.

C. Data-driven Approach

Data-driven methods are based upon statistical and learning techniques and are derived from routinely monitored system operating data such as oil debris, vibration signals, temperature, and pressure. Most of the data-driven approaches originated from the theory of pattern recognition [3]. They mainly comprise of Artificial intelligence (AI) techniques and statistical methods [1]. Statistical methods include state space models (e.g Bayesian networks [28], hidden Markov Models (HMM) and hidden semi-Markov Models (HSMM) [29]) and regressive models while AI techniques include neural networks [30].

Figure 5 illustrates the stages in a date-driven approach. Data acquisition involves measuring the appropriate form of data. The measured condition monitoring data can be vibration data, acoustic data, oil analysis data, etc. The data measured is polluted by different types of noise. Pre-processing removes the noise through filtering and prepares it for feature extraction. Feature extraction involves processing the filtered data. It can be performed in the time-domain, frequency-domain or time-frequency domain. After this has been done, post-processing is then carried out to prepare feature vectors for pattern-recognition stage. Pattern recognition is where a method is applied to decide the damage state based on the feature vectors extracted by signal processing techniques.

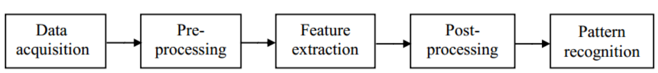

Fig. 5: Data-driven prognostic approach

Data-driven approach is advantageous over model-based approach in cases where the system is complex and thus accurate modeling becomes expensive. Moreover, data-driven approach is applicable where an understanding of first principles of system operation is not comprehensive. However, the primary drawback of such an approach is that effectiveness is not only extremely dependent on the quantity but also quality of system operational data. The systems require large amount of training data and it may have wider confidence intervals in comparison to other approaches. Furthermore, it is difficult to obtain run-to-failure data particularly for new systems because running systems to failure could be lengthy and costly.

Gebraeel et al [6] predicted bearing failure time by using the ANN approach. An experimental setup was developed to perform accelerated bearing tests where vibration information was collected from a number of bearings that are run until failure. This information was then used to train neural network models on predicting bearing operating times. Vibration data from a set of validation bearings were then applied to these network models. The resulting predictions were used to estimate the bearing failure time. Comparisons between these predictions with the actual lives of the validation bearings and errors were computed to evaluate the effectiveness of each model. The results showed that 64% of the predictions were within 10% of actual bearing life, while 92% of predictions were within 20% of the actual life. However, the drawback of this method is that the failure thresholds were not adequately defined.

A trained dynamic wavelet neural network (DWNN) was employed by Vachtsevanos and Wang [31] in prognosis of a defective bearing with a crack in its inner race. It was noted that more extensive failure data, that is difficult to obtain in critical processes, is required to draw firm and comparative conclusions.

A Recursive bayesian technique was proposed by Zhang et al [32] to estimate asset health reliability using condition monitoring data. This method enabled reliability evaluation using observations from individual assets, rather than using failure data from a population of assets. Validation of the employed method was implemented by an experiment on bearing life testing as a case study. The accuracy of such a technique relies strongly on the correct determination of thresholds for various trending features as depicted in [2].

Hidden Markov models (HMMs) were integrated with an adaptive stochastic fault prediction model and principal component analysis (PCA) and used in bearing prognosis by Zhang et al [33]. The principal features extracted by PCA were utilized by HMM to generate a health/degradation index representing the current system health status. This was then used as an input to an adaptive prognostics component for on-line remaining useful life prediction. The merit of this approach is the on-line learning capability which increases its prediction accuracy. However, the inability to physically observe a defect n an operating unit makes it difficult to relate the defined health-state change point to the actual defect progression. Chinam and Baruah [34] also employed HMMs to model degradations on bearings, and to estimate the underlying RUL.

Dong and He [29] presented a statistical modelling methodology based on segmental hidden semi-Markov models (HSMMs). An HSMM is a hidden Markov model (HMM) with temporal structures. However, unlike HMMs, HSMMs employ explicit probability distributions such as Gaussian distribution to model the state durations more accurately. The developed method was then tested using data from a real hydraulic pump health montoring application case study. The results showed that the recognition rates for all states were greater than 96%. For each individual pump, the recognition rate increased by 29.3% in comparison with HMMs. However, this method relies on the assumption of predetermined failure threshold in order to carry out prognostics.

III. PROGNOSTIC TECHNIQUES

The various techniques that have been successfully employed for prognostics include vibration analysis, oil analysis, temperature analysis, acoustic emissions and so on. These methods are effective in describing machine performance.

A. Vibration-based Signal Processing

Vibration analysis has been used to predict the RUL of bearing by use of current and previous vibration data and for diagnosis of all types of fault, either localized or distributed. Vibration-based signal analysis can be performed in the time domain, the frequency domain or the time-frequency domain.

Monitoring the variation in statistical indices such as kurtosis, root mean square (RMS) value or crest factor can help detection of bearing faults in the time-domain analysis [35]. The disadvantage with this method is that it is difficult to determine appropriate thresholds which should not be exceeded because variations exist in different applications. Frequency-domain analysis is based on time-frequency transformation and the most popular diagnostic method uses Fourier Transform. The presence of fault characteristic frequency indicates a fault in bearing diagnosis. The main disadvantage of frequency domain analysis is inability to locate particular frequency in time domain. To overcome this problem, time-frequency analysis is used.

Time-frequency domain techniques can be used to analyze non-stationary signals. A popular time-frequency analysis is the Short Time Fourier Transform (STFT) [36] which is a Fourier-related transform that determines the sinusoidal frequency and phase content of local sections of a signal as it changes over time. However, this method is limited in its time-frequency resolution. Cocconcelli et al [37] enhanced the fault signature of a ball bearing under varying motor-speed by averaging the short-time fourier transform (STFT) for each shaft revolution in the time-frequency domain. The sum of the averaged STFT coefficients was used as an indicator of the level of damage on the bearing. However, the relationship between the damage indicator and varying shaft speed is lacking.

Feng and Liang [38] presented a time-frequency analysis method based on the Vold-Kalman filter and higher order energy separation (HOES) to extract fault symptoms in a wind-turbine gearbox under non-stationary conditions. The results showed that it was effective in diagnosing gear faults. However, investigation on how the faults evolve with time was not done.

An alternative to STFT is the Wavelet Transform (WT) [39] which has more flexible time-frequency resolution and is more applicable in fault detection. This method can be classified according to signal decomposition paradigms as continuous WT, discrete WT and wave packet analysis. Gritli et al [40] proposed the use of discrete wavelet transform (DWT) with high multiresolution analysis (HMRA) of stator currents for fault diagnosis of rotors in doubly fed induction machine (DFIM). However, this approach was only evaluated for fault diagnosis.

Guan et al [41] presented a time-frequency method that outperforms others in providing fine-resolution time-frequency preparation. The synchrosqueezing transform-based method was effective in detecting distributed and localized gear faults under nonstationary conditions. However, the method was not evaluated on ability to track evolution of the faults.

Antoniadou et al [42] presented a time-frequency analysis approach for condition monitoring of wind turbine gearboxes under varying operating condition. The Empirical Mode Decomposition (EMD) method was used to decompose the vibration signals into meaningful signal components associated with specific frequency bands of the original signal. Furthermore, the Teager-Kaiser energy operator (TKEO) approach was employed to improve the estimation of instantaneous spectral characteristics of the vibration data under certain conditions. In this approach, the relationship between the operating conditions and the features is assumed.

B. Oil Analysis

Wang and Zhang [43] predicted the residual life of aircraft engines monitored based upon available oil monitoring information. The fundamental concept behind the model is the proportional residual life that assumes the residual life is proportional to the actual wear measured by the oil analysis programmes. The oil analysis data used was the total metal concentration obtained using Spectrometric Oil Analysis Programme (SOAP) from aircraft engines. The principal component analysis PCA was applied to preanalyze the data. The goodness-of-fit test was then carried out to test the model established. The results obtained from the analysis showed that it is feasible to model the relationship between residual life and information obtained from an oil analysis program. However, this model required the determination of a threshold level to indicate defect initiation point, which is in practice, difficult to determine.

Orchard and Vachtsevanos [9] employed particle filtering for prognosis in turbo engine. Particle filtering was used in the proposed method as CM data to monitor turbine blade health. The particle filtering algorithm consecutively updated the current state estimate for a nonlinear state-space model (with unknown time-varying parameters), and predicted the evolution in time of the probability distribution for the crack length. Authors reported acceptable results in terms of precision and accuracy. However, this method registers poor performance with high dimensional data.

IV. RESEARCH GAPS

1) The research does not depict how the faults evolve with time and failure thresholds under non-stationary conditions are not defined.

2) Some of the research work done employs simplified assumptions on the relation between operating conditions and the rate of degradation
3) Some of the research work with proposed models under non-stationary conditions has not been validated with experimental investigations.

V. CONCLUSION

This paper has briefly reviewed the progress in the research and development of rotating machinery prognostics and especially rolling element bearings. The review indicates that most of the existing prognostics studies have mainly concentrated on systems operated under stationary conditions. However, in real-life situations, most systems operate under non-stationary conditions. The effects of variations in operating conditions have not been properly explored and modelled for fault prognosis. Further research is also required particularly in cases where the faults evolve with time and failure thresholds are not defined. Moreover, the models discussed above need validation with experimental investigations in order to verify their application to industrial problems.

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