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Development of a diagnostic and prognostic tool for predictive maintenance in the railcar industry

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ABSTRACT

The use of a diagnostic and prognostic tool for predictive maintenance serves as a continuous inspection, detective and predictive tool for making important decisions on maintenance activities before failure occurs. The prediction of failure is important in the railway industry in reducing the maintenance and operating cost, minimizing interruptions, risk, unscheduled maintenance and accidents while enhancing higher productivity and component lifespan. In this study, a diagnostic and prognostic tool was developed to constantly monitor and predict the rate of degradation and Remaining Useful Life (RUL) of a railcar wheel bearing. The tool uses the envelope spectrum and kurtosis analysis, which employs the wheel acceleration data obtained from a primary source and the data was interpreted with the aid of statistical and computational methods. The input data was first pre-processed and important features are extracted in a MATLAB 2018b environment. The extracted features were thereafter integrated into the diagnostic and prognostic tool with a pre-set threshold value or feature for the wheel acceleration for predictive purpose. The results obtained indicate the suitability of the diagnosis and prognostic tool for the determination of the railcar wheel condition, prediction of the Mean Time to Failure (MTTF), as well as the remaining useful life of the railcar bearing.

1. Introduction

The wheel-bearing is one of the critical components of the railcar system which supports the load, hence, it determines the availability and the reliability of the overall system. The fact that it can fail catastrophically in service implies that adequate condition based monitoring and predictive system must be put in place for its real time monitoring. Its catastrophic failure pose some safety risk, as well significant ride discomfort while reducing the overall availability and reliability of the system. Furthermore, the failure of critical components usually results in an unplanned service interruption and unscheduled maintenance which is expensive compared to the practise of predictive or preventive maintenance (Wu et al., 2017; Lee et al., 2014; Zhang et al., 2013).

The development of a diagnostic and prognostic tool for predictive maintenance will reduce the risk of catastrophic failure, thus, assiting the operators to gain a competitive edge , due to improved overall reliability and availability of the system (Benkedjouh et al., 2013; Lu et al., 2016). It also enables the estimation of Mean Time To Failure (MTTF) which is the measure of the length of time an unrepairable component is expected to last in service. The process of diagnosis and prognosis is usually cost effective and can be done in real time thereby paving way for the early detection and rectification of faults before a critical failure and unscheduled downtime. Unscheduled downtime due to failure of components could attract huge penalty ranging from loss of good will to the reduction in the profit margin (Okoh et al., 2016; Dong et al., 2014; Fei and He, 2015; He et al., 2015). The process of predictive maintenance usually employs mathematical or stochastic models for prediction or driven by data acquired historically or through sensitive instruments used for measuring the critical operating parameters of the components in real time. The acquisition of such data provides useful information about the health status of the component from which internal faults can be diagnosed, assessed, measured, quantified and rectified. The model based approach employs the usage conditions and suitable model parameters to represent the behaviour of the system and to determine its remaining useful life (Jiang et al., 2017; Bui, 2015). On the other hand, for the data based aproach, the process begins with the acquisition of data relevant to

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the operation and maintenance of the component in the healthy, degradation and unhealthy state under varying operating conditions. This leads to the development of an algorithm for training the machining learning model to detect and classify faults, as well as to estimate the Remaining Useful Life (RUL) of the component. The algortithm can be deployed and integrated into the system for real time condition monitoring (Jiang et al. 2017;, Zhang, 2018). The prognostic and health management of a component encompasses the process of data acquisition and training for fault detection, prediction and decision making (Maio and Zio, 2013; Liu et al., 2018; Frosini et al., 2015; Islam et al., 2017). With the use of preventive maintenance in the railcar industry, maintenance activities can be scheduled in advance with better inventory management. This will optimize the facility lifetime while minimizing its down time. Many researchers have reported on the use of diagnostic and prognostic tools including the machine learning algorithm for predictive maintenance. For instance, Deutsch et al. (Deutsch et al., 2017), used a deep learning based approach to predict remaining useful life of rotating components while Mill et al. (Mill et al., 2013), developed a multi-steps degradation process prediction for bearing based on improved back propagation neural network. Shao et al. (Shao et al., 2015) carried out the diagnosis of rolling bearing fault using an optimization deep belief network. Li et al. (Li et al., 2018) developed a robust intelligent fault diagnosis method for rolling element bearings based on deep distance metric learning, while Liu et al. (Liu et al., 2018) performed an unsupervised fault diagnosis of rolling bearings using a deep neural network based on generative adversarial networks. In addition, Guo et al. (Guo et al., 2017) developed a recurrent neural network based health indicator for the estimation and prediction of the remaining useful life of bearings. The findings from these works show that the machine learning algorithm is a suitable prognostic tool with adequate predictive ability. The novelty of this work lies in the fact that the use of diagnostic and prognosis tool which uses the envelope spectrum and kurtosis analysis for railcar wheel bearing prediction has not been sufficiently highlighted by the existing literature.

2. Methodology

This study deals with the use of the envelope spectrum and kurtosis analysis for the detection of bearing's inner and outer race fault in a railcar. Its diagnostic part assists in detecting impeding failures while the prognostic tool predicts the remaining useful life of the component based on the condition based data collected. The combination of the envelope spectrum and kurtosis analysis for the fault's detection when compared to other methods boast of fault features extraction and early fault identification. It also provide information relating to the resonating frequency band of the components as well as information relation to the health status of the components in the time and frequency domains. The kurtosis analysis might not be sufficient for the early fault detection due to its inability to extract weak features most especially with a signal vibrating with a low signal to noise ratio. The envelope spectrum analysis on the other hand was employed to complement this limitation with the affinity for feature extraction (both the weak and strong features) from the frequency bands of the signal in order to minimize the effects on the impulse as well as the vibration of other components on the generated signal.

The bearing data of the railcar system employed which was obtained from a primary source provided information about the condition of the inner and outer race of the bearing in the healthy, degradation and unhealthy states under various loading conditions. The model of the roller bearing is shown in Fig. 1. where f_b is the fault width (m), R_b is the radius of the rolling element, (m),R_f is the radius of the fault element (m), φ_f is the radius of the outer race (m), ω is the angular speed of the rolling element (rad/sec). The

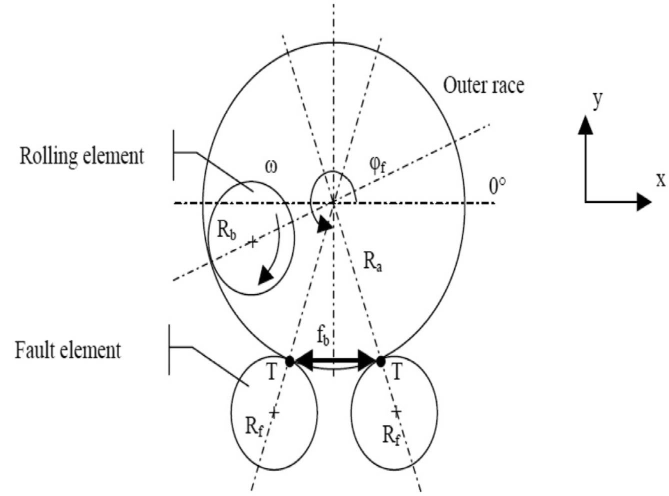

Fig. 1. The model of the roller bearing (Doguer and Strackeljan, 2009).

Nomenclature

MTTF	Mean Time to Failure
RUL	Remaining Useful Life
FI	Inner Race Frequency
FO	Outer Race Frequency
FT	Train Frequency

fault detection is based on the acceleration signals of the rolling elements. The localized faults which occurs in the inner and outer race of the rolling elements were determined. According to Randall *et al.* (Randall and Antoni, 2011), there is excitation of high frequency resonance between the bearing and the response transducer once the rolling elements comes in contact with the local fault in the inner or outer race. The frequencies of the different fault locations are the frequencies of the ball pass in the inner race (FI), ball pass in the outer race (FO), train frequency (FT) and the roller spin frequency (FS) of the bearing. These frequencies are expressed by Eq. (1)–(4) respectively.

$$FO = \frac{nf_r}{2}\left(1 - \frac{d}{D}\cos\,\alpha\right) \tag{1}$$

$$FI = \frac{nf_r}{2}\left(1 + \frac{d}{D}\cos\,\alpha\right) \tag{2}$$

$$FT = \frac{f_r}{2}\left(1 - \frac{d}{D}\cos\,\alpha\right) \tag{3}$$

$$FS = \frac{f_r}{2}\left[1 - \left(\frac{d}{D}\cos\,\alpha\right)^2\right] \tag{4}$$

where d is the ball diameter (mm), D is the pitch diameter (mm), f_r is the shaft speed (rpm), n is the number of rolling elements and α is the angle of the bearing contact (deg.).

The kurtosis which measure the peak and flatness of the distribution in comparison with the normal operating state of the component is expressed as Eq. (5).

$$Kurtosis = \frac{N\sum_{i=1}^{N}[S_i - S]^4}{\left[\sqrt{N\sum_{i=1}^{N}[S_i - S]^2}\right]^2} \tag{5}$$

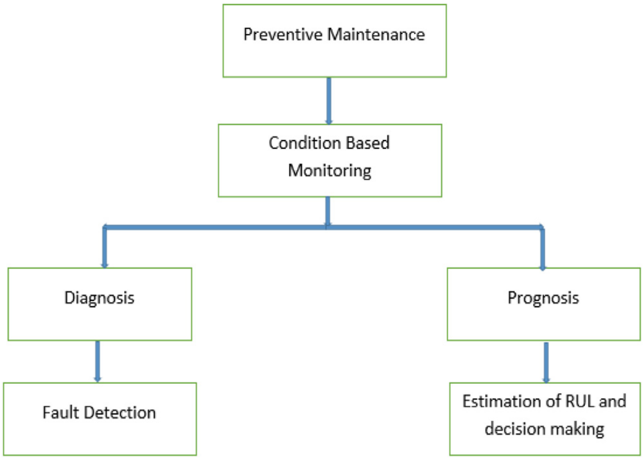

Fig. 2. The framework for the preventive maintenance tool.

where; N is the number of points in the history of signal S, S_i is the i-th point in the history of signal S and S is the mean of signal S.

When the rolling elements comes in contact with the inner or outer races, there will be a corresponding modulation on the frequencies of the bearing if the races are faulty otherwise no excitation or modulation on the frequency will be experienced. The life of the bearing is divided into three stages namely: the healthy (normal), degradation and the unhealthy (failure) stages. The envelope spectrum and kurtosis analysis were employed for the description of the bearing's conditions at each of the stages. First, the vibration signals of the bearing were obtained and preprocessed and filtered in order to reduce the noise and increase the chances of fault identification. The kurtogram of the prepocessed signals were therafter generated and the maximum kurtosis in the kurtogram was selected for implementation in the envelope spectrum. The envelope spectrum with the optimal frequency band was obtained as a reference which was used to interprete the faults developed in the original signal. In addition, the threshold of the acceleration signal of the wheel bearing obtained from the healthy bearing was compared with the acceleration signal obtained from the present wheel bearing within their time and frequencies domains. This leads to the extraction of special features from the signals and their corresponding root mean square, peak amplitude, histogram were obtained in order to determine the health status of the bearing. The feature extraction was performed in the MATLAB 2018 b environment. This was followed by the iterative training of data sets in the same environment and the value of the bandwidth amplitudes and frequencies of the inner and outer races of the bearing were employed as indicators for the identification of the different types of faults.

The frame works for the proposed preventive maintenance tool, as well as the determination of the Remaining Useful Life (RUL) and the Mean Time to Failure (MTTF) of the bearing are presented in Fig. 2 and 3 respectively.

3. Results and Discussion

Fig. 4 presents the raw signal for the inner race acceleration in the time domain of 3 seconds. The undulating or fluctuating nature of the signal indicates that there are faults in the inner race which cause displacement when the rolling elements comes in contact with the inner race as opposed to a healthy component, whose wave signal usually appear in a smooth form because of minimal displacement when the rolling elements ride on the race. From Fig. 4, the acceleration of the rolling element which is a function of the amplitude of displacement is zero appearing in a smooth form in the normal healthy status when there was no fault, but thereafter, the excitation due to displacement and fault occurrence cause it to accelerate or decelerate in a magnitude up to 40 m/s^2.

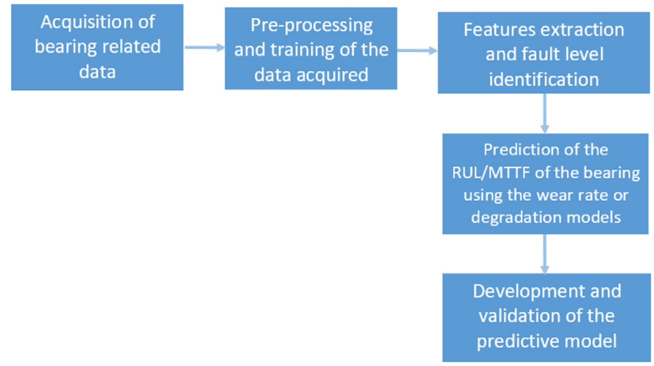

Fig. 3. The framework for the prediction of RUL and MTTF.

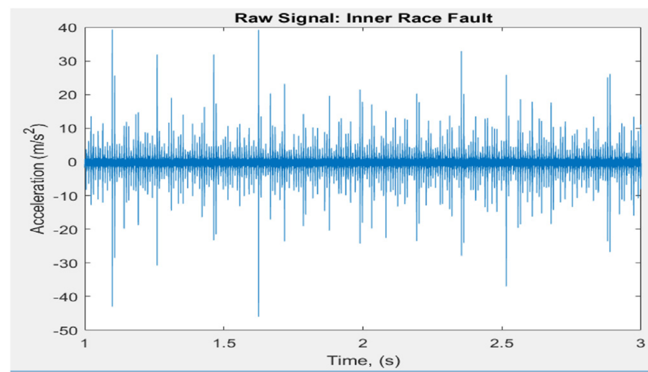

Fig. 4. The raw signal for the inner race acceleration in the time domain.

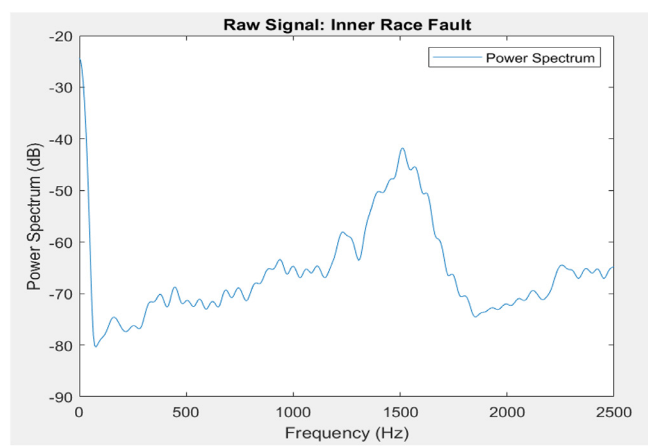

Fig. 5. The raw signal for the inner race power spectrum in the frequency domain.

Fig. 5 presents the raw signal for the inner race power spectrum in the frequency domain of 0–2500 Hz. The root mean square have been used to reduce the influence of the signal energy with the influence of vibration level signals minimized. From Fig. 5, the maximum frequency of oscillation is 2500 Hz which is the frequency produced when the rolling element encounters a local fault in the inner race. The natural frequency is 2000 Hz when no fault is encountered, hence, the differences between the natural frequency when no fault is encountered (2000 Hz) and the maximum frequency of oscillation (2500 Hz) points to the fact that there is an excitation due to occurrence of fault in the inner race.

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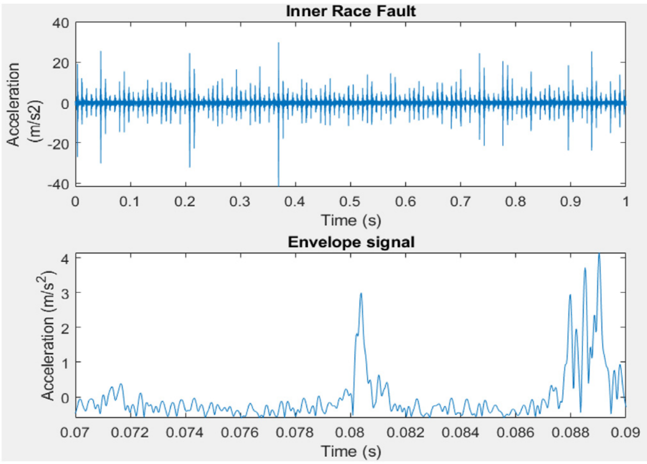

Fig. 6. The inner race and envelope signal.

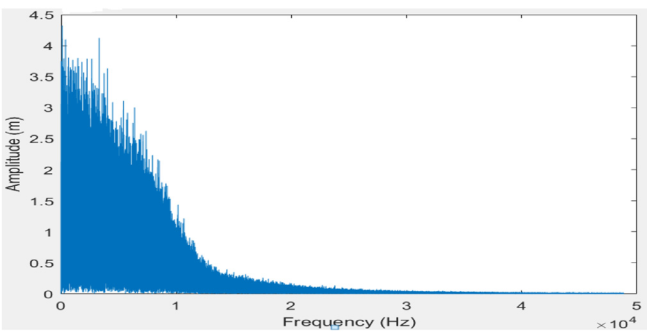

Fig. 7. Frequency and amplitude of scillation for the inner race.

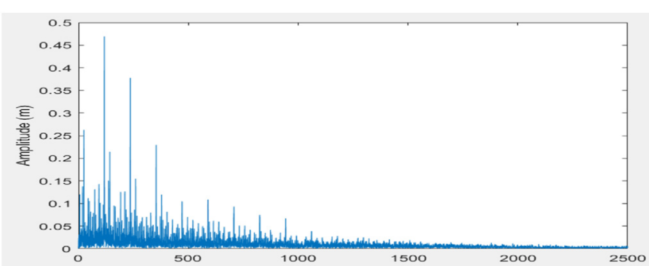

Fig. 8. Frequency and amplitude of oscillation for the outer race.

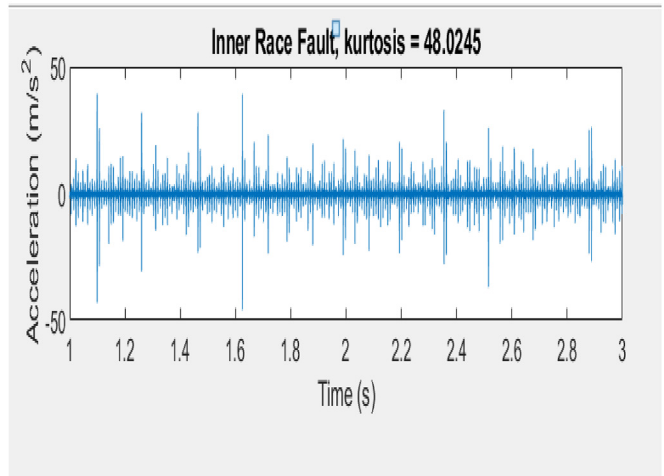

Fig. 9. The kurtosis for the inner race.

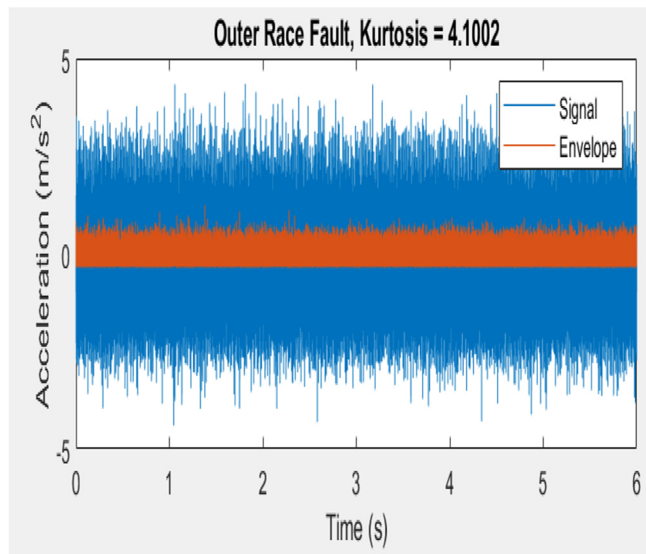

Fig. 10. The kurtosis for the outer race.

Fig. 6 shows the inner race and envelope signal. The essence of the envelope signal is to zoom into the acceleration signal in order to provide more diagnostic information about the spectrum analysis. The envelop spectrum still indicates the undulating nature of the signal which shows that the inner race of the bearing is faulty.

Fig. 7 presents the frequency and amplitude of oscillation for the inner races. The amplitude which represents the maximum displacement of the rolling elements from its mean position is 4 m. This value is significant indicating the presence of a faulty inner race fault which is prone to catastrophic failure. The result obtained shows that there will be significant ride discomfort with the continous usage of the bearing with increase in the railcar vibration and energy requirement of the system, hence, the bearing needs immediate replacement.

Fig. 8 is the frequency and amplitude of oscillation of the outer race. The maximum displacement of the rolling element from its mean position when it comes in contact with the outer race the is 0.455 m. This indicates that the presence of a slight degrading outer race bearing.

Fig. 9 shows the kurtosis for the inner race fault. The kurosis is the fourth standardized moment of a random variable which characterizes the impulsiveness of the signal or the heaviness of the radom variable at the tail. For a normal distribution, the value of the kurtosis usually fall within the range of -3 to $+3$. The value of the kurtosis (48.0245) shows evidence of a faulty inner race of the bearing with the fault signature adequately captured on the envelope spectrum.

Fig. 10 shows the kurtosis for the outer race fault. The value of the kurtosis (4.1002) shows evidence of a slight deviation from the normal distribution. This indicates a slight degradation of the outer race of the bearing with a slight amplitude of modulation as the normal signal which represent a heathy bearing does not show any evidence of amplitude modulation.

Fig. 11 shows the kurtogram and special kurtosis for band selection. This is used to determine the frequency bandwidth with the highest signal to noise ratio. The maximum kurtosis $K_{max} = 2.1956$, while the centre frequency is 3.0518 Hz and the bandwidth is 2.0345 Hz.

Table 1
The number of failures and the cycle time.

Cycle time	Expected no of failure (Inner race)	Expected no of failure (Outer race)
500	3	0
1000	2	1
1500	2	1
2000	2	2
2500	3	1
3000	4	2
3500	6	3
4000	2	5
4500	4	7
5000	2	8

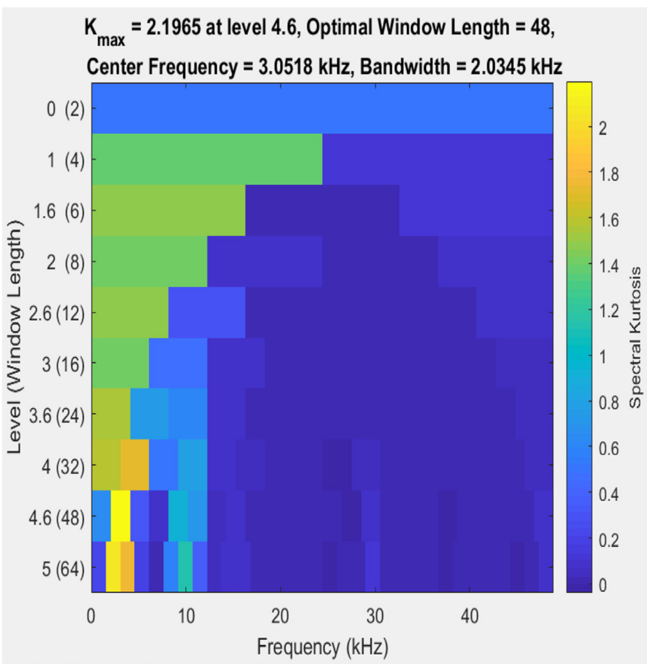

Fig. 11. Kurtogram and special kurtosis for band selection.

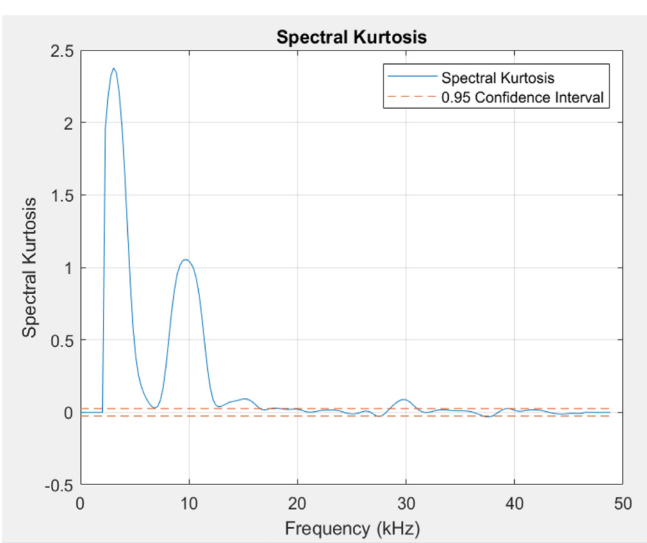

Fig. 12. Special Kurtosis at 95% confidence level.

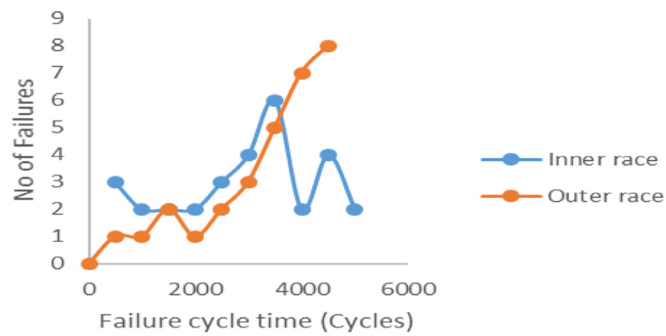

Fig. 13. The number of failures and the cycle time.

Fig. 12 presents the plot of the special kurtosis at 95% confidence level. The higher the value of the special kurtosis, the higher the power variation and its corresponding frequency.

The estimation of number of failure and the failure cycle time using the bearing data was also carried in order to determine the RUL and MTTF of the bearing. The prognostic model uses the Least Square Method and simulates the number of inner and outer races of the bearing expected to fail between 0 and 5000 cycle time of operation. The inner race show tendency for failure with short operational cycle as compared to the outer race which has longer operational cycle time for the 30 bearings considered. The results of the expected failure for the operational cycle time is presented in Table 1 and Fig. 13.

4. Conclusion

The development of a diagnostic tool for the preventive maintenance of the railcar bearing using the envelope spectrum and kurtosis analysis was carried out. The features from the historical and raw data were extracted and trained in the MATLAB 2018b environment using the diagnostic algorithm. The bandwidth frequencies of the inner and outer races were used as indicators for the identification of the healthy, degradation and unhealthy status of the bearing. The results obtained indicate that the inner race bearing needs immediate replacement with high amplitude of modulation of its acceleration and amplitude signals typical of a component in an unhealthy state while the outer bearing showed slight amplitude of modulation with evidence of degradation with continous usage. The kurtosis analysis also show heavy deviation from the normal distribution for the inner race fault while the outer race fault shows slight deviation with the risk of deterioration with time as indicated by their respective fault signatures captured on the envelope spectrums. This implies that the inner race bearing is deteriorated with high risk of critical failure, hence, the need for immediate replacement of the bearing to avoid catastrophic failure. The findings of this work will assist operators and maintenance personnels to keep track of the health status of critical components to avoid catastrophic failure in service.

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