Condition monitoring of wheel wear for high-speed trains: A data-driven approach

Peiwen Xu*, Weiran Yao†, Yang Zhao‡, Cai Yi§, Lishuai Li¶, Jianhui Lin‖ and Kwok Leung Tsui**

***Abstract*—Condition monitoring, as part of the intelligent infrastructure concept, can significantly improve the reliability, safety and efficiency of rail operations. Degradation in infrastructure can be detected before a problem occurs, without interrupting normal operations. This paper contributes to the development of analytics tools and methods for condition monitoring using sensor data. A data-driven method is proposed to monitor the wheel wear of high-speed trains using onboard vibration sensors. In this method, a number of signal processing techniques and statistical methods are applied and extended to extract useful information from multi-location vibration data and estimate the wheel wear. We test the method using real operational data collected from high-speed trains in China over half a year. Preliminary results show that the method is accurate and can be easily applied to real world operations. The method can be extended to provide fault or degradation predictions, which reduces the in-service failures, and enables predictive maintenance.**

I. Introduction

High-speed rail was introduced to China about 20 years ago but has rapidly developed into the world's most extensive network. By the end of 2017, the running mileage of Chinas high-speed railway network has reached was more than 25,000 kilometers, and accounted for more than 60% of the worlds total high-speed railway mileage [1]. With the rapid expansion of the high-speed rail network, the railway industries are facing an increasing pressure on safety, stability and reliability in operation. The concept of intelligent infrastructure and condition monitoring becomes increasing popular, which aims at detecting deterioration in infrastructure before the deterioration causes a failure or interrupts normal operations using sensing technologies. Under this concept, the health status of the railway infrastructure, such as bridges, rail tracks, track beds, and other track equipment, as well as vehicle parts such as chassis, bogies, wagons, and wheels, can be automatically monitored in real-time, which reduces inspection time and maintenance cost and improves safety and reliability. To realize such a concept, a set of methods and tools are needed to collect, process, and analyze sensor data for monitoring and predicting the health status of the various kinds of equipment of the high-speed rail system. This paper proposes a new method to monitor the wheel wear of high-speed trains using vibration data collected by sensors onboard, combing big data analytics and traditional signal processing procedure.

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The wheels are vital to a train's safety and reliability among the various kinds of equipment of the high-speed rail system. Wheel wear problems may lead to derailments, which are big threatens to lives and public property [2]. On 3 June 1998, the Eschede derailment occurred in Germany. A high-speed train derailed and crashed into a road bridge due to a single fatigue crack in one wheel, resulting in hundreds of deaths and injured. In addition, the wheel wear problem is associated with significant cost. The maintenance cost due to wear and rolling contact fatigue of wheels and rails is estimated to be about 1.2 billion yuan per year in China in 2007 [3].

Among various wheel defects, such as crack or spalling, wear is the most common and insuppressible defect which has great effect on the vehicle dynamics. Accompanied with large sliding, the regular wheel rotation over the track in the routine train operation process will lead to a friction loss of material on the surface of wheel and track, which results from the high temperatures and contact stress [3]. Those accumulated changes in material wear will cause changes in the wheel profile, which can be measured by wheel profile measurement instrument. The wear value considered is W_T, as shown in figure 1 and figure 2, which describes the difference between measured profile curve and original profile baseline in tread. In the present high-speed railway system, the maintenance of wheels is primarily based on mileage and the measured wheel profile. The wheels need to be taken out for profile measurement regularly, e.g. once every two weeks. A real-time monitoring system for wheel wear that does not interfere with daily operations would allow operators to identify problems ahead of time, optimize the maintenance strategy and reduce costs.

Traditionally, most wear prediction models are built on theories of the wheel-rail contact, multi-body dynamics of rolling stocks, and material properties of the wheel and the track. Arizon et al. [4] and Enblom and Roger [5] reviewed and compared the existing methods focusing on wear prediction. The Archard wheel wear model [6] of the 1950s is one of the oldest and commonly used models to estimate a wear depth due to sliding and many extensions based on this model have been proposed during the past decades [4]. For example, Jendel [7] built a wheel profile wear prediction model based on Archards wear model and applies it to the commuter rail

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Fig. 1. Wear profile measurement instrument

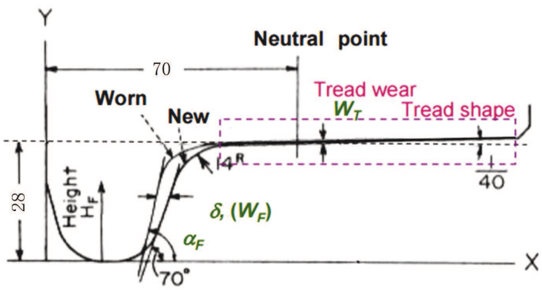

Fig. 2. Measured wear profile via measurement instrument

network in Stockholm. In Archard's model, the volume of wear is proportional to sliding distance, normal force and wear coefficient, which is corresponding to the probability to extract a wear particle by shear, and inversely proportional to the Vicker hardness of the softer material. The limitations for such models is that you must know the material properties of the wheel and the rail. The wear coefficients in Jendel's work [7] are deduced by pin-on-disc and disc-on-disc sliding tests for traditional materials used on wheels and rail. Except for Achard's model, there are other types of popular wheel wear prediction models, such as the models based on friction [8] and the models based on tread wear index [9]. Zobory [10] listed three different models under the dissipated energy wear hypothesis, the normal traction hypothesis and the simplified-combined wear hypothesis. Enblom and Berg [11] investigated the influence of non-elliptic contact models on the wheel wear rate and profile shape. Braghin et al. [12] developed a mathematical model to predict railway wheel profile evolution due to wear.

Simulation software such as SIMPACK [13] are used to build the wheel-rail dynamic interaction system and validate wheel wear prediction models. However, all these traditional models listed above are cumbersome to use, because the models are dependent on specific vehicle system dynamics, wheel-rail contact characteristics and the wear properties of wheels.

Alternatively, few statistical methods have been proposed to monitor and predict the wear of the wheel. Han and Zhang [14] proposed a binary wheel wear prediction model, in which the wheel wear characteristics are concluded based on statistical methods by analyzing a huge amount of worn profiles. Han and Zhang [14] showed a good example of combining statistical methods and traditional wear prediction model based on the worn profile data. However, real time monitoring can't be achieved if using profile data.

In summary, much research is still needed to develop methods that can monitor and predict the wheel wear in real-time and are applicable to a large and mixed types of rolling stock. This paper describes a new data-driven method to monitor the wheel wear of high-speed trains using vibration data collected by the onboard sensors. The main idea of this proposed method is to map the relationship between the wheel wear and the vibration data through statistical modeling and signal processing. The key parts include pre-processing raw data, constructing features, reducing dimensions, and statistical modeling. The proposed method could contribute to the industry move towards predictive and condition-based maintenance, in order to reduce the maintenance cost and improve the safety and reliability of the railway wheels.

The remainder of this article is organized as follows: Section II introduces the data and defines the problem, presenting a rough idea; Section III illustrates the framework; Section IV applies this framework to the real on-track tracking tests and give experimental results; Section V concludes this paper.

II. Dataset and problem description

This article is emphasized to propose a method for monitoring the wheel wear using vibration data and to do a preliminary research to map the relationship between wheel wear and vibration data based on statistical modeling and signal processing. This proposed method will be applied to the real on-track high-speed railway data to test its reliability and efficiency.

11 on-track tracking tests was carried out on a new CRH type I train across half a year on Changsha - Huaihua (CH) line from 2015 to 2016. During the tracking tests, the wheel profiles, vibration signal and the velocity of train are collected for further analysis.

During the real on-track high-speed railway tests, vibration signals for one trail car and one motor car are collected through 11 onboard sensors settled on the car body, bogie frame and axle box both on the left and right. Speed data is also collected via GPS device on trips. The test train operates under normal condition with passengers at operation speed of 250 km/h. Though under normal condition, all wheels of the motor car have been replaced once in October 2015. Only vibration data and speed data are used to build a prediction model for tread wear value. Figure 3 gives the information of vibration signals collected. Onboard sensors are placed under three different levels: axle box, bogie frame and car body. Each sensor will obtain vibration signals in the longitudinal, lateral and vertical direction.

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As presented in figure 1 and figure 2, the wear values in concern of are the tread values, which measures the differences between the measured profile curve and original profile baseline. In the real case, the wheel profiles for all 8 wheels in a car are measured around once two weeks through a mobile laser-based wheel profile measurement system, as illustrated in figure 1. Wear data is calculated accordingly.

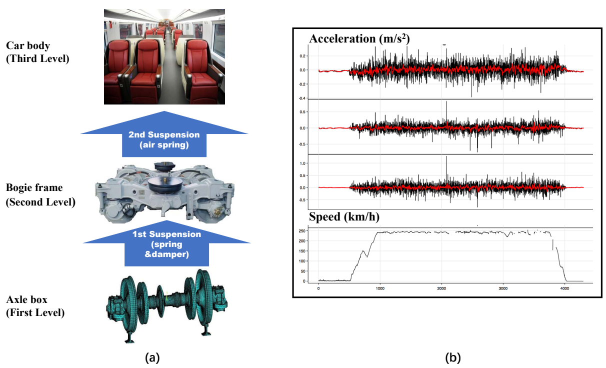

Fig. 3. (a) The positions of onboard sensors. Vibration signals under 3 different levels are collected; (b) The Longitudinal, Lateral and Vertical vibration signals collected by one sensor from axle box and speed data for one trip (From top to bottom)

III. Methodology

Based on the real tracking tests, a new data-driven industrial modeling framework based on mechanical vibration is proposed to monitor the health status of wheel in dynamic high-speed railway system. The main steps to perform this modeling framework is illustrated in figure 4.

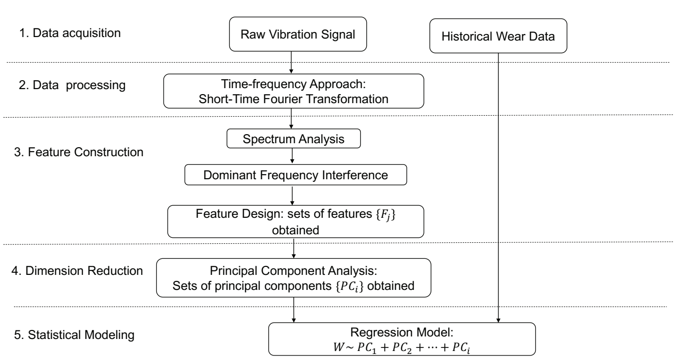

Fig. 4. The flow chart of proposed framework for wheel wear prediction

A. Data processing

The first step, data processing, is based on signal processing techniques to obtain both the time and frequency characteristics of original vibration signal. There are several popular methods for time-frequency analysis of vibration signals such as Short-time Fourier transform (STFT), Wavelet Packet Decomposition (WPD), Empirical Mode Decomposition (EMD) and Hilbert-Huang transform (HHT) [15]–[17] etc. Though WPD is also a widely used and tested approach in signal processing field, wavelet basis function has great impact on the corresponding results [16]. In real case, vibration signals are always affected by comprehensive factors and make it hard to be decomposed into a very mother wavelet. Here we choose STFT approach, due to its compliant implementation in Fast Fourier Transformation, to extract interpretable features and obtain a spectrogram (Amplitude-Frequency-Time) as representation.

Short-time Fourier transformation [15], a typical time-frequency domain method, is considered to be a good way for analyzing non-stationary signals, especially for those time-varying vibration signals with rich information. By applying a window function to multiple time series, the signal to be transformed can be regarded as locally stationary. This approach will give us a time-domain representation of the frequency spectrum of the signal.

B. Feature construction

The aim of feature construction is to utilize some prior acquisition of frequency characteristics behind the concerned mechanism vibration phenomena and reconstruct the feature extracted by time-frequency domain approaches in a better way to help improve the accuracy and the computational efficiency.

1) Spectrum analysis: Obviously, spectrum analysis is quite relevant to the data processing step. For STFT, after obtaining the amplitude spectrogram, it's a natural way to keep an eye on the key frequency components contributing to the wheel-rail contact. The spectrum analysis follows the structure by Zhai et al. who claim the existence of dominant frequency in the vibration accelerations of axle box, bogie frame and car body. Figure 5 shows the spectrums in lateral and vertical direction of car body (left), bogie frame (middle) and axle box (right) in our track tests. Obviously, there are high peaks in the spectrum of axle box vertical (plot (c) in figure 5) accelerations around 400-450 HZ, which is mainly related to the high-frequency Hertzian contact occurring in the wheel-rail interface. The second peak is the frequency range of 30-50 Hz, which describes the induced vibration related to wheel perimeter and the elastic vibration of bogie frame. For lateral vibrations of the axle box, which is weaker than vertical vibrations, the two peak values are around 200-300 Hz and 600-700 HZ. Energies mainly concentrate on the high frequency bands above 200 Hz. In figure 5, the two plots in the middle describe the result of vertical and lateral vibration of bogie frame. From those two plots, it can be found that the vibration energy mainly distributes at around 20-50 Hz, which covers the low-order elastic modal frequencies of the bogie frame. Plot (a) and plot (d) gives the results for the car body. The energies in the car body are less than the bogie frame and the axle box. There exists three dominant frequencies in car body: 1) the highest peak at around 1 Hz, the natural vibration frequency of the secondary suspension system; 2) 10 Hz is the first order natural vibration frequency of the car body vertical

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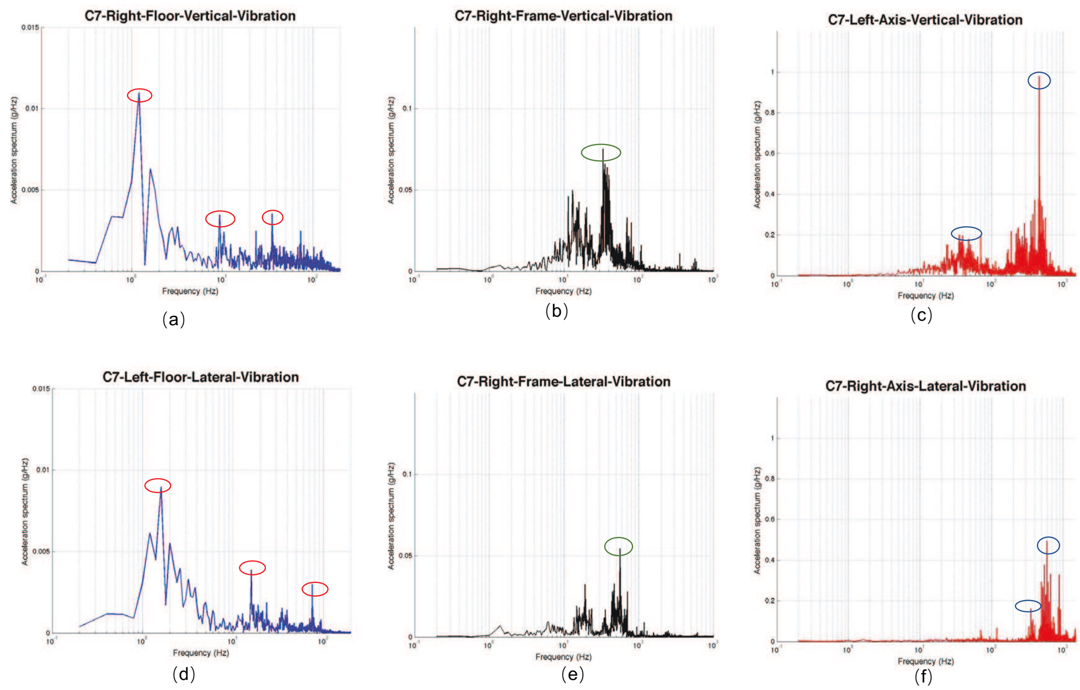

Fig. 5. the frequency spectrum in a 5s time-interval at train speed of 250 km/h:(a) car body vertical acceleration; (b) bogie frame vertical acceleration; (c) axle box vertical acceleration; (d) car body lateral acceleration; (e) bogie frame lateral acceleration; (f) axle box lateral acceleration

bending; 3) 20-25 Hz is roughly the dominant frequency of induced vibration by the excitations from the wheel.

Those dominant frequencies vary under different conditions, different wheel perimeters and different operation speeds. Based on this prior knowledge, we will be able to obtain better insight of the frequency characteristics of the concerned vibration signal. The physical meanings behind the dominant frequency is also further explained. In the all selected frequency bands with higher peak values or energy, we are more interested in those relevant with wheel-rail interface, such as the dominant frequency around 20-25 Hz which reflects the wheel induced excitations to the car body.

2) Dominant frequency inference: From the spectrum analysis, we obtain a rough estimate for the dominant frequency band. The dominant frequency around 20-25 Hz is of highly interest. Figure 6 shows the spectrogram extracted by the Short-time Fourier Transformation (STFT) in the data processing part. The horizontal and vertical axis represents time and frequency respectively; the third dimension, amplitude, is indicated by the color of each point. Deeper color means larger amplitude.

From figure 5, it's easy to conclude that the dominant frequency is around 20-25 HZ and this frequency varies as the fluctuation of speed. The fluctuation of the red line in the whole trip is actually the fluctuation of the speed. Therefore, to simplify, the dominant frequency can be presented below:

$$f_0 = k * v \tag{1}$$

where k is the parameter related to wheel perimeter, f_0 is the dominant frequency and v is the speed of train.

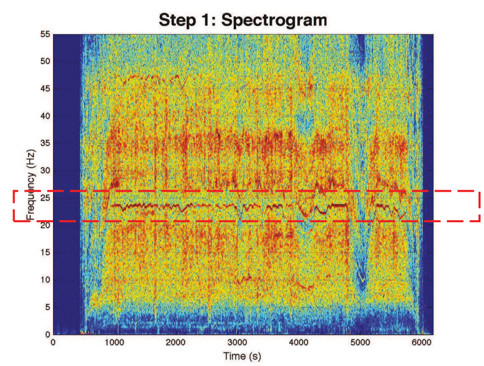

Fig. 6. the spectrogram between [0, 55] HZ under the relative steady operation mode

The inference of dominant frequency is the inference of coefficient k, which can be estimated by robust regression [18] After STFT in the section, we obtain the 3D random matrix containing the time, frequency and amplitude information. The corresponding frequency with peak amplitude between 20 HZ to 25 HZ can be extracted and used as dependent variables in the regression. In this case, $k = 0.067$ and the $R^2 = 0.9685$.

3) Feature design: One key issue in feature construction is that we don't want to lose too much information. We want to reformat those information for easier and more precise analysis process. Though the dominant frequency components may carry lots of information, other parts may also contribute

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to the wheel rail interface. The main purpose of our feature design is to extract those frequency components which may carry the most relevant information according to the domain knowledge of spectrum analysis.

Thus, the algorithm for feature construction after the inference of k is:

Step1 Get the dominant frequency and its multiple frequency up to 40 times:
$f_N = N * f_0 = N * k * v, N = 1, 2, \ldots, 40$

Step2 Calculate energy for each frequency band around mutiple frequency f_N and between two adjacent frequency bands f_N and f_{N+1}:

$$E_{f_N} = \sum_{|f-f_N|<\triangle} A_f^2,$$

$$E_{f_{N,N+1}} = \sum_{f_N+\triangle<f<f_{N+1}-\triangle} A_f^2$$

Where A_f is the amplitude of frequency f and $\triangle = 2$ is the width of the frequency band. Then each calculated energy E_{f_N} and $E_{f_{N,N+1}}$ are retained as feature.

C. Dimension reduction

Under our feature design, energy-related features will be produced. It's quite difficult for us to analyze without feature selection since almost all information is retained in the feature construction part. So for the third step, dimension reduction methods will be employed. The dimension reduction method aims to preserve as much relevant information as possible and remove that redundant information with low discriminating power [19]. After applying the time-frequency domain method to the multiple sensory signals, the signals are shown in a platform comprised of a high-dimensional multivariate random matrix. With some prior knowledge of physical phenomena in the dynamic system, features can be extracted based on the multivariate random matrix. However, carrying almost the whole information, those extracted features are difficult to be represented, visualized and analyzed.

Principal Component Analysis (PCA) will be employed for removing the redundant information and keep relevant information. Feature reduction methods can be conventionally realized in two ways: 1) select a subset of features and abandon the less relevant ones; 2) Transform the features to another space with lower dimensions. Obviously the second one is preferred due to the complexity of mechanism vibration system. PCA is a popular, linear approach to reduce dimension via projection. One advantage of PCA is that we will be able to get the corresponding loadings for each energy-related feature on principal components. Then the model is interpretable with physical meanings. Above are the reasons why we choose principal component analysis.

D. Statistical modeling

Principal Component Analysis (PCA) transforms our designed feature matrix space into a p-dimensional space with basis $\{PC_1, PC_2, \ldots, PC_p\}$. Representing W as the measured wear value, then regression model can be built under this new space:

$$W = \alpha_1 PC_1 + \alpha_2 PC_2 + \cdots + \alpha_p PC_p + \varepsilon \tag{2}$$

Ordinary Linear Regression: Statistical regression techniques are widely used for estimation and prediction in many applications [20]. In this study, linear regression methods are employed due to their interpretability. Given n observations on dependent variable Y and independent variables $X_j, j = 1, \ldots, m$, the model can be formulated as:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_m X_{im} + \varepsilon_i,$$

where Y_i is the ith observation of the dependent variable, X_{ij} is the ith observation of the jth independent variable X_j, $i = 1, \ldots, n, j = 1, \ldots, m$. β_j is the estimated coefficient for X_j and ε_i is the ith independent identically distributed normal error with $E(\varepsilon_i) = 0$ and $Var(\varepsilon) = \sigma^2$.

IV. Real case study

This proposed framework will be applied to the real datasets collected by the on-track tracking tests on Changsha - Huaihua (CH) line as mentioned before. The statistical models built under this framework should be different under different operation lines.

A. Experimental results

As stated in the previous part, firstly the short-time Fourier transform is applied to the raw vibration signal. For each trip (or observation), totally 18 spectrograms and 3D Time-Frequency-Amplitude matrices will be produced based on the longitudinal, lateral and vertical vibration signal of 6 sensors. Figure 6 already gives an example of the spectrogram.

Then as mentioned in section III, here comes the part of feature construction. Figure 5 is the result of spectrum analysis. It's already stated that the dominant frequency in our test line is around 20-25 HZ. It's noted worthy that this dominant frequency will change with the operation speed and operation line, which is a limitation of our method. The parameter k in function f=k*v is estimated by robust regression. The result of 11 trips are listed in table I. So, the dominant frequency of test lines is around 24.13 Hz.

After the statistical inference on the dominant frequency, the following part is the feature design. Only the energies under the relative steady operation mode, which means that the train is running at around the operation speed, are in consideration. Following the steps described in feature design part, the frequency components under 700 HZ are segmented into 82 frequency bands for the vibration signals in one direction of one sensor. Totally 1476 energy-related features are designed for each trip under 3 direction vibration with 6 sensors. With all designed features, then comes the modeling stage. The model can be viewed as follows:

$$W \sim F_1 + \cdots + F_{1476},$$

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TABLE I
THE FITTED K, R^2 AND ROOT MEAN SQUARE ERROR RESULTS UNDER THE ROBUST REGRESSION FOR ALL TRIPS

Fitted k	R^2	RMSE
0.0967	0.968	0.0874
0.0966	0.945	0.0596
0.0967	0.628	0.0898
0.0967	0.985	0.0580
0.0966	0.974	0.0763
0.0967	0.982	0.0741
0.0967	0.942	0.0846
0.0966	0.975	0.0826
0.0966	0.961	0.0858
0.0966	0.977	0.0897
0.0967	0.962	0.0844

each F_i represents the energy for a specific frequency band in a specific direction for a specific sensor and W is the measured wear value. With only 11 responses and 1477 independent variables ($n = 11 \ll m = 1477$), this *small data* problem is solved through two aspects: 1) data fusion; 2) feature reduction or selection.

Considering combining the wear data of all 8 wheelsets, some extra hypothesis tests are performed:

H_0: the wear for 8 wheels are the same, i.e., $W_1 = W_2 = \cdots = W_8$.

H_1: the wear for 8 wheels are not the same.

The p value for Kruskal-wall rank sum test using the wear data of all 8 wheels is 0.2046 which means that we can accept the null hypothesis H_0. All 8 wheels can be regarded as the same wheel. Therefore, the number of observations extend to 88. In addition, for the purpose of performance evaluation, the test set is composited by 8 randomly picked wear value, and the rest 80 wear values consist of training set.

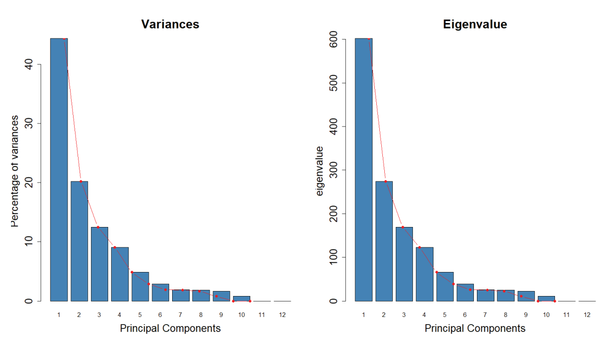

Fig. 7. The variances (left) and eigenvalues (right) of principal components

In the same time, principal component analysis technique is employed to reduce the dimension. The choice of p, the number of principal component, has great impact on the results. Figure 7 and table II shows the result of variances and eigenvalues for the first ten principal components. It's obvious that the first ten components explain almost 100 percent of the variance, so the choice of p is 10.

TABLE II
THE EIGENVALUE, VARIANCE AND CUMULATIVE VARIANCE FOR THE FIRST 10 PRINCIPAL COMPONENTS IN A DESCENDING EIGENVALUE ORDER

	Eigenvalue	Variance	Cumulative variance
PC1	591	44.1	44.1
PC2	273	20.4	64.5
PC3	169	12.6	77.1
PC4	119	8.9	86.0
PC5	61	4.5	90.6
PC6	38	2.9	93.5
PC7	28	2.1	95.6
PC8	24	1.8	97.4
PC9	23	1.7	99.1
PC10	11	0.85	100

To improve the stability, robustness and accuracy, cross-validated linear regression is applied to the ten selected principal components, the dataset is randomly split into training and test sets for 100 times, and the best performed model is selected as the final model. The model selected through validation is shown as table III. The first column is the estimated coefficients of PCs and the second column the standard error of this estimation.

TABLE III
THE REGRESSION MODEL UNDER CH LINE

	Dependent variable: wear	
	Estimate	Std.error
PC1	0.002***	(0.0002)
PC2	−0.002***	(0.0003)
PC3	0.001**	(0.0003)
PC4	0.0003	(0.0004)
PC5	−0.001**	(0.001)
PC6	−0.002**	(0.001)
PC7	0.001	(0.001)
PC8	0.001	(0.001)
PC9	0.001	(0.001)
PC10	−0.001	(0.001)
Constant	0.146***	(0.004)
Observations	80	
R^2	0.734	
Adjusted R^2	0.696	
Residual Std. Error	0.039 (df = 69)	
F Statistic	19.073*** (df = 10; 69)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

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B. Performance evaluation

Vibration signals can be reconstructed into those corresponding principal components under this framework and the wheel wear can be predicted via the above regression model. Conventionally, the original datasets are randomly separated to training sets and test sets to evaluate the performance. Here the performance of this proposed method will be measured under three popular criteria. Representing y as the real value, $\hat{y}$ as the predicted value, n as the number of observations, then the criteria chosen for performance evaluation are listed as follows:

$$MAE = \sum \frac{|y - \hat{y}|}{n} \tag{3}$$

$$RMSE = \frac{\sqrt{\sum (y - \hat{y})^2}}{n} \tag{4}$$

$$MAPE = \frac{100}{n} \sum |\frac{y - \hat{y}}{y}| \tag{5}$$

The three criteria is popular for performance evaluation in statistical field. The MAE is so called mean absolute error, RMSE is the root mean squared error and MAPE is the mean absolute percentage error.

Table IV displays the results of mean and standard deviation for MAE, RMSE and MAPE under 100 times validation under CH line. The mean absolute error and root mean square error for the wear prediction doesn't exceed 0.035 for both training and testing set, which is less than the standard, 0.5 mm in chinese standard to be repaired. Thus, the model is applicable for real world application.

TABLE IV
THE MEAN AND SD OF MAE, RMSE AND MAPE OF TRAINING SET AND TEST SET ON CH LINE

	Train(CH)	Test (CH)
MAE	0.0293	0.0340
(sd)	(8.72e-04)	(7.66e-03)
RMSE	0.0351	0.0400
(sd)	(7.94e-04)	(8.18e-03)
MAPE	27.49	25.73
(sd)	(5.76)	(6.75)

V. CONCLUSION & DISCUSSION

A real-time monitoring wear predictive model based on STFT and PCA with onboard vibration signals has been proposed and validated in the on tracking test trials. The major contribution of this work can be summarized as follows:

1. The process of feature construction is clearly explained and designed via typical time-frequency domain methods, STFT, and spectrum analysis. The key issue of the inference of dominant frequency components helps improve the precision of relevant information extraction.
2. It has been demonstrated that the vibration signal is highly correlated with the dynamic performance of the railway system and is sensitive enough for wear prediction, which can definitely reduce the maintenance cost for wheels.
3. A data-driven wear monitoring system through vibration signals has been developed. The system provides a framework for combining the signal processing technique and statistical modeling methods. The effectiveness of this proposed system is proved via the real on-tracking tests.

However, an inenvitable constraint for a data-driven model is that the precision will higly depend on the quality of the data. Outside this framework, accuracy improvement can be done through different directions:

1. Improvement on the feature construction part and other index, instead of energy may provide better design for features: Wang et al. [21] has proved that the kurtosis of temporal signals filtered by STFT is quite useful in the diagnosis of bearing faults.
2. Improvement on the dimension reduction part. Principal component analysis is not the only dimension reduction method.
3. Improvement on the Modeling part. The performance of lasso regression has been proved better than the ordinary least square regression. For some special data, nonlinear regression may work better.

Combining statistical methods and making use of the 'big data' in traditional industry is a new try and definitely deserves further observation and research. Obviously, out of high precision requirements, different data may adapt to different methods and comparisons between those methods for different type of data can be further investigated. The ultimate goal is to develop a self-adaptive algorithm to choose the best methods automatically under this data driven framework.

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