Mehran University Research Journal of Engineering and Technology

https://doi.org/10.22581/muet1982.2303.15

2023, 42(3) 154-159

Deep learning-based fault detection in railway wheelsets using time series analysis

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Received: 01 June 2023, Accepted: 26 June 2023, Published: 01 July 2023

K E Y W O R D S

Railway Wheelset

Condition Monitoring

Wheel Defects

Deep Learning

LSTM

A B S T R A C T

Maintenance of Railway rolling stock is usually scheduled based. However, the mechanical parts, especially the wheelset may wear down prematurely due to several factors such as excessive braking and traction forces and environmental conditions. This makes the scheduled maintenance less effective and sometimes it results in derailments. This paper presents a deep learning-based technique to detect wheel conditions so that maintenance can be performed promptly and efficiently. A time series dataset of axle vibrations is generated using a simulation model of the wheelset. The dataset is then used to train and test the deep learning model. Long short-term memory (LSTM) architecture is selected for this application since it is designed to perform better for time series datasets. The results show good performance in terms of training and testing accuracy. The model is tested in different defect scenarios and the mean square error in the prediction of railway wheelset parameters is around 15%.

1. Introduction

A railway wheelset is an important element in railway transport. It is different in two aspects from road vehicles. First, its tread is conical in shape, and second, both wheels are rigidly fixed on an axle. The exterior conical perimeter of the wheelset plays an important role in the proper operation of railway vehicles [1, 2]. Excessive noise and vibration are produced if the perimeter is changed. Traction and braking forces generated at the wheel-rail contact point can change the shape of the exterior perimeter of the wheel. Changes in wheel shape also accelerate crack growth on the rail tracks and lead to premature failure of the rail system [3, 4]. Therefore, for proper operation, the railway vehicle wheel tread must be maintained at the desired conicity level [5]. Finding an effective technique for wheel profile estimation has gained a lot of interest in the scientific community and is of great interest to railway operators [6, 7].

Over the past few decades, the railway industry has seen the adoption of multiple techniques, aiming to improve operations and ensure safety. Among these advancements, numerous monitoring approaches have been put forth to enable automated inspections of wheel conditions. The underlying principle behind these techniques lies in the understanding that when a wheel is defective, the forces involved in the interaction between the wheel and rail tend to increase [8, 9]. Exploiting this phenomenon, railway researchers have developed various techniques to address issues related to rolling stock conditions, thereby enhancing the overall efficiency and reliability of railway systems.

Deep learning-based methods are a powerful tool for rolling stock condition monitoring, offering significant improvement in safety and maintenance procedures. Deep learning techniques have proven to have the capability to detect anomalies at the initial stage, allowing timely maintenance action of the rolling stock and reducing the risk of accidents and financial losses to railway operators. For instance, in [10] a deep learning-based approach is proposed to detect wheel defects in railway vehicles. The proposed model achieved reasonable accuracy and demonstrated the effectiveness of the proposed method in identifying various types of wheel defects. In addition to defect detection, deep learning models have also been utilized for the prediction of running safety of railway vehicles. In [11] vibration-based method is developed to forecast rolling stock failure in real-time. This predictive capability enables proactive maintenance planning, minimizing downtime, and improving overall system reliability. To train these deep learning models, large datasets of wheel condition data are required. Collecting such datasets can be a challenging task, but efforts have been made to address this issue. For instance, Zhang et al. [12] proposed a data augmentation method to generate synthetic wheel condition data, augmenting the available dataset and improving the model's performance. While deep learning-based approaches show promise in wheel condition monitoring, ongoing research aims to further refine and optimize these models. The integration of real-time monitoring systems with deep learning algorithms holds great potential for enabling continuous and proactive monitoring of wheel conditions, ultimately enhancing the safety and efficiency of railway operations.

In this paper, a novel deep learning-based method is proposed to detect changes in the conical profile of the wheelset. The desired value of the conicity of the railway wheelset is 0.15 [13, 14]. The proposed method is capable of detecting deviations in conicity values with good accuracy. The novel contributions of the authors are listed below.

a. Development of vibration dataset of railway wheelset.

b. Development of deep earning model for wheel conicity detection.

2. Methodology

The proposed system's block diagram is depicted in Fig. 1. To replicate the wheelset's behaviour, a simulation model is constructed in Simulink, based on the mathematical model presented by the authors in [1-3]. Yaw and lateral dynamics are considered for modeling the wheelset dynamics. For an accurate generation of the dataset track disturbances induced by irregularities in track geometry are also considered. The reason for not considering other dynamics is that the impact of wheel defects is more evident on lateral and yaw dynamics which allow the deep learning model to learn quickly with an even smaller dataset.

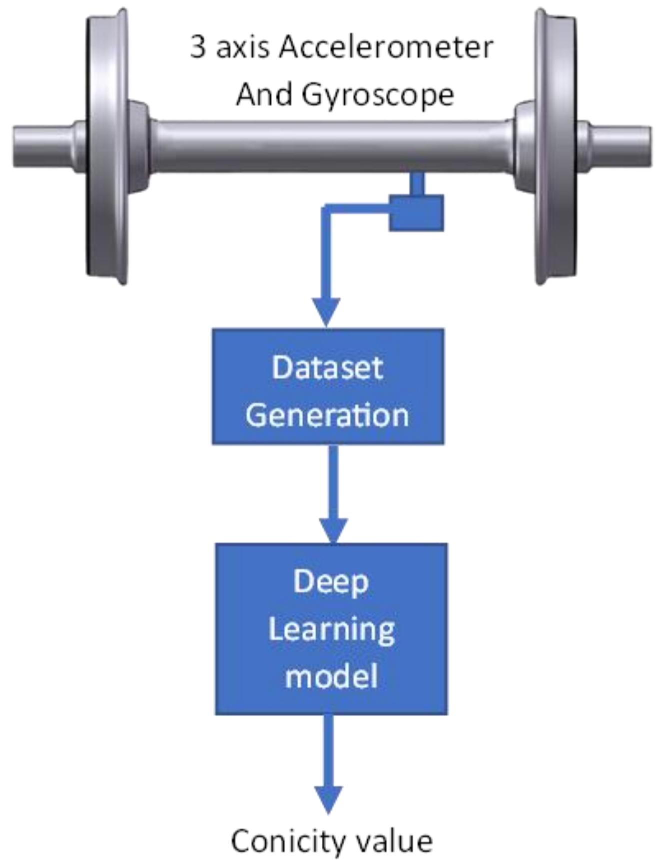

Fig. 1. Block diagram of the proposed scheme

To gather data for training and testing the deep learning model, axle vibration and yaw rate data from the wheelset are collected using an accelerometer and gyroscope. The collected data is pre-processed to create a comprehensive dataset. Simulations are run for 50 seconds at various speeds and wheel conditions, in order to generate vibration data representing all possible fault scenarios. These conditions (e.g., vehicle speed and wheel condition) are varied randomly during the simulations. Simulations are run several times to generate as much data as possible. For each simulation iteration, 500,000 data points are generated. This extensive dataset allows for robust training and testing of the deep learning model, enabling it to effectively learn and recognize patterns associated with different wheel conditions. It is important to note that the simulation model, based on the established mathematical model [1-3], accurately mimics the dynamic behaviour of the wheelset, ensuring the validity of the generated data for training purposes.

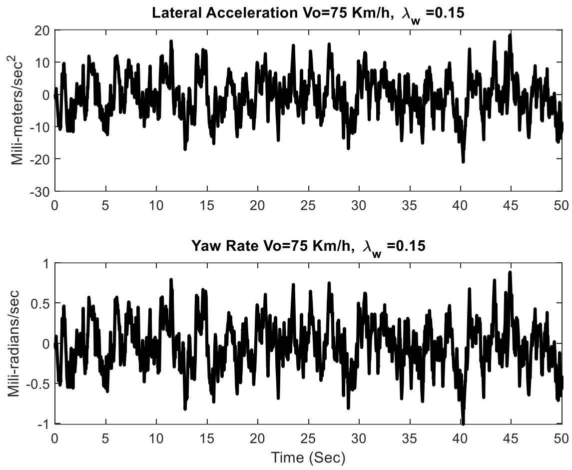

Fig. 2. Lateral acceleration and yaw rate at Vo=75 Km/h and λ_w =0.15

Fig. 2 shows the yaw rate and lateral acceleration profiles observed during simulations conducted under normal wheel conditions with a forward velocity 75 Km/ and conicity (λ_w) 0.15. It is worth noting that the frequency and amplitude of vibration exhibited by the system are influenced by both the velocity and conicity of the wheelset. The relationship between these variables can be expressed mathematically using Klingel's formula, as denoted by equation (1). This formula provides insights into the dependence of vibration characteristics on the specific combination of velocity and conicity employed during the simulation.

$$f = \frac{V_v}{2\pi}\sqrt{\frac{\lambda_w}{L_g r_o}} \tag{1}$$

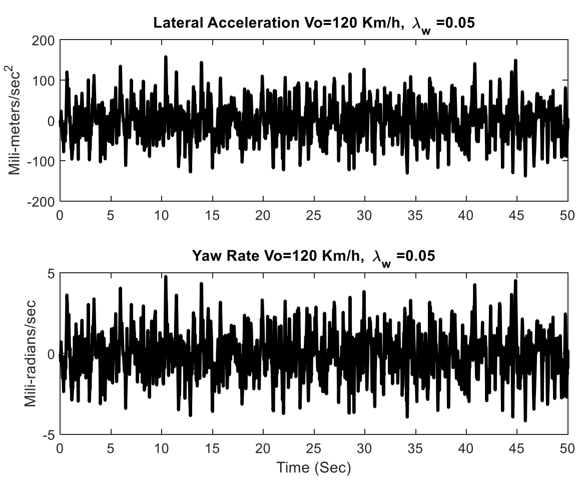

Fig. 3. Lateral acceleration and yaw rate at Vo=120 Km/h and λ_w=0.05

Fig. 3 depicts the lateral acceleration and yaw rate observed when the simulation was run at a forward speed of 120 Km/h with a conicity value (λ_w) of 0.05. This specific scenario represents a faulty wheel condition commonly referred to as a wheel flat, characterized by a reduced conical tread. The figure clearly illustrates that both the amplitude and frequency of vibrations are significantly elevated under this faulty condition. These vibrations impact the ride quality of the vehicle. Additionally, the increased vibrations often generate high-pitched noise, which may prove to be disturbing for nearby residents or occupants.

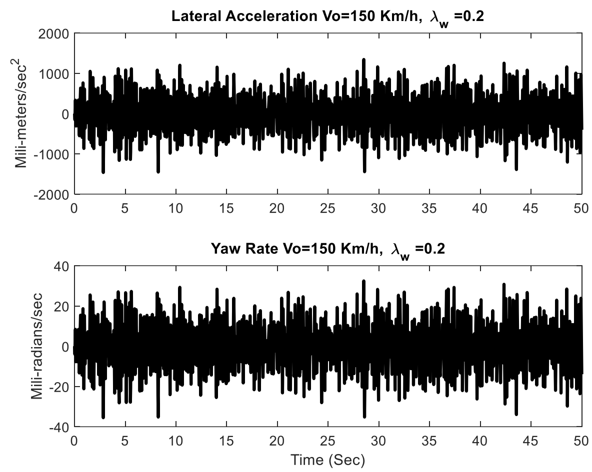

Fig. 4. Lateral acceleration and yaw rate at Vo=150 Km/h and λ_w=0.2

Fig. 4 illustrates a specific scenario known as a false flange condition, where the wheel tread exhibits wear on one side, leading to an increased conicity value. In this condition, the wheel's conical profile deviates from its intended design. As depicted in Fig. 4, this false flange condition gives rise to vibrations characterized by both high amplitude and high frequency. It is important to note that the presence of such intense vibrations poses a significant risk, as they have the potential to escalate to critical levels. If not detected and addressed in a timely manner, these vibrations may ultimately lead to derailment, jeopardizing the safety and integrity of the railway system.

Hence, accurate and timely detection of the false flange condition becomes crucial to ensure the prevention of potential accidents and maintain the overall operational safety of the railway infrastructure. By implementing effective monitoring systems and employing appropriate maintenance protocols, railway operators can mitigate the risks associated with this condition and uphold the safety standards required for smooth and reliable train operations [15,16]. However, due to the involvement of nonlinearities in railway dynamics, the presence of uncertainties (e.g., environmental conditions), and the presence of track irregularities it is extremely difficult to determine wheel condition from vibration data only. All the variable parameters must be considered to accurately detect wheel conditions. Therefore, the deep learning approach is most suitable for such types of applications.

3. Deep Learning Model

The dataset employed in this study consists of various cone sizes, namely 0.05, 0.75, 0.1, 0.12, 0.15, 0.18, and 0.2. The primary objective of this research is to train a deep-learning model capable of predicting actual conicity conditions. To achieve this goal, a Long Short-Term Memory (LSTM) model is proposed. LSTM networks are particularly well-suited for processing sequential data, capturing long-term dependencies, and mitigating the challenges associated with the vanishing gradient problem in conventional RNNs. Because of the temporal nature of the dataset, LSTMs enable the effective capture of temporal dependencies and provide accurate predictions. The reason for choosing LSTM stems from its ability to retain important information over extended time intervals, making it suitable for modelling dynamic systems such as the one under investigation. By using LSTM, a robust and accurate predictive model can be developed to predict future values of railway wheelset parameters. This predictive capability facilitates the identification and resolution of potential issues or anomalies within the dataset, offering valuable insights for maintenance and optimization purposes.

3.1 Model Training

The raw data generated from the simulation model presented in section 2 is gathered and organized into a single file for further processing. A snapshot of the data is shown in Fig. 5. After the dataset is prepared, it is divided into 70% and 30% ratios for training and testing purposes.

	year	month	day	hour	minute	second	milisecond	con 0.12 latAcel	con 0.12 Yawrate	con 0.05 latAcel	con 0.05 Yawrate	con 0.15 latAcel	con 0.15 Yawrate	con 0.1 latAcel	con 0.1 Yawrate
25054	2023	5	9	9	58	2	5054.0	-0.016435	-0.001685	0.002398	-0.000451	-0.030166	-0.002345	-0.006558	-0.001221
97230	2023	5	9	9	58	9	7230.0	-0.171495	-0.004626	-0.056004	-0.001548	-0.231814	-0.006137	-0.128000	-0.003506
70430	2023	5	9	9	58	7	430.0	-0.139875	-0.004253	0.008617	-0.000079	-0.234126	-0.006749	-0.082034	-0.002690
24943	2023	5	9	9	58	2	4943.0	0.089494	0.001865	0.044544	0.000974	0.101632	0.002086	0.081279	0.001724
79987	2023	5	9	9	58	7	9987.0	-0.010728	-0.000418	0.022774	0.000572	-0.064357	-0.001848	0.010466	0.000170

Fig. 5. Dataset in CSV format

A long short-term memory (LSTM) layer is incorporated into the deep learning model architecture. The LSTM layer is chosen due to its capability to effectively handle both past and present timesteps, making it suitable for this specific application. To optimize the model's performance, hyperparameter tuning is conducted. This includes exploring variations such as variations in the number of dense layers. Furthermore, adjustments to hyperparameters such as batch size, number of epochs, loss function, choice of the optimizer, and activation function are made to minimize the training loss. The chosen configuration for the output layer consists of a single neuron. The model is trained using a batch size of 72 and a total of 50 epochs. The mean average error is utilized as the loss function, and the Adam optimizer is employed.

After the training is completed, the training and testing losses came out to be 0.0081 and 0.0158 respectively. These values indicate the effectiveness of the model in capturing the underlying patterns and making accurate predictions. To provide a visual representation of the performance, the training and test losses are plotted in Fig. 6, offering a graphical depiction of the model's performance and the convergence of the training process. This visualization aids in assessing the quality of the model's predictions and serves as evidence of achieving the best results during the training phase.

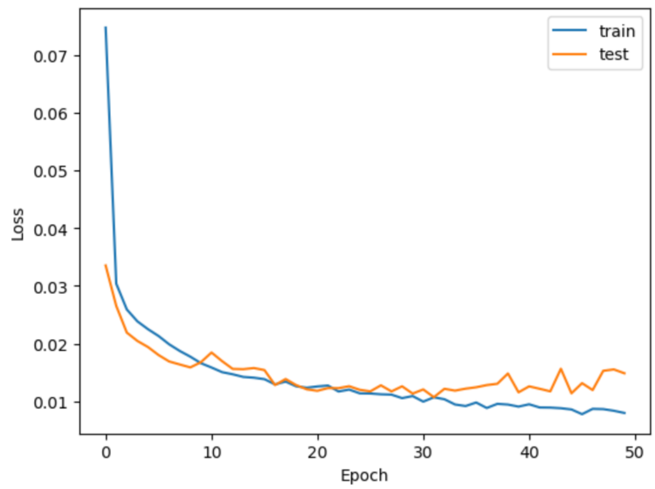

Fig. 6. Training and testing loss

The model summary is given in Table 1 with 11,851 trainable params:

Table 1

Model summary

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_3 (LSTM)                (None, 50)                11800
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 51
=================================================================
Total params: 11,851
Trainable params: 11,851
Non-trainable params: 0
_________________________________________________________________
```

4. Results and Discussion

To check the accuracy of predictions the trained model is tested in different wheel condition scenarios. The predicted results are shown in Fig. 7. The top graph in Fig. 7 shows the predicted lateral acceleration at conicity 0.12, which was not used during the training process. Similarly, yaw rate and lateral acceleration predicted values are shown at various conicity values. The mean square error in testing is less than 15% which is good accuracy given the uncertainties involved in railway dynamics.

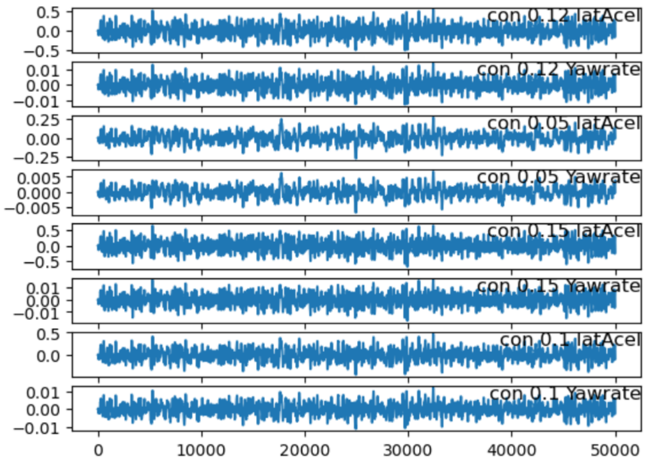

Fig. 7. LSTM prediction results

Table 2

Summary of prediction accuracy

Scenario	Velocity	Conicity	MSE (Lateral Acceleration)	MSE (Yaw Rate)
1	40 Km/h	0.08	14.31%	13.23%
2	100 Km/h	0.12	10.75%	9.13%
3	130 Km/h	0.18	15.53%	14.91%

Prediction accuracy is further summarized in Table 2. In scenario 1, the model is tested at a forward velocity of 40 Km/h and a conicity value of 0.1. The mean square error in this scenario is 14.31% for lateral acceleration and 13.23% for yaw rate. Similarly in scenario 2, the model is tested at a speed of 100 Km/h and conicity of 0.12. In this scenario, the mean square error for lateral acceleration is 10.75% and for yaw rate, it is 9.13%. In this scenario mean square error is relatively low, this is because the conicity value considered in this scenario is closer to the one used in the training process. In the third scenario, the model was again tested at a speed of 130 Km/h and a conicity value of 0.18. In this scenario, the mean square error is 15.53% for lateral acceleration and 14.91% for yaw rate.

5. Conclusion and Future Work

In this paper, a deep learning-based approach for wheel condition monitoring is presented which utilizes a dataset encompassing various conicity values. Implementing a Long Short-Term Memory (LSTM) deep learning architecture, demonstrated the capability to predict the wheel condition accurately. The deep learning model showed promising results, with very low training and test losses, indicating its efficacy. Further work can be carried out by exploring alternative deep learning architectures, such as convolutional neural networks (CNNs) or hybrid models, which could offer valuable insights into further enhancing the accuracy and efficiency of wheel condition monitoring. Furthermore, refinement of the deep learning model, expansion of the dataset, and practical implementation will contribute to the advancement of this field, ultimately enhancing the safety and reliability of railway systems. For practical implementation, the model can be deployed to an edge computing platform to detect wheel defects in real-time.

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