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Predicting Wheel Slippage in Railways using Bidirectional Recurrent Neural Networks

J. C. Jauregui-Correa, J. Rodríguez-Resendis, M. Romo-Aviles, L. Morales-Velazquez, G. Hurtado-Hurtado and T. Sandoval-Valencia

Autonomous University of Queretaro, School of Enigneering Mexico

Abstract

This paper shows the application of Artificial Intelligence to predict wheel slippage in railways. The prediction was conducted with a Bidirectional Recurrent Neural Network, and the data was produced using an experimental railcar and track. The objective is to predict slippage by only measuring the train acceleration without recording the train's speed and wheel velocity. Eighty experimental data were applied to train and validate the Neural Network, and the results show that it was possible to predict slippage using only the train's acceleration data. The method presented in this paper can be used to design a monitoring system and predict wheel wear and polygonization.

Keywords: neural networks, artificial intelligence, wheel wear, slippage, experimental data, condition monitoring.

1 Introduction

The work presented in this paper describes the application of Artificial Intelligence (AI) for predicting wheel sliding in railways. Wheel sliding is one mechanism that increases wheel wear and polygonization, plus other dynamic problems in railcars and tracks. Wheel wear is one of the most significant failures in railways because it affects railcar dynamics, braking capacity, passenger comfort, and wheel life, and the most typical failure is the profile's polygonization.

The topics that support the present work are grouped into the description of wheel wear, wheel profile, wheel-rail dynamic modelling, surrounding structures, and the application of AI for predicting and monitoring railways.

The literature review showed many publications that described those topics from theoretical and experimental viewpoints. Iwnicki et al. [1] studied the polygonization of wheels. They found that cyclic wear causes polygonization but can be related to other phenomena, such as dynamic wheel-track coupling. They reviewed different analyses conducted in different parts of the world. They described that the polygonization on locomotive wheels is caused by the axle torsional mode or a self-excited stick-slip vibration (similar to self-exited vibrations), among other factors, whereas, in urban railcars, the problem is also related to recycling over the same track and it can be related to different excitation frequencies. They also included a complete analysis of different simulation models for predicting polygonization. Song et al. [2] analyzed wheel wear and wheel-rail dynamics of high-speed trains. They reconstructed the wheel-track contact area for different track profiles and proposed a multi-body dynamic model using a lump-mass representation of the railcar and the track. They included the creep force model with the adhesion and sliding patch. For the wear model, they also applied the Archard equation. Their results were complemented with a railcar dynamic analysis due to worn wheels. Zhang et al. [3] reviewed different models for predicting rolling contact fatigue crack initiation on wheels. They combine different crack initiation theories with the contact pattern. According to them, crack initiation depends on the axle load and friction. The fracture is related to low-cycle fatigue.

Regarding the wheel-track interaction, Paul de Vos [4], in his book, described the vibration mechanisms considering a quasi-static moving load, the dynamic excitation, the track variations, unevenness of the track, rail corrugation, track singularities, and wheel out of roundness (polygonization causes modular behavior). The book includes a detailed list of applicable standards and measuring device design for recording vibrations at the track. Kouroussis et al. [5] presented a paper describing a model for predicting the impact response of surrounding structures. They proposed a model based on a combination of experimental data and an analytical formulation that predicts the effect of the railcar vibration on the surrounding structures. Their model considered the transfer function between the railcar excitation force and the soil velocity response. They tested different impact loads and measured the soil response at various distances. They used the experimental results to predict the impact of the passing trains in other locations. Hu et al. [6] studied wheel wear in switches. They identified a method for locating the accelerometers on the switch. They simulated the railcar motion and the vehicle dynamic, including wheel wear. They analyzed the responses on the bogie, the car, and the upper structure to locate the sensors. Jauregui-Correa et al. [7] proposed a methodology for predicting track defects by reading vibration signals from the railcar. They proposed a method for converting the car's vibration data into track load.

In this way, the dynamic loads can be related to track defects that cannot be inspected without a moving load, such as loose sleepers. Robles et al. [8] presented a model for predicting rail corrugations. They developed a predicting model based on field data that considered field measurements at control points along the track and an optimization multi-objective function to minimize the experimental errors. With this method, they were able to predict corrugation along the track. Jin and Ahmadian [9] presented a paper describing a method for predicting wheel wear in high-speed trains. The simulated wheel wear used actual rail data and operating conditions, the Simpack simulation software, and Kalker's theory. They used Archard's wear model.

Artificial Intelligence has shown excellent potential for predicting and monitoring railways at a system's level and individual components. Tang et al. [10] presented a literature review of the applications of Artificial Intelligence to railway systems. They classified the areas of interest as maintenance, inspection, safety, and security. Autonomous Driving and Control, Traffic Planning and Management. Most of the papers that they found are related to maintenance and inspection. This group has four significant topics: defect detection, fault diagnosis, defect prediction, and failure prediction. The defect detection is divided into tracks and rolling elements. They found the application of deep learning (CNNs) to detect wheel defects and ANNs for maintenance diagnosis of rolling bearings. The AI topics that they found were applied to railways are Expert Systems, Data Mining, Pattern Recognition, Adversarial Search, Evolutionary Computing, Machine Learning, Operational Research and Scheduling, Logic Programming, Natural Language Processing and Speech Recognition, Computer Vision and Image Processing, and Autonomous Systems and Robotics. They concluded that most papers deal with maintenance and inspection since the trend is to improve condition monitoring systems. They also remark that the data quality is crucial for improving the decision-making algorithms. Wang et al. [11] developed a simulation model with Simpack to predict wheels' wear in double-carriage railcars. They applied Archard's wear model and predicted wear, measuring a set of wheels daily. They applied a nonlinear autoregulatory model and a Wavelet Neural Network (WNN) for the prediction. They found that the mean square error calculated with the autoregulatory model produced better results than the WNN. Ji et al. [12] applied a Deep Learning approach for monitoring rail tracks; they only explained the methodology and included an example of the measuring system. They reviewed the evolution of the Deep Learning models and found more than sixty papers related to Deep Learning applications on track monitoring. The monitoring sensors that they analyzed were CCD line cameras and image processing. They applied the Convolutional Neural Network (CNN) and the Siamese Neural Network for the analysis. Najeh et al. [13] applied Deep-Learning techniques to predict wear in switches and crossings. The data was recorded from vibration sensors that were installed in the switch, and the load was produced with a six-tone bogie that excited the sensor; the bogie was equipped with a tachometer to measure the bogie's speed. They set seven data processing parameters and simplified the analysis with a matrix with the wear classification. Phusakulkarjorn et al. [14] reviewed the application of Artificial Intelligence (AI) to solve different railway infrastructure problems. They selected the track system, the catenary, the surrounding structures, and the track substructures. They complemented the analysis as the other paper.

The following sections describe the experimental setup for measuring a railcar dynamic and the wheel slippage; the data was processed with Bidirectional Recurrent

Neural Networks (BRNN) based on Closed Recurrent Units (GRU) and Long Short-Term Memory (LSTM). Eighty experiments were recorded, and the data were divided into three groups: 80% of the data was used for training the Neural Network, 10% for testing the results, and 10% for validating Neural Network predictions.

2 Experimental Set Up

The measurements were conducted on an experimental test rig with a 1:20 scale railway model [15]. The test bench is a closed-loop horizontal mounted on a plywood table 2.36 m wide, 5.68m long, and 0.92 m high. The railway sleepers are machined directly into the plywood surface, and the rails are 5 mm diameter steel wires fastened to the sleepers with epoxy resin (Fig.1).

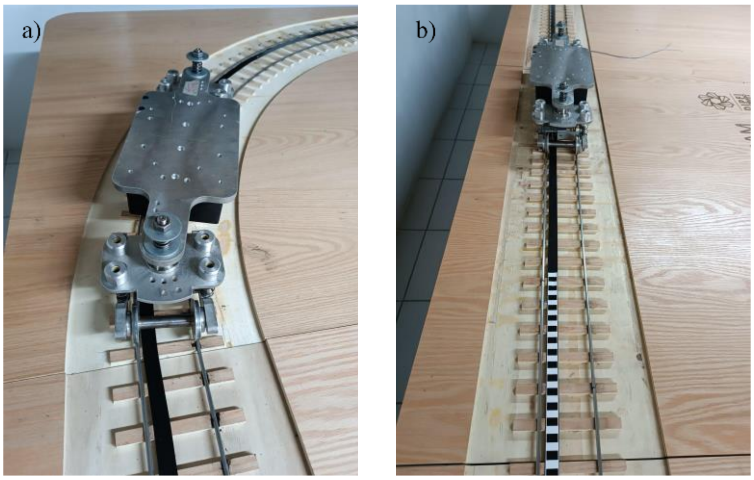

Figure 1: The test vehicle during experimental runs: a) Vehicle at the initial position before running, b) Vehicle entering the braking area.

The test vehicle consists of a single railcar mounted on two bogies designed at a 1:20 scale. The rear bogie is powered by a servo-motor that controls the vehicle's speed (Fig.2). The tracking control system has a microprocessor that programs the wheel's position and speed using pulses from a rotary encoder, model DC5-24V with 600 pulses per revolution (Fig.2a). The tracking system measures the motor's current for estimating the wheel's torque. The railcar is also instrumented with a three-axis MEMS accelerometer (model LSM6DS3) and a three-axis MEMS gyroscope (model LSM6DS3) to monitor the free-body motion. The accelerometer (Fig.2c) has a measuring range of ±4 G, and the gyroscope ±143 °/s. The microcontroller collects data via the I2C protocol.

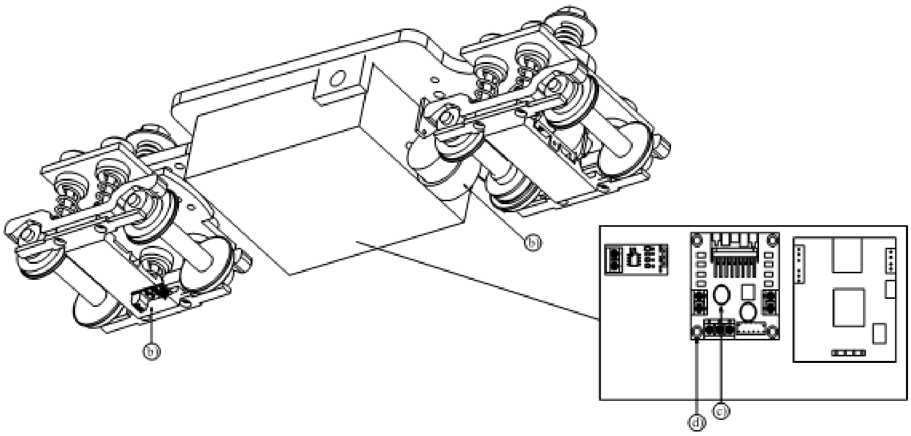

Figure 2: Bottom view of the test vehicle showing the sensors used to monitor the test variables: a) Rotary encoder, b) Infrared optical sensor, c) Accelerometer, and d) Gyroscope.

To measure the vehicle's translational speed, an infrared optical sensor TCRT5000 and a zebra tape attached to the sleepers' surface were used (see Fig.2b and Fig.3). The black tape, placed before the zebra tape, ensures the vehicle does not brake until it detects the first white strip. The combination of black and zebra tape enables automatic braking in the same area during all tests. Since the optical sensor is installed on the front bogie, the vehicle brakes just before entering the zebra tape area (see Fig.3).

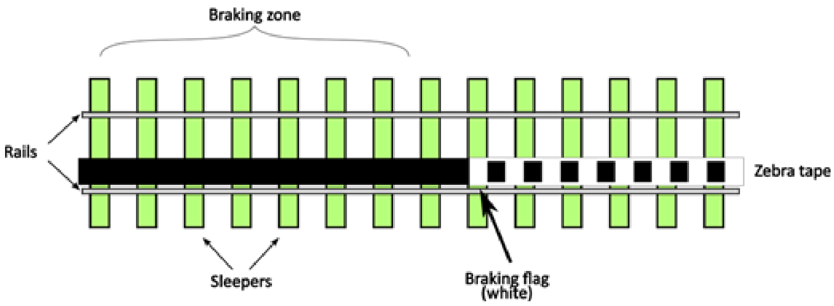

Figure 3: Detail of the braking zone. The zebra tape is used to measure the vehicle's translational speed with an optical sensor and also to trigger the vehicle to brake.

The tests consisted of accelerating the railcar to its maximum speed (1.5 m/s) and then abruptly braking to a complete stop. Vehicle braking was always carried out in the same area and on the straight part of the road. The friction coefficient was estimated with a dynamometer at about 0.3. Before starting, the rails and wheels were cleaned with a solvent-soaked cloth to remove dust and grease, and the test was repeated eighty times. Two data sets were recorded:

- The accelerometer and gyroscope data
- The vehicle's linear speed (from the optical sensor) and the wheel's angular speed (from the encoder)

All the data were recorded simultaneously to train the Neural Networks. Fig. 4 shows a sample of the recorded data. The data can be used to identify the slippage time.

3 Neural Network Application

This work introduces a novel approach to predict slippage using only the acceleration data. The key idea is to implement a monitoring system mounted on the train, eliminating the need to measure the train speed and wheel angular velocity. This not only simplifies the monitoring process but also eliminates the need to synchronize different sampling rates and data formats. The Neural Network, designed with the accelerometer and gyroscope as inputs and the wheel speed and railcar velocity as outputs, is a Bidirectional Recurrent Neural Networks (BRNN), based on Closed Recurrent Units (GRU) and Long Short-Term Memory (LSTM).

The first step was to organize the input information according to the network requirements. The input data were (six channels), and it was structured in an array with dimensions *I x J x K*, where *I* represents the number of tests performed, *J* is the number of data available from each of the six channels, and *K* represents the six channels. The out were the vehicle speed and wheel angular rotation. Before braking, each channel had 1000 data points, while after braking, they were 1500 points. The eighty experiments were arranged in three matrices. The first matrix corresponded to the wheel speed information before braking, with a dimension of 80x1000. The second matrix represented the wheel speed after braking, with a dimension of 80x1500. Finally, a matrix corresponding to the speed difference after braking was included, with dimensions of 80x1500. Finally, the information was separated into 80% for the network training phase, 10% percent for the validation stage, and 10% for the testing stage.

Once the information was organized, three recurring networks were created. The first network modeled the wheel speed before braking using information from the gyroscope and accelerometer. The second network modeled the wheel speed behavior after braking. Finally, the third network was in charge of reproducing the difference in speeds from the same input. All networks were trained using the ADAM optimizer and evaluated by the Mean Absolute Error (MAE) between the prediction and the corresponding actual signal. Thirty training iterations were performed for each network. An input layer for data normalization and a dense time-distributed output layer were included. A structured process was followed to design each of the proposed networks. Initially, the process started with an RNRB hidden layer based on GRU and LSTM, adding neurons until the error calculated by MAE in the validation stage stopped decreasing.

Figure 4 shows the structure of the three proposed recurrent neural networks. The network shown in Fig. 4a has 567,249 parameters corresponding to the weights and bias determined through the training necessary to predict the speed after braking. On the other hand, the network shown in Fig. 4b required 1,892,865 parameters to carry out the task of predicting the speed of the wheels before braking, which indicates that performing this task required a larger size of the network, implying a greater computational power and greater complexity of the input-output relationship. Finally, the network shown in Fig. 4c required 440,462 parameters, suggesting less difficulty in finding a relationship between the input data and the output of the speed difference after braking.

The following section describes the results obtained with the Neural Network and the predictions.

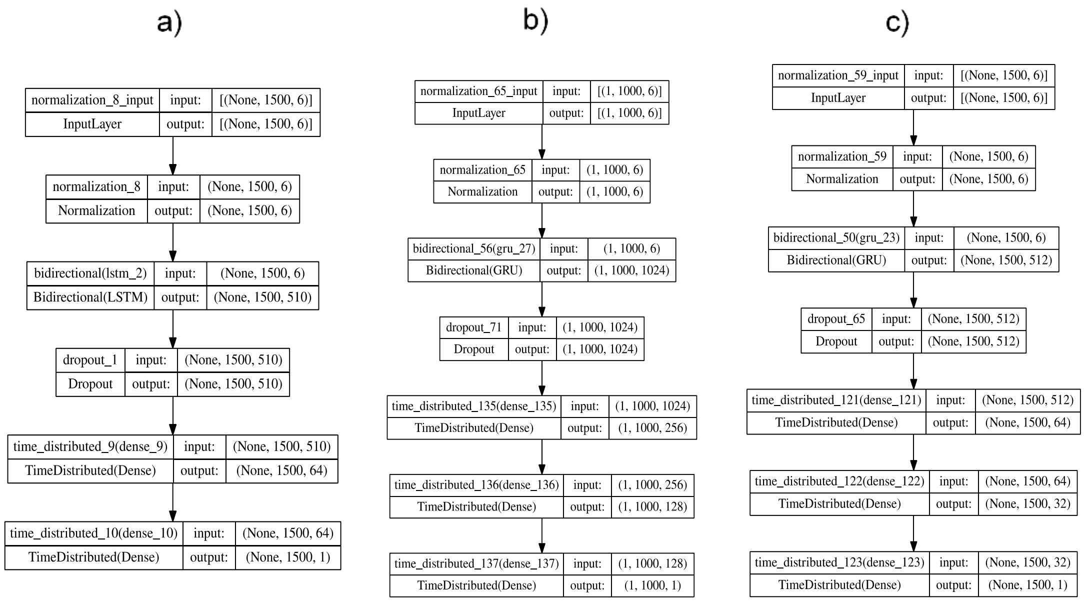

Figure 4: Schematics of the structure of the recurrent networks implemented to predict a) the speed after braking, b) the speed before braking, and c) the speed difference after braking.

4 Results

Figure 5 shows the prediction results of the first recurrent network (Fig. 4a). The blue line illustrates the absolute speed values after braking. On the other hand, the red curve reflects the values predicted by the RNN model, which are smoother and closely follow the general trend of the actual data, although with less variability. It is important to note that high-frequency oscillations do not influence determining slippage. The network captures the trend of decreasing speed from the input data of the gyroscope and accelerometer. The MAE for the training phase of this model was 0.0289, while for the evaluation stage, it was 0.0288, and finally, for the testing stage, it was 0.0265. It is observed that in all three stages, a similar MAE value is obtained, which indicates that the network managed to detect and generalize features and not just memorize the data.

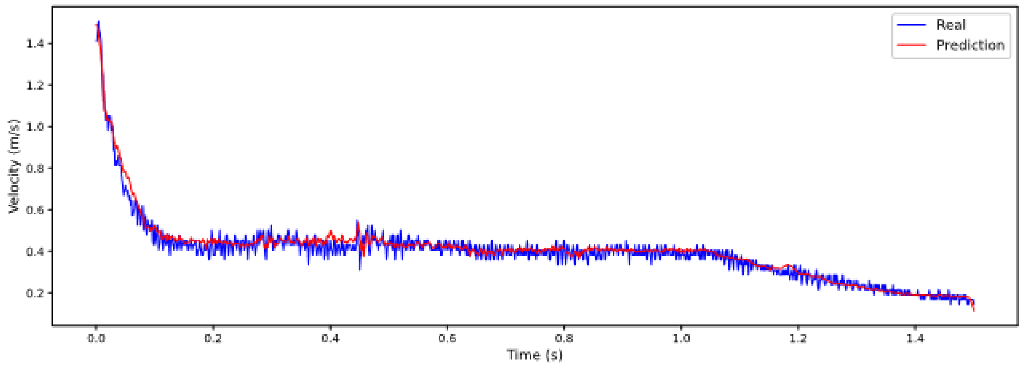

Figure 5: Recurrent neural network prediction against velocity data measured with the encoder (wheel speed) after braking .

Figure 6 compares the real and predicted wheel speed values before braking (the model in Fig. 4b). The blue line represents the real values, which exhibit variability and noise. The RNN model managed to capture the upward velocity trend over time, despite discrepancies in details due to noise in the real data. Although some differences are observed, these are attributed to inherent noise in the data or limitations of the model in capturing all the patterns present. During the training phase, an MAE of 0.0312 was recorded. The MAE increased to 0.0632 in the validation phase, indicating that the model does not generalize well to new data. However, an MAE of 0.035 was obtained in the testing stage, reinforcing the model's ability to learn patterns from the training data and its potential for real-world application.

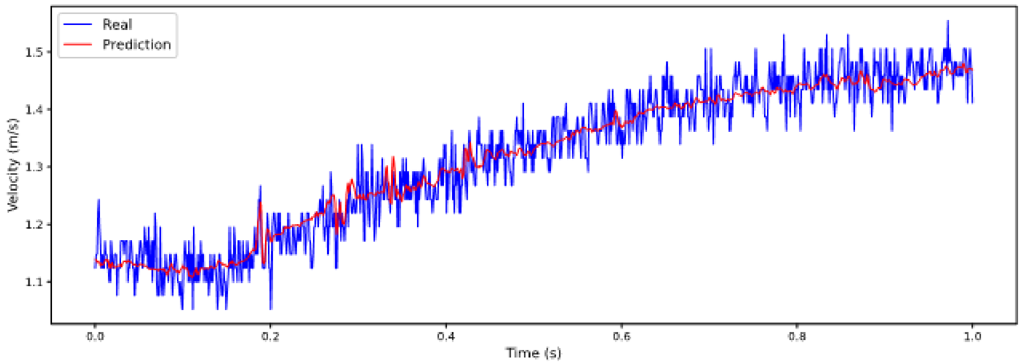

Figure 6: Recurrent neural network prediction against velocity data measured with the encoder (wheel speed) before braking

Figure 7 compares the actual and predicted values, after braking, of the velocity difference between the railcar's speed and the wheel's measured speed (model Fig. 4c). The blue curve illustrates the actual values, showing a rapid initial increase followed by a gradual decrease with some oscillations and noise as it approaches zero. The red curve reflects the values predicted by the model, which closely follows the general trend of the real values, with a similar initial rise and peak, although with less variability. Despite the discrepancies between the real and predicted values, especially in the areas with greater noise and oscillations of the actual curve, the model's ability to predict the trajectory in a smoother way is a significant demonstration of its capability to generalize the underlying patterns. For this model, an MAE of 0.0476 was obtained during training, 0.0600 in the validation phase, and 0.036 in the test phase, showing a similar behavior to the speed prediction model before braking.

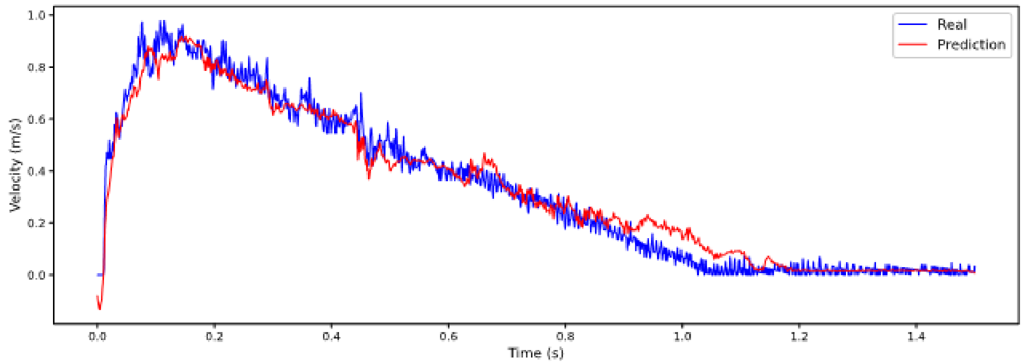

Figure 7: Prediction of the speed difference (vehicle speed and wheel speed) after braking .

It is clear that the neural network was able to predict slippage with a minimum error. Slippage occurred from $t = 0$ until $t = 1.0$ *s.* Afterwards the wheel stopped slipping and the velocity measured at the wheel was the same as the actual train velocity.

4 Conclusions and Contributions

The work presented in this paper demonstrated that a Neural Network can be used to predict wheel slippage only by measuring the railcar's accelerations. The data for training and evaluating the Neural Network was produced at an experimental test rig. The input data for training the Neural Network was the rigid body measured at the railcar (three orthogonal accelerometers and three orthogonal gyroscopes). The train's speed was measured with an optical sensor and an encoder mounted on the wheel. The difference between these two measurements determines wheel slippage. Once the Neural Network was trained, predictions were estimated using new vibration data, and predictions were found to be quite accurate.

The method presented in this paper can be used to design a monitoring system and predict wheel's wear and polygonization.

The Neural Network will be used to predict slippage using actual railway data and validate its applicability in a subway system.

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