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Train wheel damage detection based on deep learning

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Summary

The train wheel flat is one of the most common damages in the railway system. It occurs when a wheel locks up while the train is moving. The early detection of wheel-flat severity is crucial for passenger comfort and the safety of the railway operation. However, it is still challenging to quantify the properties of wheel flats (e.g., sizes) without interrupting the operations. One way is to transform this damage detection task into a model updating (parameter identification) task. In this abstract, a deep-learning approach is adopted to solve this inverse problem. It has been successfully applied to a field train track test in Singapore. The identified damage size obtained is consistent with on-site measurements.

Keywords

Damage quantification; Deep learning; Train wheel flat;

Introduction

As a part of the public transport systems, the urban rail system plays an essential role in urban development. Today, 55% of the world's population lives in urban areas. According to the 2018 Revision of World Urbanization Prospects (United Nations Department of Economic and Social Affairs 2018), the proportion will increase to 68% by 2050. There is significant pressure on the urban rail system. Take Singapore for example, in 2018, an average of approximately 3.3 million passengers a day used the MRT. To provide a reliable railway service to passengers, the early detection of severe wheel defects is essential for passenger comfort and railway operation safety.

The train wheel flat is one of the most common damages in the train-track system. It occurs when a wheel 'locks up' while the train is moving. Railway organizations have specified the removal criteria for wheelsets either based on the size of the flat spots or the maximum impact force or both. Due to the difficulty of measuring the wheel flats directly without interrupting the railway operation, indirect measurements are usually adopted. Various monitoring systems detect the occurrence of wheel flats through other measurements, e.g., rail deflection and rail-seat force.

In most practice, monitoring systems only provide an alert when the damage reaches the removal criteria. Once detected, the wheelsets are usually required to be replaced either immediately or within 24 hours. However, with the increase of population and urbanization, decision makers are facing more complicated situations when pursuing both efficiency and the reliability of the train operations. To provide more flexibility to decision makers, it requires quantitative information about the size of wheel flats.

A model-updating technique has been proposed to tackle this challenge (Cao et al. 2019). The unknown properties of wheel flats are built-in as parameters in the finite element models of the train-track system. The damage detection task is then transformed into a model updating (parameter identification) task. Cao et al. (2019) used a model-falsification approach to quantify the flat size. Zhang (2016) used an improved genetic algorithm utilizing migration and artificial election genetic (iGAMAS) to identify the wheel flat. The estimation of wheel flat size and impact position is treated as an optimization problem, with the best solution that minimizes the difference between the measured and estimated rail pad force responses. In this abstract, another approach that is based on deep learning is explored to solve this inverse problem.

Case Study

In Singapore, a field test is carried out at a test track in a train depot (Figure 1). Ten multilayered sensors, which are invented by Zhang et al. (2018) are installed on five consecutive sleepers. A train with 12 bogies ran on the track at 50 km/h. These rail pad sensors (RPS) measure the forces induced by the moving wheels on the rail pads. For more information on the test, please refer to the previous work (Cao et al. 2019). In this test, the wheel with the flat was running on the left rail track. Among the five sensors, only sensor RPS1 and RPS2 are functioning well. As a result, the measurements recorded by them are used for wheel flat quantification.

Figure 1: Photo of the tested rail track (Cao et al. 2019)

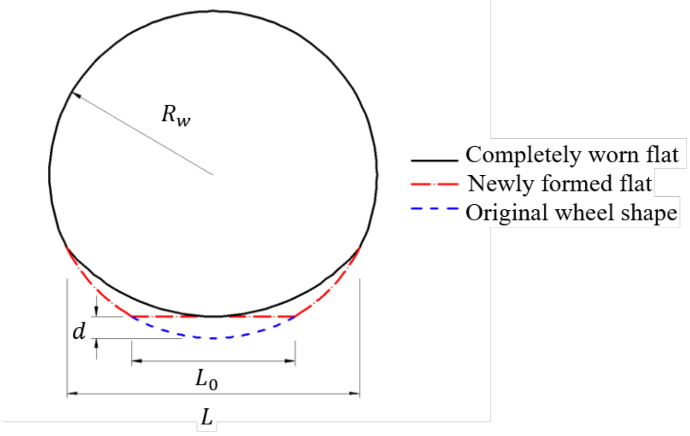

Figure 2: Schematic drawing of wheel flat (Cao et al. 2019)

In modeling the train-track system, the Timoshenko-Rayleigh beam model is used to simulate the rail, and the standard Kelvin contact-point model is adopted to simulate the rail fastening system and the sleeper support. The detailed information of the system modeling, please refer to the previous work (Cao et al. 2019). Two well-known experiments (Newton and Clark 1979; Zhai et al. 2001) have been repeated using this model. It is shown that the simulated force using this model agrees well with the measured data (Zhang 2016). The unknown parameters to identify in this case study include the length (L), depth (d) of the flat (Figure 2), the control parameter c of the wheel center trajectory, and Xp which is the location where the wheel flat hits the rail.

The verified model is used to generate datasets for deep learning. Each dataset includes the simulated response of the rail pad sensors and the parameter values. In this case study, 4000 datasets are studied in the training phase; 1000 datasets are used for validation purposes. The loss function used is the mean squared error. Convolutional Neural Network (CNN) is used to extract features from the signals automatically.

Three different cases have been investigated. Case 1 uses the simulated rail pad force at RPS1. Case 2 uses the simulated rail pad force at RPS2. Case 3 uses both RPS1 and RPS2's signals. The convergence loss of training and validation data sets is shown in Figure 3. Among the three cases, the loss in Case 3 is the lowest. It indicates that using both RPS1 and RPS2's signals is better than using only one sensor.

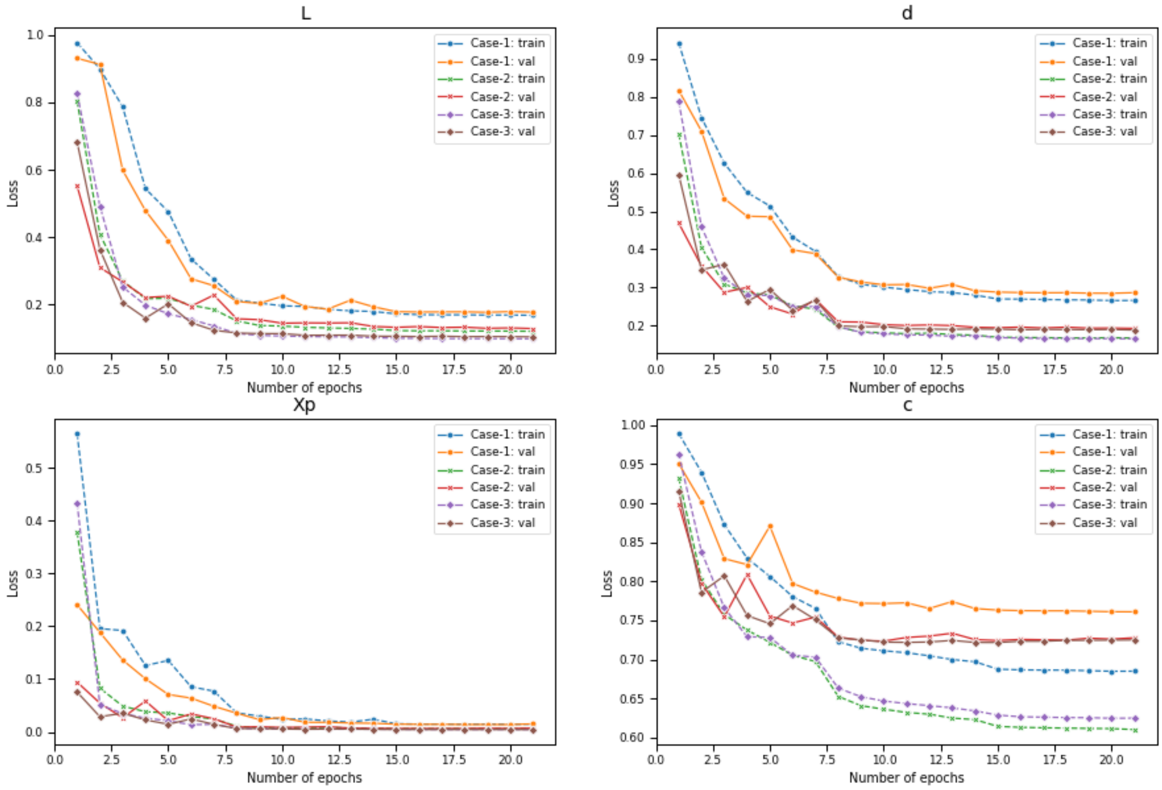

Figure 2: Convergence of loss of training and validation data sets

Using the measured signal of RPS1 and RPS2 obtained from the test, the identified depth of the wheel flat (given by CNN) d = 0.44mm. L_0 is further calculated by $L_0 = \sqrt{8dR_W}$ = 37.5mm. R_W is the wheel radius. To validate the identification result, L_0 was also measured on site with a measuring tape. It is estimated to be in the range of (30mm, 60mm). The predicted L_0 is within the range of the measured L_0.

Conclusion

This paper focuses on the quantification of the wheel flat's size using model updating (parameter identification) approach. Deep learning is adopted in solving this inverse problem. This approach has been successfully applied to a case study in Singapore. The identified size of wheel flats has been verified by on-site measurements.

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