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Ballastless track support deterioration evaluation using machine learning

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Abstract. Ballastless tracks have been widely used for highspeed rail systems globally since their maintenance is relatively minimal. However, support deterioration right beneath the in-between slabs' connectors has been usually reported and quite well known in the industry. Any water ingress can quickly undermine the condition of cement-stabilized soil that supports the track slabs. It is thus very crucial to very early detect the impaired condition of the slab supports since mudded support can result in poor ride quality and eventually endanger highspeed train operations. Therefore, the ability to predict the deterioration of track slab supports is highly beneficial to predictive and preventative maintenance in practice. In this study, track slab support stiffness is considered as a precursor to identify the severity of deterioration. The nonlinear FE models, which were validated by field measurements, have been used to populate data in order to develop machine learning models capable of evaluating the track support deterioration. Axle box accelerations are adopted in a form of datasets for machine learning models. Parametric studies have yielded a diverse range of datasets considering the train speed variations, train axle loads, and irregularities. The results demonstrate that the machine learning models can reasonably diagnose the condition of the track slab supports. The outcome reveals the potential of machine learning to evaluate ballastless track support deterioration in practice, which will be beneficial for railway maintenance.

Keywords: Ballastless Track; Deterioration; Machine Learning; Finite Element Modeling; Condition Monitoring.

1. INTRODUCTION

Ballastless tracks are popularly used in the high-speed rail industry due to their benefits such as lower maintenance requirements, relatively efficiency, and more stability. They are widely used in different countries such as Germany, China, Japan, and Korea (Park et al. 2020). However, common defects in ballastless tracks are settlements and cracks which affect the track stiffness. The deterioration is a result of high loads, vibrations, or water that accelerate the slab deterioration. This can lead to a more severe defect in the track structure in terms of track geometry, rail surface defects, and track infrastructure defects. Therefore, an ability to early evaluate the ballast track support deterioration is crucial in terms of predictive and preventive maintenances because required maintenances can be performed on time when the deterioration is not severe, the maintenance costs are not high, and the safety can be maintained in the standard criteria.

In this study, track slab support stiffness is considered as the main precursor to identify the severity of ballast track deterioration. Data used in the study are generated using finite element (FE) models which are validated with field data measurement. Then, data are used to develop machine learning models to evaluate track stiffnesses. Axle box accelerations (ABA) are used to feed into machine learning models to make predictions. Different parameters are varied to create data variations such as train speed, axle loads, or track irregularities. A machine learning technique that is used to develop a predictive model is a convolutional neural network (CNN). Hyperparameter tuning is performed to ensure the performance of the machine learning model. more information is explained in Section 3.

The expected benefits and contributions of the study are the developed machine learning model can be used to evaluate or estimate the slab track stiffness which will be beneficial to the maintenance planning. Train operators can be aware of slab track deterioration based on regular operations because ABA is mainly used to evaluate track stiffnesses. The stiffnesses are evaluated early and the maintenance can be performed in time when the deterioration is not severe. Therefore, the maintenance cost is not high compared to when the deterioration is severe, the operation is more smooth, the reliability of the system is higher, and passenger comfort is better because the track condition is always maintained in a good condition.

2. LITERATURE REVIEWS

Desai (2016) studied different types of ballastless track defects. The causes of defects were analyzed using a developed equation. From that study, it was found that the most common defect in slab track was the deterioration of concrete slab. The study mentioned different causes of slab deterioration consisting of low-quality material, environmental factors, poor design, and poor construction. Moreover, slabs were cast-in-situ concrete which cracks were commonly found due to construction, application, and environment which also resulted in slab deterioration. These critically affected slab durability and operational safety.

Guo and Zhai (2018) tried to predict long-term track geometry degradation in the ballastless track system used in the high speed railway industry. They considered different subgrade settlements as a precursor. They applied a numerical power model to study subgrade settlement affecting track geometry degradation.

Li and Berggren (2010) studied the relationship between global track stiffness and track performances which were dynamic responses. They conducted static and dynamic methods to explore the relationships. They found that dynamic responses such as sleeper acceleration, wheel-rail forces, and rail moment were related to slab stiffnesses.

From the literature reviews, it can be found that studies relevant to ballastless track support stiffness measurement and evaluation are limited. In addition, there have been no studies using machine learning to evaluate ballastless track support stiffness. Therefore, this study aims to apply machine learning to develop a predictive model to evaluate ballastless track support stiffness.

3. METHODOLOGY

3.1. FE model development and validation

This study applies FE models for numerical simulation and generates numerical data. Then, results from FE simulations are used to develop the machine learning model. The FE model is developed based on Li et al. (2020). The FE model is shown in Figure 1. The FE model is a 3D vehicle-slab model. Rolling stock is modeled using the multi-body simulation (MBS) concept. The rolling stock comprises a car body, two bogies, four wheelsets, two primary suspensions, and two secondary suspensions. The software used to develop the EF model is LS-DYNA which is a popular FE software.

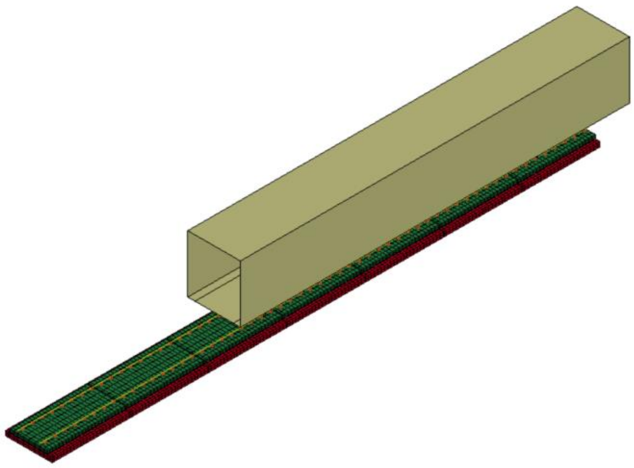

Figure 1. FE model

For the ballasted track, the track structure is a concrete slab comprising two rails that are modeled as beams (206 GPa), rail pads that are modeled as a series of springs and dampers (160 kN/mm), concrete slabs that are modeled as elastic objects (36 GPa), mortar layers (under the concrete slabs) that are models as elastic objects (0.3 GPa), and concrete bases that are models as elastic objects (32 GPa). The rails are developed using the Euler beam concepts supported by rail pads. Then, the loads are transferred to mortar layers and concrete based underneath the concrete slabs respectively which are modeled as elastic material for both of them. The detail of the ballastless track model is shown in Figure 2. The FE model is created using different keywords available in LS-DYNA. The main keyword used in the model is the keyword that is used for creating the interaction between wheels and rails which is *Rail_Track and *Rail_Train. *S01-SPRING_ELASTIC and *S02-DAMPER_VISCOUS keywords are used to model the stiffness and damping properties of rail pads as mentioned. To simulate the deterioration of ballastless track support, the stiffnesses of the concrete slabs are varied as the main precursors as mentioned.

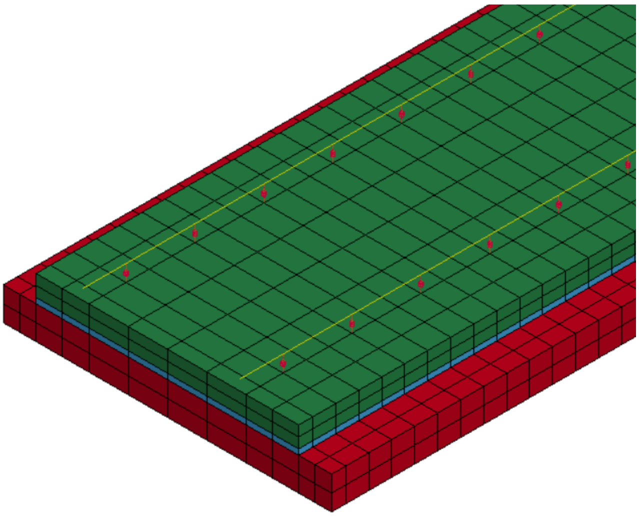

Figure 2. Detailed ballastless track model

Model validation is performed by comparing with the field measurement. The field measurement is conducted using the Suining-Chongqing railway as the benchmark. This railway line is originally constructed for test purposes. The rolling stock used in this line is Changbai Mountain. Therefore, the FE model is developed based on the rolling stock and railway line parameters. On-site, the operational speeds of the rolling stock range from 160 to 220 km/h. track irregularities are also measured to imitate the real situation. Moreover, track irregularities are varied to create data variation. More detail about data variation will be presented in the next section. Wheel-rail contact forces, maximum displacements of rail, and maximum displacements of sleeper are used as criteria to validate the FE model. Referred to the field measurement (Kaewunruen et al. 2019), the comparison of each value is shown in Table 1. For the comparison, it can be seen that the differences are less than 7% so it can be concluded that the FE model provides acceptably accurate results compared to the field measurement and can be used further to generate numerical data.

Table 1. The comparison between the field measurement and results from the FE model

Parameters	Field Measurement	FE Model
Wheel-rail contact force (kN)	100	98.4
Rail displacement at rail seat (mm)	2.606	2.596
Rail displacement at mid span (mm)	2.604	2.415
Sleeper displacement at rail seat (mm)	2.576	2.522
Sleeper displacement at mid span (mm)	2.511	2.352

3.2. Data variation and preparation

To create the data variation, different parameters in the FE models are varied. The data variation is shown in Table 2. The output from simulations used to develop the machine learning model is the vertical ABA of the front wheelset. The frequency of the simulation is 1,000 Hz. The total number of simulations is 1,458. The total length of the ballastless-track section is 15 m approximately.

Table 2. Data variation

Parameters	Range
Slab stiffness (GPa)	28.8-43.2
Speed of the rolling stock (km/h)	150-200
Size of irregularity (%)	80-120
Weight of rolling stock (tons)	35.64-43.56

In this study, raw data are used to develop the machine learning model. The raw data of vertical ABA is used in form of time-series data. That is a reason why this study applied CNN to develop the machine learning model because the CNN model is suitable for dealing with this form of data. Because the frequency of outputs from the FE model is fixed, the size of the output is varied based on the speed of rolling stock. The faster-rolling stock provides a smaller size of the output. Therefore, the padding technique is used to make the size of the data equal. It can be simply done by adding zero to the data with a smaller size to make the size or shape the same as the data with the biggest shape. An example of ABA from simulations is shown in Figure 3. The figure demonstrates the ABA from a simulation with the following parameters; the speed of rolling stock is 150 km/h, the weight of rolling stock is 43.56 tons, the irregularity is original as shown in Figure 4, and the slab stiffness is 43.2 GPa.

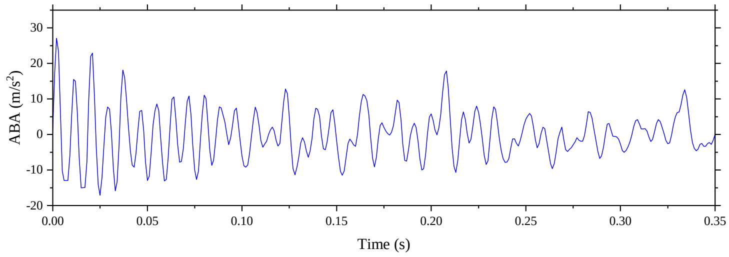

Figure 3. Example of ABA output

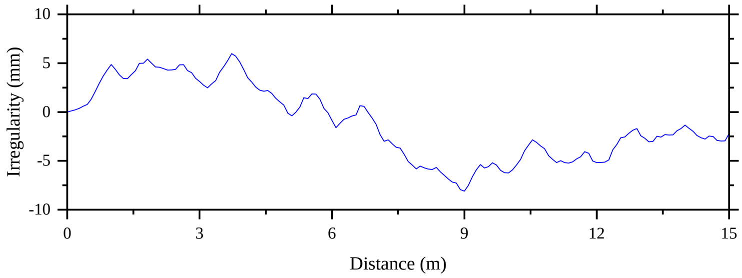

Figure 4. Original irregularity

3.3. Machine learning model development

This study applies CNN to develop the machine learning model. CNN is a powerful technique used to extract the pattern in the data. This is a benefit of the feature extraction part in the CNN architecture. Because this study uses the raw data to feed into the model, the feature extraction part is significantly useful for evaluating the slab stiffnesses. The developed model is a regression model. Outputs of the model are continuous values so the number of the output node is one.

As mentioned in the previous section, the inputs of the machine learning model are time-series ABA. The total number of samples is 1,458. 70% of data are used to train the machine learning model while another 30% are used to test the model.

To ensure the performance of the model, hyperparameter tuning is conducted to test the models with different combinations of hyperparameters. Grid search is used for hyperparameter tuning. It is a technique used to test the performance of the model when hyperparameters are varied and when performances of every combination are recorded. Then, the model with the most suitable combination of hyperparameters is reported. The list of hyperparameters for hyperparameter tuning is shown in Table 3.

Criteria used to evaluate the model performance are mean absolute error (MAE), root mean square error (RMSE), mean percentage error (MPE), and R^2.

Table 3. Hyperparameter tuning list

Model	Hyperparameters
CNN	Number of convolutional layers
	Filter
	Kernel size
	Number of pooling layers
	Pool size
	Activation function
	Batch size
	Optimizer
	Number of hidden layers
	Number of hidden nodes

4. RESULTS AND DISCUSSION

From the machine learning model development, the relationship between true values and prediction is shown in Figure 5. It can be seen that the prediction is significantly related to the true value. The R^2 is 0.94 which demonstrates that the prediction can be used as representative of the true value. Other criteria are presented in Table 4.

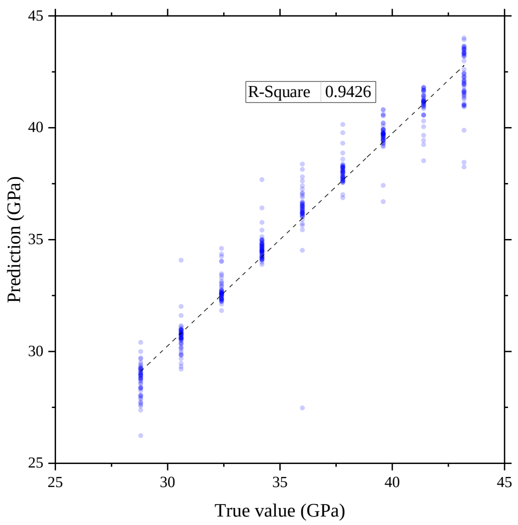

Figure 5. True value and prediction

From Table 4, it can be seen that the MAE and RMSE are 0.63 and 1.13 GPa respectively which are relatively low compared to the true value. The MPE is about 1.75% or the accuracy of the prediction is 98.25%. This indicates the developed machine learning model can be used to evaluate the ballastless track support stiffnesses with high accuracy and reliability.

Table 4. Model performance

Criteria	Values
MAE	0.63 GPa
RMSE	1.13 GPa
MPE	1.75%
R^2	0.94

From hyperparameter tuning, the combination of hyperparameters that provides the best performance is shown in Table 5.

Table 5. Tuned hyperparameters

Model	Hyperparameters	Tuned values
CNN	Number of convolutional layers	2
	Filter	64 (conv1) and 32 (conv2)
	Kernel size	3
	Number of pooling layers	0
	Pool size	N/A
	Activation function	Linear
	Batch size	8
	Optimizer	Adam
	Number of hidden layers	2
	Number of hidden nodes	100

5. CONCLUSION

This study aims to develop the machine learning model to evaluate the ballastless track support deterioration. The machine learning technique used in the study is CNN. Slab stiffnesses are used as the precursor to identify the ballastless track support deterioration.

Numerical data is used to develop the machine learning model. Validated FE models are used to generate the numerical data.

From the study, the developed machine learning model can provide a good result. The accuracy is higher than 95% and the MAE is less than 1 GPa. This indicates that the developed model can evaluate the slab stiffnesses accurately. This study demonstrates the potential of machine learning in evaluating the slab stiffnesses which there have not been previous studies studying on this aspect.

The contribution of this study is the developed model can be used with railway maintenance. The slab stiffnesses can be tracked in real-time with a regular operation because the inputs used to develop the machine learning model in this study is ABA which can be measured using an accelerometer attached to an axle box. Therefore, the evaluation can be conducted immediately and does not obstruct railway operations. Then, the evaluated stiffnesses can be used to plan the maintenance responses. Early notice of ballastless track support deterioration will be beneficial in terms of management, maintenance planning, and maintenance cost. The severity of deterioration will not be too high so the damage can be minimized and managed efficiently.

A limitation of this study is data used are numerical data. Using field data can guarantee the finding of the study. Additional features can be added to the machine learning model to improve the accuracy of the evaluation as well as data variation to improve the comprehensiveness of the machine learning model. Different machine learning techniques can be tried to explore their potential on ballastless track support deterioration.

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