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Eccomas Proceedia COMPDYN (2025) 206-218

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COMPDYN 2025
10th ECCOMAS Thematic Conference on
Computational Methods in Structural Dynamics and Earthquake Engineering
M. Papadrakakis, M. Fragiadakis (eds.)
Rhodes Island, Greece, 15-18 June 2025

ELASTIC RESPONSE AND PERMANENT SETTLEMENT PREDICTION OF A REDUCED SCALE HIGH SPEED RAILWAY TRACK PORTION USING MACHINE LEARNING

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Abstract

Ballasted railway tracks are one of the most important means in the sector of transportation. To ensure the high demands on this transportation, the number of trips and speeds of trains are increased, and this consequently leads to significant impacts on the geometry of the track and the comfort of passengers and requires repetitive expensive maintenance. Numerical and experimental studies were developed and performed to better understand the dynamic behavior of ballasted railway tracks under high-speed trains. Numerical studies vary from one-dimensional simple models to three-dimensional complex models where experimental studies involve reduced scale and on-site experiments. Recently, machine learning presented an innovative approach to predict the behavior of the track under high-speed trains and that depends only on the collected data. The aim of this present work is to predict the elastic displacement, positive and negative accelerations, and permanent settlement of the middle sleeper in a reduced scale portion of a ballasted railway track of three sleepers using decision-tree-based ensemble machine learning algorithms for various train speeds and given number of cycles.

Keywords: Machine Learning, Ballasted Railway Tracks, Elastic Displacement, Permanent Settlement, High Speed Trains, Reduced Scale Experiment.

ISSN:2623-3347
Peer-review under responsibility of the organizing committee of COMPDYN 2025.
doi: 10.7712/120125.12402.25715

1 INTRODUCTION

Ballasted railway tracks are one of the most important means in the sector of transportation. To ensure the high demands on this transportation, the number of trips and speeds of trains are increased, and this consequently leads to a significant impact on the geometry of the track and the comfort of passengers and requires repetitive expensive maintenance to return the track back to its original position. In this context, numerical and experimental studies were developed and performed to better understand the dynamic behavior of the ballasted railway tracks under high-speed trains.

The numerical studies vary from one-dimensional analytical models simulating the track with a beam supported by a series of springs or mass-spring-damper systems to three-dimensional complex models that are time-expensive due to non-linearity, viscous behaviors, moving load, and indeterministic organization of the grains of ballast. Lei and Sheng presented a one-dimensional model using a continuous Euler Bernoulli's beam supported by springs for the foundation of the rail, the model allows the application of a moving load, it can consider half of it with different stiffness where damage in the track exists, however it cannot permit damage in specific sleepers [1,2,3]. Tran et al. have proposed a one-dimensional model using a continuous Euler Bernoulli's and Timoshenko beams supported by a series of mass-spring-damper systems while including a viscoelastic behavior for the rail pad [4]. Then, Tran et al. have also proposed an Euler Bernoulli's beam model supported by series of linear elastic mass-spring systems for the components of the track under the rail, the model depends on the periodicity and can take into consideration the defect in specific sleepers [5]. Sayeed and Shahin have proposed a linear elastic three-dimensional finite element model that simulates realistic train moving loads in order to investigate the dynamic response of ballasted railway tracks with respect to the modulus and thicknesses of track substructure layers, the amplitude of train moving loads and the train speed [6]. While De Abreu Corrêa et al. have presented a three-dimensional model that considers the granular medium as a stochastic heterogeneous continuum medium and studies the influence of heterogeneity on the response of the track [7]. Shi et al. have conducted analysis of a ballasted railway track using a hybrid discrete-continuum approach; where the influence of the contact forces, ballast density and the thickness of ballast layer on the sleeper support stiffness are analyzed [8].

The experimental studies may involve materials properties identification experiments, reduced scale experiments and on-site measurements of accelerations and/or displacements in the track. One of the earliest empirical formulae used to determine the track's settlement was issued by Sato. This formula takes into consideration the train velocity, the applied load, and the effect factors for rail and subgrade [9]. Gao and Zhai have also established a more developed empirical formula that considers the coupling between track responses and vehicle dynamics [10]. One of the simplest experiments at real scale was represented by a concrete block on ballast and soil layers and conducted by Cottineau et al. at LCPC Nantes [11]. This type of experiment allows the application of dynamic forces to the block; however, it does not allow the application of a moving load. Al Shaer et al. performed a reduced scale experiment at Navier Laboratory that included three sleepers and takes into consideration the moving load aspect with various rolling speeds and different measurements including displacements and accelerations [12]. On-site measurements are also available and conducted by railway tracks societies for the purpose of monitoring track damage. Although such measurements reflect mostly the reality, they are still including noisy measurements in the track, so they require denoising of collected data before extracting any useful information that can be relied upon, and it cannot allow changes in the rolling speed of trains.

Recently, machine learning was introduced into the domain of railway tracks. So far, most of the work, including machine learning, tackles either a classification or a monitoring task and the assessment of a model is done based on the coefficient of determination, R^2. Ferreño et al. predicted the dynamic stiffness of rail pads, using several Machine Learning (ML) algorithms, depending on their in-service conditions (temperature, frequency, axle-load, and toe-load). This dynamic stiffness is crucial for minimizing maintenance costs and maximizing the durability of railway infrastructure. It was observed that the optimal algorithm was Gradient Boosting with high R^2 and low mean absolute percentage error in tested dataset [13]. Yan et al. built a prediction model of subgrade uplift utilizing Artificial Neural Networks (ANN), Random Forests (RF), and Support Vector Machine (SVM) algorithms. All three models exhibited strong predictive performance, with RF demonstrating the highest accuracy. They also offered guidance for mitigating the risks associated with subgrade uplift during the construction of high-speed railways [14]. Malekjafarian et al. proposed a railway track monitoring approach that uses acceleration responses measured on an in-service train to detect the loss of stiffness in the track sub-layers. A numerical model of a half-car train coupled with a track profile is employed to simulate the train vertical acceleration, and Artificial Neural Network (ANN) algorithm is developed based on the energies of the train acceleration responses [15]. Guo et al. proposed a method for monitoring ballast-less track slab deformation using fiber optic sensing technology for the track-side vibration monitoring and an intelligent method for identifying track slab deformation using the Random Forest model [16].

The aim of the present work is to predict the elastic vertical displacement, the positive and negative vertical accelerations, and permanent settlement of the middle sleeper in a reduced scale portion of a ballasted railway track of three sleepers using machine learning approaches for different speeds of trains and a given number of cycles. In the experiment, a cycle stands for the movement of two-axle wheels on the sleepers that was represented by a force having the shape of the letter "M" using hydraulic jacks. Collected data include both displacements and accelerations and for a variety of train speeds, namely higher speeds, where this luxury of data is not available throughout on-site measurements or other reduced scale experiments. Several machine learnings methods were used in order to predict the maximum elastic displacement, the positive and negative accelerations, and the permanent settlement for a given number of rolling cycles. The data includes 200 000 cycles for each of the following real scale train velocities 160, 210, 270, 320, 360, 380, and 400 km/h. Approximately between 68 and 160 readings were collected at each velocity for different number of cycles within the 200 000 cycles.

2 REDUCED SCALE EXPERIMENT

The experiment is represented by a portion of a ballasted railway track including three sleepers while the rail is excluded and the load generated due to passing trains is exerted directly on the blocks of the sleepers based on the velocity of the passing train and using three hydraulic jacks [12]. The scale of the experiment is one third compared to the real track, it maintains the acceleration as conserved, the dimensions are 1/3 of the real ones, and all other parameters are changed according to scale factors that are determined based on the physical equations and the adopted similitude law. Table 1 presents scale factors for some parameters.

Parameter	Scale Factor	Parameter	Scale Factor	Parameter	Scale Factor
Length	1/3	Density	1	Speed	$1/\sqrt{3}$
Acceleration	1	Force	1/27	Time	$1/\sqrt{3}$

Table 1: Experiment scale factors.

Accelerometers, force and displacement transducers were installed on the right and left concrete blocks of each sleeper, also accelerometers were added within the ballast. Figure 1 shows an overall view of the experiment and the different used transducers.

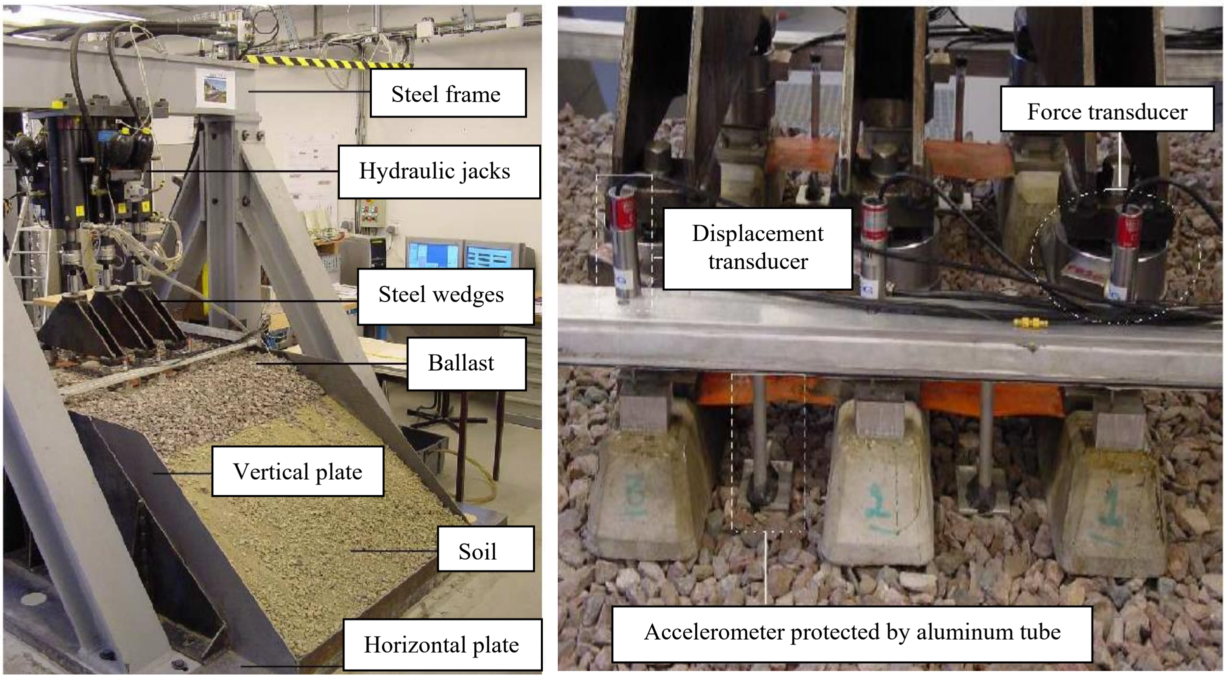

Figure 1: Reduced scale experiment and transducers.

The applied force is transmitted to the concrete blocks of the sleepers using hydraulic jacks through the steel wedges. The applied force is a force having the form of the letter "M" that is applied on the sleepers with a shift in time depending on the train rolling speed. It stands for the passing of a boogie with two axles that are 3 m apart where the distance between two consecutive boogies of two-wheel axles within a train is 18.7 m and the distance between two consecutive sleepers is 0.6 m in real scale. It is important to mention that this force depends on the load and the rolling velocity of the train, the distance between two consecutive sleepers, the distance between two consecutive two-wheel axles and the modulus of elasticity of soil. Figure 2 displays, for instance, a force that is applied on a concrete block due to a train real velocity of 360 km/h.

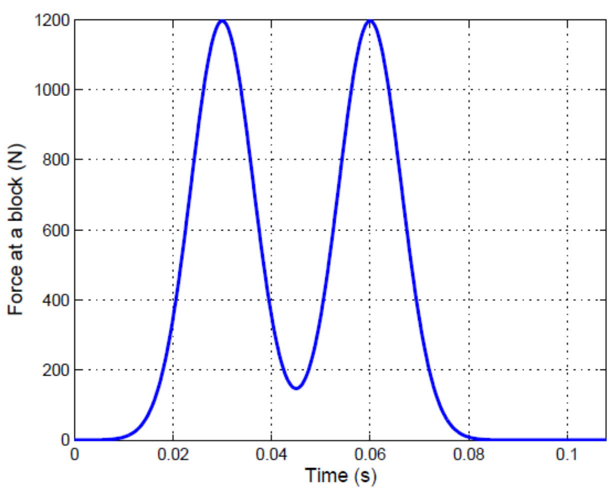

Figure 2: Applied force on a block with a train real velocity of 360 km/h.

The experiment consists in applying 200 000 cycles of passing boogies for each rolling velocity starting with the least velocity and ending with the highest one. The concerned real scale train velocities at which measurements are recorded are 160, 210, 270, 320, 360, 380 km/h, and 400 km/h. Approximately between 68 and 160 readings (displacements and accelerations) were collected at each velocity for different number of cycles within the 200 000 cycles. Also, data are extracted from four experiments that follow the same typical planning which is summarized in Figure 3.

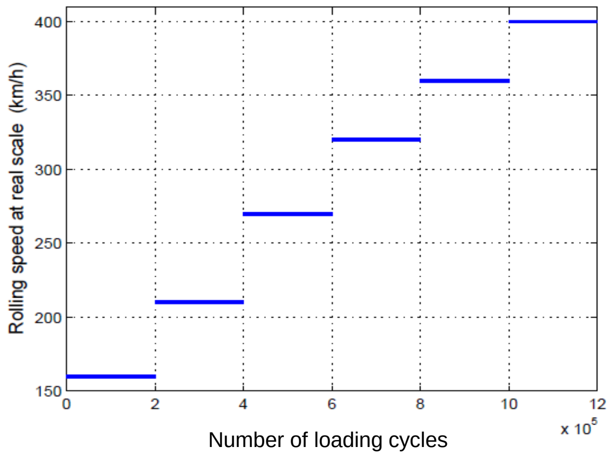

Figure 3: Planning of a typical experiment.

In this paper, interest is given to the measured vertical accelerations and vertical displacements at the left and right concrete blocks of the middle (second) sleeper as its position allows to have these blocks loaded when train reaches the first sleeper, the middle sleeper, and the third one.

3 MACHINE LEARNING APPROACH

This section is dedicated to data definition, pre-processing, training, validation and results using machine learning algorithms. It describes the data treated and the different phases through which data processing undergoes and the percentages of data that are classified for training, validation and testing. It also presents various machine learning algorithms that are used, the associated results of predicted elastic and permanent vertical displacements and maximum and minimum vertical accelerations along with the relevant R^2-scores.

3.1 Data definition

The data treated are represented by the following three parameters.

- Elastic vertical displacement: the maximum elastic displacement of a block in the middle sleeper is determined by subtracting the initial value of displacement transducer reading from the maximum value obtained in a displacement reading which has the shape of the letter “M” in accord with the applied force on the block. Figure 4 shows an example of displacement reading points for a real scale velocity of 210 km/h and a number of cycles of 128589. The displacement readings are shown as a function of the number of measuring points that are equal to 120 points along the x-axis.

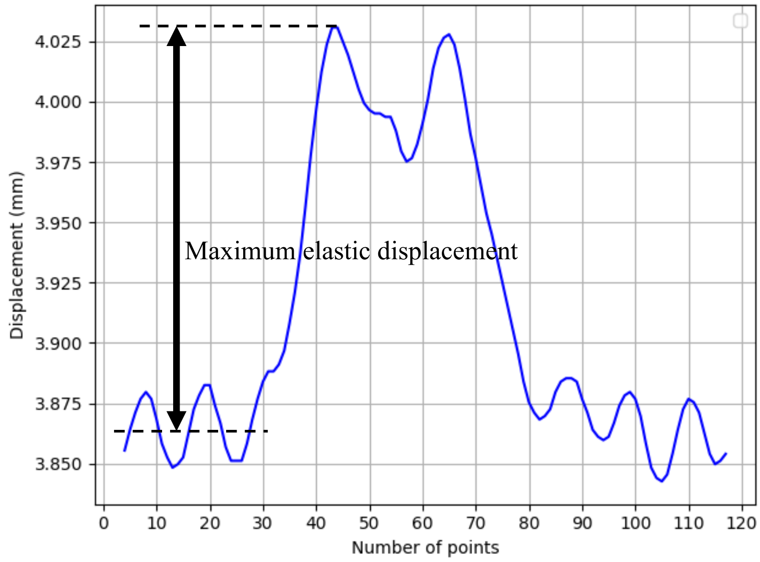

Figure 4: Maximum vertical elastic displacement for a rolling velocity of 210 km/h and 128589 cycles.

- Permanent settlement: the permanent vertical displacement of a block in the middle sleeper between two numbers of cycles is determined by subtracting the initial reading of the displacement when the block is not loaded at a given number of cycles from initial reading of the displacement when the block is not loaded at the next number of cycles at which acquisition is taken. Figure 5 shows the permanent settlement for a rolling velocity of 210 km/h between 128589 and 130212 cycles.

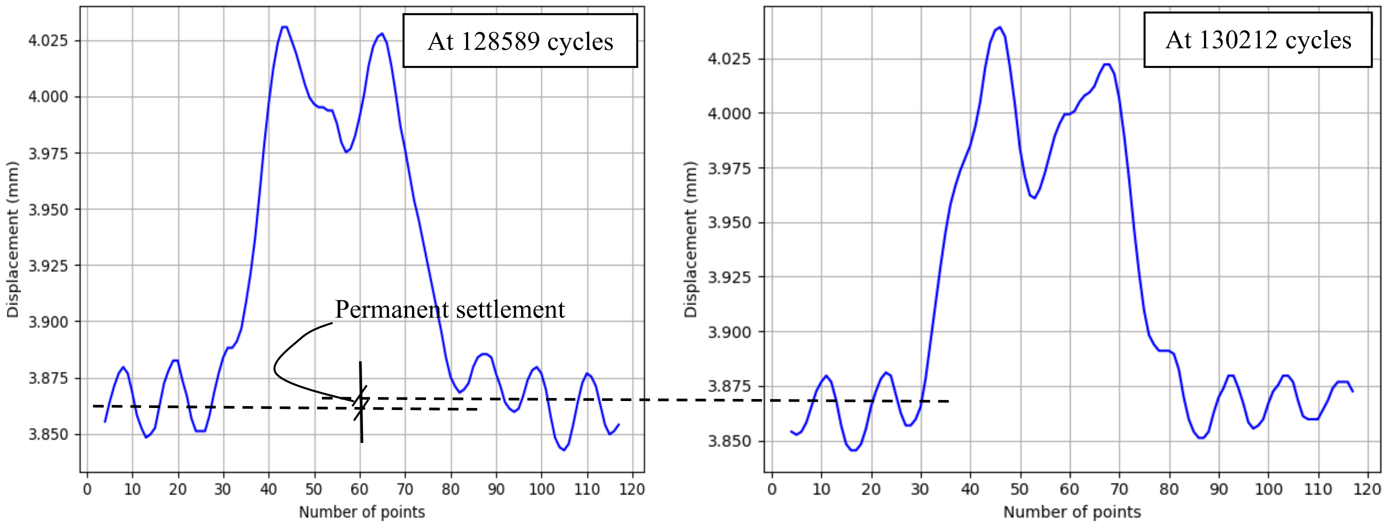

Figure 5: Permanent settlement between 128589 cycles and 130212 cycles for a rolling velocity of 210 km/h.

- Acceleration: there are two important values for the vertical acceleration of a block in the middle sleeper, one for the maximum value (upward acceleration – positive value) and the other for the minimum value (downward acceleration – negative value) that are measured by the accelerometer at a block in a sleeper for a given number of cycles. Figure 6 shows an example of acceleration reading points for a real scale velocity of 210 km/h and a number of cycles of 128589.

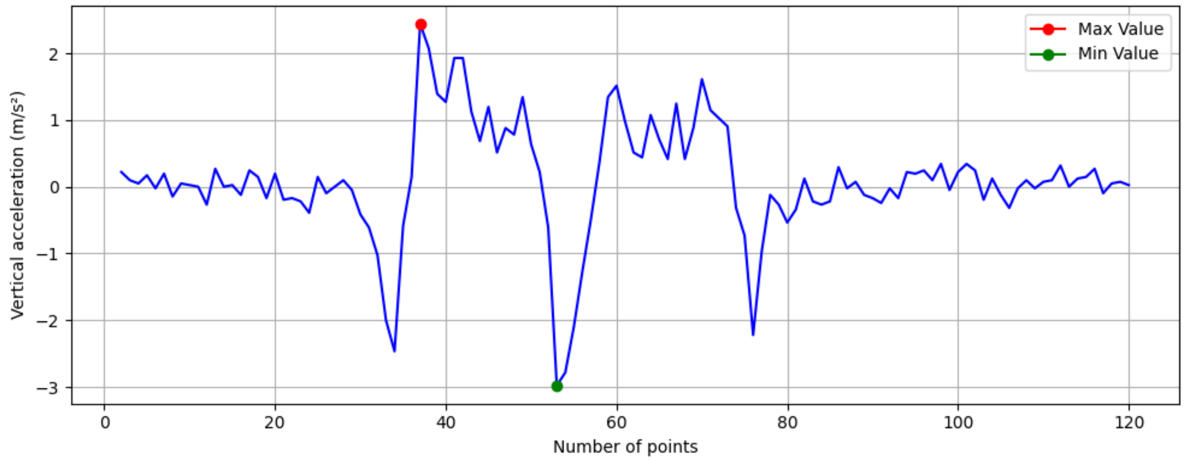

Figure 6: Maximum and minimum accelerations for a rolling velocity of 210 km/h and 128589 cycles.

3.2 Model performance, data preprocessing and model training

To assess the model's performance and ensure generalizability to unseen data, both a validation set for tuning, and a test set for final evaluation were used. The model performance is determined using the coefficient of determination (R^2-score) applied on test data. It measures how well the model's predictions align with actual values, where a perfect prediction results in an R^2-score of 1, while lower scores indicate poorer predictive performance, potentially reaching negative values.

Data preprocessing is a key stage before applying machine learning models. The preprocessing stage was the starting point for predicting maximum elastic displacement, permanent settlement, and acceleration. It is composed of three steps and was initially based on maximum elastic displacement data and then applied to other parameters. The first step involved gathering data related to various velocities and experiments, aiming to consolidate all fragmented information into a single table for model training. After the initial preprocessing step, a second step was required to refine the data further. To determine the most effective preprocessing approach, three phases were tested using the Random Forest algorithm, with R^2-scores on test data guiding the selection process.

- Phase 1: Datasets were combined into one table. Then, data for right and left blocks of the middle sleeper were distinguished. After testing the models in this phase, the Random Forest algorithm returned R^2-score of 0.69 on test data.
- Phase 2: After having a low score in phase 1, dataset related to the rolling velocity of 400 km/h is removed, as values of this data had a high fluctuation and lack of measurements when the displacement of one of the two concrete blocks exceed the transducer limit. The score was then increased after testing the Random Forest algorithm in this phase, where R^2-score becomes 0.86 on test data.
- Phase 3: In this phase, the four repeated different experiments had different results but have a very high correlation between them. Therefore, data obtained from these experiments were averaged together based on velocity and cycle numbers. After testing this phase, the R^2-score becomes 0.99 on test data.

Therefore, the adopted preprocessing step involved removing readings for the velocity of 400 km/h. The data was then grouped and averaged based on velocity and cycle numbers across the different experiments. Additionally, displacement transducers readings for the right and left concrete blocks of the middle sleeper were also averaged, therefore their mean values were considered to ensure consistency in the dataset. Finally, the cleaned and pre-processed data was split into training and validation datasets to train machine learning models, including elastic displacement, permanent settlement, and acceleration models. Figure 7 shows a flowchart summary for the conducted work where 64 % of the data was reserved for training, 16% of the data for validation and the remaining 20 % are set for testing.

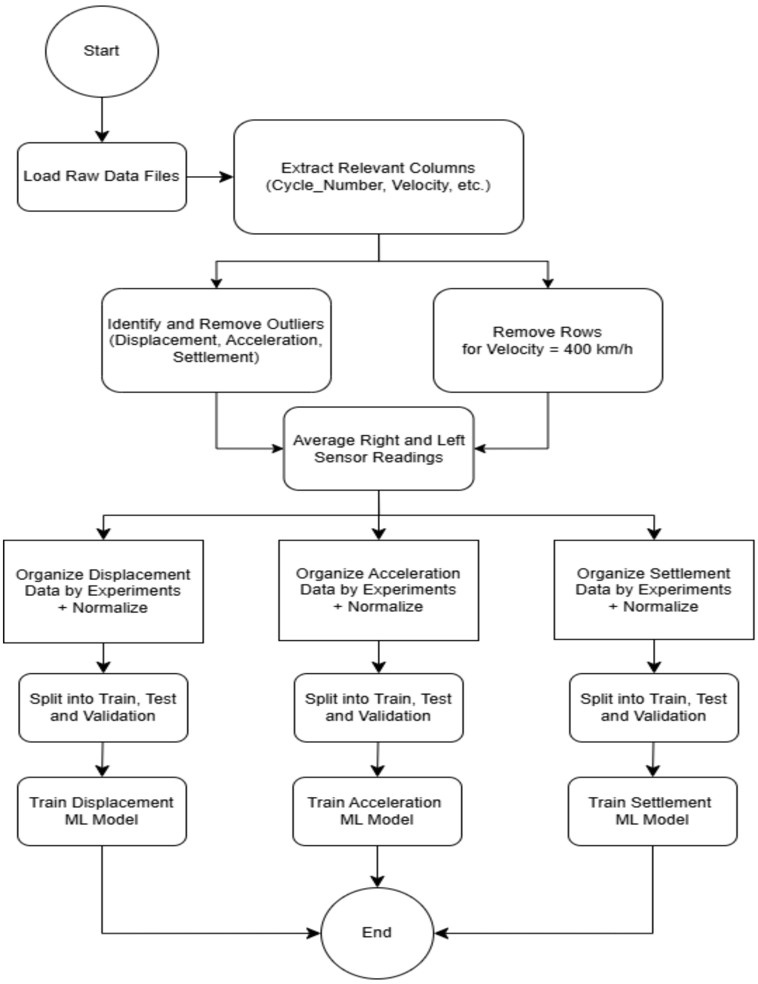

Figure 7: Work flow-chart summary.

3.3 Results and comparison

Several decision-tree-based ensemble machine learning models are tested to analyze the dataset and predict the maximum elastic displacement, the permanent settlement and the acceleration of a block in the middle sleeper. Performance of each model depends heavily on data size and complexity. The tested models are represented by Random Forest Regressor, Light GBM, and XGBoost Regressor. However, Support Vector Regressor (SVR) and Deep Learning models such as Artificial Neural Networks (ANN) were excluded since these models require a very large size of data and this requirement is not fulfilled in the present experiment.

After evaluating the models, the Random Forest Regressor and Light GBM demonstrated strong performance on the test data achieving the highest R^2-scores. Table 2 presents the obtained R^2-scores for each model's performance on the test set for the different predicted parameters.

Machine Learning Algorithm	R^2-Score			
	Elastic Displacement	Permanent Settlement	Maximum Acceleration	Minimum Acceleration
Random Forest Regressor	0.9959	0.9964	0.9976	0.9962
Light GBM	0.9959	0.9978	0.9976	-5.3076
XGBoost Regressor	-0.0171	0.7714	0.8746	0.8706

Table 2: R^2-score for various predicted parameters across different machine learning algorithms.

The Random Forest Regressor outperformed the other models, attaining the highest R^2-score, and it was selected to present the predicted results for the various parameters.

In figure 8, the predicted results in colored lines versus the measured values of the maximum elastic displacement represented by blue points are shown for a 50 000 loading cycles at each of the following rolling speeds 160, 320, 360 and 380 km/h. For high velocities the maximum elastic displacement increases as the number of cycles increases. However, for low velocity such as 160 km/h, it starts with high values at the beginning of the experiment and decreases with the increase in the number of cycles then it may stabilize for higher cycles.

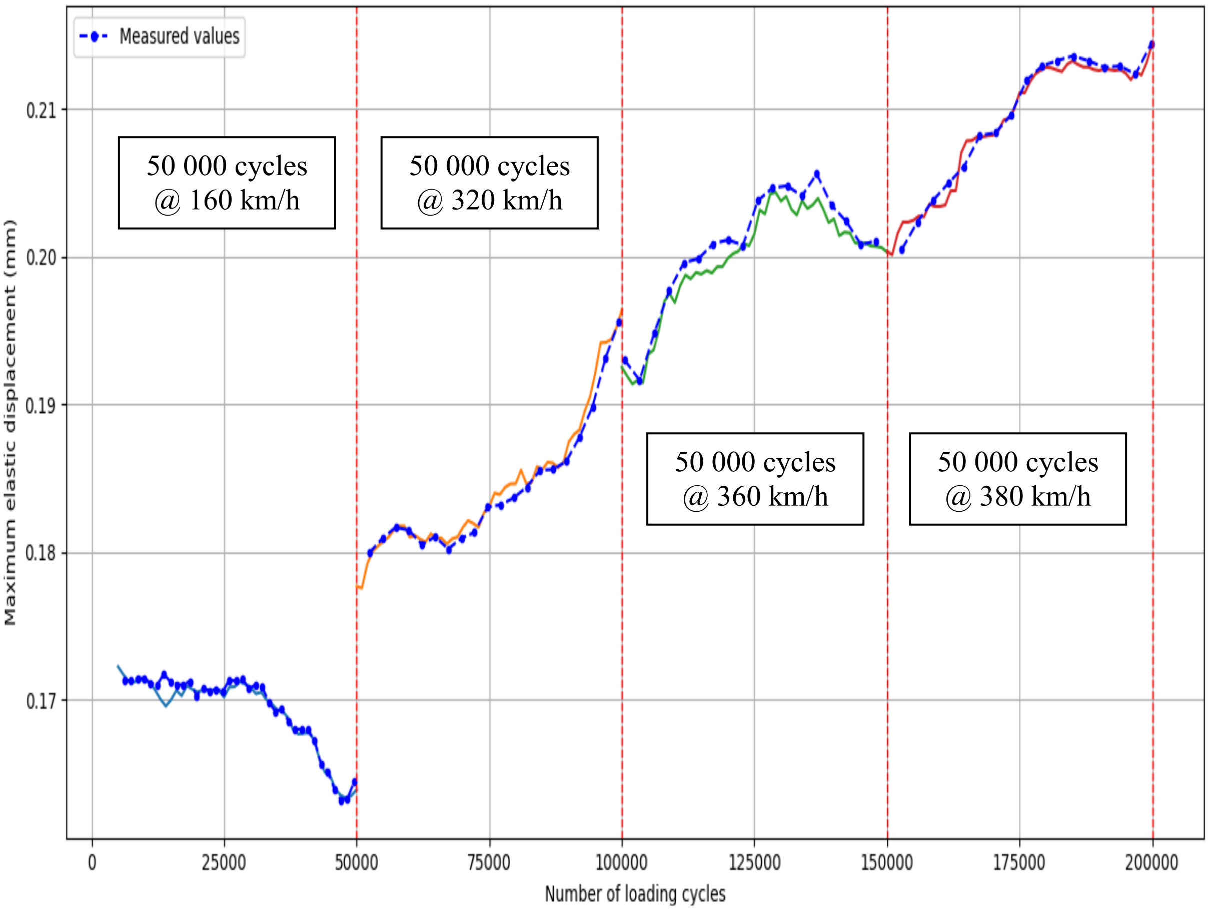

Figure 8: Predicted maximum elastic displacement versus measured values.

In figure 9, the predicted results in colored lines versus the measured values of the permanent settlement in blue points are shown for the same planning of cycles and rolling speeds.

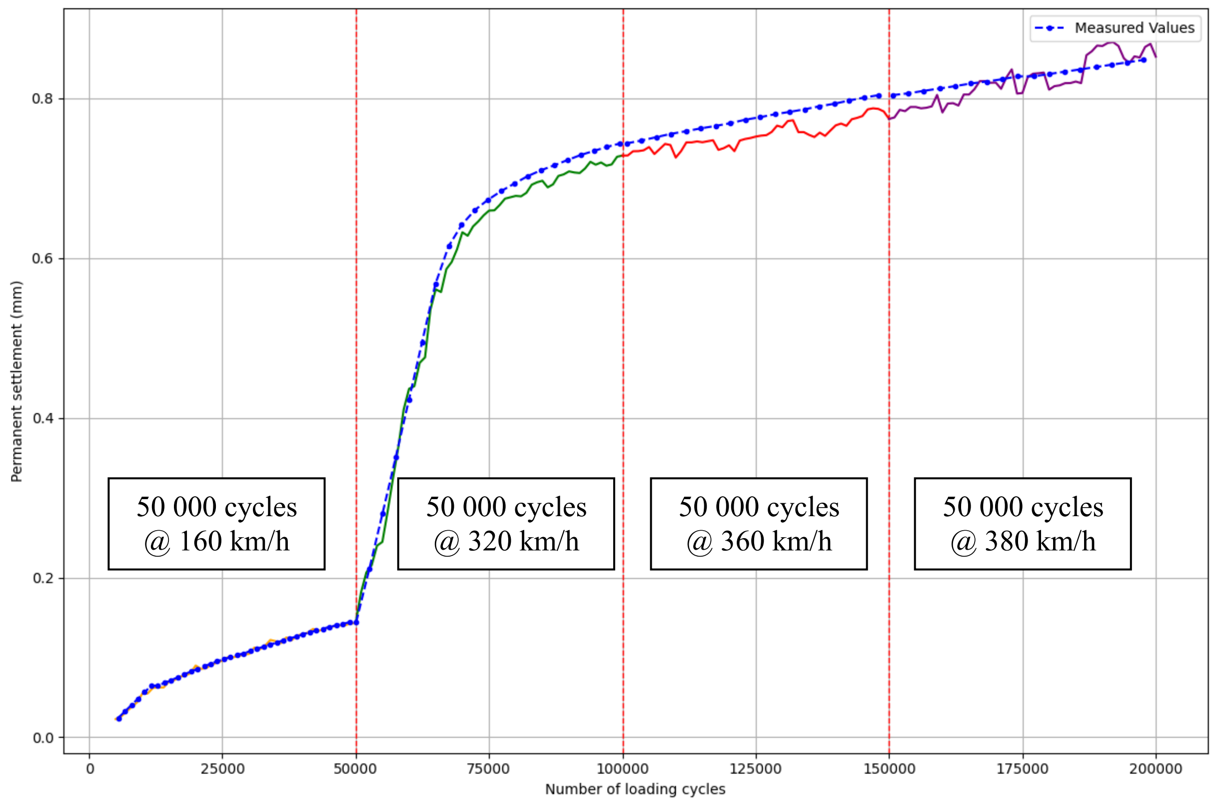

Figure 9: Predicted permanent settlement versus measured values.

In figures 10 and 11, the predicted results in colored lines versus the measured values of the maximum and minimum acceleration in blue points are shown. Accelerations are increasing with the increase in rolling speeds.

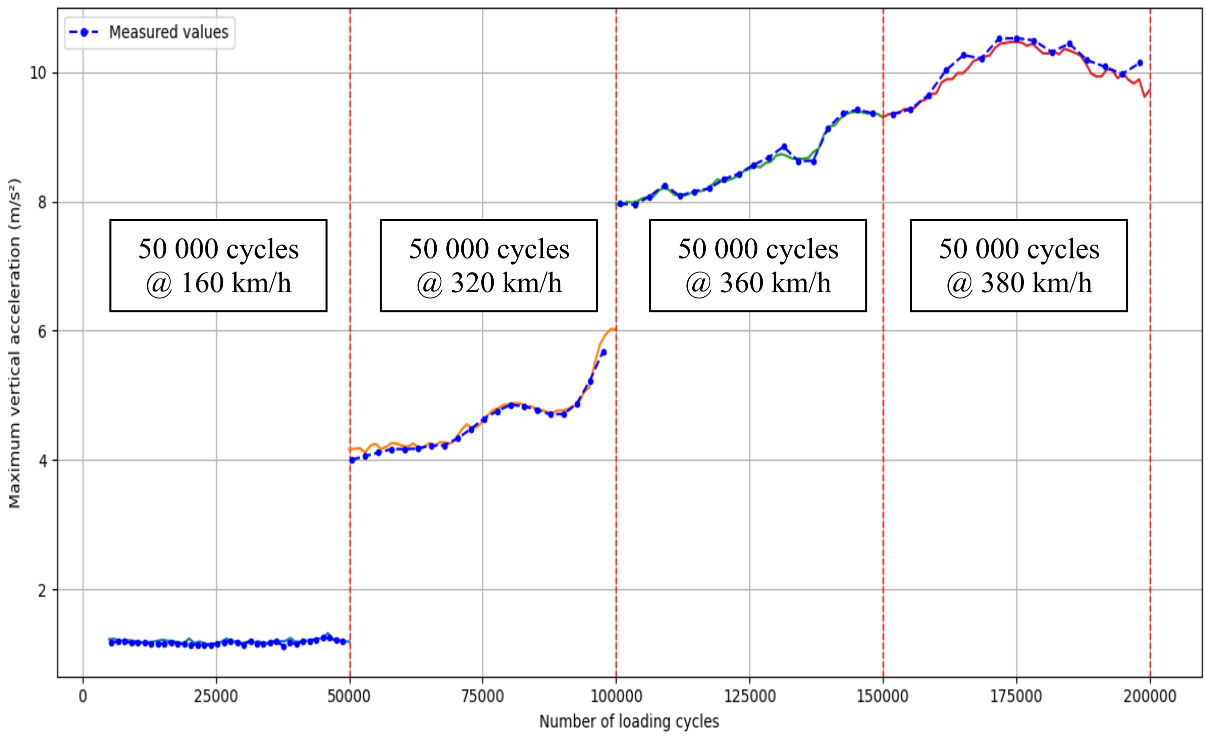

Figure 10: Predicted maximum acceleration versus measured values.

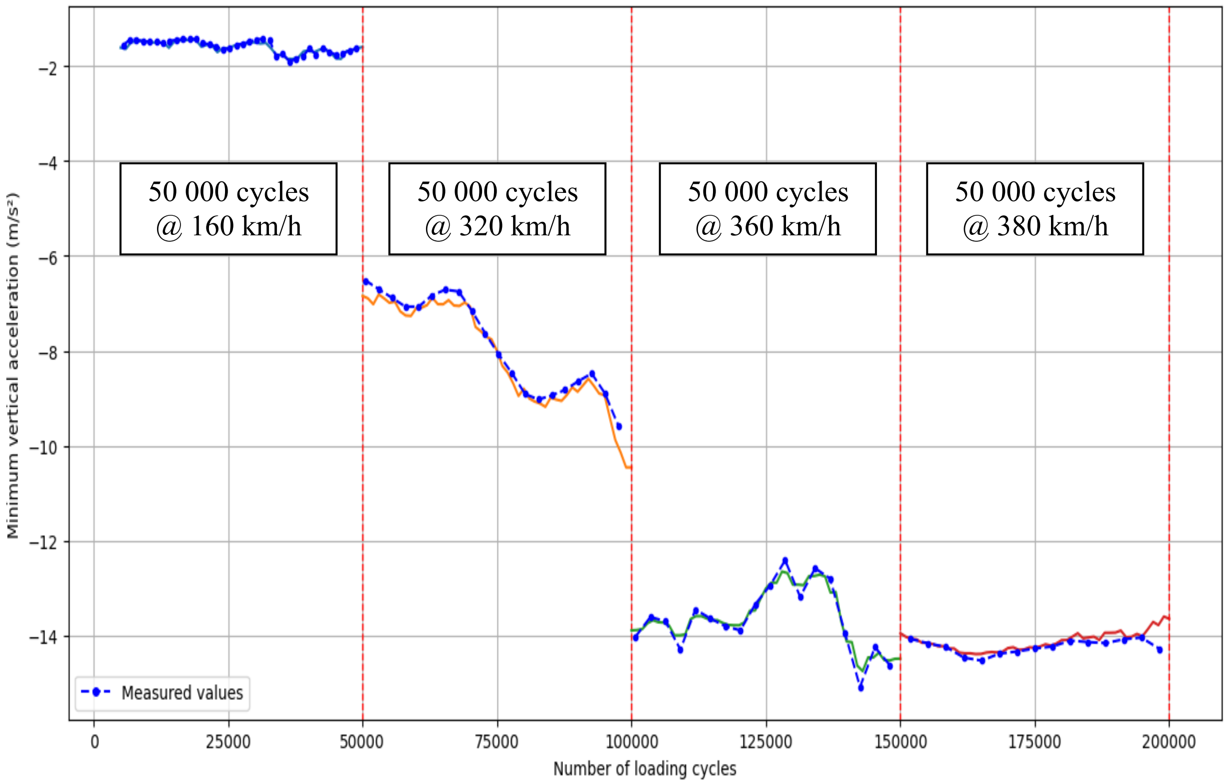

Figure 11: Predicted minimum acceleration versus measured values.

4 CONCLUSIONS

The high-speed ballasted railway tracks present challenges for researchers to understand their dynamic behavior and to predict the quality of the track. In this context, this work was conducted based on experimental data obtained from a reduced scale experiment with three sleepers, and the following conclusions were extracted.

- Different machine learning algorithms were used in order to predict the maximum elastic displacement, the permanent settlement, and the maximum and minimum accelerations of a block related to the middle sleeper for a given rolling speed and number of loading cycles.
- Random Forest Regressor outperforms the different proposed decision-tree-based ensemble machine learning algorithms with high R^2-scores for the different predicted parameters.
- Available experimental data can be employed in future work to predict via machine learning algorithms, the mechanical properties or dynamic stiffnesses for each one of the different components or layers in the reduced scale experiment.
- The reduced scale experiment is unable to provide information that could be useful in the assessment of track quality as it is restricted to three sleepers, however numerical models that are based on material identification from the reduced scale experiment could be used and combined with machine learning algorithms in order to assess the quality of the ballasted railway track with respect to the permanent settlement values.
- It would be also interesting to select a different trained data set while keeping the same percentage and studying the impact on the model's performance.

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