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AN INNOVATIVE DATA-DRIVEN HYBRID METHODOLOGY FOR RELIABLE PREDICTION OF RAIL TRACK DEFORMATION

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ABSTRACT: Accurate prediction of accumulated permanent track deformation (settlement) under cyclic loading is vital for effective track geometry maintenance and cost-efficient railway infrastructure management. This study introduces a novel approach to forecasting long-term settlement with reduced computational demands, combining advanced numerical and data-driven methodologies. Leveraging a comprehensive parameter study, the approach evaluates both short- and long-term track performance, integrating machine learning techniques to develop predictive models. A machine learning algorithm was studied, with model validation performed using field data from a ballasted track demonstrator from a transition zone. Performance metrics are used to assess model accuracy. The random forest algorithm was selected and exhibits strong agreement with measured settlement data, demonstrating its robustness and predictive reliability. By bridging the gap between numerical simulations and empirical observations, this hybrid methodology enhances the prediction of both resilient and permanent track deformation, both critical parameters in design and operation. The findings offer a cost-effective tool for railway managers, paving the way for its integration into computational decision support systems for maintenance and renewal planning. This innovative hybrid methodology not only enhances infrastructure management practices but also supports the sustainable and dependable operation of railway networks, ensuring both short- and long-term efficiency and resilience.

KEYWORDS: Machine learning algorithm, permanent deformation, prediction infrastructure life-cycle management, validation.

1 INTRODUCTION

Long-term settlement of railway tracks, induced by cyclic loading from passing trains, presents substantial challenges for railway infrastructure management, primarily due to the high maintenance demands and associated costs (Nielsen et al., 2018). This underscores the need for more accurate predictive models capable of assessing both short-term and, critically, long-term track performance (Ramos et al., 2023), enabling the development of strategies to improve system reliability and reduce life-cycle costs (Sadri et al., 2018).

The subgrade is a key factor governing the track's mechanical behaviour, exhibiting two distinct deformation responses under cyclic loading: resilient and permanent. Resilient deformation affects short-term performance during train passages, whereas permanent deformation governs the long-term structural behaviour (Ling et al., 2017). To predict permanent deformation, various approaches have been adopted, including elastoplastic constitutive models, shakedown theory, and mechanistic–empirical formulations, typically calibrated using laboratory experiments such as cyclic triaxial tests. Mechanistic–empirical models applied in the scope of the permanent deformation prediction offer a practical and straightforward approach, as they directly relate the number of load cycles to the accumulated settlement. These models are typically derived from extensive laboratory testing and require fewer input parameters than conventional elastoplastic formulations, making them easier to implement in engineering practice (Ramos et al., 2020).

To address this gap, the present study proposes a novel methodology that employs machine learning (ML) algorithm to

predict permanent deformation and settlement in railway systems. While previous research has primarily focused on short-term performance indicators such as the resilient modulus, relatively few studies have applied ML techniques to predict long-term permanent deformation (Alnedawi et al. 2019; Hao et al. 2022; Hua et al. 2022). ML approaches are well suited to this task, as they can efficiently capture complex, nonlinear relationships between input variables and target responses, even in challenging geotechnical contexts (Ghorbani et al. 2021; Rezaei-Tarahomi, et al. 2017, Tinoco et al. 2018).

The methodology developed in this study integrates a hybrid modelling framework consisting of a 2.5D FEM–PML track model and an empirical permanent deformation formulation (Ramos et al., 2021a). Model performance is further enhanced through hyperparameter optimisation.

A key feature of the work is the experimental validation of the ML predictions against independent field measurements, enabling the evaluation of model performance under real-world conditions. This strengthens the model's applicability for long-term track performance assessment.

Although ML has been increasingly explored in railway engineering, few studies have addressed the prediction of permanent deformation in track subgrades within a fully coupled vehicle–track modelling framework, with most efforts focusing on ANN-based approaches (Ghorbani et al. 2020 and 2023; Indraratna et al. 2023; Oskooeie et al. 2020). In this paper, a ML algorithm is investigated —random forest. The model is trained on a large dataset generated from numerical simulations using the proposed hybrid approach, ensuring that the key mechanical and operational features of the vehicle–track system are adequately represented.

2 DATABASE

2.1 Generation of the database

Figure 1 presents an overview of the proposed framework for model development and database generation. Starting from a validated finite element model of a railway track, a comprehensive knowledge database was constructed. This database comprises generated input parameters—each defined within a specified range—and the corresponding permanent deformations calculated for various numbers of load cycles, representing train passages. The finite element-based knowledge database was then used to train the selected machine learning model, enabling the identification of relationships between the input parameters and the predicted permanent deformation.

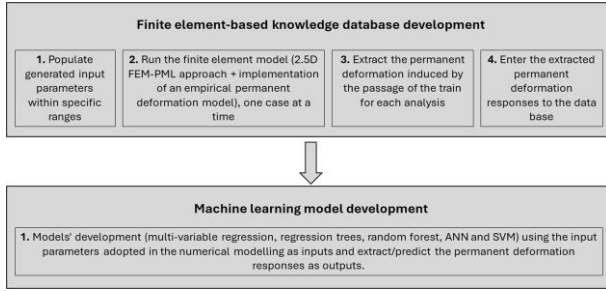


Figure 1. Example of the development approach

The short-term performance of the railway track was evaluated using a 2.5D FEM–PML approach, which offers high accuracy while maintaining low computational cost, even when accounting for the inherently three-dimensional nature of the problem (Alves Costa et al. 2010; Sheng et al. 2006; Yang & Hung 2001). This method assumes a linear structural response and an invariant cross-section along the track. These conditions are satisfied in the present study, as the analysis does not include discontinuities or transitions. Furthermore, modelling the soil as a linear elastic material is a reasonable approximation, as the investigation focuses exclusively on small-strain behaviour.

Regarding the long-term simulation, in this study, an empirical permanent deformation model was adopted to describe the development of track degradation. The chosen formulation, based on the work of Chen et al. (2014), accounts for the combined effects of the number of load cycles (N), the initial stress state ($p_{(ini)}$ and $q_{(ini)}$), and the stress levels induced in the subgrade during train passages ($p_{(am)}$ and $q_{(am)}$). In addition, it incorporates the influence of a yield criterion through the parameters s and m , which are directly related to soil cohesion and friction angle, respectively:

$$\begin{aligned} \varepsilon_1^p(N) &= \varepsilon_1^{p0} [1 - e^{-BN}] \left(\frac{\sqrt{p_{am}^2 + q_{am}^2}}{p_a} \right)^a \\ &\cdot \frac{1}{m \left(1 + \frac{p_{ini}}{p_{am}} \right) + \frac{s}{p_{am}} - \frac{(q_{ini} + q_{am})}{p_{am}}} \end{aligned} \quad (1)$$

Where ε_1^{p0} , B and a are the material constants, while m and s are defined by the criterion $q=s+m.p$.

Thus, it is assumed that the long-term permanent deformation is determined based on the short-term response (i.e., stresses generated during the train passage). Then, Eq. (1) is used to calculate the permanent deformation/strain at any given number of load cycles N

2.2 Database development

To develop machine learning models for predicting permanent deformation, a database was constructed based on a parametric study reported in (Ramos et al., 2021a). This study examined the influence of multiple factors on subgrade performance across three railway track configurations: a conventional ballasted track, a ballastless track, and an optimised ballastless track consisting solely of a concrete slab, with the underlying support layers omitted.

As the key factors influencing subgrade performance had been analysed in detail in previous work, most were selected as input variables for the machine learning models. For each variable, a range of values was defined to represent typical field conditions, rather than being randomly generated. The parameter study considered three railway track types (ballasted, ballastless, and optimised ballastless), four wavelength ranges, four train speeds, and various subgrade mechanical properties—comprising all possible combinations of three resilient modulus levels, four friction angles, and three cohesion values—as well as five positions along the unevenness profile (Ramos et al., 2021a).

For each combination of variables, the maximum, mean, and deviatoric stresses (p and q , respectively) were obtained and stored in the database as inputs for the ML model. Additional variables included the number of load cycles (N) and the empirical model constants (ε_{p1} , B , and a), as permanent deformation is strongly influenced by these parameters according to both empirical evidence and laboratory cyclic triaxial tests (Ramos et al., 2020).

Using the 2.5D FEM–PML approach, the short-term response was computed by determining the stresses, principal stresses, and corresponding mean and deviatoric stresses under quasi-static and dynamic loads. Each simulation of the short-term response required approximately two days, due to the need to compute transfer functions in the frequency domain and transform the results into the time domain. These stresses were then applied to the empirical permanent deformation model, with yield criterion parameters and strength properties (cohesion and friction angle) also provided as inputs. Long-term performance simulations, including post-processing, required 2–3 hours depending on the model size. Compared with this process, running the trained ML model required negligible computation time.

Each database entry corresponded to a single finite element model run. The short-term simulation results were first compiled into a MATLAB database containing variables such as track type, wavelength, train speed, resilient modulus, position along the unevenness profile, and mean and deviatoric stresses. This “short” database was then expanded by incorporating long-term parameters (number of load cycles, model constants, cohesion, and friction angle). The final dataset, comprising 186,000 observations, was generated by repeating the short database while varying long-term parameters. The database was then imported into R (R_Core_Team, 2021) for ML model training.

This approach enables significant computational savings, reducing the per-element simulation time by 2–3 hours compared with full FEM analysis. The ultimate objective is to predict the permanent deformation of each finite element and the corresponding accumulated permanent settlement—defined as the sum of the permanent deformations across all elements along a vertical alignment. For large-scale models, the efficiency gains from the ML approach are substantial.

2.3 Statistical analysis

Each dataset in the database is characterised by 16 inputs/predictors and the predicted variable, which is the

permanent deformation. To summarise, each dataset is characterised by the variables presented in Figure 2.

In the models, these variables are identified by the following designations x_i ($i = 1, 2, 3, \dots, 16$).

Code	Variable	Abbrev.	Category	Min	Max	Average	Unique values
x1	Ballasted track	B.t	Input	0.000	1.000	0.323	2
x2	Optimised ballastless track	O.bl.T	Input	0.000	1.000	0.323	2
x3	$1 < \lambda < 3$ [m]	$1 < \lambda < 3$	Input	0.000	1.000	0.048	2
x4	$3 < \lambda < 25$ [m]	$3 < \lambda < 25$	Input	0.000	1.000	0.048	2
x5	$25 < \lambda < 70$ [m]	$25 < \lambda < 70$	Input	0.000	1.000	0.048	2
x6	Position [m]	P	Input	-85.650	41.400	-7.473	5
x7	Resilient modulus [MPa]	M_r	Input	90.000	280.000	152.661	4
x8	Cohesion [kPa]	c	Input	0.000	10.000	5.000	3
x9	Friction angle [°]	ϕ	Input	28.000	40.000	31.952	4
x10	Train speed [km/h]	v	Input	80.000	500.000	257.290	6
x11	Maximum deviatoric stress [Pa]	q_{max}	Input	10229.920	26238.190	12914.500	62
x12	Maximum mean stress [Pa]	p_{max}	Input	5660.234	14985.950	7872.714	62
x13	Material constant a	a	Input	0.017	0.650	0.399	4
x14	Material constant B	B	Input	0.006	0.222	0.163	4
x15	Material constant		Input	0.001	0.429	0.091	4
x16	Number of load cycles	N	Input	1	996,001	498,001	250
Y	Permanent deformation (%)		Output	0.002	2.459	0.295	152.250

Figure 2. Statistical information regarding variables used to predict the induced permanent deformation

In this dataset, there are no missing values since the database was repeatedly filled during the process described previously. From the dataset, a statistical analysis was performed considering box plots and correlograms. The last ones show that the variables x7 and x9 (“Resilient modulus” and “Friction angle”, respectively) present a very high positive correlation (close to 1). This means that one of these variables should be excluded from the permanent deformation model. In this case, the “Friction angle” variable was eliminated.

2.4 Modelling process

During the modelling process, the key parameters governing the performance of the machine learning algorithm were optimised to maximise predictive accuracy. The k -fold cross-validation strategy was adopted to partition the dataset into multiple training-validation splits, thereby reducing the risk of overfitting. The efficiency, accuracy, and robustness of the predictive model were assessed using multiple evaluation metrics, including the coefficient of determination (R^2), standard deviation (σ), root mean square error (RMSE), mean absolute error (MAE), and mean squared error (MSE).

This random forest algorithm is highly robust to outliers and generally does not require extensive pre-processing. Its main limitation is lower interpretability, and although it provides accurate predictions, it often cannot outperform advanced boosting algorithms.

In this study, the *randomForest* function in R was used. By default, the algorithm constructs 500 trees, with the number of variables considered at each split set to 3. Model performance was evaluated using a plot of the error rate as additional trees were added. As shown in Figure 3, the error rate stabilizes at around 100 trees but continues to decrease gradually until reaching 500 trees, the maximum value adopted. The figure also highlights the minimum error and the corresponding number of trees.

Additionally, the optimal number of candidate variables to consider at each split was determined. The tuneRF function was employed to identify the best value of mtry, corresponding to the lowest error, thereby determining the optimal number of predictors (p) for the model.

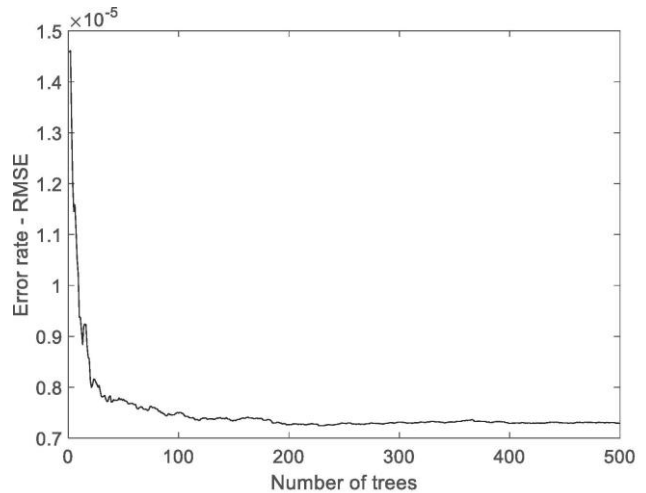


Figure 3. Development of the random forest model (minimum error=0.0027 and number of trees=229)

As described in previous section, the performance of the model was analysed in detail considering the metrics R^2 , σ , RMSE, MAE, MSE. The results are presented in Table 1.

Table 1. Random Forest performance

Parameter	Value
R^2	0.999
σ	0.5715
RMSE	0.0022
MAE	0.0004
MSE	4.966e-5

3 FIELD VALIDATION

In this section, the random forest model is validated against long-term settlement data measured in the field for the ballasted track at the transition zone (Nasrollahi et al, 2023a 2023b). Permanent settlements of the track structure were recorded at a test site on the Swedish heavy-haul line, Malmbanan, at Gransjö, north of Boden. Malmbanan is a single-track railway in northern Sweden primarily serving iron ore freight trains with axle loads up to 32.5 tonnes and speeds of 60 km/h (70 km/h in tare conditions). The annual traffic is approximately 15 MGT (Mega Gross Tonnes), corresponding to around 850,000 axles in loaded and unloaded iron ore trains.

Extensive measurements were performed in the transition zone between the conventional ballasted track and a 48 m section of a Moulded Modular Multi-Blocks (3 MB) slab track, discretely supported at a rail seat distance of 0.6 m. The 3 MB system is composed of 4.8 m modules, each with a base slab

consisting of two longitudinal reinforced concrete beams connected by two transverse beams. Each module also contains eight precast moulded concrete blocks, with four blocks positioned on each longitudinal beam. To mitigate the stiffness gradient in the transition zone, under-sleeper pads were installed in the ballasted track.

The subgrade consists primarily of moraine extending to a depth of up to 5 m before reaching bedrock, with embankment heights ranging from 2.0 to 2.5 m. Material properties for ballast, sub-ballast, and soil layers 1 and 2 were determined via in situ MASW (Multichannel Analysis of Surface Waves) testing (Nasrollahi et al., 2023b). Rail, rail pad, and sleeper properties were provided by the manufacturers. A summary of track properties is presented in Table 2.

Table 2. Adopted properties for the numerical model

Parameter	E (MPa)	ν	ρ (kg/m ³)	α	β
Rail	200E3	0.30	7850	-	-
Railpad					
(ballasted track)	97.7	0.45	1200	3.06	7.76E-5
Railpad (slab track)	2.85	0.45	1200	3.06	7.76E-5
Sleeper	38E3	0.15	2500	-	-
Block	30E3	0.20	2500	0.61	1.55E-5
Concrete slab	30E3	0.20	2500	0.61	1.55E-5
Ballast	67.5	0.20	1800	1.84	4.66E-5
Sub-ballast	161.7	0.30	2100	1.84	4.66E-5
Soil layer 1	472.4	0.25	2100	1.84	4.66E-5
Soil layer 2	800	0.25	2100	1.84	4.66E-5

A real-time monitoring system was deployed to assess the impact of traffic load on cumulative differential settlement in the transition zone (Nasrollahi et al, 2023a 2023b). Monitoring occurred from September 2022 to June 2023, with vertical displacements of sleepers 5 and 11 measured using fibre Bragg grating (FBG)-based displacement transducers positioned at the ends of each sleeper. Displacements were recorded relative to a fixed anchor embedded deep in the ground. Initially, both sleepers exhibited a high settlement rate following the installation of the transition zone.

To evaluate the transition zone performance, a 3D finite element model (FEM) was developed replicating the conditions at the Gransjö site. The ballasted track at the test site includes 60 kg/m rails, rubber rail pads, and concrete sleepers, while the slab track section includes the rail as illustrated in Figure 4.

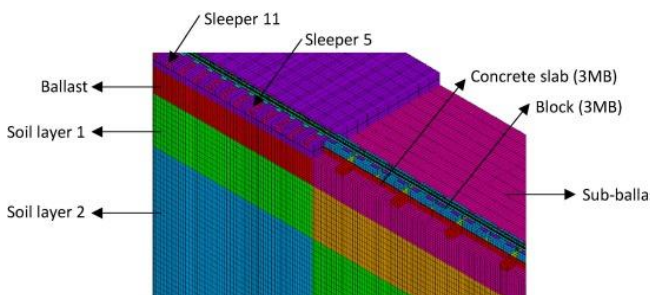


Figure 4. 3D numerical model of the transition zone

Using the calculated short-term stresses, the long-term permanent deformation and the corresponding settlement within the transition zone were predicted using the previously developed random forest model. This data-driven model was

trained to capture the complex relationships between stress conditions, material properties, and long-term deformation responses, enabling it to provide reliable estimates under varying track conditions.

For this analysis, the railway track was modeled as a conventional ballasted track system. The resilient modulus values were assigned independently to each layer—ballast, sub-ballast, and the two underlying soil strata—reflecting their respective mechanical behaviors and accounting for cohesion effects where relevant. This layer-specific characterization ensures that the stiffness contrasts across the transition zone are represented accurately, which is particularly important given the role of stiffness variability in the development of track irregularities.

A train speed of 60 km/h was assumed, representing typical operational conditions for the studied site and ensuring that the induced dynamic stresses align with realistic loading scenarios. The empirical model constants needed for the permanent deformation formulation were taken from Ramos et al. (2021a, 2021b), whose work provides validated parameter sets for similar track-subgrade configurations under cyclic loading. These constants, summarized in Table 3, serve as the backbone of the deformation prediction framework, linking applied stresses to long-term accumulation of plastic strain.

By integrating these inputs into the random forest prediction scheme, the analysis captures both the immediate mechanical response and the progressive deterioration expected over extended traffic loading. This enables a comprehensive evaluation of settlement development within the transition zone, supporting both model validation and the broader assessment of track performance.

Table 3. Adopted material constants for the empirical permanent deformation model

Parameter	ϵ_p^{p0}	a	B
Ballast	0.65	0.2	0.0093
Sub-ballast	0.65	0.2	-0.000041
Soil layer 1	0.65	0.2	-0.000041
Soil layer 2	0.65	0.2	-0.000041

Mean and deviatoric stresses vary according to the depth of each finite element and material type. Permanent deformation was predicted for each element of the 3D model. Subsequently, the cumulative settlement over the depth of each geomaterial element was calculated using the following equation:

$$\delta = \sum_{i=1}^n \epsilon_p^i \times h_i \quad (2)$$

Where i represents the number of elements, h_i is the thickness of each element (in m), and ϵ_p^i is the permanent deformation (dimensionless) of element i obtained through Equation 1.

The predicted long-term track deformation and the measured settlements are compared in Figure 5. The results indicate that the random forest model can effectively predict both permanent deformation and cumulative settlement in the ballasted track, providing a close match to the field observations. In particular, the model successfully captures the deformation trend after approximately 0.5 MGT, a phase during which the rate of settlement typically stabilizes and long-term behavior becomes more evident. This ability to reproduce the evolution of deformation over a significant loading history underscores the robustness of the model's learned relationships and its capability to generalize beyond the training dataset.

It is noteworthy that the field measurements—most prominently those corresponding to sleeper 5—are located near the transition zone. Such zones commonly exhibit highly variable mechanical responses due to abrupt changes in stiffness, support conditions, or material properties. These local variations often lead to irregular settlement patterns that are difficult to predict using traditional empirical or numerical methods. The fact that the random forest model is able to capture the deformation behavior in this challenging area highlights its adaptability and predictive strength.

Overall, this outcome serves as a strong cross-validation of the proposed methodology. The model not only performs well under uniform track conditions but also demonstrates reliability in complex scenarios where track behavior departs from standard assumptions. This reinforces the model's potential for practical implementation in track monitoring, maintenance planning, and the design of resilient transition zones in railway infrastructure.

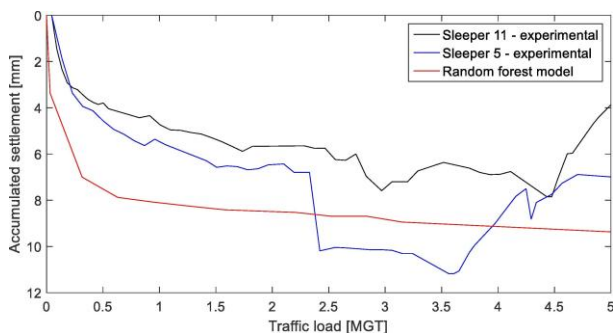


Figure 5. Measured evolution of unloaded sleeper displacement (settlement) from September 2022 to June 2023 for sleepers 5 and 11 from the transition versus settlement predicted by the random forest model.

4 CONCLUSIONS

Accurate prediction of permanent deformation in railway subgrade is essential for ensuring long-term track performance, safety, and cost-effective maintenance planning. Excessive deformation can lead to service disruptions, increased maintenance demand, and reduced infrastructure lifespan, making reliable forecasting tools a critical component of modern railway engineering.

In this study, a novel methodology is introduced that leverages machine learning techniques to estimate permanent deformation in railway subgrade layers with improved accuracy and computational efficiency. The proposed framework is built upon a comprehensive database generated through advanced numerical simulations, combining a hybrid 2.5D FEM–PML model with an empirical deformation formulation. This hybrid modeling strategy enables the representation of complex track–subgrade interactions while maintaining manageable computational requirements.

A machine learning algorithm—specifically, the random forest—was trained and evaluated using multiple performance metrics to assess predictive capability, robustness, and generalization. Among the algorithms investigated, the random forest model consistently demonstrated the highest predictive accuracy and stability, benefiting from its ability to handle nonlinear relationships and reduce overfitting through ensemble learning.

To validate the methodology, the trained model was applied to a well-instrumented Swedish test site. The results showed strong agreement between the predicted and observed permanent deformations, confirming the model's reliability under real-world conditions. This successful validation

highlights the model's potential to support predictive maintenance strategies and optimize design decisions for railway infrastructure.

Overall, the proposed machine-learning-based approach offers an efficient and reliable tool for forecasting railway track deformation. By significantly reducing the time and computational effort required compared to traditional numerical methods, it provides a practical solution for engineers and infrastructure managers seeking to improve track performance evaluation and long-term asset management.

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