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Data-Driven Rail Wear Prediction Along the Network

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Abstract

Accurate prediction of rail profile evolution is essential for optimising maintenance planning and extending infrastructure life. Existing wear models are typically calibrated under specific conditions, limiting their reliability when extrapolated to network scale with different operational scenarios and local conditions. This paper presents a hybrid measurement-simulation framework for distributed rail wear prediction along an operational railway network. Measured rail profiles are used to derive spatially resolved effective wear coefficients across different contact regions (rail head, transition zone, and gauge face), enabling the representation of local wear behaviour along the rail profile with high reliability. Based on these measurements, characteristic wear states are defined through geometric parameters associated with specific worn areas in the contact regions. These wear states provide a compact parametric description of rail profile evolution and allow the reconstruction of profiles according to wear levels in a consistent and efficient manner. Multi-body dynamics (MBD) simulation results enable the prediction of worn rail profiles also for scenarios where measured profiles are unavailable or highly limited. The methodology is applied to a measurement campaign including multiple rail materials and curve radii, showing a good overall agreement. The proposed framework enables systematic comparison between measured and simulated profiles and provides a scalable, data-informed tool for spatially adaptive rail wear modelling and network-level maintenance planning.

Keywords: rail, wear, MBD Simulation, rail profiles, track measurement, wheel-rail contact

1 Introduction

Rail wear is a major factor affecting the safety, performance and maintenance costs of railway infrastructure. Changes in the shape of rail head profiles alter wheel-rail contact conditions, influencing vehicle dynamics, noise generation and fatigue development. Accurate prediction of rail profile evolution along operational networks is therefore critical for optimising maintenance strategies and extending infrastructure life. Traditional wear models often rely either on experimental results or on massive amounts of multi-body dynamics (MBD) simulation [1-4].

While the first one is limited by transferability of the results to scenarios where no measurement data exist, the second one is close to a physical reproduction of reality dynamic contact quantities, such as normal forces, creepages and energy dissipation, under realistic traffic conditions [5-6] but must also rely on estimations for hardly known or even unmeasurable quantities e.g., actual adhesion coefficients, track irregularities, stiffnesses or damping, limiting the applicability under realistic and heterogeneous operating conditions.

More recent studies have tried to combine the two approaches by creating hybrid models that first train their profiles on measured data and later use only a as few-as-possible MBD simulations for scaling. However, these approaches have only been presented for wheel profiles, not for rails [7] or they only predicted the wear rate instead of the full rail profile shapes [8].

2 Methods

The proposed methodology uses one field measurement, performed on different tracks with varying geometry and curve radii to simulate worn rail profiles under unmeasured scenarios. Due to the numerous differences among the measurement campaigns, it was necessary to define a unified approach for processing and analysing the data, ensuring that the results can be consistently interpreted. This method is made of six consecutive steps, which are depicted in Figure 1.

1. Alignment of measured profiles to a standard CAD reference
2. Segmentation of each profile into three contact regions - rail head, transition zone and gauge face
3. Calculation of worn areas as the difference between measured and reference profiles
4. Derivation of wear rates for each material and location via linear regression models
5. Reconstruction of profiles by defining wear states along the contact zones
6. Prediction of unmeasured scenarios by using MBD simulations.

In the context of this work, results from one measurement campaign will be discussed.

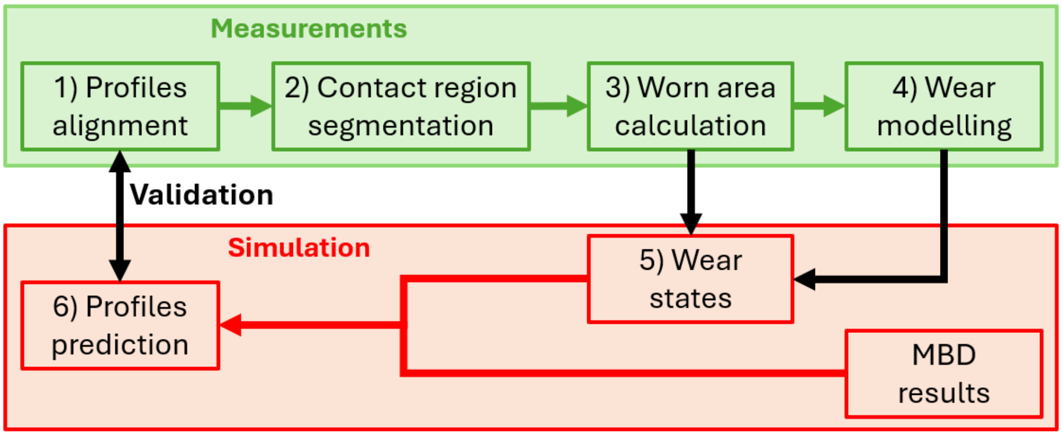

Figure 1: Scheme of adopted methodology

2.1 Profiles alignment

Measured rail profiles were first aligned to a standard CAD reference geometry. This is done by applying a specific alignment algorithm to each measurement campaigns, depending on the quality of the provided data. An example of aligned measured profiles from a single position of the investigated datasets carried out in different periods of time is shown in Figure 2, which refers to a specific material (R260). A local reference system is defined on the rail profile, with origin at the reference point of the rail head. The z-axis is oriented vertically, while the y-axis represents the lateral direction towards the gauge side. Sequences of translations and rotations were applied to each measured profile until it satisfies specific conditions, such as being inside the contour of the standard CAD profile both on the sides and at the top. Moreover, for each position, the maximum of the first measurement in time must be higher than the others, so that the relative distance between the standard and the measured increases over time, in agreement with a progressive wear of the rail. Furthermore, by convention, the worn sides (gauge face) are all placed on the right side. As expected, the last measured profile over time (*Meas 5*) shows the highest wear, and it is further analysed in this work. This step of profile alignment provides a consistent baseline for all positions and measurement campaigns.

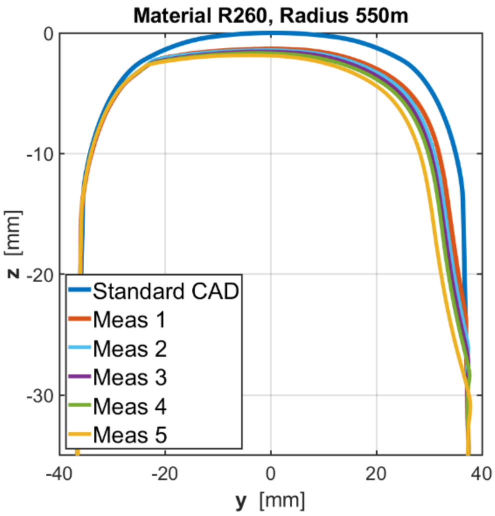

Figure 2: Aligned measured profiles for one position made of material R260

2.2 Contact region segmentation

Each measured rail profile was divided into three contact zones: the rail head, the transition zone and the gauge face. Segmentation allows the wear analysis to capture differences in contact behaviour and material loss across the rail cross-section, thus for a more accurate modelling of the wear area. Figure 3 shows a measured profile (yellow line) compared to the CAD reference of a 60E2 profile (blue). Also depicted are three different segments: the Rail-Head (1) left of the Rail-Head-Border, the Transition-Zone (2) between Rail-Head-Border and Gauge-Face-Border, and the Gauge Face (3) at the right side of the Gauge-Face-Boder. The Rail-Head-Border and the Gauge-Face-Border are inclined at 45° with respect to the horizontal axes. This is inspired by the definition of the wear value W3 often found in the literature [9]. The intersections between CAD profile and the segment borders are primarily defined by the shape of the CAD profile and, thus, must be chosen for each profile type separately. This segmentation approach is applied to all measured profiles of all positions, to ensure a consistent and comparable evaluation of the wear modelling.

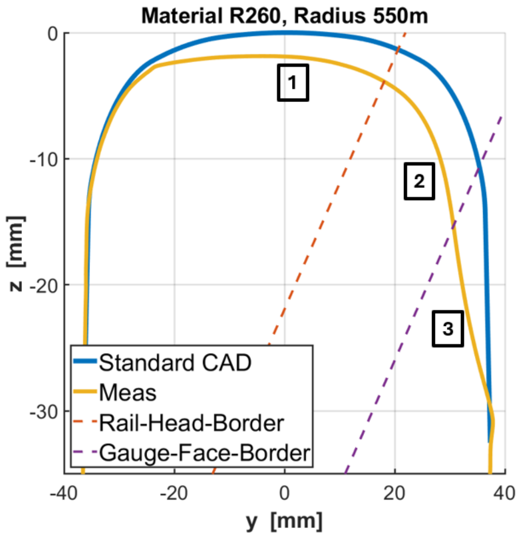

Figure 3: Segmentation of contact region for one measured profile. Shown is the Rail-Head (1) left of the Rail-Head-Border, the Transition-Zone (2) between Rail-Head-Border and Gauge-Face-Border, and the Gauge-Face (3) on the right side of the Gauge-Face-Border.

2.3 Worn area calculation

For each contact region, the wear area was calculated by first cutting the measured and CAD reference profile at their intersections, then combining both into a single polygon before using the Gauss area formula (also called Shoelace formula) to calculate the area of the polygon.

2.4 Wear modelling

Wear coefficients for each material and measurement position were determined by correlating the measured wear areas with the accumulated railway traffic load, expressed in MGT (mega gross tonnes). The cumulative traffic corresponding to each measurement campaign was calculated from the annual traffic volume (MGT/year). Consequently, each measurement point can be associated with a cumulative MGT value, which defines its position on the horizontal axis. Linear regression was applied to the data in the following form:

$$A_{W,\mathrm{Model}} = c_0 + c_1 L \tag{1}$$

where L is the traffic load in MGT, c_1 corresponds to the average wear rate and c_0 to the offset related to the initial condition and a non-linear run-in phase. This procedure was applied to each segment (rail head, transition zone, gauge face) of each measured profile, shown in Figure 4.

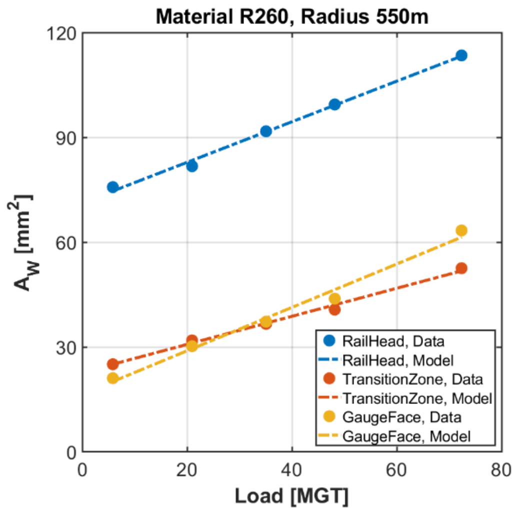

Figure 4: Results for the linear regression modelling the wear for rail head, transition zone and gauge face based on the measured wear.

Now, it assumed that the wear rate of each segment is related to a material dependent calibration factor (α) and the weighted sum of the wear numbers and related stresses acting on the contact (W_S):

$$c_1 = \alpha\, W_S \tag{2}$$

while c_1 can be derived from measurements if the data is available, W_S can be calculated based on MBD simulations for the same scenario.

2.6 MBD Simulations

Several MBD simulations were performed over a wide range of scenarios, allowing the evaluation of contact parameters related to wear, namely the maximum tangential stress in the contact (τ_{Max}) or the wear number (T_γ) depending on the wear regime [6] for mild and severe wear, i.e. the rail head, the calculation is based on τ_{Max}, while T_γ is used for catastrophic wear. A vehicle mix was defined to weight the wear values according to the traffic composition (including passenger coaches, commuter trains, freight trains, and locomotives), leading to an MBD-based weighted sum W_S:

$$\begin{aligned} W_{ms} &= \sum_i h_i \left(\frac{\sum_j \tau_{\text{max,j}}}{n}\right) \text{ for mild and severe wear} \\ W_c &= \sum_i h_i \left(\frac{(\sum_j T_{\gamma,j})}{n}\right) \text{ for catastrophic wear} \end{aligned} \tag{3}$$

where h_i is the probability associated with the i-th component of the traffic mix, and $j = 1, \dots, n$ denotes the considered wheels. The parameter W_S can be further analysed using statistical tools to assess the influence of both the vehicle mix and the MBD simulations on the resulting wear rate. By comparing the simulated W_S to the measured wear rate c_1 (see equations 1-2), it is possible to derive the material dependent calibration factor α for measured scenarios as follows:

$$\alpha = \frac{c_1}{W_S} \tag{4}$$

Once α is calibrated by measurements, it can be used to predict the wear rate c_1 for a new scenario once W_S was calculated by MBD simulations.

2.5 Wear states

During its life, the rail profile experiences a series of certain wear states. To predict these states, mathematical descriptions of the worn profiles as well as their evolution are necessary. As a first step, each measured profile was reduced to a certain number of specially chosen profile points p. To reproduce the profiles, these profile points are connected by a series of quadratic polynomials. So, each point $P(y,z)$ along the profile is given by

$$P(y,z) = f_j(y, p_{1,s}, \dots, p_{n,s}) \text{ with } s = 1,2,3 \tag{5}$$

where s represents the according segment, i.e. rail head, transition zone, or gauge face and n the number of profile points used in each segment. A typical result of such a reproduced profile is shown in Figure 5.

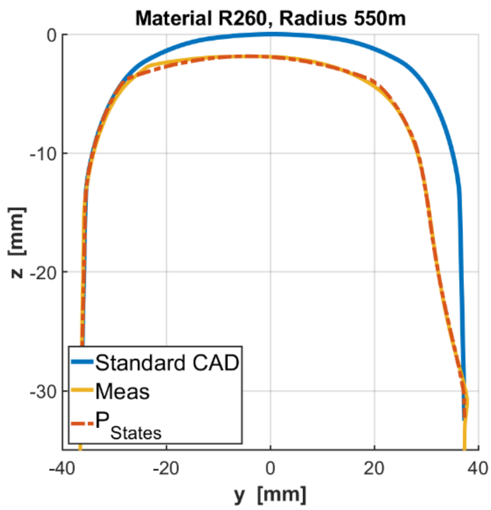

Figure 5: Reproduction of worn profile through wear states.

Next, the evolution of the profile points is predicted by a linear regression based on the wear area.

$$p_i = g_i(A_{W,\text{Meas}}) \tag{6}$$

Using equations 5 and 6, it is possible to predict a profile for a given wear area, hence these equations and their respective parameters are called wear states.

2.6 Profiles prediction

To finally predict the correct profile, the wear states described by equations 5-6 are scaled by the wear area prediction of equations 1-2 for a given calibration factor α and the weighted sums W_S calculated with MBD simulations and given by equation 4. Consequently, the approach enables the estimation of wear evolution along an entire railway network without the need for dedicated measurement campaigns, significantly reducing both time and costs.

3 Results

The method presented in the previous chapter uses a calibration based on measured wear rates and profiles, combines them with MBD simulation results for the measured scenario to finally apply them to any scenario that can be covered by MBD simulations.

3.1 Wear area modelling through linear regression

First, the measured wear area was investigated (see Figure 4) to validate chosen approach (see equation 1) for the different segments of the profile. The wear area shows a very linear increase depending on accumulated traffic load for all investigated cases (adjusted R^2 values were always higher than 0.98). As expected, most of the wear is concentrated on the rail head, where values are approximately three times higher than those observed in the transition zone and along the gauge face. This behaviour can be attributed to the higher normal loads and more frequent wheel-rail contact occurring in the rail head region, which lead to increased tangential stresses and energy dissipation.

3.3 Wear model validation through MBD results

After calibration on the measured data given in a 550 m curve, the presented approach was applied to predict profiles for two additional scenarios: a curve with 1,000 m radius and one with a 10,000 m radius, assuming the same rail material (R260) and the same vehicle mix. The results are shown in Figure 7. As expected, for increasing curve radius, the wear on the rail profile diminishes, resulting in a simulated profile which is closer to the standard CAD profile (60E2). The simulated profiles result to have a realistic shape, both on the sides and on the top. This confirms that the proposed methodology can be applied to predict the worn rail profile evolution along the network, under different conditions of curve radius, material, and traffic load.
The results can be further enhanced by adjusting the profile points and the shape describing polynomials (see equation 5) or by including statistics regarding wear rate, calibration factor and input parameters of the MBD-simulations.

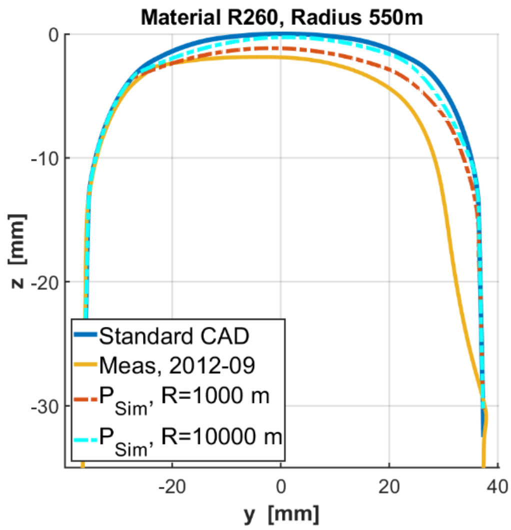

Figure 6: Comparison between measured and simulated worn profiles for different curve radii

4 Conclusions and Contributions

This study presents a hybrid measurement-simulation framework for rail wear prediction along the network. A comparison between measured and reconstructed profiles by defining so-called wear states shows a strong overall agreement across all investigated positions, indicating that the proposed approach captures the main wear patterns effectively. Deviations are generally small and mostly concentrated in the transition zone, which corresponds to areas with complex contact conditions and rapidly varying geometry. Some refinements could further improve the reconstruction accuracy, such as adjusting the profile points and the shape describing polynomials (see equation 5). Measured wear areas were used to derive wear rates that are then used – together with MBD simulation of the measured scenarios – to find a material dependent calibration factor. To predict the profile evolution in different scenarios, the calibration factor and MBD simulations of these scenarios are combined to scale the wear profiles accordingly. As example, the resulting rail profiles are shown for the measured curve radius as well as two unmeasured ones. The predicted profiles show a realistic shape, with decreasing wear rate for increasing curve radius. This enables to predict the shape of worn profiles along a railway network with different characteristics.

The adopted methodology is flexible, accommodating different materials, measurement densities, and contact regions, and it can be readily integrated with multi-body simulation outputs to support predictive, network-level maintenance planning. Overall, these results demonstrate the framework's ability to combine real-world measurements with physics-informed modelling, providing a practical and versatile tool for data-driven infrastructure management.

Future work will focus on extending the framework to the other available datasets, with a further statistical analysis of all the uncertainties. This will allow a deeper understanding of the influence of vehicle mix, MBD results and dynamic wheel-rail interactions on the derived wear coefficients. In addition, the sensitivity of the methodology to uncertainties in the regression slopes used to define the wear states will be analysed, providing a more rigorous quantification of how modelling assumptions propagate into the reconstructed profiles.

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