



A Fast, Reliable and Practical Method to Predict Wheel Profile Evolution

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Abstract. The reliable prediction of wheel wear can help to reduce maintenance costs. With the help of two common approaches (statistical, contact mechanics based), it is possible to predict wheel profile shapes either quickly and precisely, but for a unique operating situation only, or for varying operating scenarios in a more time-consuming, but often less accurate way because so many, sometimes even unknown, input data are needed. There is no method available for predicting worn wheel profile shapes quickly, accurately, and generally. The hybrid approach presented in this work combines the two state of the art approaches mentioned above in order to exploit their advantages and eliminate their disadvantages. The new method was calibrated and validated on wheel measurement data taken from the field. A good agreement between measurements and predictions was observed when using maximum wheel-rail contact shear stresses as the wear measure in the methodology.

Keywords: Wheel profile prediction · Wear prediction · Hybrid approach

1 Introduction

The evolution of wheel profiles in railway service relies on many factors, which makes an accurate and reliable prediction challenging. Reliable predictions are of great interest, however, to enable better planning of maintenance activities or to reduce risks related to running dynamic aspects caused by unfavorable profile shapes. Currently, two main approaches are used to predict wheel profile evolution: statistical and contact mechanics based methods.

The first method includes profile measurement data of a certain vehicle type at given operating conditions in order to quickly predict future profile development [1, 2]. However, as soon as the operating conditions change, the predictions become inaccurate or even impossible. The contact mechanics based approach uses multi body dynamics (MBD) simulations to obtain wear measures on wheel-rail contact level [3–9]. Based on this, material is removed locally from the wheel surface according to the wear law used. One of the most widely used wear laws is based on the wear number $T\gamma$ [10–14]. Here,

the traction force T at the contact point is multiplied by the slip γ . A new approach to predict wear is based on the maximum shear stress τ_{max} in the contact patch [15]. This approach showed a better agreement with twin disc measurement data compared to a $T\gamma$ -based wear law. The wear law application is followed by further MBD simulations with the updated wheel profiles in the next loop and so on. This method is computationally intensive and requires a lot of input data to obtain realistic wear distributions across the wheel profile. This input data is difficult to obtain and is sometimes not available at all. However, the advantage of this method is that other vehicle types or changing operating conditions can be considered easily.

There is currently no methodology that can predict the development of wheel profiles quickly, precisely and generally (accounting for varying scenarios). This paper presents a new hybrid approach which combines the advantages of the two state of the art methods described above.

In Sect. 2, the idea of the hybrid approach is presented. In Sect. 3 the available measurement data and their analysis is presented. The calibration and validation of the method are described in Sect. 4. Finally, the results are discussed at the end of Sect. 4 and conclusions are drawn in Sect. 5.

2 Methodology

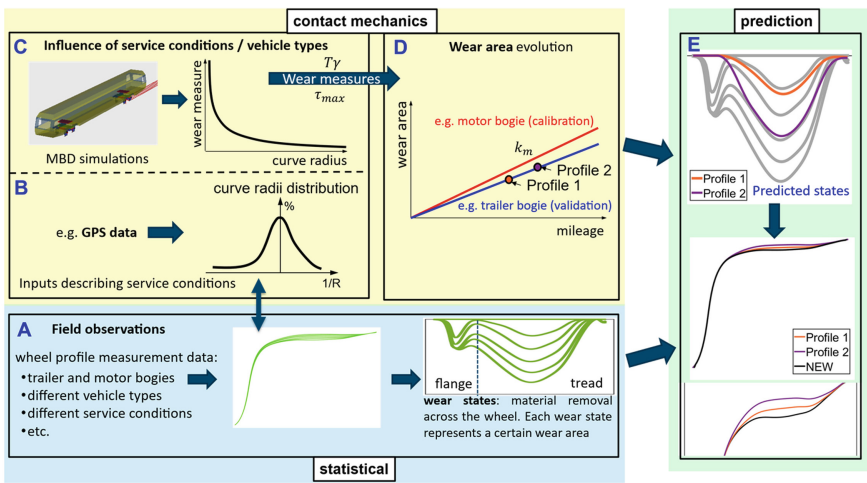


Fig. 1. Overview about hybrid wheel profile evolution prediction method

The idea of the hybrid approach is to combine statistical and contact mechanics based methods in order to use the advantages of both state of the art approaches. The statistical part (Fig. 1 – A) is based on historical data sets. These include specific wheel profile measurements of different wear levels (mileages). These profile measurements include a wide variety of often unknown influencing factors (distribution of coefficient of friction,

worn rail profile shapes, etc.). The main hypothesis of this work is that the wheel profile shape is not significantly influenced by the service conditions (type of vehicle, curve radii distribution, speed, vehicle loading conditions, etc.), but only their rate of development as wear area over mileage (wear rate, assumed as linear). In this case, the wheel profile always passes through the same so called wear states, only with a different wear rate k_m (Fig. 1 – D). Flange and tread regions are separated in the methodology resulting in wear states for both, tread and flange regions. The wear states are formed from the measured wear curves (the vertical material loss of a measured profile). For this purpose, similar wear curves are selected and averaged to form a wear state.

As mentioned before, the wear rate varies depending on the considered scenario. As an example, a motor bogie (MB) might show a different wear rate compared to a trailer bogie (TB) in the same train, because of their different curving properties (Fig. 1 – D). From the calculated wear area for any scenario (for a given mileage), a new wear curve can be interpolated between the existing wear states because each wear state corresponds to a certain wear area. With this, worn profiles can easily be predicted for given scenarios. Here, only the influence of the curve radii distribution on which the investigated vehicle is operated has been considered. Effects from traction and braking were not considered due to the large distances between stops and to keep the method as simple and practicable as possible (including consideration of most important effects only). Changing the scenario results in a different wear rate. This is the link to the contact mechanics part of the method (Fig. 1 – B), where MBD simulations are used to make profile predictions for new scenarios possible (Fig. 1 – C). This is done by extracting wear measures (τ_{max} or $T\gamma$) from the MBD simulation results for the relevant scenarios. These wear measures are summed up and weighted according to the curve radii distribution on which considered vehicle is operated leading to so called weighted wear measures P_m . For example, a train operates on a track consisting of two curve radii ($R_1 = 500$ m, $R_2 = 300$ m), with the occurrence 50% each. One simulation each for R_1 and R_2 must be carried out. Then the weighted wear measure is calculated by multiplying the simulation results ($T\gamma$, τ_{max}) with the occurrence factor (0.5 each) and summing them up.

The model is calibrated according to Eq. (1). Here the calibration factor c_s is calculated from the wear rate k_m taken from measurements and the weighted wear measure P_m calculated from the MBD simulation results for the calibration scenario.

$$k_m = c_s P_m \quad (1)$$

The model is now ready to be applied to other operating scenarios by calculating a new weighted wear measure for the consider new scenario (P_s) based again on the MBD simulation results. Subsequently, the new wear rate k_s according to Eq. (2) can be used to interpolate new profile shapes for a given mileage from the wear states. The calculated wear rate k_s for new scenario is directly proportional to the ratio of the wear measures P_s (new scenario) and P_m (calibration scenario).

$$k_s = c_s P_s = k_m \frac{P_s}{P_m} \quad (2)$$

3 Measurements

Worn wheel profiles were measured on two identical Electric Multiple Units (EMUs) mounted on TBs and MBs. A total of 40 wheels (20 axles) were measured up to a mileage of approx. 430 tkm per train. However, track data for determining the curve radii distribution (Fig. 1 – B) were available for train 1 up to approx. 210 tkm and for train 2 up to approx. 109 tkm.

First, the measurement data for train 1 were evaluated. The hybrid methodology was then calibrated using the measurement data from the MBs of train 1 and validated using the measurement data from the TBs of both trains.

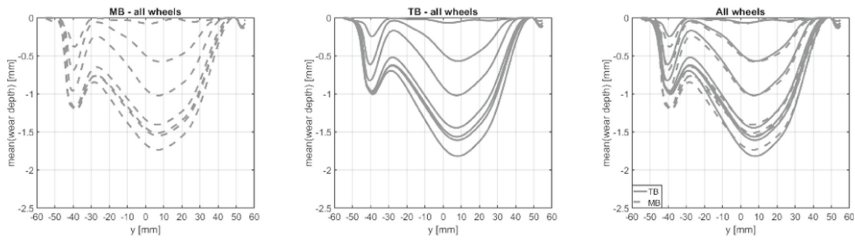


Fig. 2. Average of all measured profiles separated in MB and TB using profiles from both sides of the train

Figure 2 shows the averaged wear curves of all profiles (independent of train side) for different mileages, separated into MB and TB. Each measurement was carried out on the same date. All measured wear curves have a similar shape, whereat in the flange region ($y \leq 30$ mm), MBs show slightly more wear than TBs, while on the tread ($y \geq 30$ mm) MBs and TBs have similar wear values. Some curves of MBs and TBs even overlap there. So, the wear rate at the flange is higher for MBs than for TBs. But again, the focus of this investigation was on the shape of the wear curves separating tread and flange region, meaning that even if the wear rate might be different, the wear curve shape looks similar. This hypothesis was confirmed by this analysis. Based on this, the wear states shown in Fig. 3 were calculated using the method explained in Sect. 2.

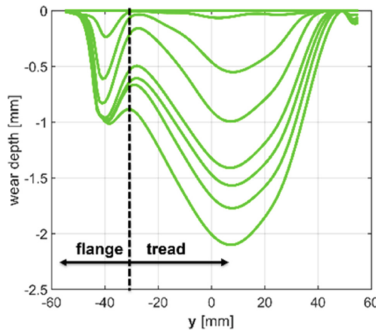


Fig. 3. Wear states valid for TBs and MBs calculated from all profile measurement data of train 1

4 Results

4.1 Calibration and Validation

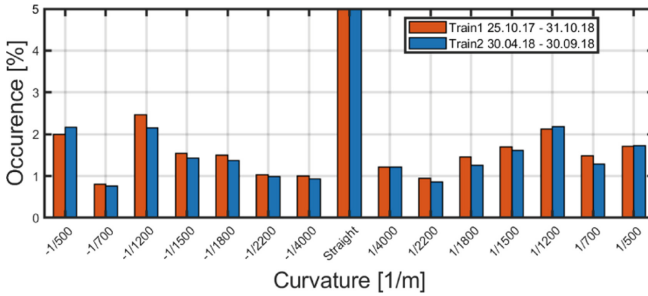


Fig. 4. Curve radii distribution on which train 1 and train 2 are operated

The model was calibrated on the MBs of train 1 and validated on the TBs of both trains. For each curve radius shown in Fig. 4, one MBD simulation with unworn wheel and rail profiles was carried out with Simpack. First, the validation was done based on the wear area development over mileage (wear rate) using the measurement data from train 1 (TBs). Then, several profile shape predictions for certain mileages were used to validate the methodology at a profile level on both trains.

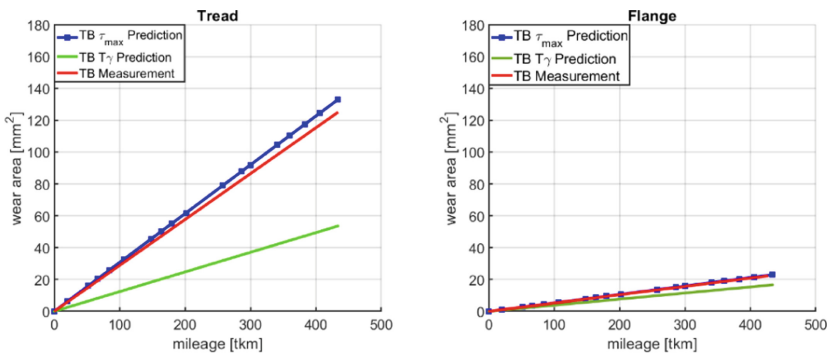


Fig. 5. Validation of methodology on TBs of train 1

Figure 5 shows wear area evolution over mileage (wear rate) for TBs of train 1 separated for the tread and the flange region. The red lines represent the averaged wear rates of all TB measurements. Note that a linear relationship was observed. The blue and the red lines represent predictions of the hybrid method calibrated on the MBs for validation (τ_{max} - and $T\gamma$ -based). For both, the tread and flange region, the τ_{max} -based prediction shows a better correlation with the measurement data than $T\gamma$ -based predictions.

Figure 6 shows validation results at a profile level for several wheels mounted on the TBs of train 1. As shown before, for wear area evolution over mileage, the τ_{max} -based approach correlates better with the measurement data compared to the $T\gamma$ -based approach. The same is true for the validation on train 2 (see Fig. 7).

To summarise, the comparison between measurement results from the field and predictions with the new methodology revealed that using τ_{max} as a wear measure shows a better agreement than using $T\gamma$. This confirms the work published by Al-Maliki's et al. [15] τ_{max} which was based on twin disc measurement data.

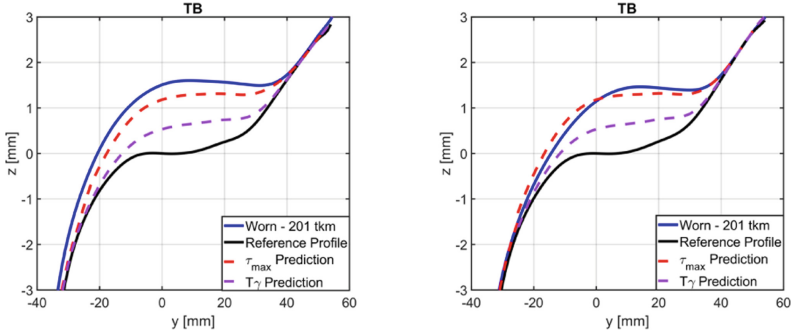


Fig. 6. Validation on TB profiles from train 1

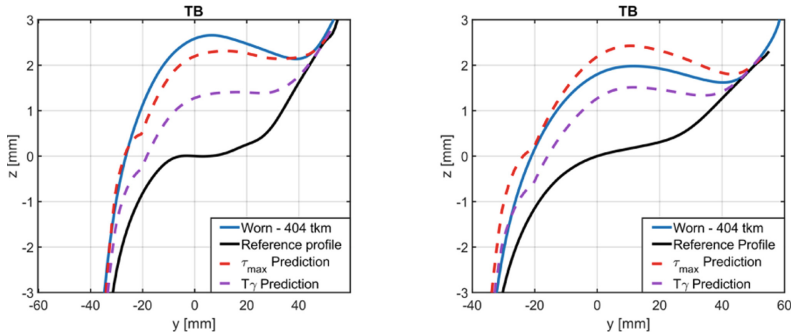


Fig. 7. Validation on TB profiles of train 2

4.2 Discussion

The validation results showed that the methodology works and that the τ_{max} -based predictions correlate better with the measurements than the $T\gamma$ based predictions. The difference in agreement between the two methods (τ_{max} , $T\gamma$) is due to different ratios P_s/P_m of the weighted wear measures, see Eq. (3). As already described in Sect. 3, there is hardly any difference in the measurements between MBs and TBs at the tread. The τ_{max} -based predictions agree with these observations meaning that the ratio P_s/P_m

is around 1 resulting in very similar wear rates for MBs and TBs. In the case of the $T\gamma$ -based predictions this ratio is about 0.5, meaning that the MBs should show twice the wear compared to the TBs, which was not observed in the measurements.

4.3 Application

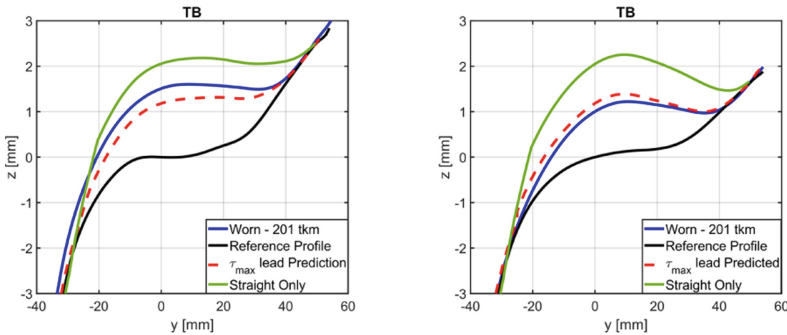


Fig. 8. Model application to a tangent track compared to the case shown in Fig. 4 (old curve radii distribution) for TB

With the new hybrid methodology created, it is now possible to predict worn wheel profiles quickly and accurately for any scenario. Figure 8 shows exemplary predictions for a 100% tangent track compared to the curve radii distribution shown in Fig. 4. The results show different wear curves with significantly more wear in the tread region.

In future work it is planned to extend the methodology by considering the influence of different wheel materials as well as the influence of traction and braking which is important in the case of locomotives.

5 Conclusion

The methodology created to predict worn wheel profiles is based on a new hybrid approach that takes advantage of two widely used approaches (statistical and contact mechanics based). The statistical approach is based on historical data sets, which makes it possible to predict the worn wheel profiles quickly and accurately, but only for one specific operating scenario (where the data are from). The contact mechanics based approach includes MBD simulations in combination with different wear models on contact level. One of the most widely used wear model is therefore based on the wear number $T\gamma$, while a new approach predicts wear based on the maximum shear stress τ_{max} in the contact patch.

The validation of the new hybrid approach by using τ_{max} as wear measure shows a good correlation with the measurement data.

Acknowledgments. The publication was written at Virtual Vehicle Research GmbH in Graz, Austria, together with all listed co-authors. The authors would like to acknowledge the financial

support within the COMET K2 Competence Centers for Excellent Technologies from the Austrian Federal Ministry for Climate Action (BMK), the Austrian Federal Ministry for Digital and Economic Affairs (BMDW), the Province of Styria (Dept. 12) and the Styrian Business Promotion Agency (SFG). The Austrian Research Promotion Agency (FFG) has been authorised for the programme management. They would furthermore like to express their thanks to their supporting industrial and scientific project partners Siemens Mobility GmbH, voestalpine Rail Technology GmbH and the University of Sheffield.

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