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Uncertainty propagation in rail wear prediction using an analytical method and field observations

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Abstract

Rail wear management based on accurate rail wear prediction is essential for railway maintenance. The implementation of rail wear prediction models in maintenance decision tools is not yet available due to detailed modelling and the absence of direct coupling with operational conditions. A method that does not provide any confidence interval on the prediction is not very helpful if one wants to use the results of the prediction for maintenance decision-making and there is variation in the input. Therefore, in this study a wear prediction model that does take into account these limitations is used to predict the amount of rail wear with certain confidence bounds. The uncertainty in the output of the model is quantified. This is realized by considering probability distribution functions for the input parameters and analytical analyses. The results obtained from these analyses are then compared with field measurements and a good agreement is found.

Keywords: rail, wear, maintenance, prediction, modelling.

1 Introduction

Rail wear is an inevitable damage mechanism of the railway tracks [1-3]. Although several detailed rail wear prediction models are available in literature, implementation of these models by infrastructure managers has not been realized yet. The reason for this is the absence of a rail wear model that couples the operational conditions as measured by infrastructure managers directly to the rail wear rate prediction. The models that are currently used and enable this coupling are data driven models which are based on historic data and experience from the past [4]. The disadvantage of these models is that the rail wear rate prediction becomes unreliable for operational conditions that are different from the past. In order to ensure the reliability of the wear rate prediction the wear model as proposed by [5] is used in this study. This wear prediction model is argued to be efficient as it replaced the time-consuming vehicle dynamic simulations with meta-models. The limitation of this model is that it is deterministic. Hence, before it can be utilized for rail wear rate prediction such that it is accurate, reliable and efficient for infrastructure managers, the uncertainty of the prediction needs to be determined. Uncertainty is often expressed through probability distribution functions [6]. In this study the uncertainty propagation in the wear prediction model is calculated using an analytical approach. This is realized by considering probability distribution functions for the input parameters, and analyzing the effect of the input uncertainty on the model response variation. The results obtained from the uncertainty propagation approach are then compared with field measurements. The uncertainty calculation process can become very time consuming if a large number of evaluations is required, which is true for the considered case study. Therefore, an approach to reduce the number of evaluations is also proposed in this study.

2 Methods

The process of the rail wear prediction that is used is schematically depicted in Figure 1. The meta-models in this process are in the form of second order polynomials and are defined as follows:

$$y(\boldsymbol{x}) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{k+i} {x_i}^2 + \sum_{i=1}^{k-1} \sum_{j>i}^{k} \beta_{i,j} x_i x_j \tag{1}$$

where y is the wear area in mm^2, $\boldsymbol{x}$ is the vector of x_i which are the various input parameters and β_i are the fitted model parameters.

There are nine input parameters ($k = 9$) in the rail wear prediction model which include axle load, curve radius, vehicle speed, longitudinal and lateral stiffness of the primary bogie, rail profile geometry, material hardness, friction coefficient and rail cant. Furthermore, the rail profile geometry is represented by the vertical wear depth at the rail head.

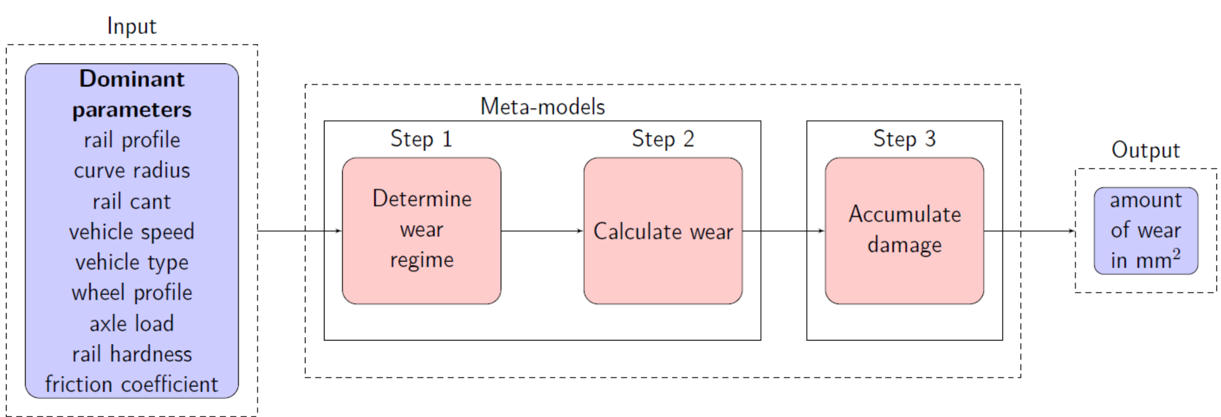


Figure 1: Rail wear estimation process by means of meta-models [5].

The analytical approach of the uncertainty propagation analysis calculates the mean (μ) and standard deviation (σ) of the response (in this case the wear area) [7]. The input parameters are also represented by a mean and a standard deviation. The probability distribution function (pdf) of both the response and input parameters are assumed to be normally distributed. However, from field measurements it is evident that the pdfs for the vertical wear depth, the hardness and the friction coefficient are not normally distributed. In this case multiple normal distribution are combined to obtain the actual distribution. The formulations for μ and σ for a second order polynomial meta-model are as follows [7]:

$$\mu(x) = \beta_0 + \sum_{i\in\Re} \beta_i\mu_i + \sum_{i\in\Re} \beta_{ii}{\sigma_i}^2 + \sum_{i\in\Re}\sum_{j\in\Re, j\geq i} \beta_{ij}\mu_i\mu_j + \sum_{i\notin\Re}\left(\beta_i + \sum_{j\in\Re}\beta_{ij}\mu_j\right)x_i + \sum_{i\notin\Re}\sum_{j\notin\Re, j\geq i}\beta_{ij}x_ix_j \tag{2}$$

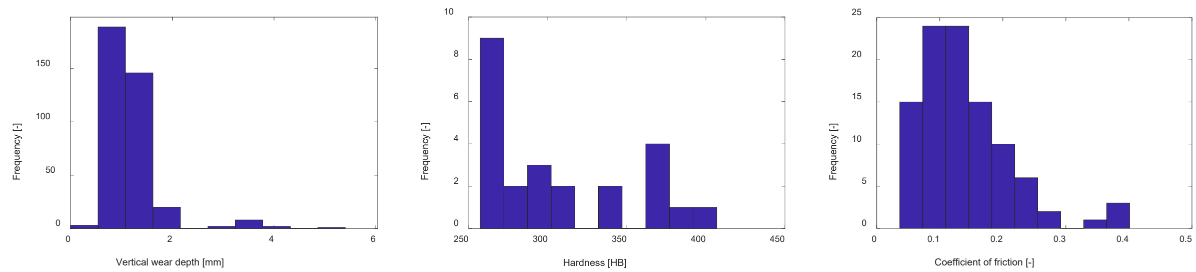
$$\sigma^2(x) = \sum_{i\in\Re} {\beta_{ii}}^2{\sigma_i}^4 + \sum_{i\in\Re}\sum_{j\notin\Re, j\geq i} {\beta_{ii}}^2{\sigma_i}^2{\sigma_j}^2 + \sum_{i\in\Re}\left(\beta_i + \beta_{ii}\mu_i + \sum_{j\in\Re}\beta_{ij}\mu_j + \sum_{j\notin\Re}\beta_{ij}x_j\right)^2{\sigma_i}^2 \tag{3}$$

Due to the large number of wheels it has been decided to divide the total number of wheels into 40 discrete bins (defined in terms of vehicle type, wheel type, axle load and vehicle speed) and then the evaluation of mean and standard deviation is performed for the obtained bins and subsequently accumulated.

In order to validate the results of the prediction model the results of the predictions are compared with field measurements. For this purpose, a case study between the cities Weesp and Almere is selected. The rail profiles of the considered track are measured by means of the RailMonitor over a period of nine months. The rail profile measurements are conducted to determine the amount of rail material loss.

3 Results

As stated in the previous section, the analytical uncertainty propagation approach considers only normally distributed pdfs. However, the measured vertical wear depth, friction coefficient and material hardness distributions do not meet the requirements of a normal distribution, see Figure 2. Therefore these distributions are approximated with multiple normal pdfs. An example of such an approximation with multiple normal pdfs is depicted in Figure 3 for the friction coefficient.



(a) *(b)* *(c)*

Figure 2: Probability distribution functions for measured data.

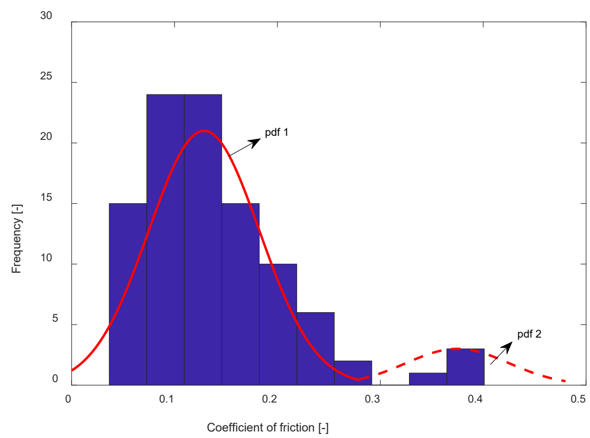


Figure 3: Multiple pdfs for the friction coefficient.

The analytically predicted results for the considered case study are in agreement with the field measurements. Figure 4 compares the pdfs of the wear area for the analytical approach and the field measurements. From this figure it can be seen that the measured and predicted distribution functions for the rail wear area are not identical, but do have a considerable amount of overlap. The mean and standard deviation of the measured wear area are equal to 14.31 mm^2 and 5.97 mm^2, respectively, whereas the mean and standard deviation of the predicted wear area equal 20.81 mm^2 and 11.77 mm^2.

The large variation is due to the fact that rail wear is assumed to be uniform in the wear prediction model, which is not the case in reality. Local wear is induced due to velocity variations in the curve radius, braking, traction and hunting oscillation of the vehicle while entering and leaving the curve. Another source of the large variation is the (varying) friction coefficient. The wear prediction model can be improved by considering the actual pdf for the friction coefficient and including the above mentioned usage variations in the curved track.

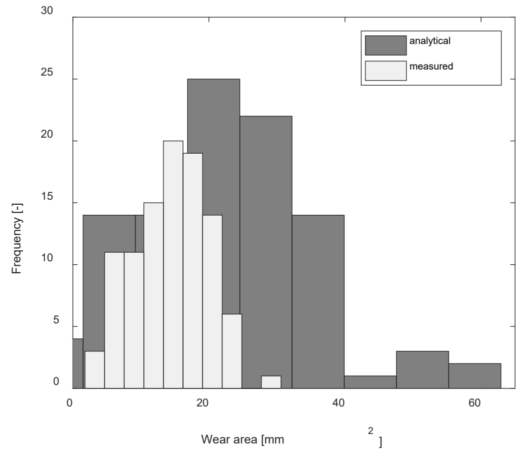


Figure 4: Wear area results comparison.

4 Conclusions and Contributions

It can be concluded that for rail wear prediction the proposed analytical approach is effective for its computational efficiency and the lower number of evaluations required. Furthermore, the coupling between operational parameters and an efficient wear prediction model is achieved. The uncertainties have been evaluated through an analytical analysis and it can be concluded that the results from this analysis correspond to a large extent with the measured data.

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