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To cite this article: Cyprien Hoelzl *et al* 2024 *J. Phys.: Conf. Ser.* **2647** 182024

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Data-Driven Railway Vehicle Parameter Tuning using Markov-Chain Monte Carlo Bayesian updating

Cyprien Hoelzl¹, Lisa Keller¹, Thomas Simpson¹, Charikleia Stoura¹,
Claudia Kossmann² and Eleni Chatzi¹

¹Department of Civil, Environmental and Geomatic Engineering, ETH Zürich, Switzerland
E-mail: {hoelzl,charikleia.stoura,simpson,chatzi}@ibk.baug.ethz.ch

² Strategic Asset Management Track, SBB, 3000 Bern, Switzerland
E-mail: claudia.kossmann@sbb.ch

Abstract. Understanding the dynamics of the interaction between railway vehicles and tracks is essential for forecasting vehicle and track conditions and performing maintenance actions to preserve the safety of railway infrastructure. In this work, physics-based models are deployed to predict the dynamic response of railway vehicles to track alignment and irregularities. Such models comprise a large number of parameters that need to be validated and possibly tuned, a task often accomplished on the basis of expert knowledge or trial-and-error without necessarily reflecting the condition of the operating system as-is. Therefore, model uncertainties persist due to assumptions on the actual system behavior, as well as due to varying operational parameters (e.g., wheel profile, rail profile, rail moisture). To improve modelling accuracy, this study adopts a multi-body vehicle model, realized in SIMPACK software, and performs parameter tuning based on on-board measurement data (accelerations and forces) from an instrumented tilting train, which regularly traverses the Swiss Federal Railways (SBB) network. The pertinent vehicle model is optimized in terms of the interaction forces at the wheel-rail contact using a Bayesian model updating approach, relying on Markov-Chain Monte Carlo (MCMC). Specifically, the MCMC method is applied to estimate both optimal vehicle parameters and their uncertainty by minimizing the mean squared error between simulated and measured contact forces, leading to an improved vehicle twin.

1. Introduction

Ensuring the quality and safety of rail transport requires monitoring and evaluating the condition of rail infrastructure. Specifically, for the track system, continuous monitoring can identify faults at an early stage [1, 2, 3, 4], preventing severe damage to track and vehicle components, reducing rolling noise, minimizing passengers' discomfort due to excessive vibrations, and, ultimately, enhancing the overall safety of rail transport [5, 6]. This degradation of tracks mainly owes to vehicle load cycles and vehicle-track interaction [7, 8]. For this reason, the modelling of the dynamic interaction between railway vehicles and tracks has been a topic of significant research over the past decades [9, 10], with some studies also proposing operational criteria to avoid adverse effects due to vehicle-track interaction. For example, Knothe and Stichel [10] proposed a set of short- and long-term criteria regarding the dynamics a vehicle must meet for operational approval [11]. Short-term criteria are those related to the vehicle's operation (e.g., excitation of the vehicle to the rails). In contrast, long-term criteria relate to consequences on the infrastructure after hundreds or thousands of cycles (e.g., damage to the infrastructure due



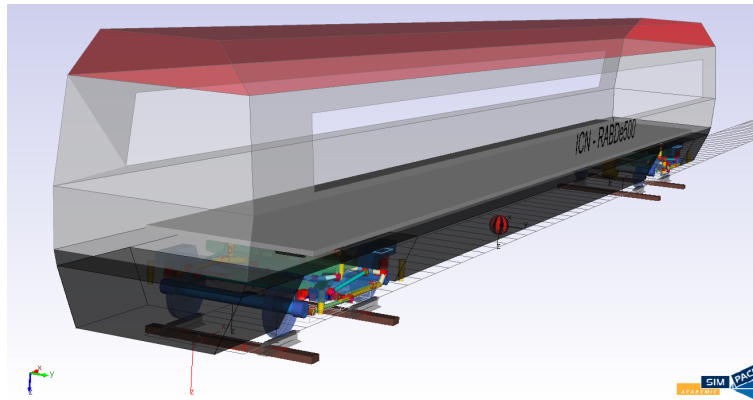


Figure 1: 3D multi-body simulation model of the ICN RABDe500 wagon in SIMPACK software [18].

to fatigue). To define these criteria, diverse factors are considered, mainly associated with three essential aspects: safety, comfort, and cost.

However, in order to develop such safety operational criteria, accurate models that reflect the actual dynamic behavior of coupled railway vehicle-track systems are required. Simplified or reduced-order models are often adopted for simplicity or to reduce computational complexity when studying specific components or processes, such as the vehicle axle response [12]. For example, Dertimanis et al. [13] used a two-dimensional (2D) half-car model approximating the vehicle dynamics to estimate the track roughness and vehicle-track forces. Although computationally more efficient, reduced-order models may not fully represent the actual dynamics of the vehicle. To this end, full-order vehicle models (Fig. 1) enable more realistic vehicle-track dynamic simulations since they can capture more complex dynamic phenomena than the simplified models [9, 10]. However, such models are composed of a large number of bodies and connections whose properties are inherently uncertain and may sometimes vary with environmental conditions [14]. The calibration of full-order models nowadays often relies on trial-and-error approaches or requires specific dynamic tests performed in the lab [14]. To avoid such cumbersome approaches, more comprehensive parameter optimization methods relying on genetic algorithms are often used to tune the vehicle parameters [15].

Towards this direction, in this study, we use a Markov-Chain Monte Carlo (MCMC) algorithm to optimize the parameters of the vehicle model. MCMC-based approaches are commonly applied to estimate the parameters of a system which are inherently uncertain. For example, Arcieri et al. [16] modelled the problem of optimal railway maintenance scheduling policies as a partially observable Markov decision process and inferred the underlying transition dynamics and observation-generating process via MCMC sampling. MCMC sampling has also been used to calibrate finite element models for structural dynamics problems [17]. Thus, in the same premise, this work employs an MCMC method to optimize vehicle parameters by minimizing the error between simulated and measured wheel-rail contact forces via iterations. Simulations are performed with the aid of the ICN ("Intercity Neigezug") wagon (RABDe 500) of SBB [18] in the multi-body simulation software SIMPACK [19]. The on-board monitoring (OBM) system installed on the same train measures contact forces and accelerations, which are then used for calibrating the model.

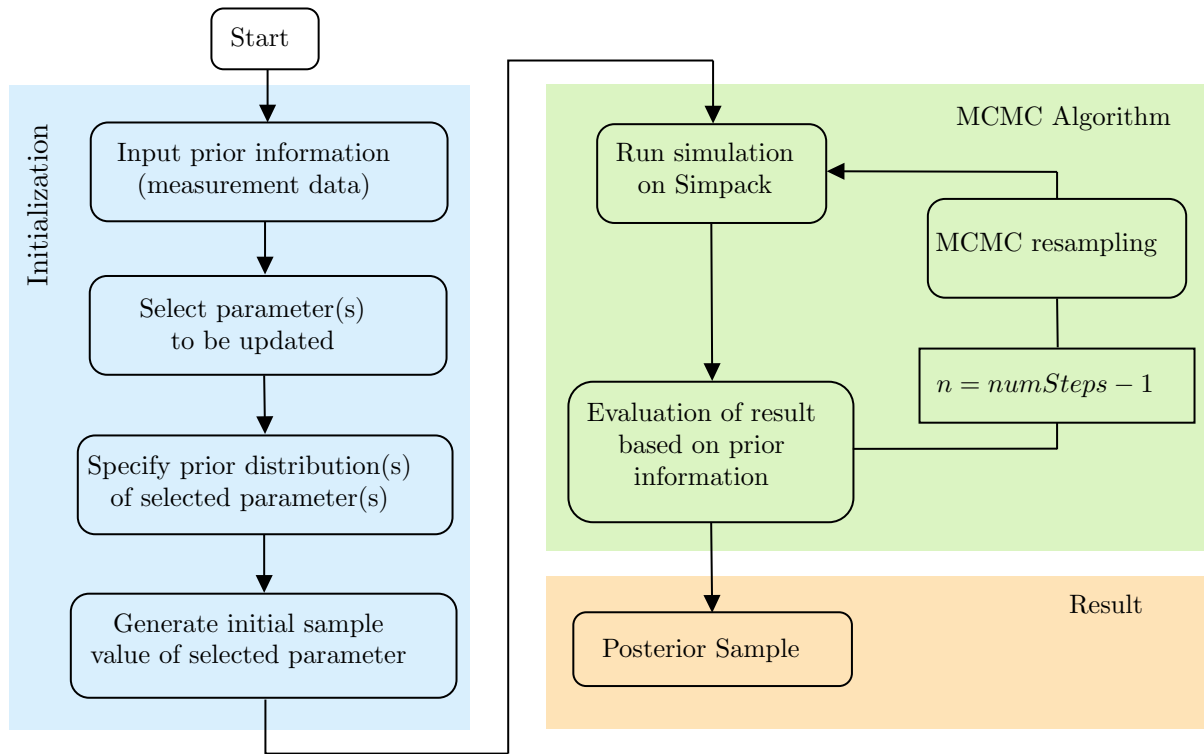


Figure 2: Proposed methodology for vehicle parameter optimization.

2. Methodology

This section presents a methodology to calibrate the ICN RABDe500 model. Fig. 2 graphically illustrates the proposed calibration method step-by-step. The goal is to estimate optimal vehicle parameters that minimise the mean squared error (MSE) between the wheel-rail forces as predicted by the simulations in SIMPACK software and those measured on-board. Minimising the MSE between estimated and measured contact forces results in a well-calibrated wagon model which can be used in subsequent simulations.

2.1. Simpack Simulation Model

Fig. 1 demonstrates the three-dimensional (3D) ICN RABDe500 wagon model [18], implemented in SIMPACK software, which comprises a first-class carriage modelled as a rigid body. The track on which the train runs is modelled as a continuously supported two-layer model (the rail and sleeper layers) composed of two rails elastically connected to a sleeper. The track gauge is set to the Swiss standard of 1435 mm. Both rails and sleepers are modelled as rigid bodies. The rail-sleeper and sleeper-ground contacts are realised via force elements of linear stiffness and linear damping. The *mm*-accurate track geometric layout and excitation, used as an input for the simulation, are obtained from measurements of a diagnostic vehicle [3].

The interaction surface between the wheels of the wagon and the rails is modelled as discrete elastic, i.e., it considers the actual wheel-rail contact area for the estimation of the normal and tangential forces. The normal (vertical) force is composed of an elastic normal force and a damping normal force evaluated at each slice of the contact patch. For the tangential and lateral interaction, the FASTSIM method of J.J. Kalker is used [19]. The Kalker weighting factor is set to 1, and the friction coefficient is initially set to 0.35. The input variables for initiating the simulation are a geometry profile (track layout), an excitation profile (geometric

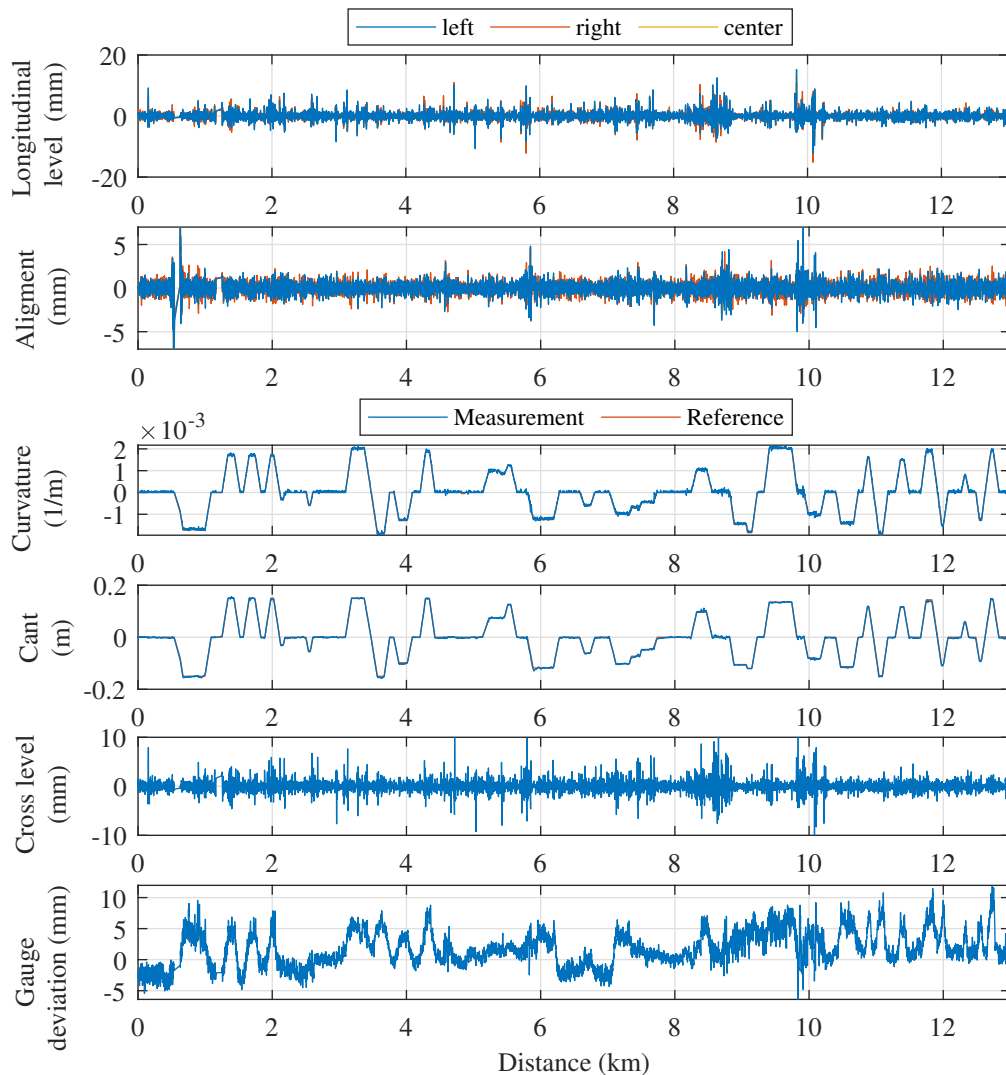


Figure 3: Geometry profile (curvature and cant) and excitation profile (longitudinal level, alignment, cross level, and gauge deviations) measured by the diagnostic vehicle of SBB [4].

irregularities), a velocity profile and a tilting profile and, optionally, a measured wheel and/or a measured rail surface profile. Fig. 3 illustrates the geometry and excitation profiles for the selected section. The velocity profile is taken directly from a measurement run, while the tilting profile is calculated from several measurement properties of the corresponding measurement run. For each of the measurement runs, both wheel-rail force and accelerations are measured.

The initial simulations, using the default parameters, have a reasonably good performance in approximating the measured wheel-rail forces. However, their values can further be improved by incorporating changes that may be attributed, for example, to environmental parameters, which can vary in day-to-day operations. For instance, the vertical forces are influenced by the train's body mass and centre of gravity, which changes under different passenger loads. On the other hand, lateral forces are strongly affected by the wheel-rail friction coefficient, which is unknown and dependent on environmental conditions [10]. Therefore, in the next section, an MCMC methodology for parameter optimization is proposed which provides probabilistic estimates of these parameters in an automated manner.

Table 1: Overall posterior parameter optimization results and comparison with individual MCMC given the prior estimates.

Parameters	Prior estimate, $\mathcal{N}(\mu, \sigma^2)$, $\mathcal{U}(a, b)$	Individual result	Overall result	Difference ($ \mu_{\text{overall}} - \mu_{\text{indiv}} $)
Car body mass	$\mu_{\text{prior}}=35487$ kg, $\sigma_{\text{prior}}=3000$ kg	$\mu_{\text{indiv}}=37027$ kg, $\sigma_{\text{indiv}}=325.7$ kg	$\mu_{\text{overall}}=36891$ kg, $\sigma_{\text{overall}}=92.3$ kg	136 kg
Centre of gravity sideways	$\mu_{\text{prior}}=-0.0267$ m, $\sigma_{\text{prior}}=0.5$ m	$\mu_{\text{indiv}}=-0.0611$ m, $\sigma_{\text{indiv}}=0.01$ m	$\mu_{\text{overall}}=-0.0405$ m, $\sigma_{\text{overall}}=0.01$ m	0.02 m
Friction coefficient	a=0, b=0.7	$\mu_{\text{indiv}}=0.1993$, $\sigma_{\text{indiv}}=0.02$	$\mu_{\text{overall}}=0.2137$, $\sigma_{\text{overall}}=0.02$	0.01
Flange friction coefficient	a=0.6, b=0.18	$\mu_{\text{indiv}}=0.1393$, $\sigma=0.02$	$\mu_{\text{overall}}=0.1687$, $\sigma_{\text{overall}}=0.005$	0.03
Navigator factor	$\mu_{\text{prior}}=1$, $\sigma_{\text{prior}}=0.25$	$\mu_{\text{indiv}}=0.8403$, $\sigma_{\text{indiv}}=0.04$	$\mu_{\text{overall}}=0.8399$, $\sigma_{\text{overall}}=0.03$	0.00
Primary spring cx factor	$\mu_{\text{prior}}=1$, $\sigma_{\text{prior}}=0.25$	$\mu_{\text{indiv}}=6.2835$, $\sigma_{\text{indiv}}=1.07$	$\mu_{\text{overall}}=5.1403$, $\sigma_{\text{overall}}=0.11$	1.14

2.2. MCMC-supported Parameter Optimization

The parameters of the model presented in Section 2.1 are optimized using the MCMC algorithm. A thorough treatment of the MCMC algorithm can be found in [20], while this Section will also provide a brief overview. Fig. 2 also gives a general insight into the procedure for optimising the parameters.

First, in the initialization phase, the parameters to be identified are chosen, and suitable prior distributions are assumed for their initial values. The MCMC algorithm then updates these prior distributions to find the posterior distributions on these parameters, or, in other words, the likely distribution of these parameters given the measured forces and assumed model. This process works through sampling; samples are drawn from the prior distributions, and simulations are run using these samples as the model parameters. The sampled parameters are then evaluated using a defined likelihood function which determines how well the simulation outputs correspond to the measurements. Given this likelihood value, the sampled values are accepted or rejected by the Metropolis-Hastings algorithm [21], thus updating the distribution. This process is repeated until convergence is achieved, and the final output consists of the samples from the posterior distribution. The MCMC updating process is implemented in Matlab software using the UQLab toolbox [22]. As previously mentioned, the MCMC algorithm requires a likelihood function that evaluates a certain parameter vector to be defined. In this case, the likelihood is chosen as the MSE between the estimated and measured forces in both lateral (Y21 and Y22) and vertical (Q21 and Q22) directions for a 1 km long section of the 13 km long track that the wagon runs on.

Table 1 demonstrates the results of the optimization procedure. The parameters update assumes a single measurement run with a specific speed and tilting profile. The first column of Table 1 presents the optimized parameters using the MCMC-based scheme. Table 1 also shows the posteriors resulting from the MCMC optimization, which are discussed in Section 3. The selection of the initial values of the vehicle parameters relies on prior knowledge of the vehicle dynamics. In Table 1, cx denotes the factor which is multiplied with the translational stiffness

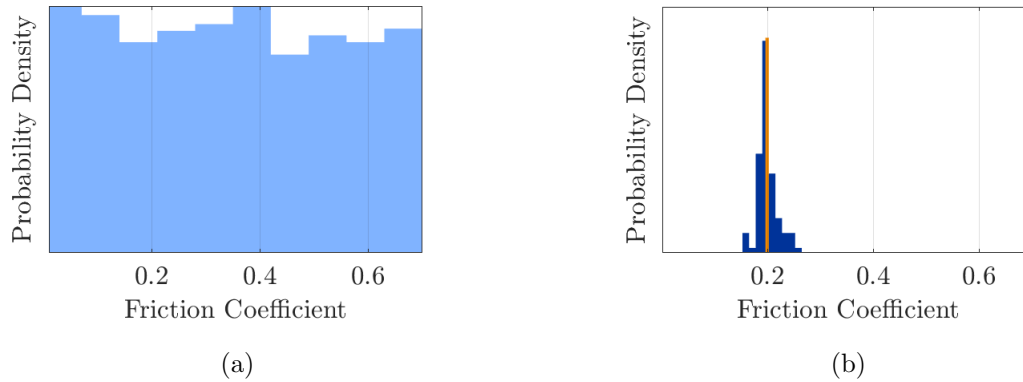


Figure 4: Prior (a) and posterior (b) distribution of the friction coefficient according to the MCMC algorithm.

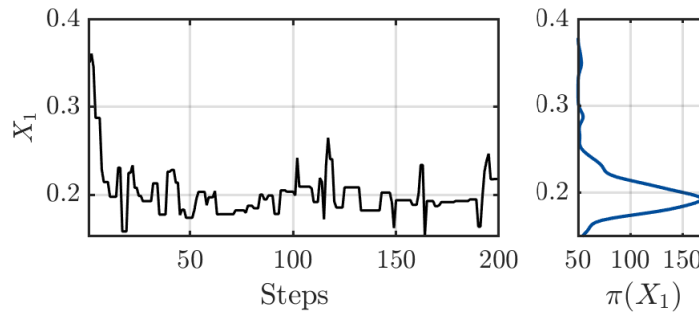


Figure 5: Illustration of the convergence of a single chain for the friction coefficient.

constant of the primary suspension in the x -direction (longitudinal direction of the rail). The navigator factor indicates how much the axes can be adjusted radially. A factor of one means that both axes (leading and trailing) are perfectly perpendicular to the rails. Note that a perfect coupling is usually not observed in practice due to friction and parasitic stiffness. The body mass and center of gravity can vary under passenger load and thus are modelled with Gaussian priors $\mathcal{N}(\mu, \sigma^2)$. The wheel-rail friction coefficient is modelled with a uniform prior $\mathcal{U}(a, b)$. In the next section, the results of the MCMC-based optimization are presented.

3. Results & Discussion

The force data measured by the OBM system installed on the in-service ICN vehicle are compared with the simulations in SIMPACK software for a case study that considers a 13 km track section. First, the simulation is carried out with the initial parameter values, and the predicted wheel-rail forces are compared with the measured values recorded by the recording system of the ICN vehicle. Then, MCMC is used to optimize the initial parameters, as those are likely to strongly influence the response of the vehicle. It is worth noting that the parameter optimization uses a shorter track section (of 1 km in length), while the performance of the simulation is assessed across the entire length of 13 km. This 1 km track segment, highlighted in Fig. 6, was used for the MCMC identification as it includes curves in both directions. The good results along the entire 13 km track section indicate that the parameters identified by the MCMC are generalizable, performing well also on track sections not included in the training data.

This Section further elaborates on the MCMC identification process for a single parameter,

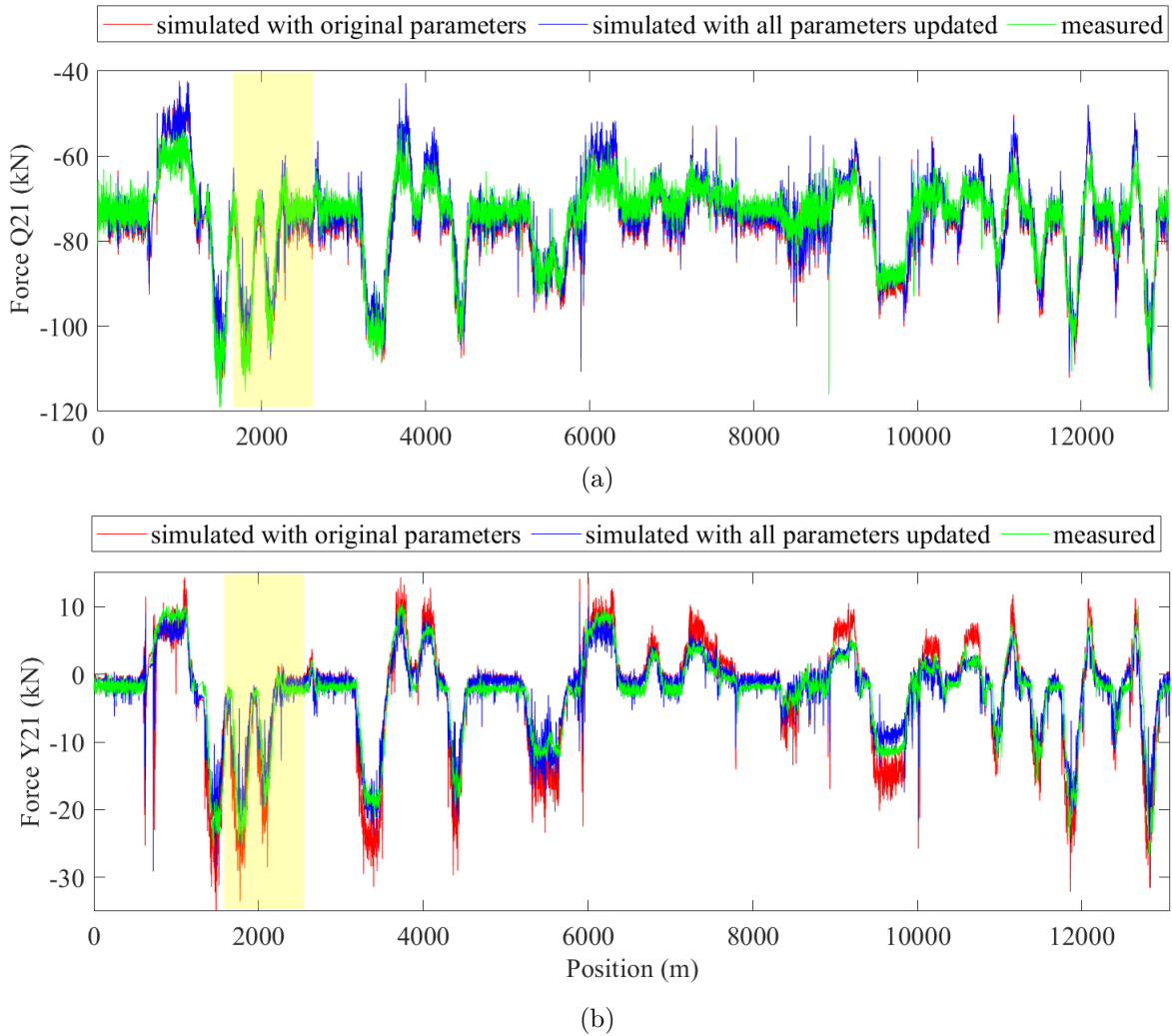


Figure 6: Force-position histories of the (a) vertical Q21 and (b) lateral Y21 contact forces of the right wheel of the second wheelset of the wagon, for simulations with the initial (red) and updated (blue) vehicle parameters, along with the measured contact force values (green). The highlighted yellow section indicates the section used for the MCMC algorithm.

the friction coefficient. Fig. 4a shows a sample drawn from the assumed prior distribution for the friction coefficient, which assumes a uniform distribution between 0 and 0.7. Fig. 4b shows the identified posterior distribution of the friction coefficient following the MCMC process. The distribution has significantly narrowed, and both shape and mean value have considerably changed. Fig. 5 shows the process of parameter identification through the convergence of one of the Markov chains used in the MCMC algorithm, where only the first 200 steps are shown for visualization purposes. The chain quickly converges to the mean value of the identified posterior distribution. The kernel density estimation of the posterior distribution is also shown, which is estimated based on the samples from this Markov chain after the first 50 % of values have been discarded as the *burn-in period* [20]. All identified parameters converge, and their posterior estimates demonstrate low variance, as shown in Table 1.

Fig. 6 shows the time series for the vertical (Q21) and lateral (Y21) forces of wheel 21 (right wheel of the second axle in rolling direction) along the track. The lateral forces (Fig. 6b)

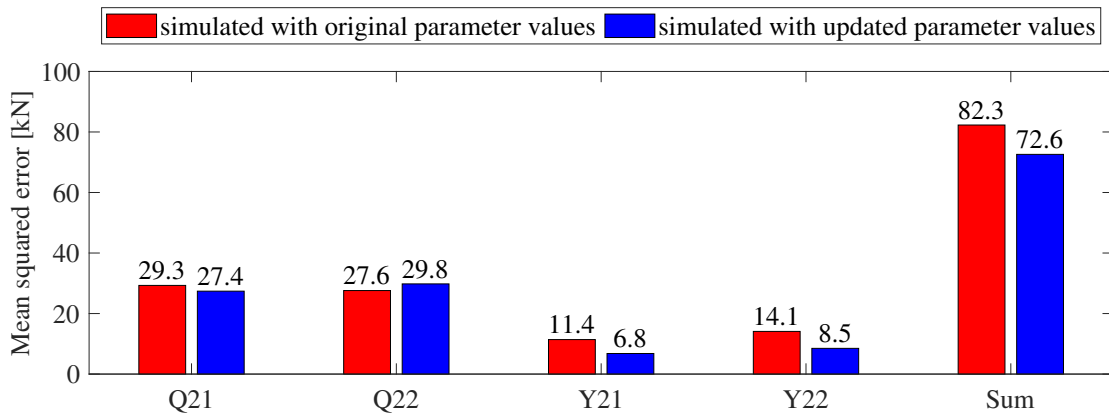


Figure 7: MSE between simulated and measured contact forces in the vertical and lateral directions for simulations with the initial (red) and updated (blue) vehicle parameters.

Table 2: Simulation times

Simulation specification	duration [hh:mm:ss]
Single run $\approx$ 13 km	$\approx$ 00:35:00
Single run $\approx$ 1 km	$\approx$ 00:02:30
MCMC simulation, 6 parameters updated, 400 steps, $\approx$ 1 km	$\approx$ 15:30:00

resulting from the simulation with the initial parameters do not perfectly match the measured accelerations, especially in the curved track sections, which are identified as the regions of high amplitude lateral forces. However, after optimization of the parameters via MCMC, we observe that the simulated lateral forces show better agreement with the measured lateral forces. On the other hand, according to Fig. 6a, the vertical forces after parameter optimization improve less than the lateral ones.

Fig. 7 further supports this finding showing that the MSE shows significant improvement only in the case of lateral forces (Y21 and Y22). In contrast, in the case of vertical forces (Q21 and Q22) the MSE is practically the same before and after optimisation. Table 1 summarizes the mean and standard deviation (or a , b of the uniform distributions) of the prior estimates. The statistics on the posteriors of the individual and overall optimizations deviate only slightly. The larger standard deviation of the lateral forces compared with vertical forces stems from differences in the friction coefficient, which is strongly influenced by environmental conditions (weather, humidity, etc.), among other parameters. Thus, lateral forces are more sensitive to variations in the rail surface moisture [10] and other rail surface contaminants, such as oil and dirt [23], that can affect the contact between rails and wheels. However, specific conclusions about the interdependence of weather and lateral forces are difficult to draw; thus, further analysis is required.

The MCMC algorithm is programmed in MATLAB R2022a software using the UQLab toolbox[22]. The simulations invoked by the algorithm are performed using SIMPACK Version 2021x.6 on a device with "Intel(R) Xeon(R) CPU E3-1246 v3 @ 3.50GHz" processor. This results in simulation times listed in Table 2. MCMC is computationally expensive; however, this offline process does not require engineering judgment and, thus, direct supervision. Moreover, parallelization, which was not implemented herein, can further reduce computation time.

4. Conclusion

To preserve and further develop railway infrastructure, it is crucial to understand vehicle-track dynamics and develop simulation models that can capture the actual dynamics of coupled vehicle-track systems. One way to achieve that is by fusing physical models with data-driven approaches for model updating. Therefore, in this study, we employ an MCMC Bayesian updating method to tune/optimize the parameters of an ICN RABDe500 wagon model system based on actual OBM measurements from an ICN RABDe500 in-service train. This leads to a well-calibrated model that can be used for predicting loads and damage, and improving maintenance periods.

To realize this scheme, we first perform simulations based on the initial wagon model values. These initial simulations already show a good agreement with the measured data in terms of contact forces. However, there is still space for improvement by updating the simulation parameters of the wagon. To this end, MCMC proves to be a very efficient and suitable tool to accomplish this task. MCMC optimizes the wagon model parameters by minimizing the MSE between the contact forces of the simulation model and the forces measured by the OBM system of the ICN train. The friction coefficient between the rails and the wheels appears to be a critical optimization parameter, the tuning of which significantly improves the prediction of lateral forces. On the other hand, the vehicle's body mass and centre of gravity mainly influence the vertical contact forces, but the effect of those parameters is not as strong. Opposite to current approaches that calculate optimal values using a trial-and-error approach, MCMC determines these values automatically. However, this process requires a prior selection of a set of parameters and the definition of their prior distribution. A key feature of the MCMC approach is that the resulting output offers a posterior probability distribution of the parameter, enabling uncertainty quantification of the predicted results. Eventually, the calibrated model can be used for further simulations.

MCMC is a suitable tool for vehicle modelling updating, which can increase simulation accuracy and decrease model building workload. However, further investigation is required to enhance its performance and ease of application. An extension could define an automatic termination criterion instead of implementing a fixed number of iterations at the beginning of the algorithm, which could decrease the computation time. Such a termination criterion would be based on the convergence of the likelihood evaluation. Furthermore, a different evaluation criterion, other than the MSE between contact forces, could be chosen in the log-likelihood function, such as frequency differences estimation, to improve accuracy and computational efficiency. In addition, since more than 50 vehicle parameters are monitored, a similar approach combining acceleration measurements could be implemented. Finally, incorporating the probabilistic nature of parameter estimates provided by MCMC could help capture uncertainty in the simulation predictions. Lastly, the proposed approach is extensible to other vehicle types and track sections.

5. Acknowledgements

This work is supported by SBB as part of the Mobility Initiative program under project OMISM - On board Monitoring for Integrated Systems Understanding & Management Improvement in Railways, by the Stavros Niarchos Foundation through the ETH Zürich Foundation, and the ETH Zürich Postdoctoral Fellowship scheme. This research project is carried out in close cooperation with the Metrology (MUD) and Strategic Asset Management of the Track departments (SAFB) of the SBB. We would like to thank in particular our partners, Oliver Schwery and Aurelia Kollros, for their continuous support in project coordination.

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