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Research agenda and practical recommendations

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DOI
10.1109/ITSC55140.2022.9922542

Publication date
2022

Document Version
Final published version

Published in
Proceedings of the 2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)

Citation (APA)
Cunillera , A., Bešinović, N., Lentink, R., van Oort, N., & Goverde, R. M. P. (2022). Train motion model calibration: Research agenda and practical recommendations. In *Proceedings of the 2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)* (pp. 1049-1054). IEEE. https://doi.org/10.1109/ITSC55140.2022.9922542

2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)
October 8-12, 2022, Macau, China

Train motion model calibration: research agenda and practical recommendations

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Abstract— **An accurate train motion model is a key component of a wide spectrum of railway applications, from timetabling algorithms to Automatic Train Operation systems. Therefore, model calibration has become crucial in the railway industry, although this topic has not received the attention and recognition in academia that its practical relevance deserves. Several data-driven techniques have been devised to calibrate train dynamics models, although an overview that describes the current state of the art in the field and highlights the following steps to be researched is still missing in the literature. Thus, this article has four main goals. First, giving a brief insight into the broad variety of techniques used for train motion model calibration, focusing on those techniques that use on-board measurements and are applicable in railway operation. Second, highlighting the main research steps to be tackled, considering the current main challenges in railway research. Third, outlining practical recommendations to practitioners who need to calibrate their algorithms and applications. And fourth, contributing to giving train motion model calibration its due recognition.**

I. INTRODUCTION

Nowadays, a wide variety of railway applications rely on a model of the train dynamics that is usually modelled by means of Newton's second law. This train motion model considers the tractive and brake effort that a train engine can apply, the running resistances that affect its motion and the effect of the track geometry on the train dynamics. This model has proven to be able to reproduce and predict train dynamics accurately. However, the precision of this model depends strongly on an accurate description of both train and track characteristics [1]. Moreover, research showed that the model parameters are generally not provided accurately and therefore have to be calibrated using operational data [2].

An accurate train motion model calibration may impact railway industry in various areas. Timetable planners need accurate rolling stock and track data, since the feasibility and future performance of their plans depends significantly on the performance and precision of the models and information used for their design [3]. However, planners usually face a high level of uncertainty at this early stage, hindering their work and jeopardising the feasibility of the designed projects at later stages [4]. Moreover, feasible train paths have to be determined over lines, networks and stations. For instance, timetable planners use a calibrated train motion model in microscopic simulations to check the feasibility of the designed timetables, and to detect and predict conflicts among train services [5]. Moreover, infrastructure capacity is one of the most challenging issues at several levels of railway planning. Among other approaches, accurate planning and effective operation help to predict and mitigate capacity issues at bottlenecks [3]. Beyond planning, the train motion model is also the core of simulators and railway operation applications like energy-efficient train trajectory calculators, Driver Advisory Systems (DAS) and Automatic Train Operation (ATO). Thus, an accurate model calibration may contribute to achieving high punctuality rates, leading to higher passenger satisfaction and better freight service. Ultimately, emerging technologies like moving block and virtual coupling will also need an accurate train motion model calibration, since they aim to push the existing boundaries of the network capacity [6].

In this article, we briefly review the train motion model calibration techniques present in the existing literature, focusing on the techniques that use on-board measurements. We consider references published from January 2000 to December 2021, since the new types of sensors implemented in the railway industry evolve continuously, and so the measured types of data do. This leads to the phase out of classical calibration techniques and to the development of new ones. We propose a research agenda based on the current state of art in train motion model calibration, mentioning several research gaps and the main challenges to be faced in the following years. This analysis has been performed in line with the current demands in a wide range of railway applications, namely energy-efficiency, automation, capacity and accuracy in planning and operation.

The main contributions of this article are:

- A brief overview of the existing train motion model calibration methods, with a special focus on those that use on-board measurements as input data.
- A research agenda based on the current state of art and research challenges in railways.
- Practical recommendations regarding train motion calibration for practitioners, software developers and rolling stock manufacturers.
- Highlighting the importance of train motion model calibration in the railway industry and research and giving its deserved recognition.

The rest of this article is organized as follows. In Section II the train motion model parameter estimation problem is described. Section III shows the current state of the art in train motion model calibration. A research agenda is proposed in Section IV, along with research gaps and techniques that

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2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC) | 978-1-6654-6880-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/ITSC55140.2022.9922542

might be of interest for this topic in the following years. Last, Section V summarizes the main conclusions drawn from this article.

II. Train Motion Model Calibration

The train motion model that describes a train's dynamics is obtained by means of Newton's second law

$$m\rho\dot{v} = f(v) - r(v) - g(s), \quad (1)$$

where v is the train speed, s is the location, the dot represents a time derivative, m is the mass of the train, ρ is the rotating mass coefficient that accounts for the inertia of the rotating parts of the train, $f(v)$ is the applied tractive and brake effort, $g(s)$ is the resistance to the train motion due to the track geometry, namely the effect of grades and curves on the train dynamics. r represents the running resistance of a train, which is usually described as a quadratic function of the speed, which is generally called the Davis equation [7],

$$r(v, s) = r_0 + r_1 v + r_2 v^2, \quad (2)$$

where r_0, r_1 and r_2 are the running resistance parameters that model the train dynamics. Physically, the running resistance parameters should be strictly positive, although some authors neglect the linear factor r_1 [8]–[14].

Furthermore, adhesion and the engine and brake characteristics limit the maximum applied effort,

$$f_b(v) \leq f(v) \leq \min(f_t, p_t/v), \quad (3)$$

where f_t and $f_b(v)$ are the maximum traction and brake effort, respectively, and p_t is the maximum traction power.

Likewise, the train acceleration may also be bounded to ensure passenger comfort in the case of passenger trains, and to preserve the integrity of the rolling stock composition in the case of freight trains. Moreover, trains are often assumed to brake under normal operation conditions following predefined brake curves with piecewise constant deceleration rates. Therefore,

$$-a_{\min}(v) \leq \dot{v} \leq a_{\max}(v). \quad (4)$$

Note that most of the parameters and bounds mentioned may show spatiotemporal variations, but these dependences are not made explicit.

However, the train motion model is essentially linked to a train's trajectory, namely its movement along the track between two stops. Usually, four different driving phases can be distinguished in a train trajectory. Acceleration, coasting, which implies letting the train run without applying traction or braking, cruising at a certain target speed, and braking, which often requires matching a certain deceleration rate.

Usually, coasting is the most relevant driving phase for parameter estimation. In this phase, no effort is applied and the running resistance can be calibrated from speed measurements, assuming that the track geometry is represented accurately in the track description. The acceleration phase is generally considered to be the second most relevant driving phase since the train driver can be instructed to accelerate with maximum traction and control the applied effort f in (1) in the estimation process. However, this approach requires knowing the maximum applied effort or the efficiency of the traction engine and the energy consumption. In turn, cruising adds an extra layer of difficulty to model calibration, since there are several ways of driving close to a target speed. Furthermore, the combination of brake effort and running resistance may lead to an overestimation of the resistance parameters [15].

Moreover, in the case of manually-driven trains, the maximum effort applied and the brake curves performed may show small variations and deviations. This may compromise the performance of simulators and eco-driving-based techniques, which use these bounds and curves as input and aim to incorporate and reproduce the driving style accurately in order to generate realistic results. As a consequence, driving-induced parameter variations also have to be considered when performing train motion model calibration.

The mass, the rotating mass coefficient, the three running resistance parameters, the maximum tractive and brake efforts, the maximum power, and the brake curves have therefore to be calibrated in order to guarantee the performance and feasibility of the applications in which the train motion model is embedded.

Furthermore, besides driving-induced variability, physical sources of spatiotemporal parameter uncertainty and variations also exist. Adhesion limits the maximum tractive and brake effort. It can be low when snowing and raining, in autumn, due to fallen leaves on tracks, and due to a bad maintenance condition of wheels and rails. However, adhesion can be estimated by comparing the wheel rotation speed with the train speed. Furthermore, at higher speeds the maximum effort is determined by the maximum tractive power. The engine temperature and wear and the electric power available in the catenary may alter the applicable power. The maximum brake effort is also affected by wear and weather conditions, however, Automatic Train Protection (ATP) systems usually assume brake rates lower than the maximum capacity of a train. Therefore, neglecting bad adhesion conditions and brake failures, trains usually follow predefined brake curves in normal operation conditions, which in turn may be the target of the calibration. The mass and rotating inertia coefficients can be introduced in the rest of the parameters, obtaining mass-specific parameters and reducing the number of parameters to be estimated by two. However, the mass can be estimated by summing the rolling stock tare, passengers and freight load and the mass of staff and operational resources needed, like fuel and water. It is usually considered to be constant between consecutive stops. Furthermore, the track description constitutes an extra source of uncertainty that might impact the accuracy of the train motion model. The track geometry, namely the grades and curves, is usually described to be piecewise constant, and sometimes its values are linked by means of parabolic terms. Moreover, not all the grades and curves are represented there, but only the most restrictive ones in each track interval.

The running resistance parameters have received most attention in the train motion calibration literature since they determine the energy consumption of the train. Generally, it is considered that r_0 and r_1 model the mechanical resistance. In particular, r_0 is mass-dependent and contains the influence of the wheel and rail contact and the internal frictions, while r_1 accounts for the flange friction between rail and wheel and the resistance due to the air momentum. Parameter r_2 models the contribution of the aerodynamic drag into the running resistance, which in turn depends on the train head geometry and cross section. This term also accounts for the extra resistance due to the extra air pressure when running through a tunnel. Moreover, r_1 is also supposed to contain the non-quadratic contribution of the aerodynamic drag. Thus, the wind may influence their values along the trajectory of a train [16]. Although there are several empirical or semi-empirical formulas that try to model the running resistance, most of them are outdated and tend to overestimate the actual resistance [17].

Thus, train motion model calibration constitutes a difficult challenge for the accurate performance of railway applications. We show the current state of the art in the next section.

III. State of the Art

Three main classical types of full-scale tests for determining the running resistance exist: cruising, pulling and coasting tests [8], [18]. The European Committee for Standardization describes such tests in a European standard [19]. The first method consists in measuring the power consumed by the traction system of a train running at a constant low speed. To this end, the energy efficiency of the traction system must be known and is highly sensitive to undesired accelerations and uncertainties in the track gradients. The second method implies pulling a train by means of a cable and measuring the resistance force using a dynamometer. However, the train has to be pulled smoothly on a straight track with constant gradient. Moreover, this method is only applicable at low speeds and is sensitive to accelerations and delays in the applied effort. In the third method, the rolling stock is accelerated until a certain target speed and then the traction and brake commands are disconnected, so that the rolling stock decelerates by coasting. These tests have to be performed in a straight, level track in order to guarantee their accuracy. Again, the method is sensitive to variations in the track geometry and it has to be repeated several times to obtain accurate statistics, although no energy consumption or tractive efficiency data is needed. These three test methods are resource-demanding and the accuracy of the first two is significantly lower than that of the coasting test.

Further methods to estimate the quadratic parameter of the running resistance, r_2, are modelling the air drag on the rolling stock by means of Computational Fluid Dynamics (CFD) and performing scaled wind tunnel tests [2]. Nevertheless, these methods usually lead to overestimated values of the running resistance, so an estimation based on operational data is of special relevance for the large amount of data available, low resource demand and cost and potential precision. Moreover, the estimates obtained from scale tests in wind tunnels require a scale correction. Particularly, freight trains of variable rolling stock composition and geometry benefit from operational data-based parameter estimation, where tests and CFD model calibration are not available [13].

Moreover, [20] and [21] propose new full-scale tests that do not require using track geometry data. Running resistance parameters r_1 and r_2 are calculated from three or more coasting tests at different speeds at the same location and applying (1) to the difference of speed measured during the tests. The mass factor ρ and parameter r_0 can be calculated by performing swinging tests at low speeds in a steep uphill track section, that is to say, by letting the train coast and run backwards due to the force of gravity.

Beyond tests, model calibration can also be performed using operational data. Two main approaches can be described. On the one hand, offline calibration techniques analyze historical operational data, obtaining the set of parameters that fit best to the considered data set or to each individual trajectory. On the other hand, online algorithms estimate parameters on-the-go, being able to monitor parameter variability along the train run. Tables I and II outline the offline and online calibration techniques available in the existing literature, respectively.

TABLE I

Offline calibration methods

Method classification	**Technique used**	**Estimated parameters**	**References**
Regression	Least squares regression	r_0, r_1, r_2	[13], [17], [22]
		r_2 in tunnels	[12]
Constrained optimization	SQP: Sequential Quadratic Programming	m, r_0, r_1, r_2 mechanical efficiency	[8]
Maximum likelihood estimation	Expectation–maximization algorithm	m	[23]
Kalman-like state observers	Iterative learning identification	r_0, r_1, r_2	[24]
Metaheuristics	Simulated annealing	max. effort cruise speed coast length brake rates	[25]
	Genetic algorithm	max. effort cruise speed coast length brake rates	[11]
		train length r_0, r_2, f_t, p_t cruise speed brake rates	[9], [10]
	Bilevel evolutionary algorithm + SQP	r_0, r_1, r_2	[26]
Simulation	Simulation-based optimization	r_0, r_1 braking distance	[27]
		r_0, r_2	[14]
	Iteration-based search	brake rates cruise speed	[28]

TABLE II
ONLINE CALIBRATION METHODS

Method classification	Technique used	Estimated parameters	References
Regression	Recursive least squares	r_0, r_1, r_2	[29]
		m, r_0, r_1	[30], [31]
	Multi-innovation least squares	r_0, r_1, r_2	[29]
Kalman-like state observers	Unscented Kalman filter	r_0, r_2	[32]
		r_0, r_1, r_2 f_t, p_t brake rates switching points	[15]
	Extended Kalman filters + Gaussian sum theory	r_0, r_1, r_2	[33]
Bayesian statistics	Particle filter	r_0, r_1, r_2	[34]
Gradient descent	Multi-start gradient optimization	r_0, r_1, r_2	[35]

IV. RESEARCH AGENDA AND PRACTICAL RECOMMENDATIONS

Several research directions and recommendations for scholars and practitioners based on the analysis of the references reviewed in this article are outlined as follows:

A. *Research agenda*

- The implementation of on-board eco-driving-based applications like real-time train trajectory optimizers, DAS and ATO could be promoted and favoured if an easily-implementable parameter estimation framework for such applications has been developed [15]. This framework should be capable of performing an accurate online estimation of the maximum amount of input parameters of eco-driving algorithms as possible in real time, while consuming the least amount of computational resources. An initial step has been taken in this direction [15], although the method presented there is difficult to be tuned and does not make use of traction and brake measurements, which are required for a more accurate model calibration. Particularly, freight trains of variable rolling stock composition could benefit from such an on-board online calibration framework [35].
- An on-board calibration framework should be robust under anomalous or missing data however, few of the techniques reviewed deal with this problem [8], [29], [35]. For instance, the GNSS signal may be lost or its accuracy may be low when passing through tunnels or in station areas. More effort should be put into developing such robust calibration techniques, since they should be able to produce reliable estimates in adverse scenarios.
- Although the main sources of train motion parameter variation are widely thought to be known among the railway community, some of the references analyzed show that this general belief is not always correct [22]. Moreover, only a few references have focused on verifying the impact of each individual source of variation [12], [22], [36]. Therefore, a research on gauging the impact of individual sources of parameter variation could be of special interest for both scientists, practitioners and rolling stock manufacturers. Particularly, rolling stock designers may particularly benefit from it. This research should emphasize on the impact of tunnels in the running resistance parameters, as may boost the accuracy of energy consumption calculations and eco-driving-based applications [12], [37]. The impact of weather conditions, namely wind strength and direction, precipitations and temperature could also be gauged thanks to the availability of public weather data sources [37]. Moreover, the wind-dependent running resistance equation proposed in [16] could also be verified. Last, the impact of some rolling stock characteristics and rail and track conditions could also be assessed. For example, assessing the parameter variability in a fleet of trains of the same rolling stock composition could lead to highlighting the importance of individual train calibrations and train-tailored railway solutions [15], [36].
- The variability of the maximum applied tractive effort and power, the deceleration rates and the switching points between driving phases also depend on the driving style, particularly in the case of manually-driven trains [9], [15], [25]. Researching the influence of the driving style on the parameter variability is still to be researched. In particular, the driving-induced parameter variability under different punctuality conditions, namely for delayed, on-time and early trains, is still to be explored systematically [25]. Moreover, each driving phase could be studied separately, although historically most efforts have been addressed towards researching the coasting phase in order to calibrate the running resistance and, ultimately, to gauge its impact on energy consumption. Note that not all the parameters can be explored in the mentioned driving phase. For instance, accurate parameter bounds and statistics could be determined and used as input for offline stochastic simulation methods [9], [25].

B. *Practical recommendations*

- One of the main obstacles towards a rigorous model validation and comparison of the proposed parameter estimation techniques is the lack of ground-truth data for the real value of the parameters to be estimated. Several of the references presented in this article validate the techniques proposed using simulations, however, this approach does not guarantee that the simulated case studies may represent real operation faithfully or that the proposed technique may also be accurate when using real data. Therefore, we suggest the establishment of a publicly available data set for validation and comparison of train motion model calibration frameworks. Railway undertakings or rolling stock manufacturers interested in this topic could publish from 50 to 100 runs of the same rolling stock unit in a certain line. This data set should contain track description data, including track geometry and speed limits, GNSS location and speed measurements and tractive and brake effort applied. Energy consumption, locomotives' tractive wheels rotation speed and rolling stock mass could be an asset. There is no such a publicly available data set for operating trains [38].

- In several of the references covered in this literature review the authors found difficulties when estimating the linear parameter of the running resistance, r_1, particularly when applying least squares-based regressions and analyzing data from coasting tests [8], [13], [14] This parameter is recognized to be the most difficult running resistance parameter to be estimated, and it is sometimes neglected and set equal to zero [8]–[14], while other authors consider it to be strictly positive [15], [21], [22], [35]. Furthermore, sometimes least squares regressions lead to a negative value of this parameter, which physically is not correct [29]. Therefore, to solve the mentioned constrained parameter optimization problem by means of least squares regressions, we recommend using a modified version of the standard regression that is able to cope with non-negativity constraints, like including a regularization term in the objective functional or applying any other constrained optimization technique. Moreover, speed measurements have an uneven distribution since trains usually run at certain speed intervals close to a cruise speed during most of their journey [12]. Therefore, the data used has to be weighted to account for this uneven speed distribution and avoid overfitting the resistance parameters in the mentioned speed operation interval and underfitting them, for instance, at low speeds. Furthermore, the value of the rotating mass coefficient may influence the estimation of the running resistance parameters [12], although few of the references analyzed take this into consideration.
- Offline model calibration frameworks may have some advantages over online algorithms, depending on the scope of the application in which they are embedded. Some of them can be implemented and used more easily than their online counterparts. Furthermore, offline techniques are able to process larger amounts of data, which may lead to more accurate estimations for some applications. Moreover, these offline frameworks usually produce a single set of estimated parameters for each trajectory or a set of trajectories, which constitute a more convenient input for some applications. Thus, offline calibration frameworks are more suitable for planning and timetabling applications [9], [25], while online frameworks are more relevant for real-time on-board applications [15] and for freight trains with variable rolling stock composition [35].
- The race for achieving higher grades of automation and energy-efficiency in railways generates some needs in terms of measured data for automation algorithms and their calibration [15], [29], [35]. To this end, regarding new rolling stock, we recommend train manufacturers and rolling stock owners to develop and purchase rolling stock that incorporates sensors and equipment for measuring GNSS location accurately, speed, the applied tractive and brake effort, energy consumption if possible and the rotation speed of the locomotives' tractive wheels. According to the references reviewed, measuring the acceleration directly leads to noisy data and to inaccurate parameter estimations [39], so new calibration techniques may not rely on accelerometers until their accuracy is not enhanced. Regarding the measurement rate, we recommend a sampling rate of 1s, since a higher measurement rate requires subsampling, noise filtering and more storage capacity, while lower rates may not be suitable for all applications or may compromise the estimation accuracy.
- Due to the potential influence of the track description uncertainties on the performance of the train motion model and its associated applications, we request infrastructure managers to commit to describe the network geometry in the most accurate possible way. This will also benefit the computation of continuous braking curves in the latest generation of train protection systems such as ETCS.
- Last, in order to contribute to highlighting the relevance of model calibration in research we recommend researchers to explicitly mention in the abstract and keywords of scientific articles when model calibration is performed. We have observed that researchers tend to not mention this explicitly when calibration is not the central topic of the article.

V. CONCLUSIONS

In this article the train motion model calibration problem has been described and a research agenda and practical recommendations based on the current state of the art have been proposed. An accurate calibration of eco-driving-based applications, the development of robust on-board calibration frameworks and gauging the individual impact of individual train characteristics, weather and driving variability on the train motion model parameters are among the research challenges outlined. Moreover, several practical recommendations to researchers and practitioners are outlined, including the establishment of a publicly available data set for validation and comparison of model calibration frameworks, some advice on running resistance parameters estimation, an analysis of the applicability of online and offline calibration frameworks, recommendations on the most relevant variables to be measured on-board for facilitating parameter estimation and a request to infrastructure managers to describe the track geometry in the most accurate possible way. We expect that this article contributes to giving train motion model calibration its deserved relevance in the railway academia and industry.

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