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Enhancing the calibration of train resistance parameters with power measurements

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Abstract

The on-board collection of data related to train operation enables a better calibration of the train resistances, which are fundamental for the elaboration of optimized train control solutions. Here, the possibility to implement a calibration of train resistances models based on power measurements is investigated. For this purpose, a huge dataset of train runs data collected by a Swiss train operator has been analysed. The train runs of three train types, operating on three different lines, have been extracted and used for the calibration phase. The calibration model is formulated as an optimization problem for parameters fitting and a Global Optimization Multi Start approach is used for finding the suboptimal solution. The performances of the model are therefore discussed together with possible further investigation.

Keywords: calibration, resistance parameters, optimization, power measurements

1 Introduction

The calibration of train motion models is a key aspect for the elaboration of optimal train control strategies. Train resistances are a fundamental part of the train dynamics and are usually computed through well-known polynomial formulations dependent upon speed [1]. Their parameters values' estimation has been defined in the first decades of the last century, and sporadically updated by the scientific community [2] or by train operators. In the last decade, the sensors invasion and the consequent availability of huge datasets on train monitoring have highlighted a high variability of energy consumptions between same passenger trains in same operating conditions (see e.g. [3]), which cannot be explained by the current formulation of train resistances. On the other side, these datasets open to the opportunity to overcome typical assumptions like the adherence to the traction curve at maximum power. Some interesting insights have been already highlighted in recent papers, such as in [4, 5, 6].

In this paper, a microscopic calibration model of train resistances' parameters based on power measurements at the pantograph is discussed. The purpose of the work is summarized in the following contributions:

- Specification of a microscopic calibration model for train resistances based on data collected on board.
- Discussion on possible requirements and limitations.

The reference modelling for the present work is composed by:

- the dynamic train motion model derived from the Newton's second law (eq. 1), which relates the forces applied to a train (tractive efforts, train resistances) with its motion parameters (acceleration, speed, position),
- the relation between the electric power measured at the pantograph and the tractive efforts measured at the wheels (2)
- and the vehicle resistances' polynomial formulation (3).

According to the time step Δt_k of the recorded observations k and $k+1$ (for instance, 1 sec), equation (1) (2) and (3) are here treated with a difference equation approach, as follows.

$$F^{tr}(v_k) - F^R_{veh}(v_k) - F^R_{inf}(s_k) = f_t * m * {}^{(v_{k+1} - v_k)}/_{\Delta t_k} \tag{1}$$

$$F^{tr}(k) = \frac{\eta P_k}{v_k} \tag{2}$$

$$F^R_{veh}(v_k) = A + B * v_k + C * v_k^2 \tag{3}$$

Where F^{tr} are the tractive efforts, F^R_{veh} are the vehicle resistances, f_t is the rotating mass factor, m is the mass of the train, P is the power measured at the pantograph, v is the speed, η represents the losses related to power transmission. The parameters A, B and C are the resistances parameters to calibrate. For this work, infrastructure resistances F^R_{inf}, dependent on train position s, are not discussed but included in the calibration model as exogenous input.

2 Methods

From the set N of recorded observations, the calibration model is formulated as an optimization problem for parameters fitting. The setup of this specific problem requires the identification of a GoF (Goodness of Fit) function and of a MoP (Measure of

Performance). The first evaluates the adherence of the model's output, given a set of parameters, to a set of observations. From similar experiences (see [6]), the RMSEp function, a.k.a. the normalized version of RMSE (Root Mean Square Error), has been chosen. The second is a variable that is used by the GoF for the evaluation of the model. Same as the GoF choice, F^{tr} has been chosen as MoP. We can formulate the problem of calibrating the resistance parameters as follows:

$$(\hat{A}, \hat{B}, \hat{C}) = \text{argmin}\, GoF\left(MoP\left(\,v(k, k+1), A, B, C, \quad f^t, m, F^R_{inf}(s_k)\right), \overline{MoP}(k)\right) \quad \forall k = 1 \ldots N \qquad (4)$$

The optimization problem is subject to constraints for ensuring adherence conditions, through the Curtius & Kniffler formula, and for respecting the maximum tractive effort available.

The data used in the current work are part of a huge set of data (over 100 GB) collected by a Swiss train operator through their onboard monitoring systems and their trackside data system, which belongs to three different passenger train types, namely the ICN, the RABe521and the Re 460. For each train type, a subset of trains operating on the same track and with the same wagon composition has been created.

Data for each train course include time, speed, GPS position, power at pantograph (sampling frequency of one second). The parameter η, which is usually a function of speed, is treated here as a constant, and its value has been estimated by the train operator. Moreover, infrastructure data such as radius, gradient, speed limitations (per each train category), are available.

In a preprocessing phase, data collected near and within tunnels have been neglected, to avoid the error connected to position and speed. The identification of tunnel areas has been performed through a matching of the train position (namely, between DCS on board data and RCS trackside data). In this way a larger area than the tunnel itself is identified, i.e. a Virtual Tunnel, out of which the measurements are considered reliable (see figure 1). Moreover, the average of power measurements at stops has been used as a proxy of the power dedicated to the train's auxiliary systems (e.g., heating).

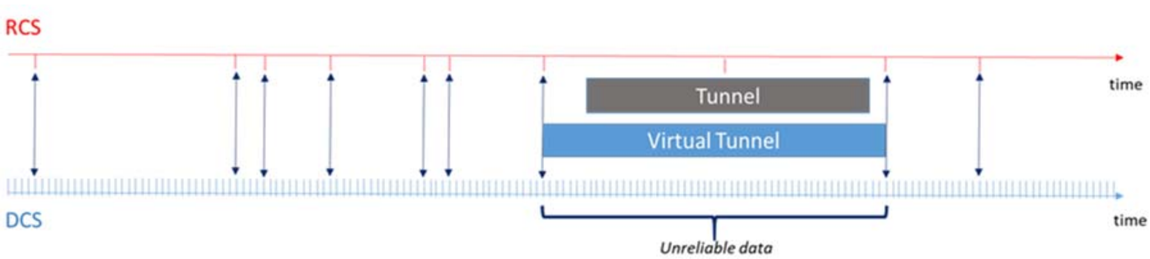

Figure 1. Schematic representation of tunnel areas, in which speed measurements are considered not reliable

3 Results

The optimization problem has been implemented in MatLab and solved with the Global Optimization toolbox, which includes a Multiple Start algorithm for avoiding local minima. Experimental results are discussed as follows: first a stability analysis has been performed to evaluate the proper dataset dimension for calibration, then the parameters estimation for each train type is performed.

The stability analysis has been conducted on a set of 300 calibrations per train type by varying the dimension of the calibration set, i.e. the number of trajectories that composes the calibration set, from 1 to 10. For each dimension, the calibration has been repeated 30 times, each time by randomly choose the trajectory/ies composing the calibration set (see Figure 2). As an example of the performed analyses, the analysis results of ICN trains on the Biel-Lausanne track are shown. Similar trends have been found for the RABe521 operating between Basel and Porrentruy, and for the Re 460 on the Baden-Bern track.

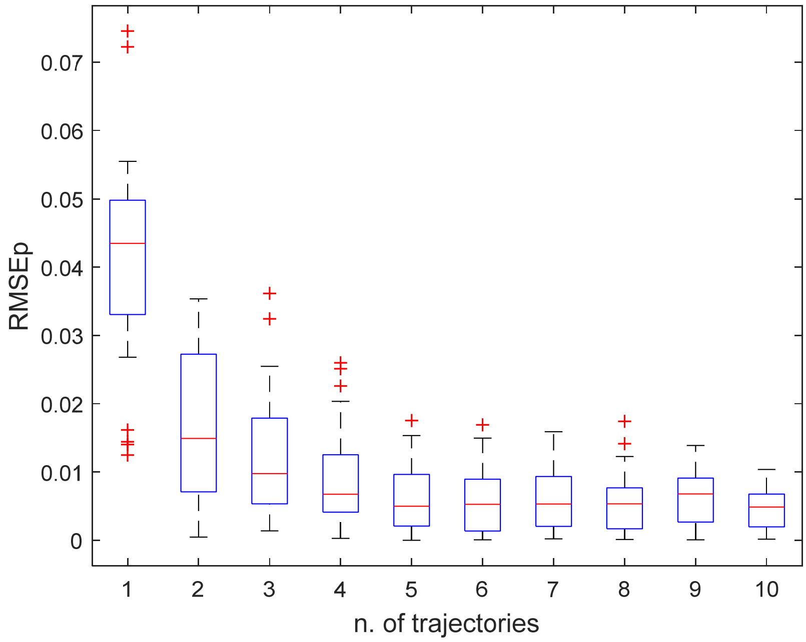

Figure 2. Stability tests - RMSEp trend by varying the calibration set dimension.

The parameter's values estimation, i.e. values of A [N], B [N s/m] and C [N s2/m2], has been performed similarly to the stability analysis in order to highlight the properties of the calibration results. The elaborations refer to the same calibration set used for the RMSEp evaluation. In figure 3, The A, B and C values estimation for the ICN train type is reported.

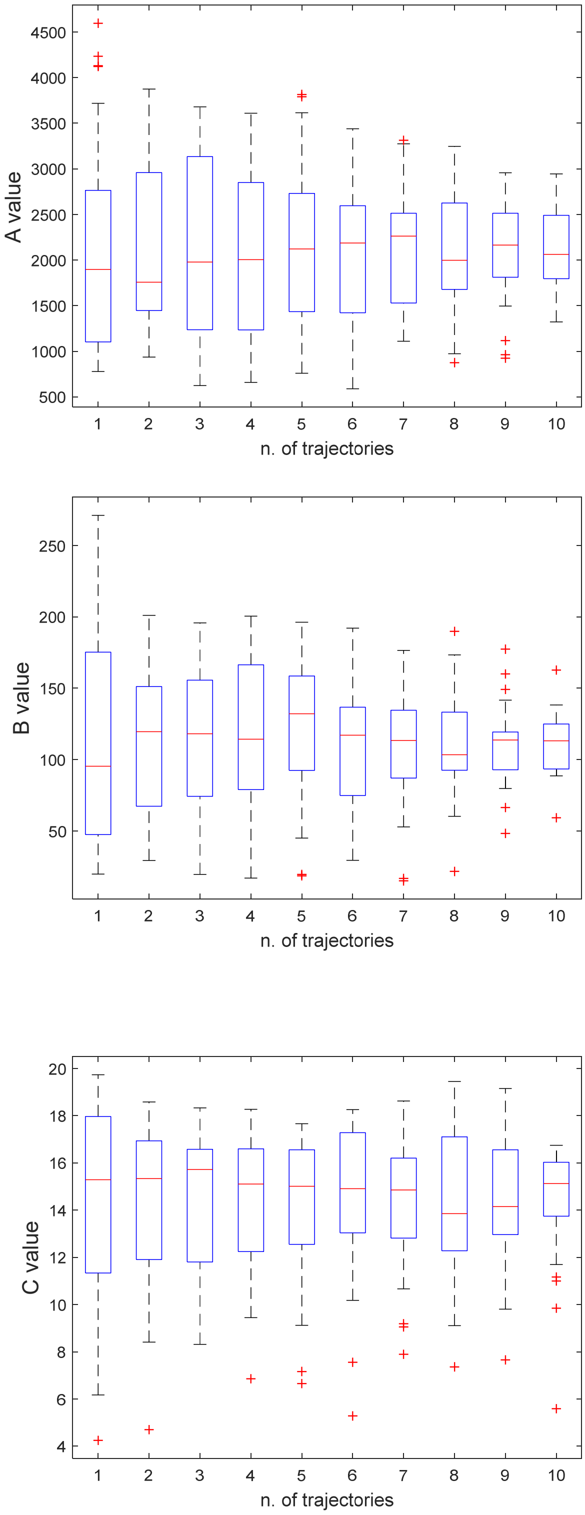

Figure 3. Stability tests - Parameter’s values estimation, 30 repetitions.

The parameters values have been evaluated in number of times the same value has been estimated:

- A value [N] = 2124.84 (value obtained 13/30 times, tolerance 10 e-3); both dimension sets 9 and 10 reached this value
- B value [N s/m] = 115,46 (value obtained 14/30 times, tolerance 10 e-3); reached by dimension 9, dimension 8 and 10 both reached 13 times this value.
- C value [N s^2/m^2] = 14, 27 (value obtained 12/30 times, tolerance 10 e-3); reached by dimension 10.

The calibration results for the three train types are reported in Table 1:

ICN **Biel-Lausanne**	**RABe 521** **Basel-Porrentruy**	**Re460** **Baden-Bern**
A=2594 [N] B=106.6 [N s/m] C=8.70 [N s^2/m^2]	A=2125 [N] B=115.3 [N s/m] C=14.27 [N s^2/m^2]	A=3148 [N] B=88.2 [N s/m] C=14.94 [N s^2/m^2]

Table 1. Results of the calibration phase for three train types

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4 Conclusions and Contributions

This work aimed at specifying a microscopic calibration model for train resistances' parameters based on power data collected on board. Within the set of experiences here presented, some interesting conclusion can be highlighted.

The calibration with power measurements allows including non–modelled dynamics into the trinomial formulation of resistances models. For example, weather aspects, like wind, and geographical characteristics of the track, like canyon effects, are difficult to be modeled and usually neglected. By referring to the power used to win the resistances, the physical meaning of the parameters is thus enlarged to included non–modelled dynamics, in a "black-box" approach. Within the calibration model set up, some typical issues linked with power measurements have been addressed and solved. For example, the amount of power dedicated to auxiliary systems is usually difficult to evaluate and it varies from train to train. For each train, the average power consumptions during the stops is computed and assumed as a proxy of auxiliary systems' power needs. This value varies from train to train, and it has also a seasonal trend.

The computation time of the calibration varies with the dimension of the dataset. In worst conditions, with a calibration set composed by 10 trajectories (each considered trajectory ranges from approximately 1800 to 2500 records), a single calibration is performed in more than an hour. Since this is an offline procedure, this is not a problem. However, the problem can be further constrained by setting the hyper parameter of the global optimization algorithm and/or by further constraining the parameters' search; in these conditions, some experiences show that the time can be drastically reduced to 15-20 minutes approximately.

From the conclusion, further investigations are also identified. Since the vehicle resistances are affected by the orographic configuration of the track area, it is also plausible that the proposed calibration model can show different resistances between two different tracks. This may lead to a new and more precise definition of train resistances parameters, which depend on the specific track. Further investigations to deepen this assumption are needed, to understand the real dependance of these aspects to the parameters' estimation.

The calibration process assumes the power losses as constant. In empirical studies of the conducted by the train operator, the values of parameter η are described as a function of speed. A further development of this work is to include the η variability in the optimization problem.

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