Journal of Rail Transport Planning & Management 3 (2013) 126–136

Contents lists available at ScienceDirect

Journal of Rail Transport Planning & Management

journal homepage: www.elsevier.com/locate/jrtpm

A simulation-based optimization approach for the calibration of dynamic train speed profiles

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A R T I C L E   I N F O

Article history:
Received 3 June 2013
Revised 25 October 2013
Accepted 28 October 2013
Available online 5 December 2013

Keywords:
Train dynamics
Running time models
Calibration
Simulation-based optimization
Speed profile estimation

A B S T R A C T

Predictions of railway traffic are needed for the design of robust timetables and real-time traffic management. These tasks can be effectively performed only by using train running time models that reliably describe actual speed profiles. To this purpose calibration of model parameters against field data is a necessity. In this paper a simulation-based optimization approach is proposed to calibrate the parameters of the train dynamics equations from field data collected. Furthermore, a procedure for the estimation of train lengths has been developed. This method has been applied to trains with different rolling stock running on the Rotterdam–Delft corridor in the Netherlands. Probability distributions for each parameter are derived which can be used for simulation studies. The results show that the train length estimation model obtained good computation accuracy and the calibration method was effective in estimating the real train path trajectories. It has been observed that some of the parameters of tractive effort and resistance do not affect the train behaviour significantly. Also, the braking rate is significantly smoother than the default value used by the railway undertaking while calibrated resistance parameters tend to have lower mean than defaults. Finally, the computational efficiency of the approach is suitable for real-time applications.

Introduction

Recent demand growth for passenger and freight transportation in railway systems has raised the need for practitioners to increase the level of network capacity while keeping a high standard of service availability and quality. To achieve this aim railway traffic needs to be scheduled according to robust timetables that guarantee higher levels of capacity usage also in presence of stochastic disturbances. On the other hand, suitable control measures (e.g. train retiming, reordering and/or rerouting) must be applied in real-time by dispatchers to provide rescheduling plans that mitigate the effects of observed conflicts on network performances. Both robust timetabling and real-time management of railway traffic aim at supplying conflict-free train paths computed on the basis of off-line and on-line predictions of traffic behaviour. In the first step, train trajectories must be computed taking into account microscopic details of the infrastructure (e.g. lengths, gradients, curvatures of rail tracks, speed limits), signalling system (e.g. positions of signals, block section lengths, braking behaviour imposed by the automatic train protection), train composition (e.g. number of wagons, rolling stock characteristics), and current traffic information when the prediction is performed on-line. Then, based on the estimated train trajectory a conflict-free schedule is constructed by solving a mathematical problem (e.g. optimization, heuristics), or by relying on rule-of-thumbs or experience of the operator (i.e. a planner in timetabling and a dispatcher within real-time operations). The effectiveness of these schedules depends on the reliability of the estimated train trajectories and the precise identification of potential track conflicts. Inaccurate forecasts can lead to wrong detection of possible conflicts and to traffic schedules that are ineffective or even infeasible when put into operation. In this context, accurate traffic prediction models must be used to confidently describe the real evolution of train behaviour. To this purpose a proper calibration phase is needed to estimate input parameters against train data (e.g. position, speed) collected from the field, so that the model can reproduce the real train trajectories as much as possible.

This paper presents an approach to derive the most probable speed profiles of train runs from observed track occupation/release data. The train behaviour is modelled according to the Newton dynamic motion equations which are numerically integrated over distance employing the Runge–Kutta method (Butcher, 2003). A simulation-based optimization approach is adopted to calibrate input parameters of the equations describing the tractive effort, the motion resistances, the braking effort, and the cruising phase. These parameters are fine-tuned for different classes of train composition (defined by the number of wagons, the type of traction unit, and the length of the train) by minimizing the gap between observed and simulated running times, using a genetic algorithm. Additionally, since the train composition is not known with

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http://dx.doi.org/10.1016/j.jrtpm.2013.10.008

certainty beforehand, a model for train length estimation is developed. For each composition the calibration experiment is performed over a significant set of observed train runs. This enabled estimating the probability distributions the different input parameters for each class of train compositions. This aspect gives also insight in different driving behaviours adopted during real operations. The proposed approach is applied to train runs operating along the corridor Rotterdam–Delft in the Netherlands. Results illustrate the effectiveness of this method in calibrating parameters of the Newton's dynamic equations versus track occupation/release data collected at the level of track sections.

With this paper the authors provide the following main contributions:

- A novel simulation-based method to calibrate the parameters of the train dynamic motion equations against observed track occupation data. This approach allows the derivation of train speed profiles from the real distance–time trajectory collected at discrete points from track-free detection sections.
- A procedure to assess the length of trains from time to distance data collected by track-free detection sections
- A statistical assessment of parameters relative to both physical–mechanical characteristics of trains (e.g. coefficients of resistance and traction equations) and the behaviour of train drivers (e.g. compliance to the max speed limit on the track, braking rate applied).
- A practical application to a real test case which proves the applicability of the proposed approach and the usefulness that results can have for both practitioners (e.g. more reliable predictions of train trajectories) and academics (e.g. distribution of parameters suitable for robust timetabling design).

Section Literature review gives a literature review on the different approaches proposed to model train running times and calibrate model parameters. In Section Methodology, the methodology proposed in this paper is described. Section Case study: the Rotterdam-Delft corridor illustrates the case study considered for the application and provides the corresponding results. Conclusions and final comments are given in Section Conclusions.

Literature review

In the literature, several approaches are presented for estimating train running times taking into account microscopic features of both trains and the infrastructure (including the signalling system). In particular, models can be mainly divided in the ones using kinematic motion equations and others adopting a dynamic representation of the movement, basically by means of Newton''s motion formula (Hansen and Pachl, 2008).

Albrecht et al. (2006, 2010b) described train motion based on the kinematic equations and calibrate their parameters (speed and acceleration) versus track occupation data collected by means of train describer systems (Daamen et al., 2009; Goverde and Meng, 2011). Albrecht et al. (2010a) use calibrated kinematic models to understand the influence of the Dutch signalling and ATP system on train speed profile and energy consumption. The disadvantage of these models is that they calibrate only the parameters of the kinematic motion equations which are trajectory-dependent and cannot be used anymore when considering a different train run even if the rolling stock is the same.

Medeossi et al. (2011) use a dynamic equation for each phase of the train motion (i.e. acceleration, cruising, coasting and braking) and fine-tunes the respective performance parameters against GPS data collected on-board of the trains. A probability distribution is then estimated for these parameters to characterize stochastic variations of running times.

Hertel and Steckel (1992) proposed a model that computes running times based on theoretical stochastic distributions of train parameters (e.g. resistance coefficient, braking rate) instead of using typical deterministic parameters as commonly considered in practice. The parameter distributions adopted in this work are however not derived from any realised train run.

Kecman and Goverde (2013) adopt a method suitable for real-time predictions, that represents train trajectories by means of a weighted graph that evolves dynamically each time that new information is gathered from the field; weights of the arcs are train running and dwell times and minimum headway times measured by means of detailed track occupation/release data from train describer records collected at the level of track sections (e.g. axle counters, track circuits).

During real operations stochastic variations to individual train runs are observed due to changes in the rolling stock condition, rail deterioration, as well as variations in the train driver behaviour and weather circumstances. These unpredictable variations induce an alteration of train characteristics such as the deceleration and the acceleration rates as well as motion resistances (e.g. due to gradient, air viscosity, rail curvatures) and consequently, a change in train trajectories (Kecman and Goverde, 2013). According to this, approximated parameters estimated by manufacturer or train operators should not be taken for granted (Radosavljevic, 2006), but need to be computed for each train composition and railway corridor separately.

This work helps filling the gap between practice and theory under the following perspectives:

1. So far, research approaches proposed in literature were mainly focussed on calibrating parameters of the kinematic train motion equations (Albrecht et al., 2006, 2010a,b) or only performance factors of the dynamic train motion equations (Medeossi et al., 2011). This work instead has the objective to calibrate all the parameters of the dynamic train motion equation and not only performance factors as in Medeossi et al. (2011). The fact that we consider and calibrate all the parameters of the dynamic equation, gives to our model a higher flexibility than (Medeossi et al., 2011) since it can accurately describe every kind of observed trajectory. This means that it can reproduce every type of observed driving behaviour.
2. Compared to the previous work by Medeossi et al. (2011), the main advantage of our approach is that we manage to accurately describe observed train trajectories on the basis of track occupation data and not GPS. Currently, only in rare cases it is possible to use GPS data, given that the most part of railway networks in Europe are not equipped with these systems. Most part of the railway networks are equipped with track-free detection systems that detect the occupation/release of a certain track from a train. This means that the model proposed in this paper can be used for all those networks having track-free detection systems since we use exactly these data to calibrate train parameters. Moreover, these data are automatically collected which provides a big amount of data for detailed analyses.
3. The presented methodology provides probability distributions of train parameters fitted on data gathered from the real field, which can be used for more reliable robust timetabling (where train running times are generated from random distributions) or as more realistic input for the model of Hertel and Steckel (1992) to calculate train running times.

To the best of the authors' knowledge no efforts have been addressed in literature to the estimation of parameters relative to tractive effort and motion resistances based on actual track occupation data.

Methodology

A simulation-based framework to calibrate dynamic equations of train motion

To provide a reliable prediction model able to accurately reproduce real train trajectories it is necessary to calibrate model parameters against real data collected from the field. In this paper the calibration process is performed by developing a simulation-based framework that integrates a genetic algorithm with a microscopic running time model based on dynamic motion equations as given by Newton.

This framework has been developed in Matlab and consists of several components (Fig. 1). The entire framework is based on data relative to the infrastructure (e.g. track length, gradient, speed limits, signal and station positions), the rolling stock features (e.g. train length) and the track occupation/release collected from the field. A pre-processing phase is necessary to convert the different input data into a suitable format and combine them in order to derive information needed to initialize the calibration model. In particular these data are combined to identify the exact route (i.e. the sequence of track sections, switches, signals, and stations crossed by the train during its run) and the train length (which is related to the composition) of each observed train run. Train length has been used to group the observed train runs in different classes of train compositions. Parameters of the running time model are estimated separately for each class.

Also, track occupation/release data are processed to derive discrete space-time trajectory data for each observed run that are used to evaluate the objective function at each iteration of the optimization algorithm. The calibration experiment is performed only against distance–time data relative to unhindered trains, thus train runs that are not disturbed by the presence of other trains on the network. This assumption consents to understand how the value of train parameters varies over different runs only due to the behaviour of the train driver and not to the interactions with other trains.

The proposed algorithm developed for the optimization problem is customised genetic algorithm which is implemented in Matlab. Output of the framework consists of: calibrated parameters of the dynamic equation for each train (i.e. braking rate, parameters of the tractive effort equation, coefficients of the resistance equation, speed adopted in cruising phases) and the corresponding train trajectories (i.e. distance–time diagrams, speed–time and speed–distance diagrams).

This framework has been applied to calibrate a significant set of train runs for each class of train compositions. By doing this, it has been possible to estimate the probability distribution relative to the input parameters of the running time model for each train class.

Input data

Input data to the proposed framework are relative to the infrastructure characteristics, the rolling stock features and observed track occupation/release data collected at the level of track sections for a significant set of train runs. In this section a detailed description of each of these data is provided as follows:

- Infrastructure data contains detailed information about microscopic characteristics of railway network. These data describe lengths of track sections, curvature radii, gradients, static speed limits, positions of stations, signals and switches as well as the braking behaviour and the supervised speed codes by the Automatic Train Protection system (in this case represented by the Dutch ATB). All this information is derived from infrastructure maps and digital InfraAtlas data (version 2011) provided by the Dutch infrastructure manager (IM) ProRail.
- Rolling stock data specify the features regarding rail vehicles such as train compositions (number of wagons, type of traction unit), mass, parameters of the tractive effort-speed curve as well as coefficients of the resistance equations. This data have been supplied by the main Dutch railway Undertaking (RU) Netherlands Railways (NS).
- Track occupation/release data are gathered from field measurements that return the event time that a given train has occupied or released a certain section on the network. This information has been collected by means of the train describer system in the Netherlands called TROTS (ProRail, 2008). This system logs generated train number messages and incoming infrastructure messages (from signals, switches, track sections) to provide a list of events in a chronological order. The advantage of the TROTS system is that it is able to record train number steps at the level of track sections. Measured occupation/release times are rounded down to the full second and are affected by an error (i.e., delay) of release of track circuits, that has been defined for

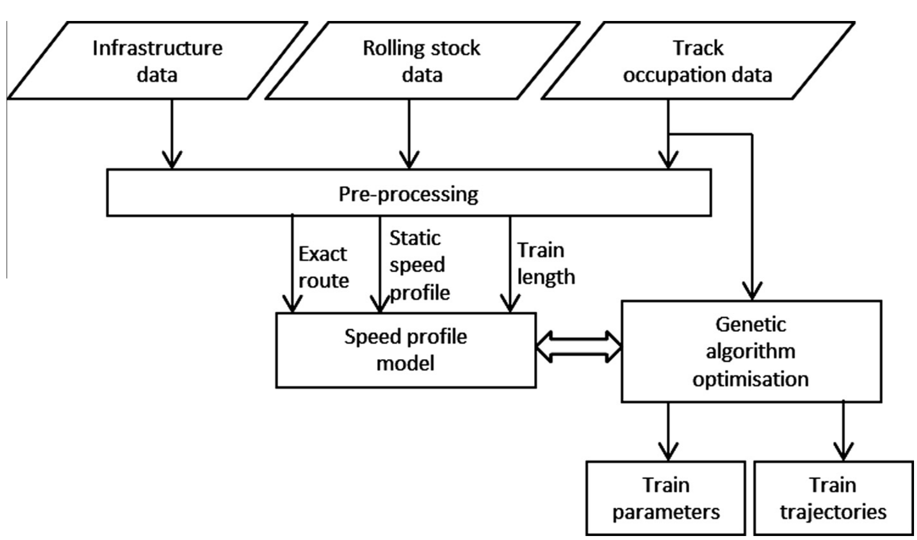

Fig. 1. Functional scheme of the simulation-based optimization framework.

safety reasons. This measurement inaccuracy has a big influence on very short sections when short occupation times are observed. These data are pre-processed by using the data mining tool developed by Kecman and Goverde (2012).

Data pre-processing

The main function of the pre-processing phase is to: (i) convert the different input data into a format that is usable by the developed framework, (ii) combine these data in order to derive additional information which are needed to initialize and apply the calibration model. Specifically, the latter process is addressed to provide for each observed train run: the exact route and the train length.

The route of a train is defined as the sequence of infrastructure elements (i.e. track sections, switches, signals, station platforms) traversed during its run. To determine the route relative to a certain observed train run, it is necessary to combine track occupation/release data corresponding to that run together with the infrastructure data (InfraAtlas maps). The track occupation/release data is a chronological ordered list of the IDs (identification number) relative to the infrastructure elements crossed by the train during a certain run. By coupling this list of IDs with the infrastructure data it is possible to identify the route followed by that run in terms of length of track sections, gradients, static speed limits, curvature radii, the switches used, the signals approached, and the platforms at which it stopped.

In the Netherlands, different rolling stock is used in service and these variations may be observed even at a single train line. Despite the existing rolling stock plans for each day of operation, the realised rolling stock tends to differ due to both real-time situations that cannot be predicted in advance (i.e., train delays and track obstructions) and the actual rolling stock availability (e.g. due to breakdowns or unplanned maintenance). Moreover, both planned or realised rolling stock may be unavailable to the infrastructure manager. Hence, there is a need for detecting train compositions that have been actually used during real operations. This detection can be performed by estimating train lengths by means of track occupation/release data. To explain this procedure it is possible to refer to the example illustrated in Fig. 2 where two track sections s_i are represented together with their respective section joints x_i and x_{i+1}.The average speed of train run j when traversing track section s_i can be calculated as:

$$\bar{v}_{i,j} = \frac{x_{i+1} - x_i}{t^{occupy}(s_{i+1}) - t^{occupy}(s_i)} [\mathrm{m/s}] \tag{1}$$

where $t^{occupy}(s_{i+1})$ and $t^{occupy}(s_i)$ represent the time in which the head of the train enters track section s_i and s_{i+1}, respectively. Also, $t^{release}(s_i)$ is the time instant in which the tail of the train releases track section s_i. As said in Section Input data, the release time $t^{release}(s_i)$ is affected by an accuracy error δ that is the time delay between the perceived and the actual instants in which a train releases section s_i (i.e., $t^{release} \pm \delta$). Due to this delay we can only estimate an interval I_j for the length of train j. The width of interval I_j (expressed in m) is easily assessed as:

$$I_j = [\overline{v}_{i,j} \cdot ((t^{\text{release}}(s_i) - \delta) - t^{\text{occupy}}(s_{i+1})), \overline{v}_{i,j} \cdot ((t^{\text{release}}(s_i) + \delta) - t^{\text{occupy}}(s_{i+1}))]. \tag{2}$$

Consequently, we assume that the expected length l_j of train j coincides with the median of interval I_j.

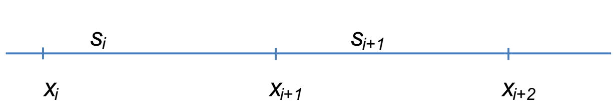

Fig. 2. Track sections and respective joints.

Assume that from the analysis of rolling stock data we observe different possible train compositions c_1, c_2, c_3, c_4 with associated lengths L_1, L_2, L_3, L_4, respectively. To assign the composition to a given train j, l_j is compared with the lengths L_i of each possible composition c_i (i = 1,2,3,4). The composition assigned to j train will be therefore the one whose length L_i is the closest to the estimated length l_j, i.e. the one which minimizes the difference $|Li - l_j|$. When the estimated interval I_j is too wide, it may happen that multiple composition lengths are covered. Also, it may happen that no train lengths are feasible. In these cases it is not possible to assign a specific composition to train run j.

Microscopic speed profile model based on dynamic motion equations

The developed running time model is based on Newton's dynamic motion equations, where the train is modelled as a mass point. This assumption is widely accepted and used in practice (Hansen and Pachl, 2008), since practical applications have shown satisfactory results. The train length is not neglected in the model since the trajectory of the tail of the train is obtained from the one of the head shifted back for the train length. Referring to the Newton's motion law, the force $f_s(v)$ (surplus force) that is used to accelerate a train is produced by the difference between the tractive effort $f_t(v)$, and the resistance forces $r(v)$. The tractive effort is generated by the traction unit and applied at the wheel's rim. The resistance forces are obtained as the sum of the resistances due to air viscosity and line characteristics (e.g. gradient and curves). This relation can be formally expressed as:

$$f_t(v) - r(v) = f_s(v) = m \cdot dv/dt \tag{3}$$

The tractive effort is assumed a piecewise function of the train speed v consisting of a linear and a hyperbolic part (Hansen and Pachl, 2008):

$$f_t(v) = \begin{cases} c_0 + c_1 v, & v \leqslant v_{overheat} \\ c_2/v, & v > v_{overheat} \end{cases},$$

The linear part of the function ($c_0 + c_1 v$) is valid for values of the speed lower than the so called overheat speed limit $v_{overheat}$, while a hyperbolic characteristic is denoted for higher speeds and presents a limitation due to adhesion and tractive power. The resistance forces $r(v)$ acting against the train movement are modelled as a second-order polynomial of speed, expressing resistances on a flat and straight line ($r_0 + r_1 v + r_2 v^2$), and constant resistances due to the topology of tracks, i.e., gradient (f_G) and curve alignment (f_C), respectively (Hansen and Pachl, 2008):

$$r(v) = r_0 + r_1 v + r_2 v^2 + f_C + f_G. \tag{5}$$

The coefficients r_0, r_1 and r_2 depend on several variables such as type of the rolling stock, train composition and number and type of train axles. The constant and linear term with coefficients r_0 and r_1 represent the mechanical resistance of the rolling stock, while the quadratic term models the aerodynamic resistance. In this model extra resistances relative to the presence of tunnels are not considered. Fig. 3 shows a typical trend for the tractive effort and the train resistances as described by (5) and (6), respectively (see Fig. 4).

It should be noted that the mass of the train is implicitly included within the coefficients of resistances and tractive effort equations. Indeed, these are specific coefficients since they are expressed per mass unit. Also, weather conditions such as wind speed, are embodied as part of the parameters. For example, if weather conditions are bad (i.e. wind against train movement direction) this will result in higher resistance parameters.

In order to estimate train trajectories, it is necessary to solve equation (4) for each phase of the motion, that is to say: (i)

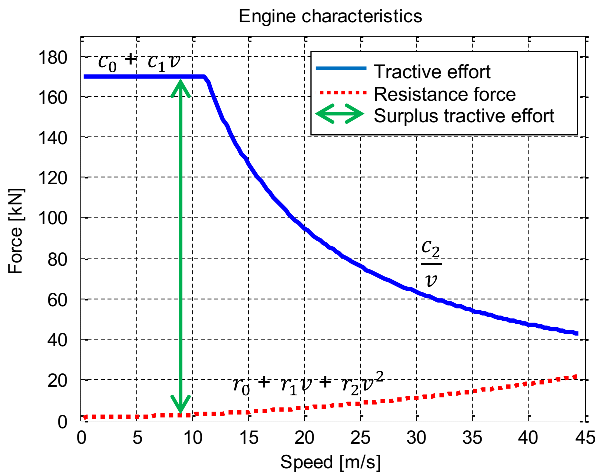

Fig. 3. Train characteristics.

acceleration, (ii) cruising and (iii) braking. The analysed corridor Rotterdam–Delft is one of the densest corridors in the Dutch network, thus it is assumed that just small running time supplements had been allocated. Therefore, the coasting phase is not included in the presented running time model. The following characteristics are considered for each phase:

- In the acceleration phase the driver is supposed to accelerate the train by using the tractive effort described by (5) until the train reaches the maximum speed allowed for a given track, or the desired value of cruising speed.
- In the cruising phase the train moves with a constant speed. For a certain track this speed can be the static maximum speed, or a certain lower cruising speed deployed by the train driver. Therefore, the rate between a static speed limit and the cruising speed actually operated is represented by $\theta_{cruising}$. This cruising performance can vary from track to track and depends on the driver behaviour.
- In the braking phase train speed is reduced to accomplish speed restrictions imposed by the track (e.g. static speed limits, switches, stops at stations) or by the signalling system (e.g. red or yellow aspects). Experimental results presented in Medeossi et al. (2011) show that during service two different braking rates are used by trains when (1) slowing down to respect static or dynamic (e.g. given by the signalling system) speed limits and (2) coming to a standstill because of stopping in a station. This assumption has been made in the present model, whereby two braking rates are used for the former (b_{limit}) and the latter case (b_{stop}), respectively. Specifically, due to the specific allocation of track circuits it has been not possible to collect time data suitable for the determination of b_{stop}. That is why a default value of 0.66 m/s^2 has been used for this parameter as provided by NS.

A partial train trajectory is determined for each phase by computing the speed v assumed by the train at a certain distance s, and afterwards calculating the time t corresponding to obtained speed and distance. Particularly, a dynamic train speed profile is modelled as a function of speed depending on distance:

$$\frac{dv}{ds} = \frac{f_t(v) - r(v)}{v}, \tag{6}$$

where dv/ds is the derivative of speed with respect to distance. The corresponding running time is expressed as:

$$\frac{dt}{ds} = \frac{1}{v}, \tag{7}$$

where dt/ds is the derivative of time to distance. The given Eqs. (7) and (8) are autonomous first-order ordinary differential equations for which several numerical solution methods have been tested in terms of speed and accuracy. As a result, the method given by Dormand–Prince (Butcher, 2003) is adopted which is a particular application of the more general Runge–Kutta approach.

Formulation of the calibration model: a simulation-based optimization problem

The calibration process is formulated as an optimization problem that aims to minimize the error between simulated and real passage running times. As explained earlier, actual running times are derived by pre-processing TROTS data.

The decision variables (i.e. the parameters that need to be calibrated) of the problem are listed in Table 1.

The optimization problem can now be formulated as:

$$\text{Minimize} \sum_{i \in N} |t_i^{\text{observed}} - t_i^{\text{simulated}}| \tag{8}$$

Subject to

$$\frac{dv}{ds} = \frac{f_t(v) - r(v)}{v} \tag{9}$$

$$\frac{dt}{ds} = \frac{1}{v} \tag{10}$$

$$c_0 \in \left[c_0^{\text{lb}}, c_0^{\text{ub}}\right] \tag{11}$$

$$c_1 \in \left[c_1^{\text{lb}}, c_1^{\text{ub}}\right] \tag{12}$$

$$c_2 \in \left[c_2^{\text{lb}}, c_2^{\text{ub}}\right] \tag{13}$$

Table 1
Decision variables.

c_0	Maximum starting tractive effort due to overheating limit (N/kg)
c_1	Linear parameter of tractive effort equation (Ns/m/kg)
c_2	Hyperbolic parameter of tractive effort function (Nm/s/kg)
r_0	Constant resistance coefficient (N/kg)
r_1	Linear resistance coefficient (Ns/m/kg)
r_2	Quadratic resistance coefficient ($Ns^2/m^2/kg$)
b_{limit}	Braking to speed limit characteristic (m/s^2)
$\theta_{cruising}$	Cruising performance (%)

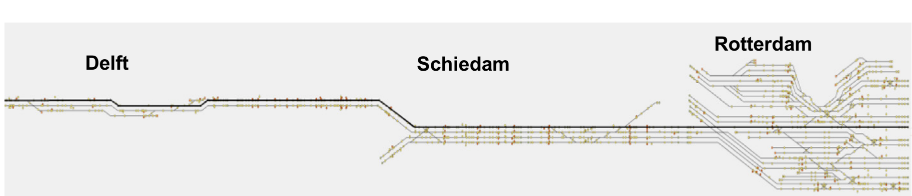

Fig. 4. Schematic layout of the corridor Rotterdam–Delft.

$$r_0 \in \left[r_0^{\mathrm{lb}}, r_0^{\mathrm{ub}}\right] \tag{14}$$

$$r_1 \in \left[r_1^{\mathrm{lb}}, r_1^{\mathrm{ub}}\right] \tag{15}$$

$$r_2 \in \left[r_2^{\mathrm{lb}}, r_2^{\mathrm{ub}}\right] \tag{16}$$

$$b_{limit} \in \left[b_{limit}^{\mathrm{lb}}, b_{limit}^{\mathrm{ub}}\right] \tag{17}$$

$$\theta_{cruising} \in \left[\theta_{cruising}^{\mathrm{lb}}, \theta_{cruising}^{\mathrm{ub}}\right] \tag{18}$$

$$v(0) = v_0 = 0, \quad v(N) = v_{end} = 0. \tag{19}$$

where the objective function (9) is represented by the absolute error between the simulated and observed passage running times for all the N measurements provided by the TROTS data. It is clear that the evaluation of the objective function requires a preliminary computation of the speed profile and the running time. This means that a numerical integration of the speed and the running time as represented by Eqs. (10) and (11) must be performed at each iteration of the optimization algorithm.

These parameters are relative to the tractive effort equation (c_0, c_1 and c_2), the resistance equation (r_0, r_1 and r_2), the braking rate used to slow down (b_{limit}) and the cruising performance adopted by train driver during cruising phases ($\theta_{cruising}$), respectively. Eqs. (12)–(19) define the optimization constraints for each of these variables imposing the lower (lb) and upper bounds (ub) of their domains. Finally, the Eq. (20) gives the initial and final speed conditions representing that a train starts the run from a standstill and stops at the end of route.

Therefore, a solution to the optimization problem is represented by the vector:

$$\beta = (c_0, c_1, c_2, r_0, r_1, r_2, b_{limit}, \theta_{cruising}), \tag{20}$$

which contains a set of values for the decision variables.

The optimization metaheuristics: a genetic algorithm

A genetic algorithm (GA) is developed to solve the optimization problem. GA is a well-known robust and adaptive method largely used in the scientific field to solve search and optimization problems. The algorithm works with a population of individuals, each representing a possible solution, in this case a set of train parameters β. Each individual produces a different value of the objective function. The population evolves towards better solutions (i.e. lower values of the objective function) by means of randomized processes of selection, crossover, and mutation (see (Mitchell, 1996) for more information on the topic). The GA used in this research has been developed in Matlab and customized to improve its performances according to the specific problem applied. Moreover, its execution has been parallelized by allocating different functions of the algorithm to different threads. This strongly reduces computing times of the optimization when adopting multi-core computers.

Case study: the Rotterdam–Delft corridor

The framework proposed in this research has been applied to calibrate a significant set of trains running along the corridor Rotterdam–Delft, which is one of the most densely operated lines in The Netherlands. The line has a length of 14.3 km with a double track layout. The Dutch signalling system NS'54 with ATB automatic train protection is implemented over the whole corridor. A detailed explanation of this system can be found in Albrecht et al. (2010a). Both regional and Intercity (IC) trains operate on this line, but for the sake of simplicity the analysis performed in this research is only demonstrated to the latter type of trains.

In particular, the intercity train line IC1900 is analysed. According to the timetable, the rolling stock used in service is reported in Table 2. Four different classes of train compositions have been observed: the electrical multiple units VIRM with four, six and ten units as well as the locomotive hauled trains ICRm with ten cars. All these trains use the same route and therefore the same platform tracks, in- and outbound interlocked routes, and block sections, with a slight difference in terms of the stop locations in stations.

The calibration of the running time model is performed for observed TROTS data collected over a 28-days period of operation in April 2010. In total 42 track sections have been considered. This means that the parameters of each train run have been calibrated versus 42 time–distance observations.

All the calibration experiments are carried out on an AMD Athlon 3300 GHz processor with six cores and 4GB of RAM. The integration of a single train trajectory takes about 0.02 s, while the computing time needed to complete a single calibration experiment is always lower than 1 min.

Analysis of parameters and model performance

A preliminary sensitivity analysis has been performed to understand which input parameters is the more influential for the running time model. This has been carried out by evaluating variation of the running time model output by changing the value of one parameter while keeping fixed the other ones. This procedure has been repeated for all input elements. Only the parameters that produced a significant variation of the running time have been selected for the calibration, since the model is more sensitive to these ones. In particular, the linear parameter of the resistance equation, r_1, does not have significant importance, given that this parameter produces a variation of running times less than 0.1%. Lukaszevicz (2001) came to the same conclusion for passenger trains. A small relevance is also identified for the linear parameter of the tractive force equation, c_1. Hence, fixed values have been assumed for these two parameters and the calibration process has been reduced to the following factors:

$$\beta = (c_0, c_2, r_0, r_2, b_{limit}, v_{cruising}). \tag{21}$$

As a result, the value of c_1 has been set to zero, while r_1 is fixed to the default value used by the RU (given by the rolling stock input data) and dependent on the train length.

A robustness analysis has been carried out to evaluate the robustness and performance of the optimization algorithm. In particular, 30 calibration experiments have been executed for a fixed realised train trajectory. This gives insight in whether the algorithm is able to return consistent results for the same calibration problem (with the same observed data). If the value returned for each parameter is not the same over the different experiments then the algorithm is not robust enough and/or the optimization problem is not well-defined. Results obtained from this test are reported in Table 3 which shows the average and the standard deviation of the values determined for each parameter over the 30

Table 2
Input data of rolling stock.

Train composition	Length (m)	$v_{\max}$ (km/h)
VIRM4	108	160
VIRM6	162	160
VIRM10	270	160
ICRm (Locomotive 1700 + 10 cars)	282	160

Table 3
Model performance output.

Parameter	Default value	Average value	Standard deviation	
			Value	%
c_0 (10^{-4} N/kg)	5.62	5.33	0.05	0.96
c_2 (Nm/s/kg)	6.21	6.29	0.00	0.00
r_0 (10^{-2} N/kg)	1.53	1.60	0.07	4.24
r_2 (10^{-5} Ns^2/m^2/kg)	4.08	3.55	0.10	2.79
b_{limit} (m/s^2)	0.66	0.24	0.00	0.00
$\theta_{cruising}$ (%)	100	101	0.00	0.00
Objective function (s)	135.76	79.00	0.34	0.42
Running time (s)	595.8	572.64	0.18	0.03

calibration experiments. It can be seen that parameters c_2, b_{limit} and $\theta_{cruising}$ converge to the same value for all the calibration experiments. Relatively low values of the standard deviation are observed for r_0 and r_2, 4.24% and 2.79%, respectively. However, variations of these two parameters produce just slight changes in the objective function value and the total running time of 0.4% and 0.03%, respectively. This outcome confirms the robustness of the algorithm used and the validity of the formulated optimization problem.

The parameters are compared with the corresponding default values provided by the RU (second column of Table 3). As can be seen the calibrated values vary around the default ones for all the parameters but the braking rate b_{limit}. The latter is due to the fact that during the observed train run a train driver adopted a braking rate that was on average lower than the one assumed by the operating company. Therefore, such aspect highlights the ability of the proposed model to estimate also the driving behaviour of the train driver.

Fig. 5 illustrates the output of a single calibration experiment: the calibrated distance-speed diagram (solid line) and the corresponding time–distance trajectory (dashed line). The circles depict measured time–distance as given by TROTS. The effectiveness of the calibration performed is immediately visible since the simulated time–distance trajectory practically overlaps observed data. This means a very high accuracy of the model. The gradient profile of the track is reported with the blue line at the bottom while the static speed limit is depicted with the dashed blue line. Yellow blocks represent the approach indication corresponding to those block sections in which trains has to start braking because of a restricted aspect imposed by the NS'54/ATB system.

Train length estimation

The train lengths are estimated by means of the process explained in Section Data pre-processing. Fig. 6 shows the obtained

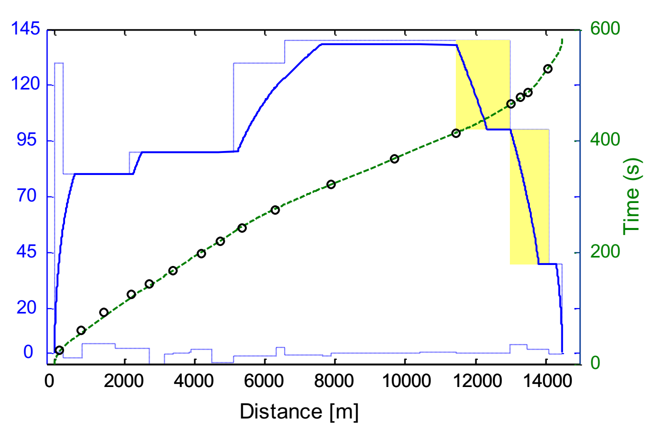

Fig. 5. Estimated speed profile and time–distance diagram for a single train run.

intervals for the train lengths of the observed trains. Horizontal lines show the width of this interval for each train run, while vertical lines indicate the four lengths associated to each of the four compositions considered. A different line style has been used to represent the estimated length. A dash-dotted line is adopted for the class VIRM4, dotted for VIRM6, dashed for VIRM10, and solid for ICRm, while solid grey is employed to represent cases in which it was not possible to have a correct estimation of train length (i.e. when no composition length falls inside the interval).

As can be seen these intervals of train lengths have different ranges. This depends on the value of the measurement error δ that affects release times of track circuits. Specifically δ is the time delay between the time in which the train actually releases a track circuit and the time that instead this track circuit perceives this release. It is easy to understand that as effect of this inaccuracy the average train speed and consequently the intervals of train lengths are estimated with some tolerance as can be observed in Fig. 6. In order to understand how the value of error δ affects the accuracy of the estimated intervals of train lengths, we assessed these interval against three different values of δ, namely 0, 1 and 2 s. Such an assessment exposed that by assuming a value of δ = 1 s (Fig. 6b) it was possible to estimate the lengths of the largest amount of observed trains. Therefore we adopted this as the value of the time delay during the whole analysis.

Calibration results

Calibration of parameters is undertaken for the four classes of train compositions. For each class 70 train runs have been examined. Parameters of the running time model have been calibrated for each of the train runs. This means that 70 sets of calibrated parameters β is provided for each train composition. This consents to estimate variations of a certain parameter over different train runs for a given composition. A probability distribution has been assessed for each parameter by applying the method of the maximum likelihood estimation (MLE). The goodness-of-fit of the distribution to the data has been tested using the Kolmogorov-Smirnov (KS) test. The probability distributions that we obtained for a certain parameter are identified as the distributions having the best fit with the observed data, i.e. the lowest value of the KS-statistic. The KS-statistic assumes indeed low values for a good distribution fit, while high values for a bad fit. On the other hand, the *P*-value ranges between 0 and 1, and it is close to 1 for a good fit while close to 0 for bad fit. Figs. 7–9 show the results obtained for the train class VIRM4. In particular, for each train parameter the figures report the corresponding probability distribution, the related distribution parameters, and the corresponding values of the KS-statistic and the *P*-value. It should be noted that similar distributions are obtained for other compositions that for brevity are not explicitly reported.

Fig. 7a gives the distribution of the constant parameter of the tractive effort. It shows that this parameter fits best to a Weibull distribution. As expected, not all the observed train runs use the maximum tractive effort while accelerating from a standstill. Nevertheless, some runs exceeded the theoretical maximum tractive force given by the RU. Fig. 7b shows that parameter c_2 fits best to the generalised extreme value (GEV) distribution. It is observed that in a certain number of train runs c_2 was higher than the experimental maximum.

The constant parameter of the resistance equation r_0 (Fig. 8a) shows a fit to a uniform distribution. It can be observed that calibrated estimates tend to undervalue the theoretical value. The distribution of r_0 can be explained by recent developments in rail-wheel contact and consequently, expected reduction of mechanical resistance. On the other hand, higher values may be an effect of deteriorated rolling stock or a train occupancy. The quadratic

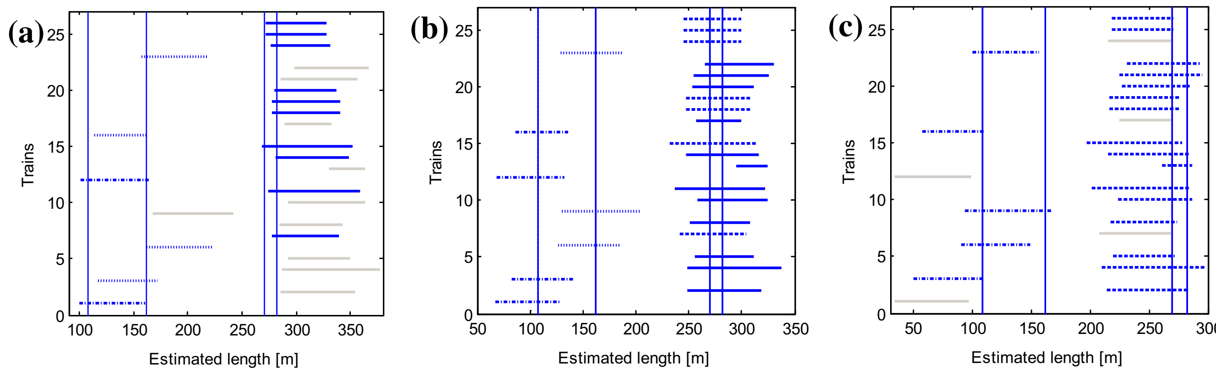

Fig. 6. Estimation of trains lengths for: (a) actual measured release times, (b) measured release times delayed by 1 s and (c) measured release times delay by 2 s.

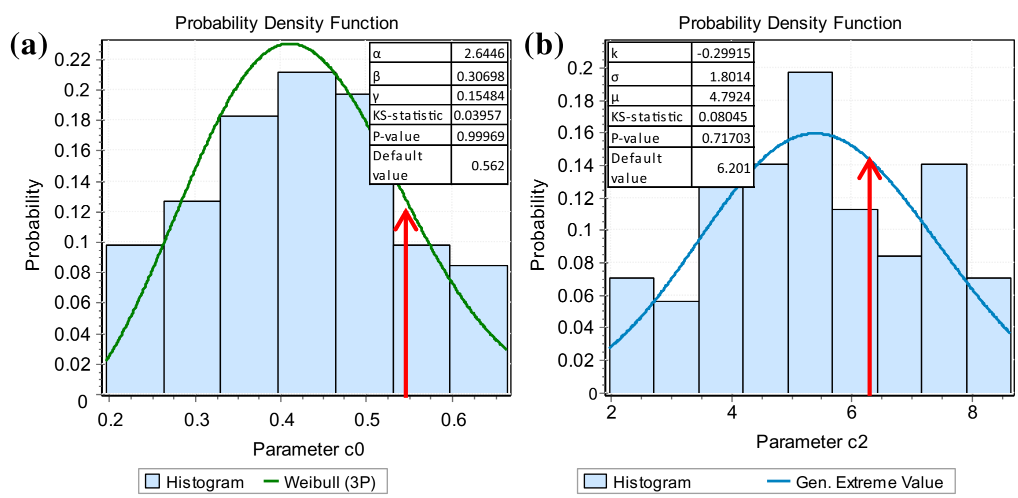

Fig. 7. Distributions of tractive effort parameters.

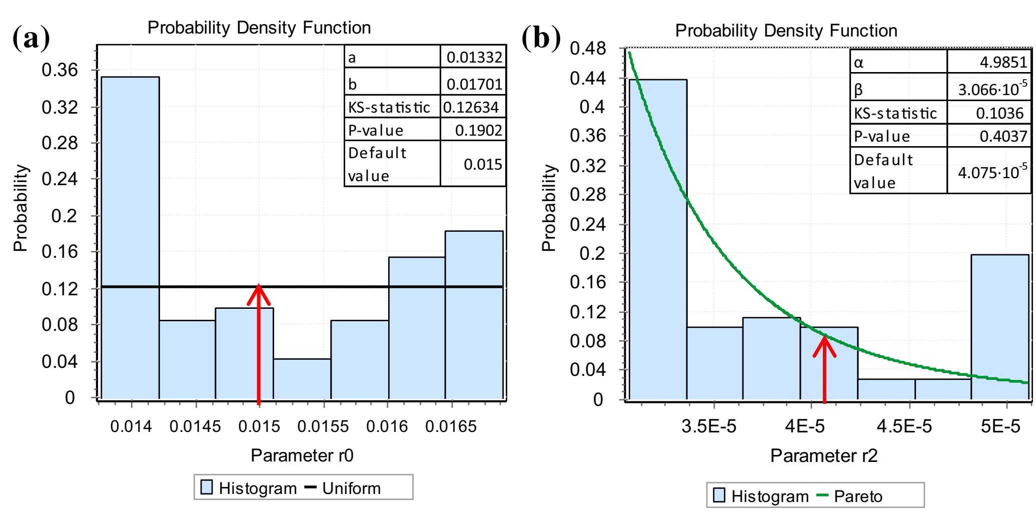

Fig. 8. Distributions of resistance parameters.

parameter r_2 shows the best fitting to a Pareto distribution. From Fig. 8b can be distinguished the variance of the aerodynamic resistance, which may be considerable while taking into account adverse weather conditions. Thereby, it may be assumed that the default value is slightly overestimated.

The distribution of the braking rate (due to speed restriction) is shown in Fig. 9a. It can be observed that the most probable rate is significantly less than the default value used by the RU which is 0.66 m/s^2. Some of the higher values of the parameter can be evaluated as an error in calibrated parameters regarding the inability of the current model to detect and reconstruct coasting phases. For example, in case of coasting, a simulated train speed profile tends to have a higher speed at the approach indication than the realised train behaviour with coasting and it would consequently assume a

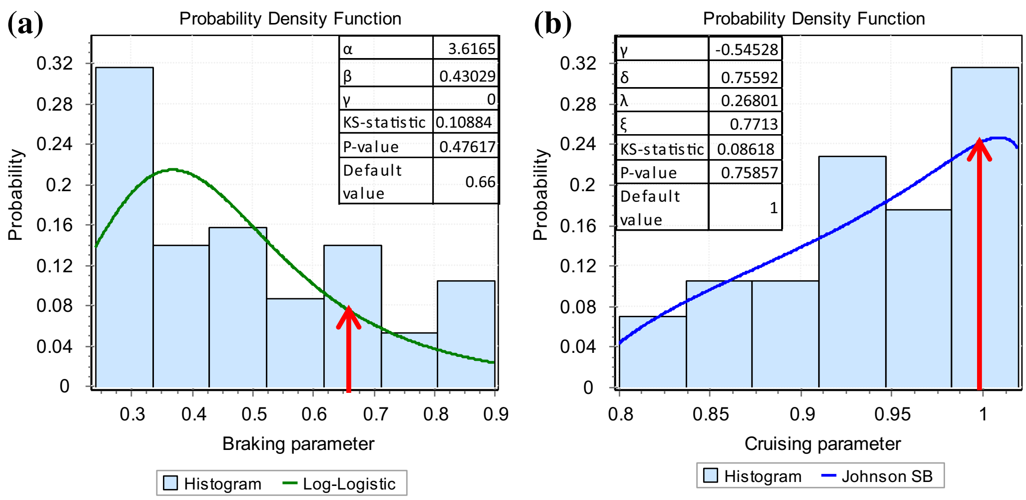

Fig. 9. Parameter distributions for: (a) braking rate, (b) cruising performance.

Table 4
Calibrated parameters for the four train compositions.

	VIRM4	VIRM6	VIRM10	ICRm
c_0 (10^{-3} N/kg)	[0.251, 0.621]	[0.440, 0.600]	[0.200, 0.511]	[0.283, 0.503]
c_2 (Nm/s/kg)	[3.144, 8.648]	[3.669, 7.075]	[2.555, 7.355]	[3.341, 11.792]
r_0 (N/kg)	[0.014, 0.016]	[0.014, 0.016]	[0.010, 0.020]	[0.019, 0.022]
r_1 (10^{-4} Ns/m/kg)	2.162	1.939	3.341	3.342
r_2 (10^{-5} Ns^2/m^2/kg)	[3.499, 4.678]	[2.910, 3.904]	[1.774, 3.597]	[2.672, 3.616]
b_{limit} (m/s^2)	[0.24, 0.9]	[0.24, 0.9]	[0.24, 0.9]	[0.24, 0.9]
$v_{cruising}$ (m/s)	[0.89, 1.02]	[0.81, 1.02]	[0.89, 0.98]	[0.81, 1.02]

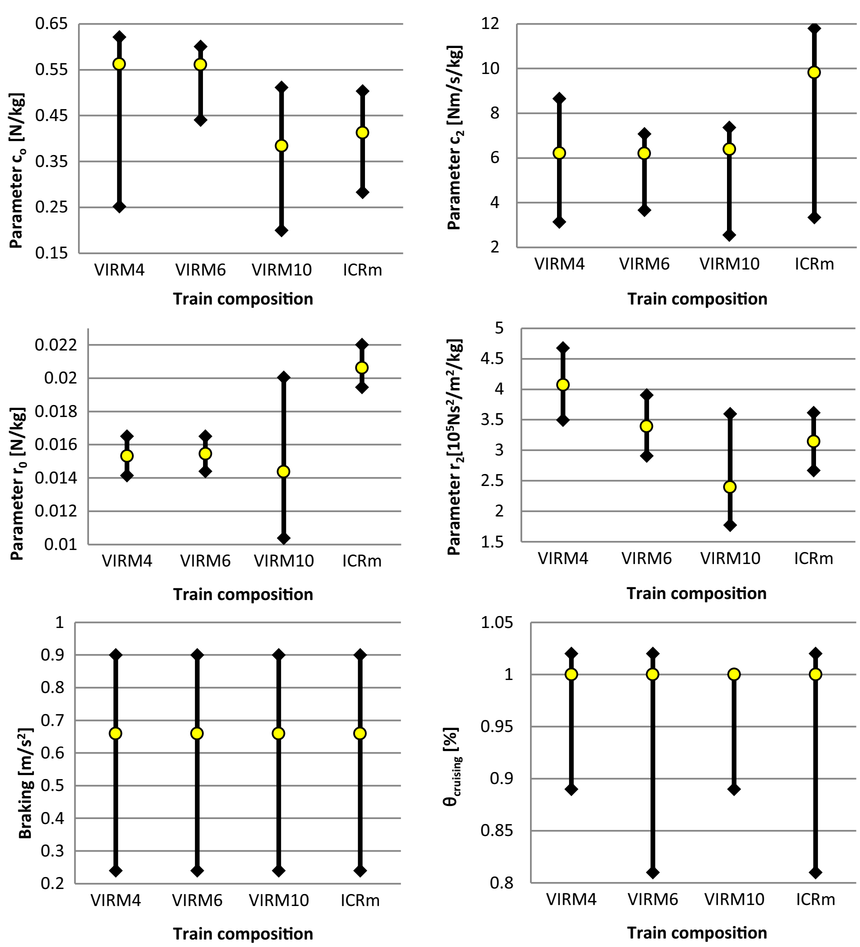

Fig. 10. Calibrated parameters for the four train composition.

higher braking rate. The braking parameter shows the best goodness of fit with the log-logistic distribution. This parameter shows a relevant variation over the different train runs. An explanation to this can be the consistent difference in the driving behaviour for different train drivers.

Finally, the cruising performance is depicted in Fig. 9b. It is shown that the most part of the trains tend to run at the maximum allowed speed given by the static speed limit while some of them even overrun this limit for 1–2%. However, it has been observed that some trains run only at 80% of the maximum speed, which presents a significant diversity in the driver behaviour. This parameter fits best to the Johnson bounded distribution (Johnson, 1949).

Table 4 present the ranges of calibrated parameters for all the train compositions. Parameter r_1 is not given as an interval since it was not part of the calibration and set to a fixed default value, while the parameter c_1 equals zero, as provided by the RU.

Fig. 10 illustrates results from Table 4 and gives a comparison with the default values of parameters provided by the RU. As can be observed the default values (yellow dots) represent neither the upper bound nor the average value of the distributions of the calibrated input parameters. This aspect can be clearly seen for the factors relative to the tractive effort, c_0 and c_2. The default values given by the RU for these parameters are usually employed for the calculation of the minimum running time, and therefore should represent the upper bound of these intervals since it is assumed that the train accelerates with the maximum power of the engine. Instead, the results of the calibration experiment show the presence of train runs that overcome these values in the reality. Furthermore, parameters of the resistance equation, r_0 and r_2, supplied by the RU are within the estimated distributions, for all the train compositions. For r_0 was expected to be the lower bound of these intervals. Parameter r_2 describes the aerodynamic resistances and takes into account the effect of the wind in the same or the opposite direction of the train run. The expectations were that the default values supplied for these parameters would correspond to the means of the corresponding distributions. Nevertheless, it has been observed that the default values tend to represent slightly overestimated values comparing with the observed distributions. On the other hand, large variation intervals are revealed for the braking rate. This denotes a consistent variation in the driving behaviour of train drivers. The default value for braking rate cannot describe this aspect. Moreover, this value does not coincide with any representative value of the distribution (i.e. mean, lower or upper bound). For the cruising performance the same conclusions can be drawn as the braking rate.

Conclusions

Predictions of railway traffic are needed by designers and dispatchers respectively for the design of robust timetables and the real-time management of perturbed conditions. These tasks can be performed effectively only when using train running time models which reliably describe actual trajectories. To this purpose the calibration of model parameters against field data is necessary.

This paper presented an approach to derive the most probable speed profiles of train runs from observed track occupation/release data. The train behaviour is modelled according to the Newton dynamic motion equations, which are numerically integrated over distance employing the Runge–Kutta method. A simulation-based optimization approach is adopted to calibrate input parameters of the equations describing the tractive effort, the motion resistances, the braking effort, and the cruising phase. These parameters are fine-tuned for different classes of train composition (defined by the number of wagons, the type of traction unit, and the length of the train) by minimizing the error between observed and simulated running times, using a genetic algorithm. For each composition the calibration experiment is performed on a significant set of observed trains running along the Rotterdam-Delft corridor in the Netherlands. A probability distribution has been estimated for the input parameters of each class of composition. This aspect gives also insights in different driving behaviour adopted during real operations.

The results show that the train length estimation model obtained good computation accuracy. To this aim the error due to the delay of the release time has been distinguished. Further, the results illustrate the effectiveness of the proposed optimization method in calibrating parameters of the Newton's dynamic equations versus track occupation/release data collected at the level of track sections. It has been observed that some of the parameters of tractive effort and resistance do not affect the train behaviour significantly, i.e., the linear parameter of tractive effort as well as the linear parameter of resistance force. Furthermore, the comparison with the default parameters provided by the RU highlights that some of the default values tend to be inadequate for the calculation of the technical running time for which they are generally used. Tractive effort parameters seldom overreach the corresponding default values, therefore showing that the latter are not the absolute maximum values, but a train has an extra power reserve that can be used for faster running. On the other hand, the parameters of the resistance equation tend to be slightly overestimated based on the received distributions. The realised braking rate is significantly smoother than the default one; therefore trains traverse the braking distance faster than computed in the minimum running time. Also, train drivers do not always follow the maximum static speed limit. Instead, it has been observed that in some cases the cruising performance is just 80% of the maximum. Finally, it has been shown that a specific calibration process should be performed to understand the variation in the coefficients of the dynamic motion equations over different train runs. In this way it is possible to set more reliable values to generate stochastic running times during robust timetabling.

Instead, in a real time context the model can be used to predict train trajectories for the detection of track conflicts. In particular, the implementation may be considered in two different ways: (i) By applying parameters only for a given train, we can perform a deterministic and accurate prediction of its trajectory over a certain time period ahead and consequently for a set of trains anticipate the future conflicts, (ii) By using distributions for a category of trains we can identify a set of probable trajectories that a train can have over a certain period ahead. In this case we can develop a statistical conflict detection model that can derive probabilities of possible conflicts.

The current work can be extended in several ways. First, the calibration model could be performed on different lines to evaluate possible different behaviour of train drivers as well as to distinguish parameters for different train compositions. Second, it would be noteworthy to compare realised and simulated running times based on achieved stochastic parameters as well as analyse the dependency of running time and distributions of dynamic train parameters. Third, analyses to understand the train parameters variation between delayed and on-time trains can be undertaken. Moreover, the computation time of the proposed simulation-based model can be enhanced by adjusting parameters of the implemented GA. Finally, proper validation of the speed profiles obtained by this model will be realized against GPS data.

Acknowledgements

This research is funded by the European FP7 project Optimal Networks for Train Integration Management across Europe (ON-TIME) under Grant Agreement number FP7-SCP0-GA-2011-265647. We also thank the Dutch infrastructure manager ProRail and the Netherlands Railways (NS) for the data provided, and Pavle Kecman from TU Delft for processing the data.

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