Estimating train motion using detailed sensor data

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5108 words
10 figures

Abstract

This paper presents results of a research project on collecting detailed train operations data. The detailed data was collected to help calibrate a train motion equation for use in developing stochastic blocking times to improve the timetable planning process. Stochastic blocking times recognize the fact that in real world operations blocking times vary and therefore it makes sense to develop probabilistic estimates of the amount of time required for each operation. In other words trains do not always operate exactly as planned. The data collected as part of the project confirmed this fact and led to several interesting findings concerning the variability of driving styles among drivers and of single drivers. This paper presents results of the research and recommendations for further study.

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1. Introduction

It is critical for railway authorities to use their infrastructure as close to maximum capacity as possible if they are to be profitable. Many techniques have been developed to help determine the optimum operating parameters (e.g. operating speed) for any given section of track to enable that track to operate at maximum capacity. These techniques assume that trains will actually be operated close to these ideal parameters.

Unfortunately, real life does not always follow the ideals due to human factors, weather, unplanned changes to schedules, differing vehicle performance characteristics and a wide variety of other factors. In the past it was difficult to quantitatively evaluate these issues since they require detailed analysis of huge amounts of data that were difficult to collect. However, with the advent of more powerful data processors, the growing use of automated sensors for data collection and the easy availability of mobile data collection devices these problems are being solved.

Obtaining more accurate information about how trains are actually operated is important because this information can be used in train operations models to better evaluate capacity, create more reliable timetables, and to identify cost effective capacity improvements.

The goal of this paper is to present findings from the data collection effort regarding the actual operation of trains under different motion phases. While these data will ultimately be used to develop the stochastic blocking time model, they also provide some very interesting insights into train operations in and of themselves. Therefore this paper describes these data and their implications for planning railway service.

Section 2 of the paper summarizes the collection and analysis of train operating data used in the modelling of train behaviour. Section 3 summarizes key insights observed from the data collected as part of the research project. Section 4 presents conclusions and outlines further research.

2. Collection and Analysis of Train Operating Data

The blocking time model has become a standard tool in timetable development since it provides a very precise description of infrastructure occupation. A blocking time model represents infrastructure usage as a time interval in which a section of track is exclusively allocated to a specific train and therefore “blocked” from use by other trains.

Today most blocking time models correspond to purely deterministic train movements, but an analysis of real traffic data shows clearly that there is variability in process times (caused by e.g. human factors). Therefore, timetables created using fixed blocking times may appear conflict-free on paper but might not be reliable in actual operations. Replacing fixed blocking times with stochastic blocking times (which reflect the real variability of process times) could increase model precision. In other words, using blocking times determined as a function of actual running times rather than theoretical running times.

Several methods have been developed to introduce stochastic process times in simulation or to estimate their impact on real traffic [Steckel [1], [2] [3] [4,5,6]. However most of these methods were developed for specific infrastructure and/or do not make full use of the rapidly growing ability to collect and use more detailed train data. To address these shortcomings the authors have proposed using a set of *performance factors* to introduce stochastic elements into each part of the motion equation. [7]

This project extends that idea with the objective of developing an improved method for creating stochastic blocking time models [8].As part of this effort the project collected detailed train data on the mixed-traffic, double-track line between Trieste and Venice. These data provide interesting insights into train operations that can be used to help better understand train behaviour and to suggest important new research opportunities. This section describes the data collection and analysis approach.

2.1 Railway Operations Data Collection

Railways have always been leaders in adopting information technology to help make processes more efficient and cost effective. They were among the first to fully use computers in the administration, record-keeping and accounting processes. The rapid improvement in sensor technology and use of mobile devices for data collection provides new opportunities for using real data to improve operations and service planning. There are two key parts of the process: data collection and data analysis.

There are three main ways to collect railway operational data: via sensors embedded in the infrastructure, sensors in the rolling stock (i.e. train event recorders) and mobile devices fitted with geographical positioning systems (GPS).

An important characteristic of these different approaches to data collection is the type of data collected: traditional infrastructure based sensors generate point specific data while train event recorders and mobile GPS sensors collect continuous data. Continuous data can be used to reconstruct exact time-space representations while point based data forces analysts to estimate train behaviour between the data points.

The three methods of collecting data are summarized below.

2.1.1 Infrastructure Sensors

Infrastructure sensors are trackside devices that record the passage of trains at timetabling points. These train passing data are automatically collected at each timetabling point by the train describers, which identify trains at their first station and then keep track of their progress along their route. The log files developed from these data can be used to perform an efficient, but limited analysis of the train traffic, since they contain no information about the effective infrastructure usage nor the train movement between the timetabling points (often several kilometers apart).

After pioneering work performed by Herrmann [9] in Germany, the analysis of the train describer data was implemented by Ullius [6] in the software tool OpenTimeTable for the Swiss Federal Railways (SBB). OpenTimeTable has two elements: the NetAnalyzer and the CorridorAnalyzer. The NetAnalyzer automatically notifies users when a user-defined limit is exceeded (e.g. x% of trains are delayed at station y for over z minutes). This identifies the critical points in the network and/or trains in the timetable. The CorridorAnalyzer is used to evaluate and present schedule data from the problematic corridor in a variety of formats. Planners can use this data to help determine the delay causes and impacts. [10]

In some countries, (e.g. The Netherlands) train describers collect occupation time data at all main signals, track circuits and switch detection systems. Such data allow a precise estimation of the infrastructure occupation, and enable the train speed profile to be reconstructed [11].

More accurate analysis could be carried out on the basis of the log files of the ETCS Level 2 used on many recently built high-speed lines in Europe. The ETCS Level 2 is a digital radio-based signal and train protection system. Movement authority and other signal aspects are displayed in the cab for the driver. However, the occupation and release of tracks is still based on track circuits or axle counters. The system continuously stores both the occupation of the (virtual) block sections and the speed of the train, allowing a reconstruction of the speed profile of the train and the corresponding infrastructure usage. At present, no scientific work based on the analysis of such data can be found in literature.

2.1.2 Train Event Recorders

Train event recorders store very accurate data based on odometer readings. For example, the digital *Driver Information System (DIS)* installed on all locomotives and trainsets in Italy provides a wide range of data including the speed limit calculated by the protection system, the signal aspects, the throttle and brake percentage use. These data do not require any additional filtering since tracking data are filtered in real time by comparing two odometers and using the beacons *(Balises*) of the Automatic Train Protection system for discrete calibration of distances.

Thanks to the high accuracy and the amount of complementary data included in these log files, these data represent the ideal starting point to investigate the real behavior of drivers and to estimate the process times and driving styles. However, no mention of using this type of data for scientific work can be found in the literature, due to the relatively limited adoption of the digital train event recorders in most countries and to confidentiality issues of the log files, which contain information about the driver.

2.1.3 Mobile Device (GPS)

The simplest method to track a train along its entire route is to install an on-board GPS device. A GPS log file allows a simple visualization of the train speed profile; however it doesn't contain any information about the aspect of signals, nor the block sections.

While it would be possible to analyse the real behaviour of drivers with a sufficient degree of accuracy using simple GPS loggers, professional devices with more functionality could provide a higher sample frequency and have an external antenna to increase the quality of geographic information. In this research GPS tracking data was collected using a semi-professional GPS performance meter designed to track race cars.

2.2 Railway Motion Equation

The research goal was to develop a stochastic blocking time model for use in railway timetable planning and simulation. The conventional running time calculators used in railway models use a set of empirical parameters to solve the motion equation. These parameters have been measured over many years for different types of rolling stock [12] and using them it is possible to calculate detailed train speed profiles.

The proposed method uses *performance factors* to add a stochastic element to running time calculation. The performance factors generally reduce train performance to more accurately represent real driving. Th e authors have previously recommended that separate performance factors be used for each motion phase since a single parameter does not allow a precise representation of speed [7].

This effort required preparing a detailed statistical analysis of individual elements of the railway motion equation (a detailed description of the train motion equation is provided in [12]). Train motion is divided into six parts:

- Acceleration
- Cruising (maintaining speed with throttle manipulation)
- Coasting (train operation while the throttle is idle before braking)
- braking for a station stop
- braking for speed restriction and
- braking for a restrictive signal aspect

For each motion phase detailed speed data was collected and plotted versus distance. This actual data was then compared to theoretical data.

As outlined below data was collected for almost 100 train trips. The data collected for each train trip was first separated into one of these six categories. Then it was analyzed using standard statistical methods to (1) better understand each of these motion phases, and (2) for use in developing an optimized set of performance factors distributions for use in the blocking time model.

The next section describes the data collection and filtering process; Chapter 3 summarizes key findings from the statistical analysis of train motion in terms of these six phases.

2.3 Railway Operations Data Analysis

Once the data has been collected it must be analyzed. Again, rapid improvements in information technology hardware and software have made it possible to vastly increase the amount of data that can be analyzed quickly and accurately. This has made it possible to use not only data collected at infrastructure level (2.1.1-2), but also the log files of GPS and train event recorder installed on the trains, which by its nature consists of a huge amount of data, to help identify trends and develop statistics that can be used to increase understanding of train operations. This understanding can then be incorporated into models and operating strategies to improve real railway operations.

As outlined above, the objective of this research was to better understand behaviour for specific elements of train motion. Therefore, as part of the project, the data from individual trips were aggregated by type of motion and service and processed, as described in the following section.

2.4 Research Project Data Collection and Filtering

The case study data were collected on the Trieste – Udine rail line in Northeast Italy. This line plays an important role in regional transport and as a freight corridor between Eastern Europe and Italy as well as serving the port of Trieste. It is an electrified double track line approximately 80 km long. It is provided with SCMT, a digital, discrete ATP similar to ETCS Level 1.

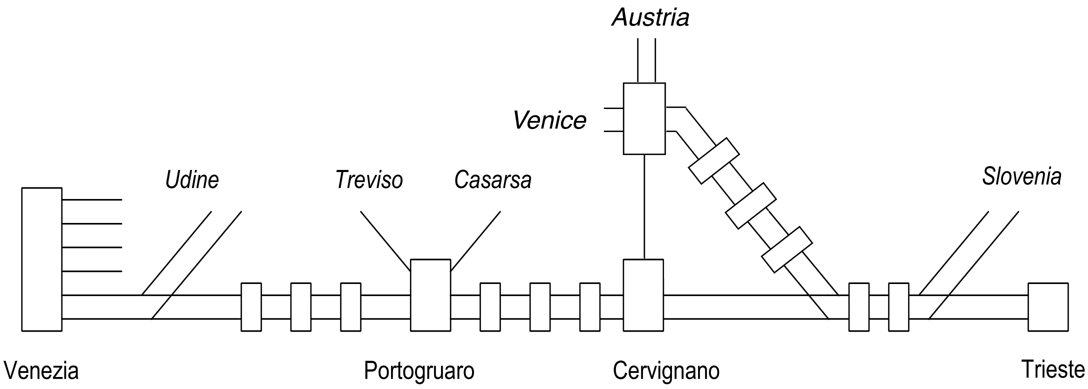

Figure 1: Layout of the Trieste – Udine/Venice line

Data were collected from approximately 100 train runs operated with the same rolling stock. While 100 data records could theoretically be enough to provide a statistically complete analysis, it proved to be insufficient to fully explain all the phenomena identified in the detailed analysis of train speed due to the very high variability of external conditions (traffic conflicts, other delays), and of driving styles. It is important to note that the data set was filtered to remove the impacts of heavily delayed trains.

Once the data was collected it needed to be processed so that it could be used to correlate the time-space information with railway infrastructure and operations data (e.g. signal aspect). In this respect, data collected using mobile devices (GPS tracking data) is significantly more difficult to prepare for use in the motion equation calibration process than train recorder data.

In this research the GPS tracking data was post processed using a proven algorithm based on the Kalman filter (currently used to reconstruct the trajectories of race cars [13]). The filtered data are sufficiently precise, but do not contain any information on signal aspects, which is required in order to reconstruct driver behaviour.

To fill this gap, the recorded speed profile is compared to the planned speed profile (in which the train brakes only for track speed reductions and at stations). When unplanned braking actions are found, the planned speed profile is recalculated by assuming that a yellow signal aspect was displayed at the corresponding signal.

On lines with discrete ATP, the braking curve based on the approach speed and distance to next signal is computed, since the train is not allowed to re-accelerate before passing the corresponding main signal balise.

On lines equipped with continuous ATP, where the train is allowed to accelerate as soon as the man-machine interface shows the green aspect again, the instant when the train re-accelerates is obtained by the local minimum of the real speed profile.

The planned speed profile was then modified to include the braking and re-acceleration. A key weakness of this method is the lack of a procedure for automatically distinguishing between unplanned braking actions caused by “normal” traffic conflicts and failures in which the protection system activated the emergency braking.

The filtered GPS tracking data, supplemented with corresponding signal aspect data and train event information, were saved and used as the basis for the calibration procedure.

The next section summarizes the data and findings for each of the six parts of train motion analyzed as part of this research.

3. Insights into Train Operations by Motion Phase

In the process of planning railway schedules it is generally assumed that trains operate at a specific performance level. This is a good first assumption, and in the past was necessary in order to simplify the analysis process sufficiently to generate feasible schedules given the computing power available. However today's improved levels of computing and data collection enable planners to use a more accurate estimation of train behaviour to develop schedules.

Figure 2 presents a good example of the difference between maximum performance and actual performance on a specific rail segment. Figure 2 compares the speed-distance data for four real trains (GPS 1-4) to simulation results for maximum performance (100%) and to the speed limit (Speed Limit). The figure shows how individual train performance varies compared to theoretical performance. The wide variation in train performance clearly shows the need for more accurate modelling.

This chapter presents insights from the data collected as part of this research. The data is described in terms of each phase of the motion equation. The chapter ends with a short description of how the data will be used to calibrate the stochastic blocking time model.

3.1 Acceleration

Two types of acceleration were considered in the analysis: acceleration taking place as trains depart from stations and acceleration taking place after speed limit changes. Interestingly, the data showed that while trains departing stations normally accelerate with relatively high performance (between 70-103%), trains accelerating after a speed limit change accelerate with lower performance and often travel a significant distance after the speed limit change point before beginning to accelerate.

Figure 2 illustrates acceleration behaviour after a speed limit change. The figure shows real train tracking data (GPS 1-4), the calibrated simulation for the first record (FIT 1), the simulation with maximum performance (100%) and the speed limit (Speed Limit). The acceleration variability and delay is shown clearly. Importantly, the acceleration delay observed in this data is not due to mechanical or pneumatic issues (as might be the case for freight trains) since all trains use the same trainset, an EMU with electronic traction drives.

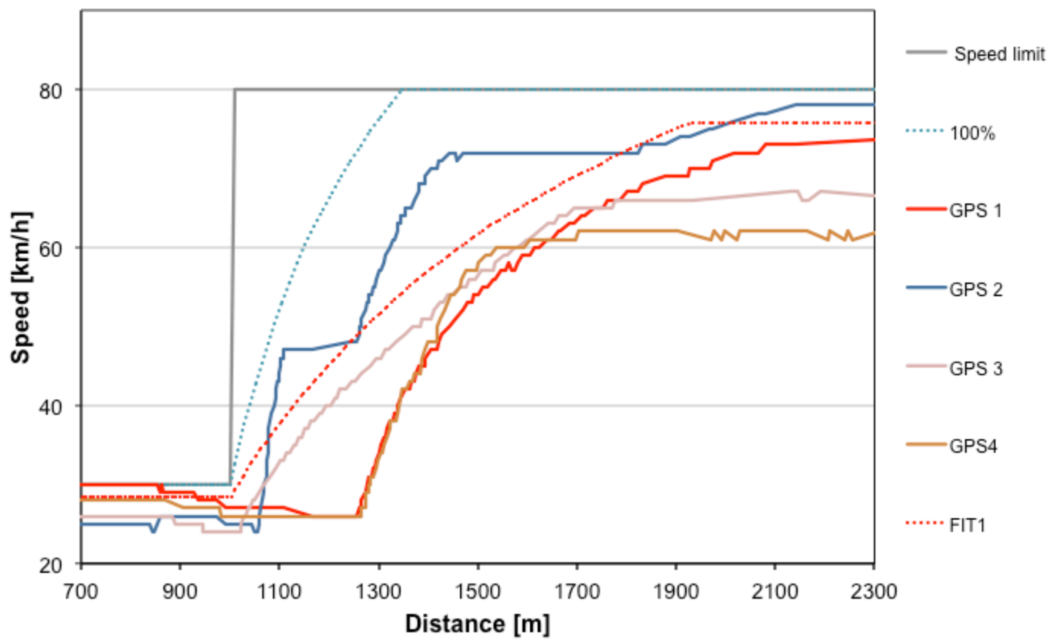

Figure 2: Speed profile of acceleration after speed limit change (GPS 1-4), compared to a fitted record (FIT 1) and the speed limit.

The observation that some trains start acceleration at a point later than allowed is particularly interesting because the standard motion equation used in modelling train behaviour does not include a delay term. A good topic for further research might be assessing the need for adding a delay term to the motion equation.

Figure 3 illustrates eight speed-distance profiles from different trains (GPS 1-8) showing acceleration after the same stop (with no restrictive signal aspect), compared to simulations with 95% and 103% acceleration performance factors.

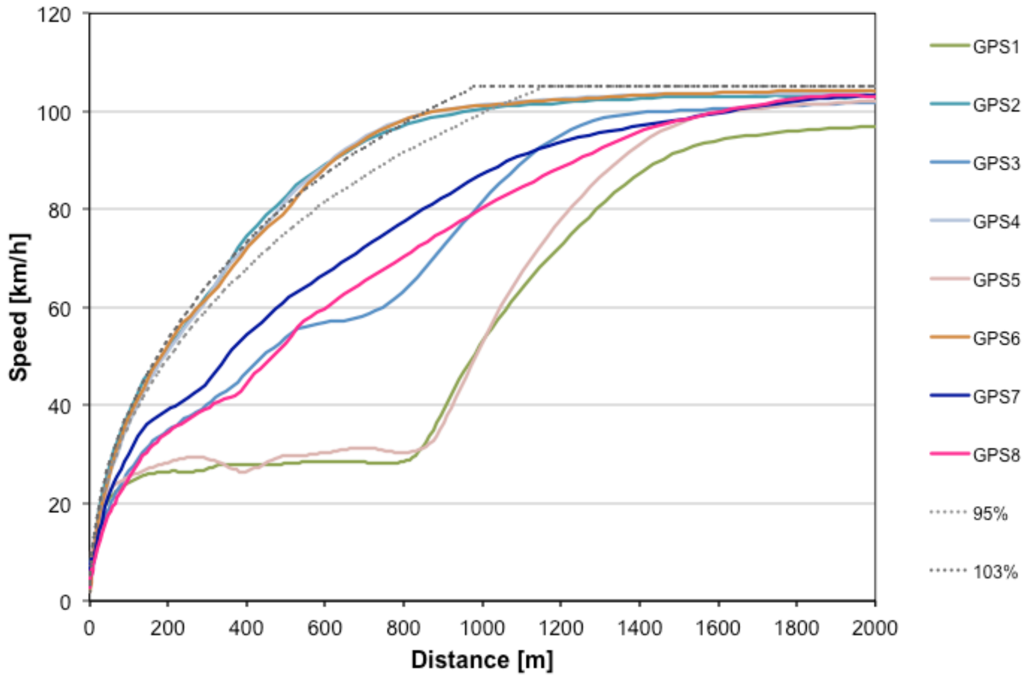

Figure 3: Speed profile of acceleration after stops (GPS 1-8), compared to 95% and 103% acceleration.

An interesting result, also observable in Figure 3, is that in about 5% of cases the acceleration rate is slightly higher than the (theoretical) rate, although this was limited to a few seconds over the entire train run. In particular in the trackings GPS2 and GPS6 the acceleration was nearly 103%, up to 100 km/h. Unfortunately the number of data records was insufficient to explain this finding, although it could be due to conservative estimation of tractive effort, a very low number of passengers on the specific train, or to very good adhesion.

While the finding that different drivers have different driving styles is interesting, it is also interesting to analyse the behaviour of the same driver over a number of stations. In Figure 4 the speed profiles during acceleration after all stations of a Trieste – Udine local train are compared. Considering only sections without gradients, very different performance levels have been measured, with a variability of more than 30%, from 60% to 92%.

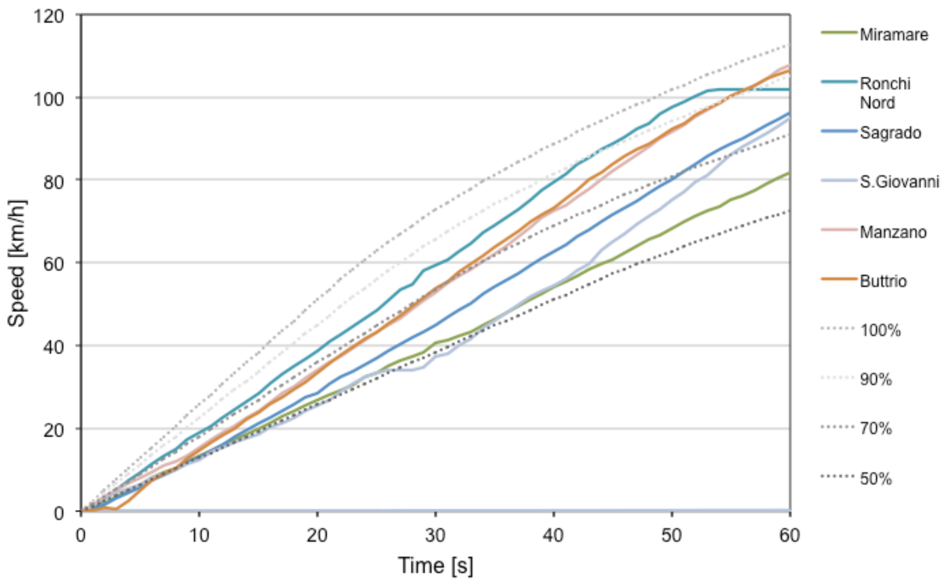

Figure 4: Speed vs Time plot of the acceleration after stops for a single train run compared to speed with different performance factors.

3.2 Cruising

An analysis of the case study data showed that there was a very low variability of cruising performance between on-time and delayed trains, in all cases cruising performance ranged from 94 to 98%.

In contrast, early trains generally keep a constant but lower speed (up to 89%) and show much more variability in behaviour. For example some early trains run at normal speed and than wait at stations while others cruise at lower speeds on open track.

While this may be useful to distinguish between early, punctual and delayed trains to describe and reproduce the different cruising styles in more detail, the data analyzed in this study indicates that this may be a difficult task, especially concerning early running and punctual trains. In fact, some drivers – interviewed during data collection – reported that they drive slowly from the beginning of a trip, already estimating that they will reach the next station early, while others accelerate normally and then cruise at lower speeds. Therefore it is difficult not only to estimate a threshold to separate punctual and early running trains, but also where this threshold should be measured. In any case, a larger data set and more case studies are needed to further improve the accuracy of driving behaviour representation. Figure 5 shows the histogram of the performance factor during cruising.

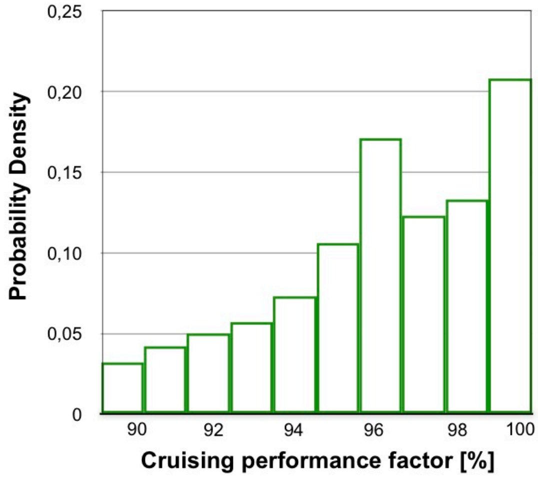

Figure 5: Histogram of the cruising performance factor over 100 train runs.

3.3 Coasting

Coasting takes place before braking, when the tractive effort is equal to zero and the train is decelerating due to resistance. The case study data shows that coasting is generally limited to the time necessary to deactivate the throttle and start the braking action (which includes a pneumatic delay). In approximately 90% of the records, coasting time is less than 10 seconds. The data does show that some drivers use coasting on early running trains for 10 to 20 seconds, to decelerate from 100 km/h cruising speed.

Figure 6 shows an example of speed vs distance diagram with a relatively long coasting section (on the left) and the histogram of the duration of coasting over 100 train runs.

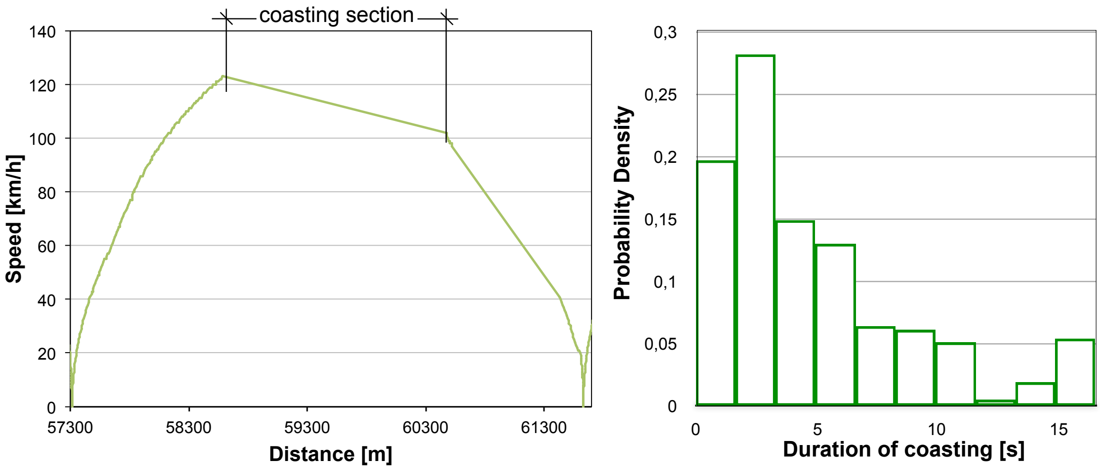

Figure 6: Speed vs Distance plot illustrating coasting behavior (left) and probability density (right).

3.4 Braking

The signal aspect and the planned timetable data can be used to identify three separate reasons for braking: braking at stations, braking for speed limit changes, and braking for restrictive signal aspects. An analysis of the data showed that there was a significant difference in the braking curves for these three types of brake application.

Braking for speed limit changes showed the lowest rate of deceleration, followed by braking at stop signals and then braking for restrictive signal aspects. Moreover, at speed restrictions heavy trains often reach significantly lower speeds than allowed based on the speed limit and show very different deceleration rates.

3.4.1 Braking for Speed Limits

An analysis of the data shows that braking for speed limits appears to be strongly influenced by significant in-advance decelerations and by disturbances caused by early-running trains. Often trains brake to a speed lower than required and then quickly reaccelerate which generate further noise in the data; in some sections after reductions drivers keep a slightly higher speed than the speed limit. The estimated braking performance factor for speed reductions is very variable, depending on the speed reduction and the rolling stock. Figure 7 illustrates braking behaviour before a speed limit change. The figure shows real train tracking data (GPS 1-11the simulation with 80% performance (80%) and the speed limit (Speed Limit).

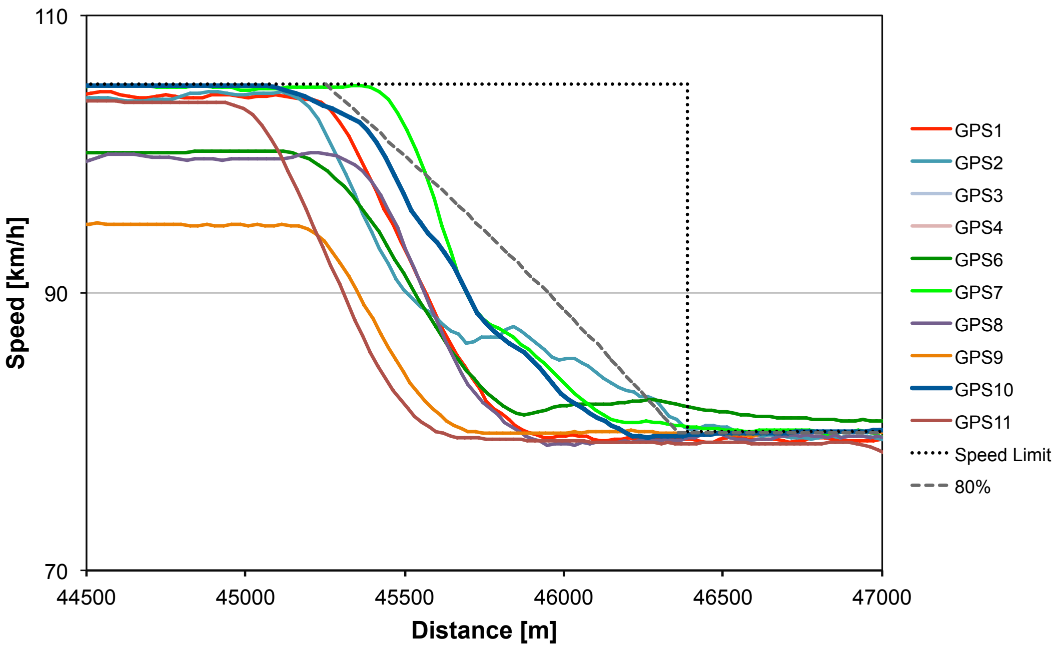

Figure 7: Speed vs Distance plot of braking for speed reduction (GPS 1-11) compared to 80% decelerations and the speed limit.

3.4.2 Braking at Restrictive Signals

Unfortunately there was not enough data collected to develop a statistically robust evaluation of train behaviour at restrictive signals, however the data qualitatively show that trains decelerate significantly when they see the distant signal (and therefore before passing it). The deceleration rates become gradually lower, with trains keeping the approach speed of 30 km/h for a significantly longer distance compared to the prescribed 200 m.

3.4.3 Braking at Stations

In terms of braking at stations the data show that delayed trains brake at a much higher rate (80-90%) than non-delayed trains (20-60%).

The data also shows that many trains use a two-step braking procedure: first they brake to about 30-40 km/h, then they coast and finally they brake again to reach the stopping point (Figure 8). Although in the two braking steps the deceleration rates are comparable to high performance factors, the intermediate coasting leads to lower average values, since the UIC formula (assuming constant deceleration) is used in modelling train behavior.

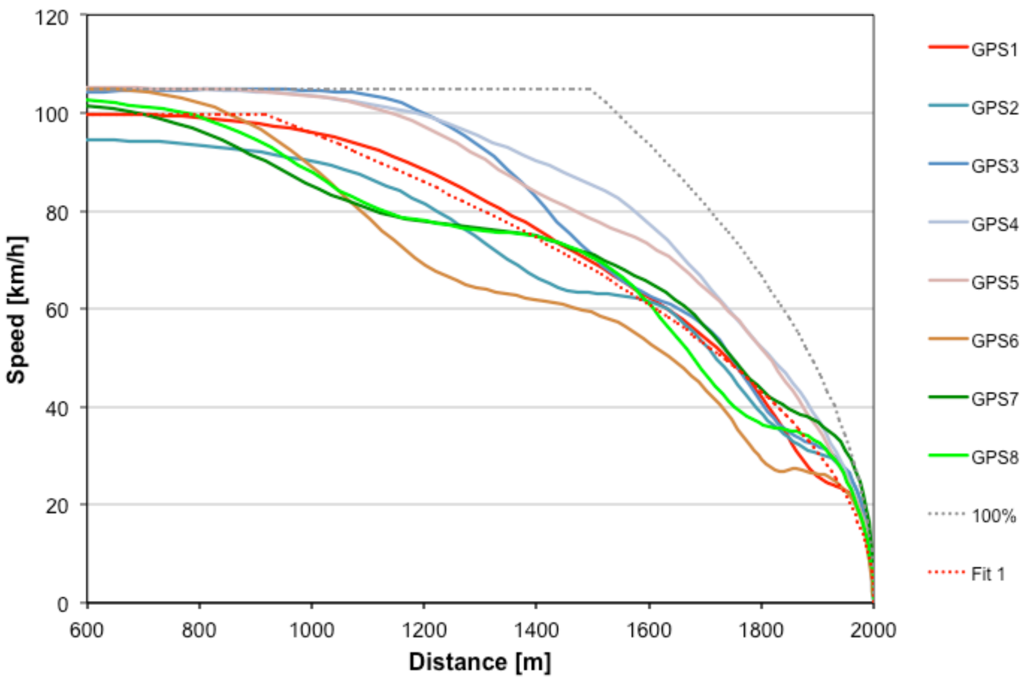

Figure 8: Speed vs Distance plot of braking at stations (GPS 1-8) compared to 100% decelerations and the fitted 1st record (FIT1)

The analysis was also performed considering a single driver.. In Figure 9 the speed profiles during braking at stops for a Trieste – Udine local train are compared. Considering only sections without gradients, very different performance and very irregular braking actions were measured, with a variability of more than 40%, and a range from 30 to 75%.

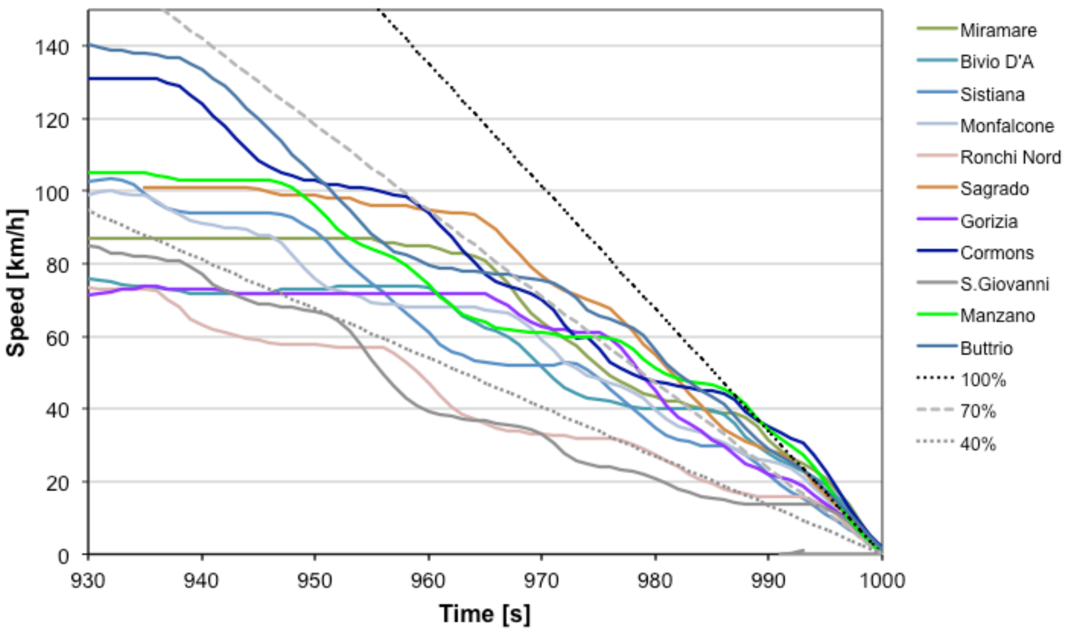

Figure 9: Speed vs Time plot of braking at stops for a single train run compared to speed with different performance factors.

3.5 Using the Data to Develop Stochastic Blocking Time Model

The data collected in this project was used to help develop a stochastic blocking time model. The procedure for estimating stochastic blocking times begins by simulating a specific train course many times combining the “deterministic” inputs (timetable, infrastructure and rolling stock) with the stochastic elements. The performance factors collected in this project was used reperesent the behavior of drivers. The departure delay distribution at the first station (initial delay) and the stop time distribution at each intermediate station - collected using tinfrastcructure sensors - completed the set of stochastic parameters.

More specifically, the behaviour of a single train is estimated by running the train on a microscopic simulation model many times using the calibrated motion equation. After each iteration, the corresponding blocking times are saved and stored.

At the end of the process the stored blocking times from all iterations are displayed on a time-distance diagram (Figure 10). The diagram illustrates the probability that a specific block will be occupied. On the figure the darker an area, the higher the occupation probability. When a second train is inserted a conventional headway time after the first one, the probabilistic occupation steps of the two trains can overlap, showing a conflict probability graphically. The corresponding numeric value is computed and indicated. Moreover, the not only the overlapping areas are measured, but also different kinds of conflicts are indicated. For example, the conflicts due to an early-running train overlapping a slower one are coloured differently than conflicts due to delayed services. The probability to have a complete stop, is computed separately from the probability to only brake at a distant signal and then re-accelerate again.

The procedure for estimating stochastic blocking times is then repeated for each scheduled train. Once all trains have been considered, the blocking probability for all trains is drawn on the same time-distance diagram as shown in Figure 10. The resulting graphic effectively illustrates the conflict probability by showing the overlaps between the stochastic blocking times for different trains.

The method is described more fully in another research paper. [8]

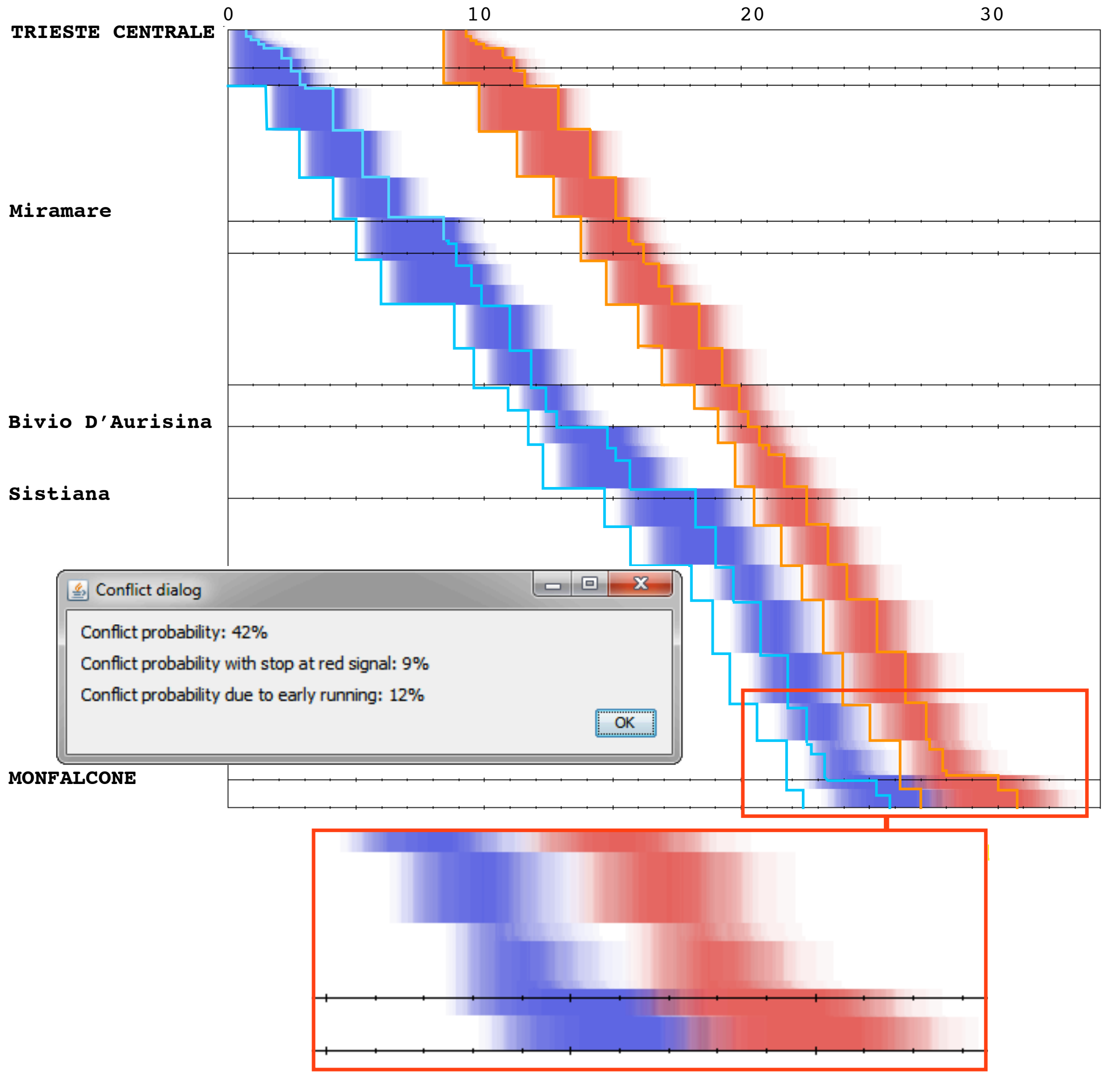

Figure 9: Time-distance diagram with stochastic blocking times, the window indicates the conflict probability; the light-blue and organge steps indicate the occupation steps with 100% performance.

4. Conclusions and Recommendations for Further Research

This paper summarizes some interesting insights into train driver behaviour based on data collected as part of a larger research project designed to improve the railway timetable planning process.

The paper takes advantage of improvements in data collection and processing capacities to obtain and analyze detailed train performance data. The data was collected using mobile GPS equipped devices which measured exact distance and time data over a continuous section of track. This enabled researchers to evaluate the differences in train behavour for different trains and showed that there is a wide variation in train behaviour.

The wide variation in train behaviour described in this paper makes a strong case for the research project's main goal: developing a method for easily introducing stochastic data into the railway timetable planning process (stochastic blocking time model). The authors are currently involved in developing and improving this method. [8]

The authors plan to extend the research in several ways. Data collection and analysis will be carried out on different lines to estimate the impact of weather conditions and of different rolling stock on driver behaviour. These tests should also lead to more statistically relevant findings separated for punctual, late and early running trains.

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