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ProRail

Simulation of train driver behaviour using a data-driven agent

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Abstract

The Dutch railway infrastructure is getting crowded with over 390 million passengers last year. Several innovations are created to improve the capacity by improving the infrastructure as well as the driving behaviour of train drivers. Within the latter, pilots are performed to gather feedback. However, feedback gathering is done on a per train basis and disregards the effect on a larger scale. Within the railway industry, trains are being monitored with multiple systems for different purposes. This thesis compares several monitoring systems and from some a model representing a train driver is created. The behaviour of multiple train drivers is simulated using a multi-agent system. An agent is used to simulate the behaviour of a train driver on a larger scale. The effects of the simulation are measurable at certain points, and the entire route is compared to trains without innovation giving a relative gain, hence the benefit of the innovation.

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Contents

Chapter 1

Introduction

1.1 Motivation

ProRail is the company responsible for the rail infrastructure in the Netherlands including the tracks, train stations, and the scheduling of all traffic on this network [33]. The goal of ProRail, the Dutch Railways (NS), and other operators is bringing their passengers and cargo safe and in a timely manner on their destination.

More people are travelling by train [36, 15, 20]. ProRail and the Dutch Railways are looking for new opportunities to increase their capacity, further elaborated in section 2.2. High-frequency passenger trains is a major part of it, the idea behind it is that more trains can travel on the same track with less distance between them. However driving closer to each other is difficult in the current safety mechanism.

To improve the capacity of the railways, some innovations are conceived such as Dienstkaartje+. Dienstkaartje+ is an improved timetable used by train drivers and conductors. A timetable denotes the arrival, passing, and departing times at train stations and is rounded to whole minutes. Dienstkaartje+ is an improved timetable showing arrival, passing, and departure times with a six-second accuracy. The times denoted in Dienstkaartje+ are deduced from actual driving times making the times more realistic.

Before making any large commitment, ProRail would like to know the effects of such an innovation. Simulations are used to indicate the effect of an innovation on a larger scale. In these simulations, the behaviour of train drivers can be modelled in numerous ways, among them using multi-agent systems[11, 16, 25, 37].

To simplify and improve the process of validating an innovation real-world data is used to plot, learn and eventually simulate behavioural changes in train driving. For most innovations, a pilot is performed to retrieve feedback from train drivers and conductors. Driving a single train with such an innovation can provide insights into the effect of an innovation.

ProRail uses FRISO [32, 33], a micro-simulator, to simulate signs, switches, and train driver behaviour with a basic model for a train driver. To improve the simulations, Tielman created an agent to simulate a more realistic acceleration- and braking behaviour of train drivers used in FRISO. Simulations will be discussed more in detail in section 2.5.

Within ProRail and the Dutch railways, data is gathered from all trains equipped with a GPS sensor, including trains driven using an innovation. There are several data formats and different systems that gather data for different purposes with each their peculiarities.

1.2 Problem

To measure the effect of an innovation, the gathered data can be used to find behavioural changes. The effect of innovations is measured for a single train. The effect of several trains using an innovation is not measured. Simulating the use of an innovation on a larger scale would give better insights into an innovation e.g. Dienstkaartje+. Using the available data, the behaviour of a train is simulated on a scale where it affects other trains. Hence the effect of Dienstkaartje+ is measured on a larger scale. For the analysis of the effect of Dienstkaartje+ on larger scale, the following research question is formulated;

How to efficiently and effectively measure behavioural changes, evaluating

Dienstkaartje+ on a large scale using simulations?

Moreover, this research question can be divided into four questions;

- How to efficiently read data from different sources like track-occupation, GPS, and simulator data to compare?
- How to define a data-driven model to simulate acceleration- and braking behaviour of train drivers?
- What is the effect of Dienstkaartje+ on a larger scale using a simulation?
- What is required to generalise measuring the effects of innovations using a data-driven model?

1.3 Methodology

During this research, a literature study is done to find similar researches and to get a grasp of the railway industry. Included in this study are some manuals used by train drivers and traffic dispatchers. Furthermore, a visit to the traffic control centre and a ride-along with a train driver is planned.

Following the literature study, an empirical research looks into the available data formats for a data-driven train driver model. The coupling of location data with data from signals, signs, and the timetable is described in section 3.3.

The entire process of gathering data to simulating train driver behaviour is written down in a manual. A novice should be able to reproduce these steps. The process is simplified by writing a prototype automating some steps.

The effect of Dienstkaartje+ is measured using an experiment. Selected trains have driven on the A2 corridor using Dienstkaartje+. The A2 corridor is a stretch of track between Heerlen and Schiphol passing several train stations. Concluding the effect of Dienstkaartje+ during this particular experiment gives insights in this innovation.

Several simulations are required to measure the effect on a larger scale. Hence the effect when all train drivers use Dienstkaartje+ on the A2 corridor.

Simulating a situational-aware operator using a data-driven approach can be used in numerous fields. However, this paper uses the train driver as leading example and will be validated on train driver behaviour.

1.4 Outline

In the second chapter the current situation in data-driven models and the situation on the Dutch railways is described followed by the progress ProRail has made on simulations. The third chapter describes the empirical research done evaluating the different data types and coupling the required data types for creating a model. A proposed method is elaborated in chapter four. In the fifth chapter an experiment is reported using an improved timetable. And finally chapter six concludes this paper and some recommendations are explained. In the appendices different data types are denoted and the data-driven models are shown.

Chapter 2

Background

Simulating an operator, or in this case a train driver, can be a comprehensive task depending on the actions it can perform. A train driver has a basic interface; a train driver can accelerate and brake. The moment a train driver should undertake an action is denoted in their manual [34, 30].

2.1 Dutch railways

The Netherlands has 7.021 kilometres of track, 7.071 switches, and 12.036 signals transporting more than 390 million passengers in 2015 [20, 1, 15]. A computer program called ARI (in Dutch; Automatische Rijweginstelling) is implemented to dispatch a path to a certain train using a schedule and will not allow other trains to cross this path. ARI will set the switches in the correct position and the signals to green to ensure safe passage for each train [17]. Traffic controllers oversee this process and can intervene if required.

Safety has a high priority in the Dutch railways, ProRail and the transporters are looking at new ways to improve the safety and capacity [4, 7]. In the Netherlands block signalling is used as a safety measure as shown in figure 2.1. If a block is occupied by a train the signal at the beginning of that block is red. To ensure trains can break before they

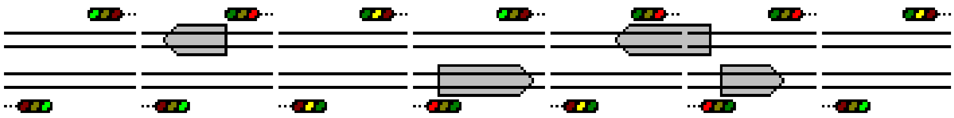

Figure 2.1: Block signalling [10] is the safety mechanism used within the Dutch Railways. It ensures that only one train can be present in a block at the same time. If a block is occupied its signal shows red, the block before is showing yellow such that train drivers can break for the upcoming red signal.

encounter a red signal (trains tend to have long stopping distances) the block before is signed yellow. A yellow signal means slow down and prepare to stop for a red signal, the maximum speed decreases to 40 km/h and the train has to slow down. Hence the length of a block is at least as long as the stopping distance of a train holding into account the speed allowed on that stretch of track [38, 40].

One of the key components of the safety on the track is Automatic Train Protection (in Dutch; 'automatische treinbeïnvloeding'). ATB brings a train to a complete stop if a signal and audible alarms are ignored. Hence ATB enforces the block signalling and speed restrictions [7]. However, due to bad timing, the distance between two trains can be as much as two blocks long.

2.2 High-Frequency Rail Transport

In 2008 and 2010 the Dutch government started a program to improve the capacity [2, 3, 5]. In these plans, ideas are explained to increase the capacity for passenger trains as well as freight trains on the Dutch railways without building too much new expensive infrastructure.

One of the most important aspects of improving the capacity is high-frequency passenger trains on major corridors. Running high-frequency passenger trains requires trains to drive closer to each other. This program is designed to drive trains with just 10 minutes in between on selected corridors [33, p. 3264]. To make this possible, train drivers have to drive more precise not interrupting each other. Furthermore new infrastructure is constructed for known bottlenecks e.g. the disentanglement of Utrecht [5].

2.3 Train driving

Next to improving the infrastructure, improving the train driver behaviour can increase the capacity. As previously discussed a train driver can accelerate and brake. However, the strength and timing of braking and accelerating is onto the driver itself. Braking should be done in a safe and comfortable manner such that passengers do not have to cling on when they are about to walk towards the doors and without overshooting the train station. Drivers have different driving styles; some are more aggressive drivers than others especially when trying to catch up with their delay.

A train driver uses signs, signals, and their knowledge of the track to undertake an action. A train driver has to stop at a red signal. A green signal shows the driver can accelerate to a communicated speed. And a train driver has to slow down to 40 km/h once a yellow signal is passed [38, 40]. On passing a green signal train drivers have different driving styles. Train drivers as described by Tielman [39, p. 63-65] can either; accelerate fast and coast for the remainder of their path to the next stopping point, accelerate and maintain constant traction to keep their speed, or drivers can alternate between coasting and applying traction.

The knowledge of a train driver is quite comprehensive. Train drivers have to be certified to drive on a section (in Dutch; baanvak) and can operate a train of that specific type. Furthermore train drivers need to be aware of their fast-moving environment and handle accordingly. Many tasks performed by a train driver are based on both prior knowledge and track familiarity. A train driver anticipates on situations that may occur as they happened in the past.

A few innovations are developed supporting the train driver. For example, Dienstkaartje+ is a new timetable. Dienstkaartje+ shows arrival and passing times of stations in a six-second accuracy instead of whole minutes. The aim of the timetable is to give better feedback of delays and allow traiers to drive closer to each other. Furthermore a conductor has a smaller window to start the closing door procedure. Decreasing the window from 60 seconds to 6 seconds should narrow the spread of departing on train stations. A few train drivers and conductors are using Dienstkaartje+ as a trial gathering feedback.

Simulating behaviour of an operator can be quite comprehensive depending on the actions it can take and the information it has to process [30, 13]. The main goal of any train driver is to reach their destination in a safe and timely manner. A train driver decides his action based on information from the environment, such as signals and signs, and their knowledge.

2.4 Data-driven model

There are several possibilities to model the behaviour of a train driver. For example, a normative model can be constructed with a number of rules which simulates the optimal behaviour of train drivers and requires extensive knowledge of human behaviour [16, 25, 11, 8, 14]. This model will take knowledge of train driving and time to model all possible situations a train driver can encounter. A normative model will not regard the interpretation and prior knowledge of the track and signals under the circumstances a train driver is driving on. Where the main topic of this thesis is based on the driving behaviour of train drivers under different conditions with different innovations this is not the desired method.

Therefore descriptive models are interesting relying on the behaviour of train drivers using data-driven models [26, 42, 28, 24]. Using data from real train drivers a model can be learned to mimic the behaviour of train drivers. Using the data gathered from train drivers using an innovation during a pilot allows us to measure the gain of such an innovation. Data-driven models can be interpreted by an agent to behave like a normal train driver in a simulated environment such as FRISO as disclosed in section 2.5.

Building a descriptive model is the classification of real-world data finding common occurrences in certain situations. A descriptive model describes the different situations based on real-world data classifying the possible outcomes. Depending on the operator's abilities and the possible outcomes in the world a suitable method should be used to describe the alterations that can occur [21, 19].

However due to the interpretation of a train driver, an action is not sufficient to model the train driver behaviour. The magnitude of the action is important as well. As mentioned before a train driver has a certain range wherein a lever can be positioned. This deviation in magnitude results in different driving behaviours. The range wherein an action can be performed is enforced by signals, signs, and a manual but still has some interpretation by a train driver [34, 35].

Statistical learning is used to find the deviation in driving behaviour in certain situations [26, 31]. Using the restrictions a train driver has, we can show the possible situations a train driver can encounter and the possible actions a train driver can undertake according to newly gained information, such as passing a signal.

ProRail and the Dutch railways are gathering data using several methods. The two companies tend to share data after one or two days ensuring a large data set accessible for learning purposes. For a specific train the following resources are required;

- Location data
- Infrastructure data
- Signal data
- Timetable data

Location data has different formats and purposes. Usually, they consist of a GPS location, speed, acceleration, and the time of this event occurring in a certain interval. For example, MTPS is a real-time service tracking the location of trains if a train has a built-in GPS sensor and a data connection. The trains of the Dutch railways(NS) are all equipped with an onboard GPS sensor.

ProRail keeps track of their infrastructure in such a way it is possible to deduce which signs and signals a train has passed on their journey. The format of signs is cumbersome; a sign is assigned to a particular switch which in turn is connected to three other switches building the entire network. This network is split up in different train dispatched areas and distances between infrastructure is denoted per train dispatched area. Signs and signals are in between two switches with a distance to a switch in a particular direction.

Furthermore, the signals are logged showing or deducing the colour of a signal, or the so-called aspect of the signal. Per train it is possible to deduce the allowed speed of a sign a train driver has passed. A part of the signals in the Netherlands are permissive signals which base their colour on sensors in the track and the block signalling system. The colour of a signal is also called aspect of a signal. In the logging some of these aspects of permissive signals are deduced of the locations of trains in the vicinity and its GPS location.

Finally, the timetable is updated with realisation data showing the arrival, passage, and departure times of train stations or so-called timetable points (in Dutch; dienstregelpunten). The time of arriving and passing a train station denotes the time a train enters a train station and not the time a train has stopped at a platform. In the next chapter the coupling, filtering, and analysis of the data will be discussed.

2.5 Simulations

Simulation is used in this thesis to evaluate Dienstkaartje+ on a scale with multiple trains driving with this innovation. Within the railway industry simulation is well known and used in two different settings. A large part of simulations is used to educate and retrieve feedback from train drivers. And secondly, some simulations mimic the behaviour of multiple trains in a simulated environment. [27, 18, 16]

Within ProRail there are a number of simulations conducted on micro- and macro-level for different purposes. For this thesis, the simulator FRISO is most suitable since it allows the interaction with software agents [32, 33]. FRISO is a micro simulator for a section of tracks where it simulates a number of trains using several agents. These agents represent a train driver on a stretch of track with other trains in its vicinity and affect the blocking signalling system, creating obstructions and delays [12, 23].

In this research FRISO will be used as the simulated environment. The agent Tielman implemented will be adapted to model the driving behaviour of an innovation. ProRail currently is evaluating more simulating tools, for example, OpenTrack and RailSys. In the future, there is a possibility these alternative simulating tools may be used instead if it allows the incorporation of an agent.

Chapter 3

Empirical research

The chapter elaborates the research done to find suitable data sources required for modelling train driver behaviour. Followed by the coupling of the data to create a format used for learning and plotting the train driver behaviour.

ProRail has a variety of data sources. These data sources range from train data gathered from GPS sensors, sensors in different locations, and timetable data deduced from sensors in the track. However documentation is not available. Hence the first step of this research is to find out what is stored in the data files and how it can be used.

Following from an assessment of the different location data types a comparison is made. A location data type stores the exact location of a train. Within the comparison several properties are held to account e.g. interval and availability. The comparison is shown in appendix A.

Furthermore signal, timetable, and infrastructure data are gathered in a fixed format. The infrastructure data consists of several files and updated periodically. Signal and timetable data is gathered in a fixed format per day and per train respectively.

3.1 Location

MTPS (in Dutch; Materieel en Trein Positie Service) is the most available location data. All trains of the Dutch railways have a GPS tracker and logs the trains latitude, longitude, acceleration, and current speed every 10 seconds. MTPS is used for real-time monitoring of trains for transporters, for example, the Dutch railways, and the general public.

Although MTPS data is logged every 10 seconds, the exact moment of passing a sign is not known. This results in some inaccuracy finding the action taken on passing a sign. Especially finding the exact moment of reacting relative to passing a sign.

Another challenge is the location of the GPS tracker. The exact position of the tracker is not known. The tracker can be positioned in front, at the end, or in the middle of a combined train. The location of the GPS sensor can be figured out at a train station using the platform the train has to stop at and the location of the train relative to the platform once the train is stationary. However at train stations due to the surrounding buildings, the interference on the GPS sensor is relatively high.

European Train Control System is a new safety mechanism under development within the European Union. Trains are connected and retrieve messages informing a train driver with information such as the maximum allowed speed. This data is sent through radio block centres, RBC for short, which has a two-way connection with trains in their area. A radio block centre logs all messages send from and to trains, including the position of a train every six seconds and infrastructure information.

Data gathered from radio control centres is formatted in a chronological order, however not all information required is present. For example radio control centres do not store the travelled distance. At the moment of writing only a small stretch is equipped with ETCS in the Netherlands. ETCS is promising, especially level 3 since trains track all information, and signals and signs are no longer required.

For the purpose of validating Dienstkaartje+ MTPS is used. MTPS is logged every 10 seconds and is readily available.

3.2 Fixed infrastructure

One of the main aspects of train driving is reading signals and signs and act accordingly. ProRail has different sensors in the train tracks. These sensors monitor the occupation of stretches of track. Track sensors are used for enforcing the block signalling. The signal data contains a large number of properties such as the time a signal turned green and when a sensor is passed in the vicinity of the signal. The time logged in the signal data is accurate, except that the sensor of passing is near the signal.

In the Netherlands some signals are not logged in the signal data. These permissive signals use sensors on the track to determine their colour. Since these signals are not logged, the time of passing is estimated from the location of the train.

The sensors in the track are used to track occupancy, within the Netherlands axle counters and track circuits are used. An axle counter counts at the beginning and at the end of a section and if the difference is zero the track is not occupied. A track circuit puts a current on the track. The axle of the train completes the circuit between the two rails, hence the track is occupied [37].

Signs are not logged per day nor per train. Signs are stored in an infrastructure file with a large set of properties. Not all properties are relevant for signs except for the speed it is indicating and the location.

Within the infrastructure file a network is stored using the switches as nodes, these switches are connected with stretches of track. The position of a signal is based on the distance from a switch on a stretch of track. Since the location is not denoted as a GPS coordinate the identifier of the stretch of track is used. MTPS stores the stretch of track it is driving on. A list is created from all signs on the stretches of track driven on. From this list signs are filtered using the direction the sign is facing. The length of a stretch of track is known as well as the location of the sign of this distance. From these distances an approximation is made of the moment a sign is passed.

Finally timetable data is used to calculate the delay of a train. The delay of a train can affect the driving behaviour of a train driver. Timetable data consists of the arrival, passing, and departure times a train driver has. The data is complemented with the actual times estimated from the sensors in the track.

Once all data is gathered, the next step is to filter and combine the data to create a complete picture of the decisions a train driver made. The different data types were never designed to work with each other. After several attempts a method is found to combine the different files in a new format i.e. a storyline.

3.3 Storyline

The process of combining the different data types depends on the available date types and is required for a complete picture of the situation a train driver is in. For the purpose of Dienstkaartje+ MTPS is used. However to ensure different location data can be used a default format is proposed, a so-called storyline. An ideal storyline tells the story of a train driver in a chronological order describing the performances and decisions of a train driver, and so on the course of a train.

Starting from the location data signal and sign data is added. Signal data is added using the time denoting the passing of the train. Signs are added using the identifier of the stretch of track the train is driving on. This process can be done manually, for the purpose of this thesis a prototype is created automating the combining.

The storyline should be suitable for statistical learning. Hence it should have a format without gaps and with added classifiers to describe the decisions made. From this storyline events can be deduced describing the different events as described by Tielman [39]. These events are moments in train driving where the driver has to respond to certain situations,

20-3-2015 19:53	3572	GR	40.00	1.00	0.03	INCREASE_ALLOWED_SPEED	ACCELERATING	0
20-3-2015 19:53	3572	GR	40.00	31.00	0.42	INCREASE_ALLOWED_SPEED	ACCELERATING	144
20-3-2015 19:53	3572	GR	40.00	30.00	-0.03	INCREASE_ALLOWED_SPEED	ACCELERATING	232
20-3-2015 19:54	3572	GR	40.00	29.00	0.01	INCREASE_ALLOWED_SPEED	ACCELERATING	315
20-3-2015 19:54	3572	GR	40.00	27.00	-0.06	INCREASE_ALLOWED_SPEED	ACCELERATING	394
## 80O								
20-3-2015 19:56	3572	GR	80.00	92.00	0.31	INCREASE_ALLOWED_SPEED	ACCELERATING	495

Figure 3.1: Data format used within the prototype to learn distributions on different situations. In this table the train driver is approaching a signal higher speed on departing at a station. Quicky followed by another signal increasing the allowed speed to 80 km/h. The format used within the prototype has a date and time, train service number, allowed speed, actual speed, and acceleration. The event type and action of the train driver are added as well as the covered distance in meters. The log rule starting with two hashes is a comment showing the sign passed between two rules, within the prototype it is merely used for debugging purposes.

for example, a signal that shows yellow or passing a sign that allows higher speeds. To find these events, the infrastructure rules are used as a segregation with some overlap of location rules. An event includes an event type and the consequent of the newly gained information such as new speed restrictions. An event is deduced from previously available knowledge such as the previously allowed speed and the newly allowed speed after passing a signal or a sign. An increase of allowed speed is shown in figure 3.1.

An event consists of at least one infrastructure rule denoting the current situation and a few locations rules showing the speed over time. From the location rules, the current action is derived. Each location rule has a speed and acceleration, due to inaccuracies a mean is used to classify an event using some threshold. Hence if the acceleration increases the train is probably accelerating, otherwise if the acceleration is decreasing the train is braking. In between a train driver can coast, performing no or limited traction to let the train roll and maintain its speed.

3.4 Distributions

Modelling behaviour of an operator can be tricky. There are numerous variations even with a simple interface as a few levers used on a train. The environment has a huge impact on the behaviour of the train. Not only hills can affect the acceleration and course of the train, but it is also dependent on weather and other circumstances around the tracks. Every rolling stock type has different driving characteristics and train drivers have different driving styles.

To include these environmental variations and the variations of operators, the behaviour will be modelled with distributions [31, 30]. The different situations are modelled with several distributions denoting the relative speed, timing, and strength of an action learned from real-world data.

By default there are four situations; approaching signal higher speed, approaching signal lower speed, approaching planned stop, and approaching red signal. These four situations are required to simulate a basic train driver, approaching signal higher speed is visualised as an example in figure 3.2. Each situation has a few distributions to simulate the driving behaviour [39, p. 41-62]. These parameters depend on the course of an action and vary per train driver.

To retrieve a tangible gain of an innovation, the purpose of this innovation should be held into account. Extending situations might be required in modelling the expected behavioural changes of the train driver using an innovation. Particularly where the effect of this innovation would be noticeable for example driving on a long stretch or approaching a stop.

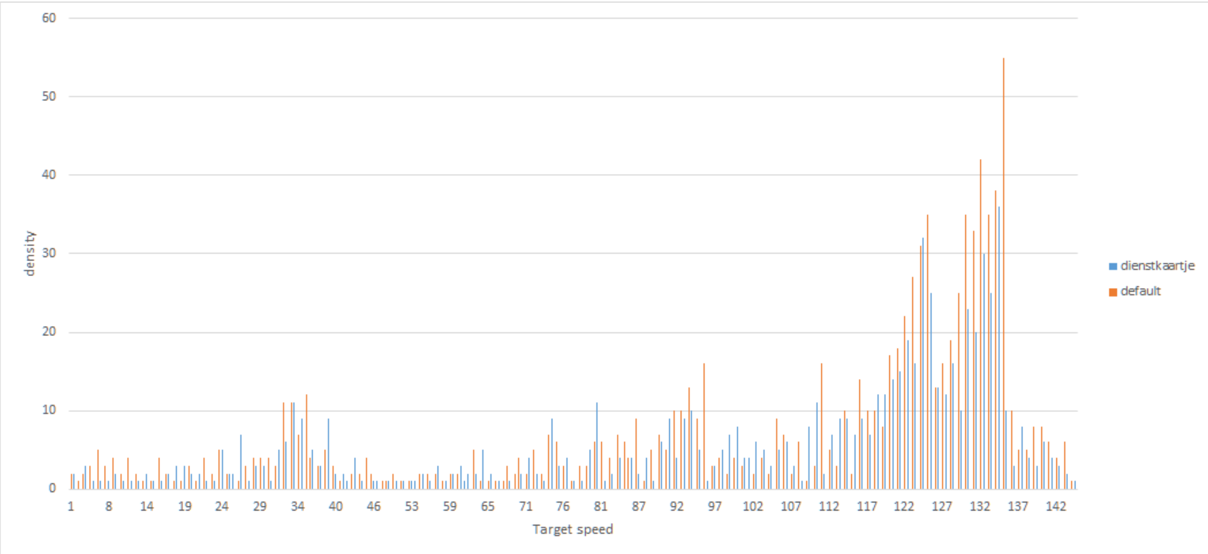

Figure 3.2: Target speed approaching signal higher speed histogram on train service 3500. The blue columns denote all trains approaching signal higher speed driving with Dienstkaartje+, the red columns denotes the other train drivers on this specific service. The target speed is deduced from MTPS data where it is the highest speed for a fixed period. A subset depicts the target speed around an allowed speed, e.g. the subset between 75 km/h and 85 km/h is the targeted speed in an 80 km/h section.

Chapter 4

Methodology

The process of evaluating an innovation using FRISO is a comprehensive process described in this chapter and explained in detail. In previous chapters, the idea behind this methodology was found. A literature study on relevant areas and an empirical research have given insights on the process. The methodology describes the steps taken to mimic the behaviour of an operator on simple tasks, in this case, a train driver driving from A to B.

The different steps taken in this chapter result in a model that is a representation of a train driver on a specific stretch of track. Some parts can be automated. However, there will be parts that should be performed manually e.g. fitting of a function. The process described in this chapter results in two models; a train driver using Dienstkaartje+ and a train driver without. Furthermore a high-level model of an agent capable of working with these models is given.

4.1 Expected behaviour

By default the train driver agent holds four situations into account; approaching signal higher speed, approaching signal lower speed, approaching planned stop, and approaching red signal. These situations give a representation of the decisive moments of a train driver using the signals, signs, and timetable. An innovation which adds a decision moment for the train driver or providing new information on which a train driver can act could create new situations based on the innovation. For example, a driver advisory system adds decision moments for the train driver on new information. Hence the expected behavioural changes of train drivers using an innovation should be held into account while creating a model of a train driver using a specific innovation.

The behavioural changes are best compared to trains under the same conditions. Therefore it would be wise to use a secondary data set with the same train series, rolling stock, and environment to compare. A model without innovation ensures a noise reduction when measuring gain against the model with a specific innovation. It is possible at this point to plot the different data sets and look for dissimilarities with for example a speed-distance diagram. This will give a first indication of the behavioural changes using this specific innovation.

4.2 Preparing data

There is a vast amount of data available for modelling train driving behaviour using their location, speed, and acceleration. Additional information about their timetable, signs, and signal passages are required to create a complete picture of the travelled path and are combined creating a storyline of a single train as discussed in section 3.2.

Prepping the location data has two stages. Firstly the location format is reduced to a few attributes; train number, date, time, speed, acceleration, and distance travelled along the track. In the Netherlands, the train number also denotes the train service number. Speed, acceleration, and distance are required to classify the current action of a train driver. If necessary values can be deduced; from two GPS logging the distance travelled is calculated, and the speed can be deduced using the time and distance. Some location formats have more information present such as allowed speed and previous signal, these attributes should be preserved. The allowed speed and previous signal from the location data source are more accurate than combining is from different data sets.

Adding information is the second stage. Time is required and should be in sync with the times denoting the passing of signals and the timetable. The time is used to combine the different files. The timetable is used for passage, arriving and departing times at stations. This is mainly used to classify braking behaviour for approaching a planned stop and might be useful to compare the different data sets explained in section 4.4.

Signals are added to the storyline to couple actions of train drivers to events happening such as decelerating for a yellow signal or an increase of allowed speed. The allowed speed is deduced from the signal unless it is green. A standard yellow sign has an allowed speed of 40km/h. If a signal is green, the allowed speed is determined by the last passed sign. The signs are added using the identifier of the specific branch of a stretch of track (in Dutch; spoortak). The moment a train driver passes a sign is deduced from the location of the sign along the track and the median between two location rules of a train service.

From this default data format, subsets are created for modelling the behaviour. A subset represents an attribute in a certain situation e.g. the target speed after passing a signal indicating a higher allowed speed. These subsets are fitted with a function as discussed in section 3.4.

Depending on the goal of creating a representative train model, the train type and train service should be kept into account. Every train driver has different driving characteristics, every train type has different acceleration and braking curves, and every train service has its challenges. Hence simulating behaviour of a particular train type on a specific service would have less dispersion than creating a model of all trains driving with a certain innovation anywhere in the Netherlands. Creating a model from a limited set, preferably a specific train service, creates a specific model. Creating multiple models on a single stretch of track with different train types and different train services would improve the result of the simulation on this specific stretch of track.

Creating two models using the same service number would be an ideal situation, an innovation is usually tested on a very limited scale such as a single train service. Therefore creating a model without an innovation on the same service number would give a relative gain of an innovation as shown in figure 4.1. Since it is not desirable to validate the model with the innovation on other services, this model can not groundlessly be used for all train services in the Netherlands. It is possible some service specific peculiarities are included in the model.

4.3 Modelling behaviour

Once the data sets are created, learning to describe the behaviour of a train driver is the next step. The four default situations, approaching signal higher speed, approaching signal lower speed, approaching planned stop, and approaching red signal can describe basic train driver behaviour. Every situation has a few distributions e.g. the point a train driver takes action and the strength of the action. For example, the behaviour during an approaching signal lower speed event has two distributions to denote when an action starts and the target speed due to this situation. These two distributions describe the action of a train driver in an approaching signal lower speed situation [39].

Distributions describing a situation are learned from a subset of the standard data format shown in figure 4.2. For example, a range from 10 kilometres around the target speed is required to create a distribution of the different speeds reached while lowering the speed in the situation mentioned above, showed in figure 4.2. A function can be fitted on a histogram as illustrated in figure 4.3 to create a probability distribution. The second histogram is the moment the train driver takes action. The moment is dependant on the time until the emergency braking is activated. With these two probability distributions, a path can be calculated to simulate the train driver behaviour during the approaching signal lower speed situations.

Modelling behaviour depends on the innovation itself and the expected behavioural changes.

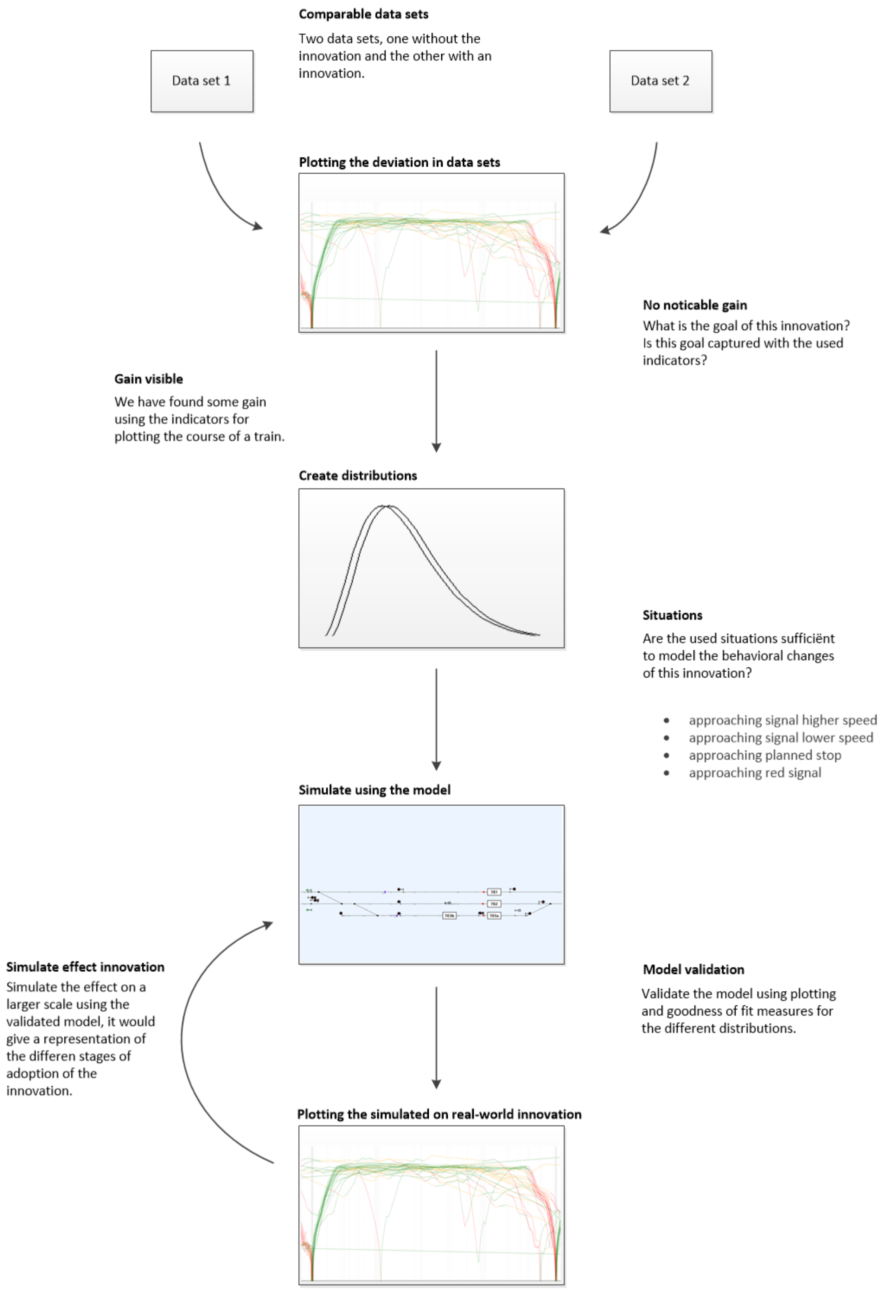

Figure 4.1: Illustrating methodology modelling an innovation to quickly validate the gain of such an innovation. The flow results in a validated model which can be used to indicate the gain of an innovation. First comparing two data sets to find a relative gain of an innovation is done to compare later one with the simulated runs using the model. The second step is creating distributions and fit function to mimic the behaviour of a train driver using a software agent. Simulation is used to validate the model, once the model is deemed valid simulations can indicate the behavioural changes on a larger scale.

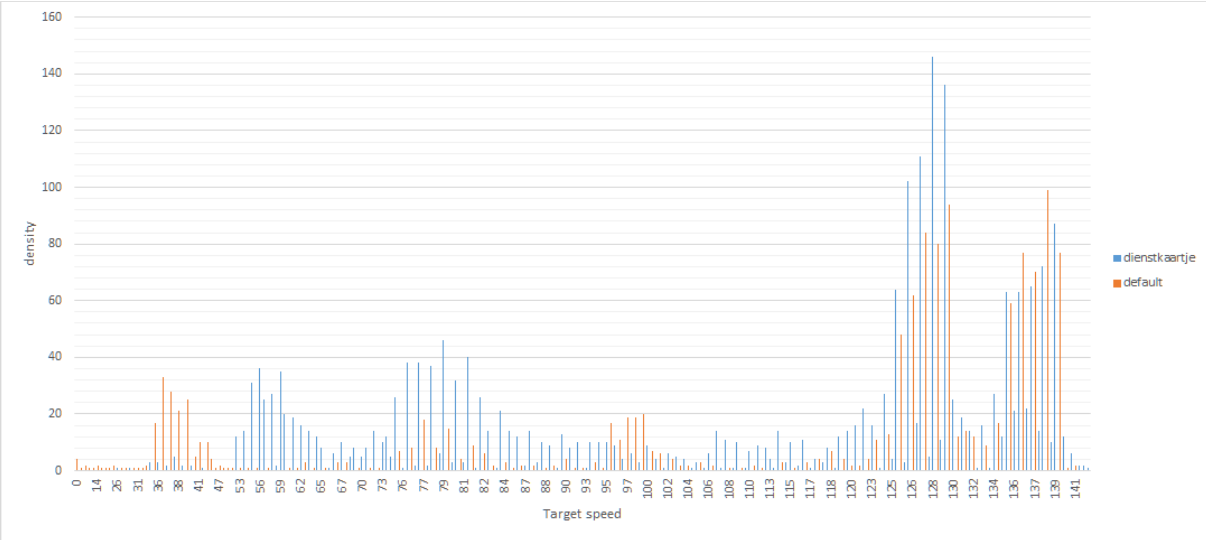

Figure 4.2: The measured target speed after passing a signal lower speed, in other words, the speed where a train driver stops with decreasing its speed before accelerating again. Data is gathered from real-world data on the 3500 service. Finding the braking behaviour of a train driver includes the target speed after braking relative to the allowed speed. From this graph, a subset is taken for example 80km/h with a 5km/h tolerance on which a distribution is fitted.

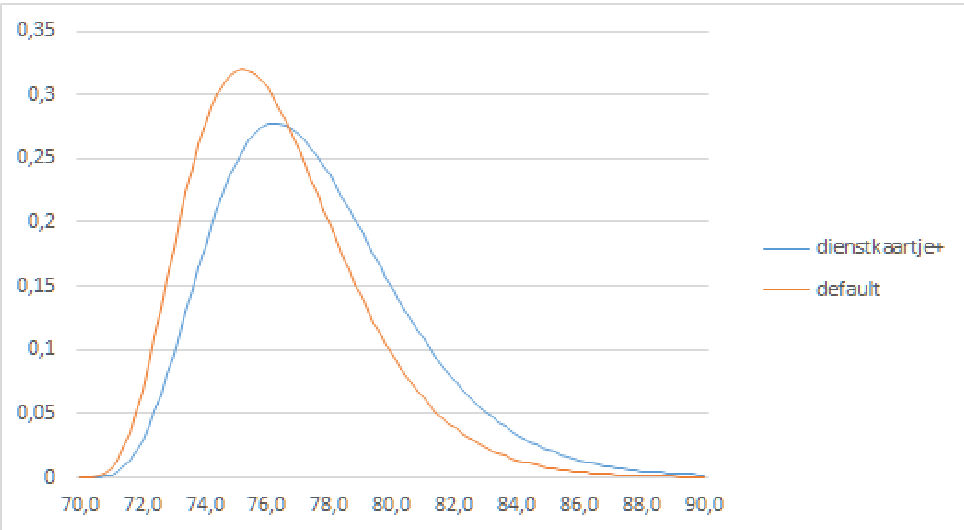

Figure 4.3: Fitted function on target speed approaching signal 80km/h with a margin of 5 km/h on train service 3500.

A driver advisory system may add decision points for the train driver. A driver advisory system can advise the train driver to slow down or accelerate resulting in at least two additional situations. These driver advisory systems should be implemented in the simulating environment and the agents used to handle these situations. The expected behavioural changes of a train driver due to an innovation should indicate additional situations to mimic the behaviour. Additional situations require some knowledge of the situation or a clear dissimilarity of the diagrams created comparing the two different data sets.

It is possible that a driver advisory system forces an action for the train driver, then it would not be required to create distributions for this innovation. These forced actions should be implemented in the mechanics of the train driver, hence the agent. General obligations of a train driver should also be implemented in the agent; these obligations include standing still in front of a red signal and stopping at train stations they have to stop at according to their schedule.

One should always keep in mind the goal of an innovation and the possible behavioural changes of the operator and reason if the created situations are sufficient to mimic the behaviour of the operator with this specific innovation.

4.4 Validating model

A model (with probability distributions) needs to be validated before the model is used for simulations on a larger scale. A model is constructed on a particular train service with a number of trains. There are a few possibilities to validate such a model explained in this section. A visual representation can be easily made using a speed-distance diagram. A speed-distance diagram is made of a number of real-world trains compared to a number of simulated runs using the created model. Similarity within a speed-distance diagram is key between simulated runs and the real-world data. Realistic train drivers never drive the same hence there would be some spread in the real-world data as should be in the simulated runs. However, the simulated runs should be in or very near this spread to indicate a similar driving behaviour to the model.

Furthermore validating on certain moments gives a measurable difference. These measurable differences will be referenced as indicators. Indicators are dependent on the path they follow and possible changes in the planning. Important is that these indicators should differentiate from the standard train driving behaviour to capture the behavioural changes in train driving. Otherwise, the lack of behavioural changes using an innovation also gives insights into the lack of gain using this particular innovation. These indicators depend heavily on the innovation but some moments are comparable for all innovations; arrival time relative to the planned time is a good indication of the gain using an innovation. The relative time a train enters or passes a train station gives an overall image of the punctuality of a train.

Probability distributions are tested using a goodness of fit measure denoting the distance between the function and the used distribution. The Kolmogorov-Smirnov test [29] in equation 4.1 gives a number on how well the function represents the fitted data. The Kolmogorov-Smirnov measures the difference between the function and the data used to fit the model, the least lower bound of these absolute distances indicates the similarity. However, the distributions do not depict the entire course of a train, but rather the decision moments in the situations discussed earlier, hence combining the Kolmogorov-Smirnov test with the measurable validation on indicators and the similarity of the speed-distance diagram indicates if the model is representing the overall train driving behaviour.

$$D_n = \sup_x \mid F_n(x) - F(x) \mid \tag{4.1}$$

where

D_n	=	Kolmogorov-Smirnov distance
$\sup_x$	=	function for least lower bound
$F_n(x)$	=	the height corresponding to x within the function
$F(x)$	=	size of bin x of the histogram

4.5 Simulating effects

Once a model is deemed valid, the simulation environment FRISO is used to simulate gain of innovations on larger scale on a specified stretch of track. A stretch of track is also called a corridor. Depending on the simulator it is possible to simulate partial adaptation of an innovation, in the sense that not all train drivers are using the innovation. Hence the noticeable gain can be figured out with a select group of train drivers or that all train drivers have to use the innovation before any effect is noticed. The overall results of all trains measured by the earlier mentioned passage times relative to another percentage or no adoption at all will give a relative gain of an innovation on larger scale.

4.6 Agent design

At the moment of writing the simulation tool called FRISO is used to simulate behavioural changes within ProRail. It has a very basic agent that represents the behaviour of a train driver. Tielman [39] created a new agent to improve the decisions within the FRISO environment. Tielman's agent is used in combination with FRISO to find behavioural changes due to Dienstkaartje+. However, this thesis is made in mind that other simulation environments and software agents can be used. To ensure similar behaviour across different environments, this section describes the requirements of such an agent and simulation environment. The workflow of an agent is visualised in figure 4.5.

An agent simulates the behaviour of a single train driver and requires some basic knowledge before becoming a train driver [34]. A part of this knowledge is enforced by the situation, and these should be implemented within the agent and enforced by safety systems. For example, if a train driver approaches a red signal under all circumstances it should halt to a complete stop. Otherwise, a safety system would intervene and it would make an emergency stop.

A simulation environment notifies the train driver when it is in visual range of a new

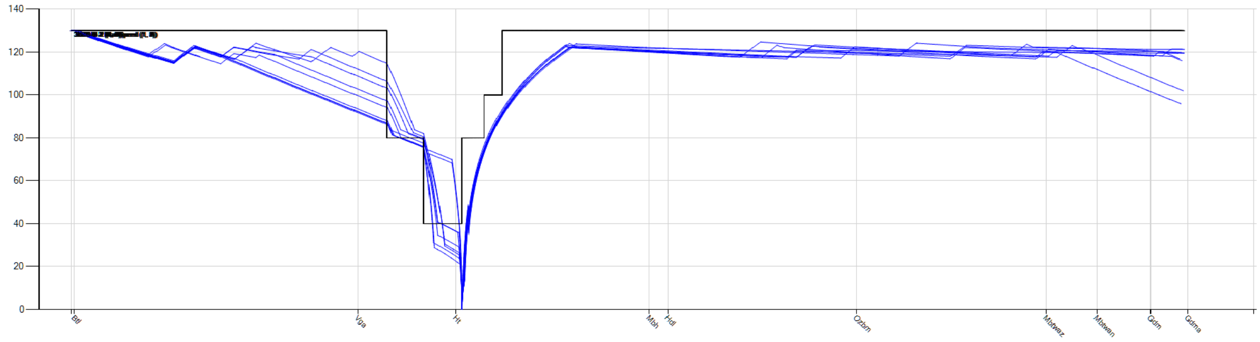

Figure 4.4: Points of new situations, the horizontal line indicates the maximum speed, hence a drop of allowed speed is a new situation started using a signal or a sign. This specific stretch of track is the arrival and departure at Heerlen from the 3500 service simulated using FRISO.

situation such as a decrease in allowed speed. An agent is informed of new situations as shown in figure 4.4. The distance of the visual range depends on the simulator environment such as FRISO. The agent can handle situations and should be able to perform an action in the environment if needed, which in turn effects the train within the simulation.

The simulation environment tracks information such as allowed speed and current speed which are accessible by the agent or notifies the agent in a certain interval. The agent should be informed or be able to change actions on certain points such as accelerating when the speed is becoming low while coasting.

A train driver has two actions with a certain magnitude, accelerating and braking. The magnitude and timing are learned from real-world data using distributions explain in section 3.4. To improve the train driver, different train types have different braking and acceleration characteristics which should be held into account.

Most situations are based on changes in the environment. These situations are simple and a train driver ought to act on such an event. Other changes made can be based on prior knowledge, the so-called track familiarity. Changes can be made due to unplanned events such as a person near the tracks, or recommended by a driver advisory system. The latter should be kept into account while modelling new situations in an agent guided by a driver advisory system for example Routelint [6]. The possible situations are approaching signal higher speed, approaching signal lower speed, approaching planned stop, and approaching

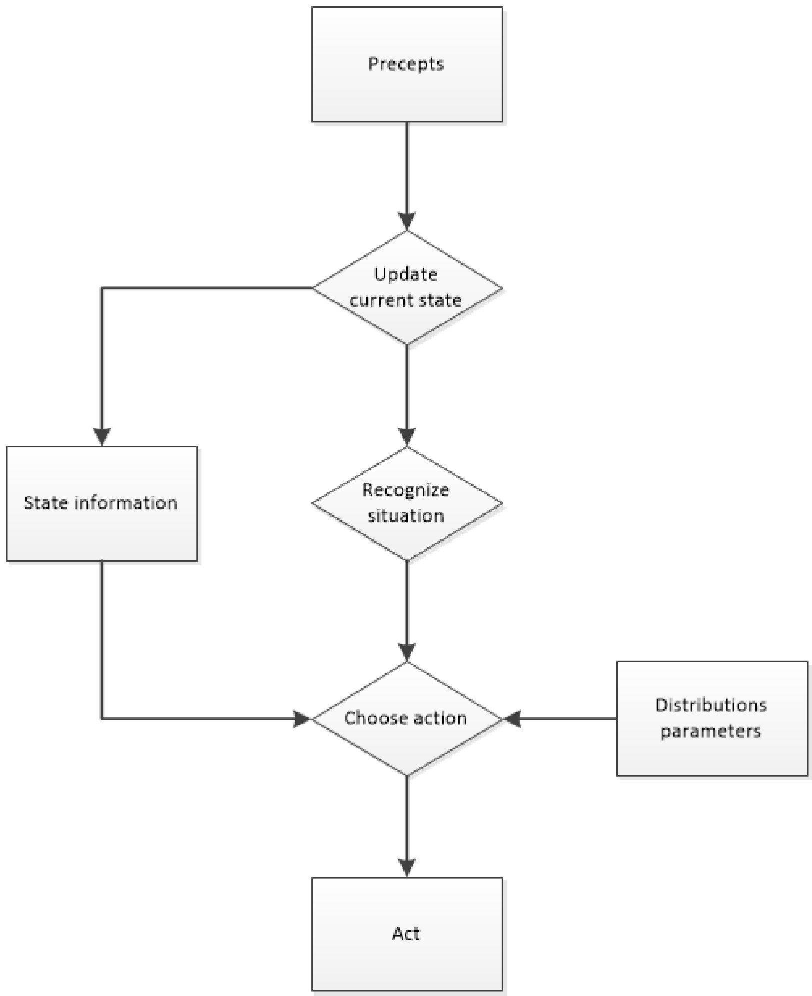

Figure 4.5: Functional design of responsibilities of an agent on receiving a message in a certain interval. Some information messages can be informative such as an update of current speed, the agent can decide to continue it's current action. Distributions parameters are learned from data explained in section 3.4.

red signal. New situations can be added if the train driver has new situations where a train driver should act for example with a driver advisory system.

Chapter 5

Experiment

The experiment uses the previously elaborated methodology to simulate the effect of Dienstkaartje+. The A2 corridor is a long stretch of track between Heerlen and Schiphol, one of the train services driving this stretch is the 3500 service. The 3500 is an intercity, skipping small stations, driving with a VIRM or an ICM train. Within the 3500 train service, there are some train drivers and conductors driving with dienstkaartje+. To simulate the effect on a larger scale, in the sense that every train uses Dienstkaartje+, two models of this specific service in one direction are created from Heerlen to Schiphol. One model is based on real-world data from train drivers using Dienstkaartje+. The second model is based on train drivers without Dienstkaartje+. There are some peculiarities such as the start of the first train is at a different location. However, the train follows the rest of the schedule.

5.1 Preparation

The goal of dienstkaartje+ is reducing the spread of trains arriving at a station for the train driver. The new timetable that belongs to Dienstkaartje+ improves the times denoted in their timetable between two stations (dutch; dienstregelpunten). Within the new timetable, drivers have a six-second window for arriving or passing a train station. The more accurate timetable will result in an area where trains can be planned closer to each other, improving the capacity. However, the times denoted in the new timetable only informs the train driver on passing and arriving at train stations. Resulting in limited feedback points for the train driver.

For the Dienstkaartje+ experiment, two data sets are created each having 90 shifts. One data set is from real-world drivers using Dienstkaartje+ during a pilot to measure the relative gain compared to the second real-world data set without Dienstkaartje+. The data was gathered in a period of three months from March till May. These months have relatively calm weather, no dreaded leaves on the tracks, or heavy storms. For this specific experiment, MTPS data is used enriched with signals, signs and timetable data. The timetable data has two variations since the Dienstkaartje+ project improved the times with more feasible arrival and passing times which should be held into account on the Dienstkaartje+ data set.

In the data preparation process, the timetables were changed manually for all trains using Dienstkaartje+. The timetable logging does not track the new planned times used in the Dienstkaartje+ pilot. The 3500 drives every half hour leaving Heerlen at exactly 14 minutes or 44 minutes past the whole hour for every hour. The actual arrival times are accurately logged, so the delay is computed by subtracting the planned time from the actual time denoted in the new timetable.

There are some gaps in the timetable where trains skipped train stations. Skipped train stations can be due to several circumstances e.g. Oost-Heeze has been added to the logging but the paper version of Dienstkaartje+ did not include this station. Furthermore, the GPS data has some gaps where there were too few satellites to triangulate the position of the train accurately, MTPS ignores these log rules creating gaps. These gaps can decrease the accuracy of some situations e.g. a train is arriving at a station but there is a 30-second window without accurate speed, distance, and acceleration available used for the second braking manoeuvre resulting in an inaccurate arrival of the train.

MTPS data is used for every train driver logging the location every 10 seconds. The

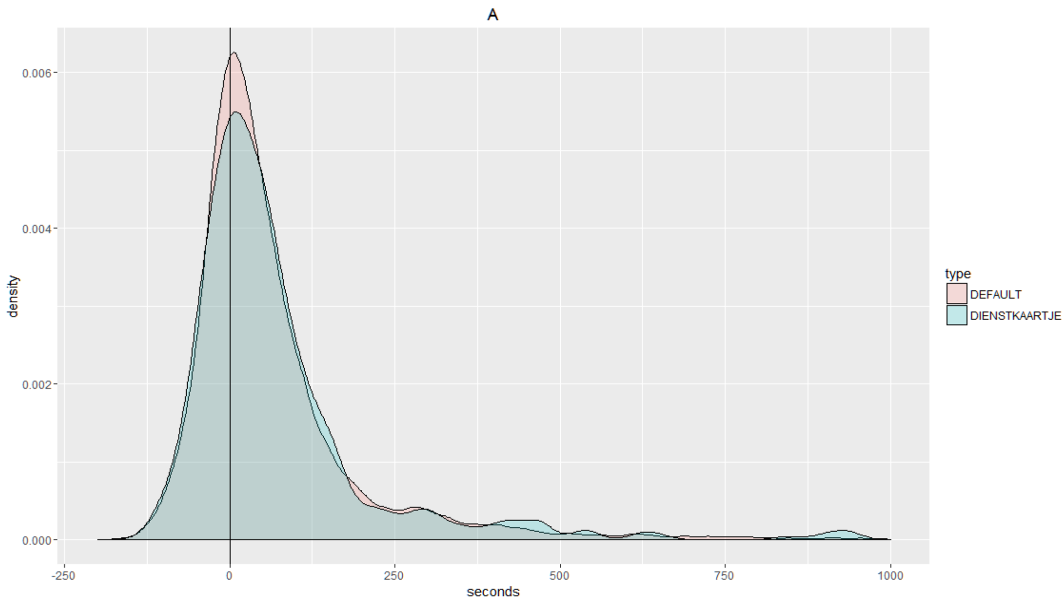

Figure 5.1: Time density graph on arriving at train stations in the 3500 service retrieved from the timetable data, the vertical line denotes the scheduled arrival.

prototype built for this thesis then adds signal, sign, and timetable information. Using the three additional data types, situations can be found describing the driving behaviour of a train driver.

The four default situations approaching a signal lower speed, approaching a signal higher speed, approaching planned stop, and approaching red signal describe the behaviour of train drivers. For each situation, there are a number of distributions denoting the course of the action during such a situation. The prototype built for this thesis creates files for each distribution with data for a histogram e.g. the target speed after passing a sign denoting a lower speed as shown in figure 4.2. Learning a function describing the target speed relative to the allowed speed is made using R and the fitdistrplus package. The fitted function that followed is then used by the software agent.

5.2 Simulating

Keeping the goal of Dienstkaartje+ in mind, a reduction in the spread of arriving and passing train stations results in a positive change in the behaviour of a train driver.

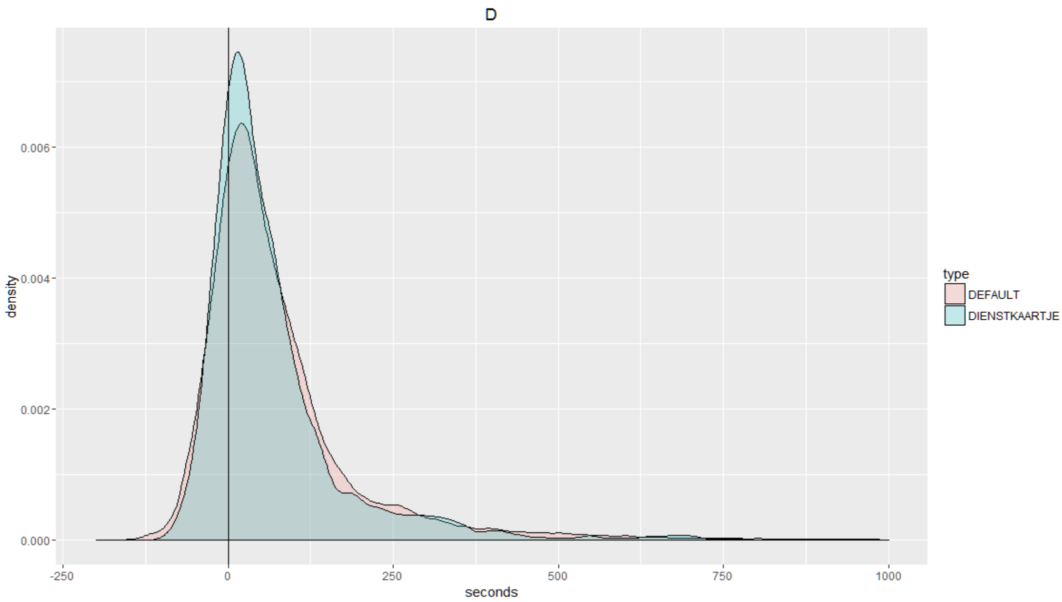

Figure 5.2: Passing train station in the 3500 service shown in a time density graph, the vertical line is the scheduled passing time.

The difference in the data set from Dienstkaartje+ drivers and regular drivers is minimal. However, there is some slight improvement at the passing of a train station and a difference in arriving at train stations showed in figures 5.1 and 5.2. To pursue the small differences two models are used, one for each set, resulting in distributions which should have a deviation. Using both models a relative gain could be found.

After the two models are constructed, the behaviour with and without Dienstkaartje+ is simulated using FRISO. Within FRISO 30 runs are performed. The output of FRISO is then used to compare the models and find the relative gain, the difference between the two models should show similar behaviour with the graphs created from the real-world data. Simulating the arriving of a train station shown in the figures 5.1 and 5.3 shows us that train drivers using Dienstkaartje+ break slightly earlier. The deviation shows no significant impact on the driving behaviour of the train driver using Dienstkaartje+.

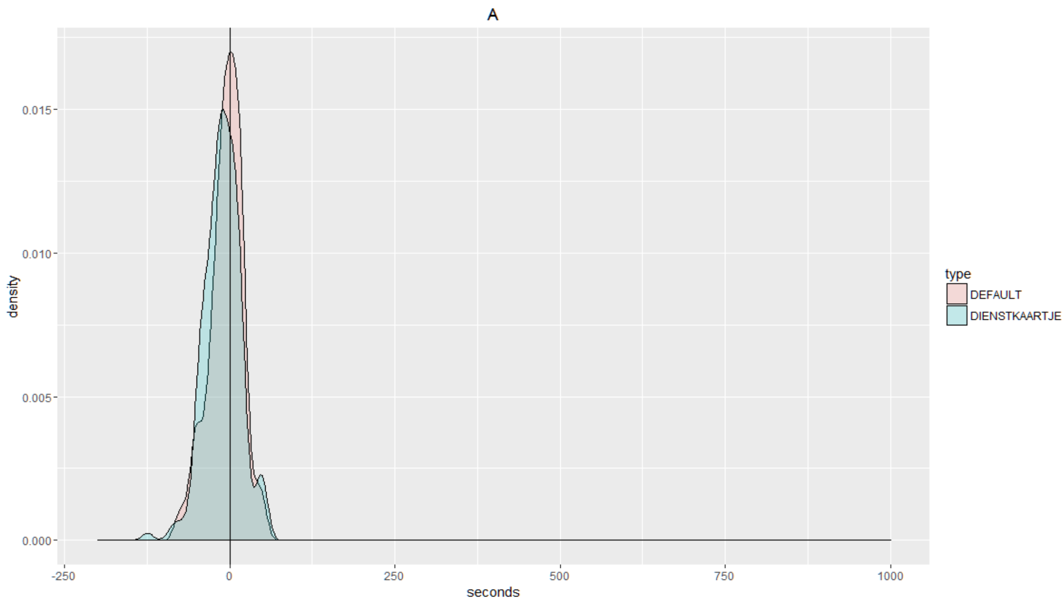

Figure 5.3: Arriving at train stations in a simulated environment denoted in a time density graph where the vertical line is the scheduled arrival. The model used for constructing this graph is based on the 3500 service.

5.3 Results

Plotting passing and arriving times shown in figures 5.3 and 5.4 shows narrower distributions in comparison to figures 5.1 and 5.2. The model does not show a very similar dispersion for passing train stations compared to real-world data. However within arriving train stations the relative gain of Dienstkaartje+ can be found since train drivers with Dienstkaartje+ tend to arrive slightly earlier than train drivers without Dienstkaartje+. The overall spread of the distributions where real-world data has a larger spread is due to the randomness possible within the agent. The agent has a small deviation on the long stretches between train stations.

The measurable points and time-distance diagram can be evaluated relative to each other, indicating a limited difference between the real-world data and the simulated data. Hence the gain of Dienstkaartje+ is not measurable with the data of the pilot done by train drivers using the situations used. Dienstkaartje+ may have an effect on train drivers. However, improved driving behaviour is not measured during this pilot.

The agent has four situations which do not seem to describe a train driver accurately. A

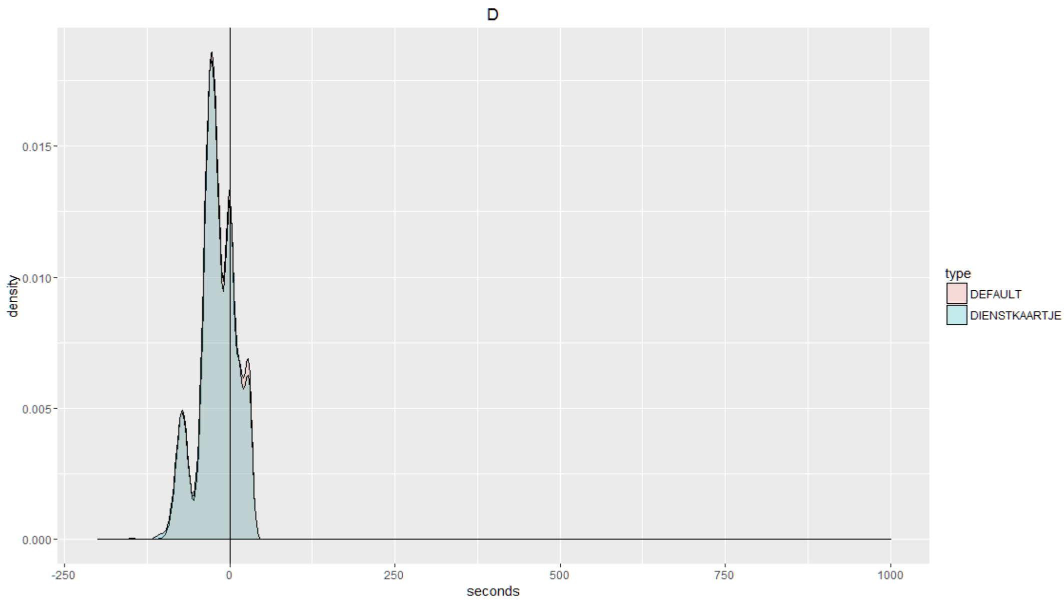

Figure 5.4: Time density graph showing the delay of passing a train station in a simulated environment based on the 3500 service. The vertical line is the scheduled time of passing.

large part of train driving is the behaviour on the long stretch, the stretch between train stations. Comparing the simulated environment in figure 5.6 with the real world shown in figure 5.5 shows a slightly different approach and departure at Heerlen. However, the spread of the simulated path is much narrower due to the timing of the first braking manoeuvre entering a train station. This is reinforced by the density distribution of passing a train station shown in figure 5.4. The figure shows a narrower dispersion and the different locations result in several peaks. Hence the approach taken to simulate a train driver on the long stretch has not enough randomness.

The time denoted in the new timetable indicates the time a train driver should pass a train station. A train driver has to act on the delay at a precise moment, the passing of a train station, while still driving the train. Because trains pass at high speed the delay is hard to recognise for a train driver however, it might give an indication. The train driver can then act on a delay accordingly. However, the exact speed a train has to drive to catch up is not known, so a train driver might be too early at the next station causing him to encounter a yellow sign. A conductor using Dienstkaartje+ sounds promising. Usually, a conductor has a window of 60 seconds to depart. Dienstkaartje+ reduces this spread. However, the closing door sequence will remain to be a human task, prone to different interpretation and circumstances.

Dienstkaartje+, in general, could reduce the dispersion of trains on measured points such as passing, arriving, and departing train stations. Within this pilot, no sufficient relative gain was measured. The model shows no significant difference in driving behaviour. However, the graphs show a narrow dispersion due to the implementation of the agent.

Figures 5.5 and 5.6 show that an agent is able to give a relative gain of an innovation. However, the agent is not yet able to completely mimic the driving behaviour. The spread of arriving and departing from a train station is more condensed in the simulated environment. Hence the agent should have more room to plan the course of a train and on the straight more randomness should be included to mimic the behaviour of multiple train driver with different characteristics. Improving the agent would improve the overall ability to model driving behaviour as has been discussed in section 4.6.

Within this innovation there are some concerns about the effect of Dienstkaartje+, such as the moment a train driver has to look at the time at a particular passing point at high speed and if these points are sufficient to change the driving behaviour. Hence does a train driver has enough input from the delay at passing stations. A driver advisory system could give a continuous update of their delay.

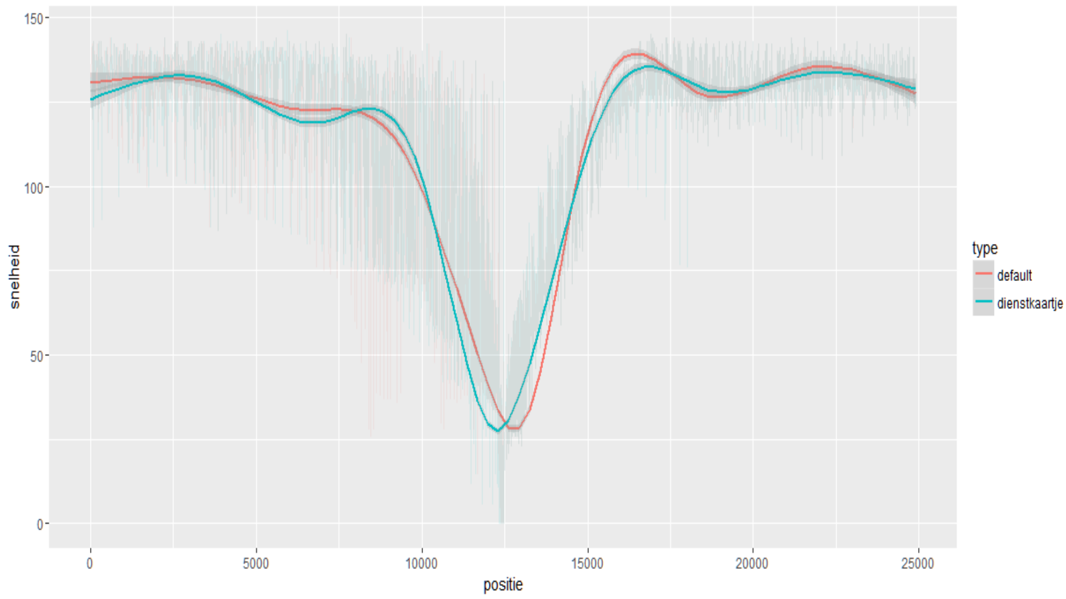

Figure 5.5: Speed distance diagram showing the arrival and departing at Heerlen of the 3500 service, comparing the default (train drivers without innovation) and dienstkaartje+ train drivers.

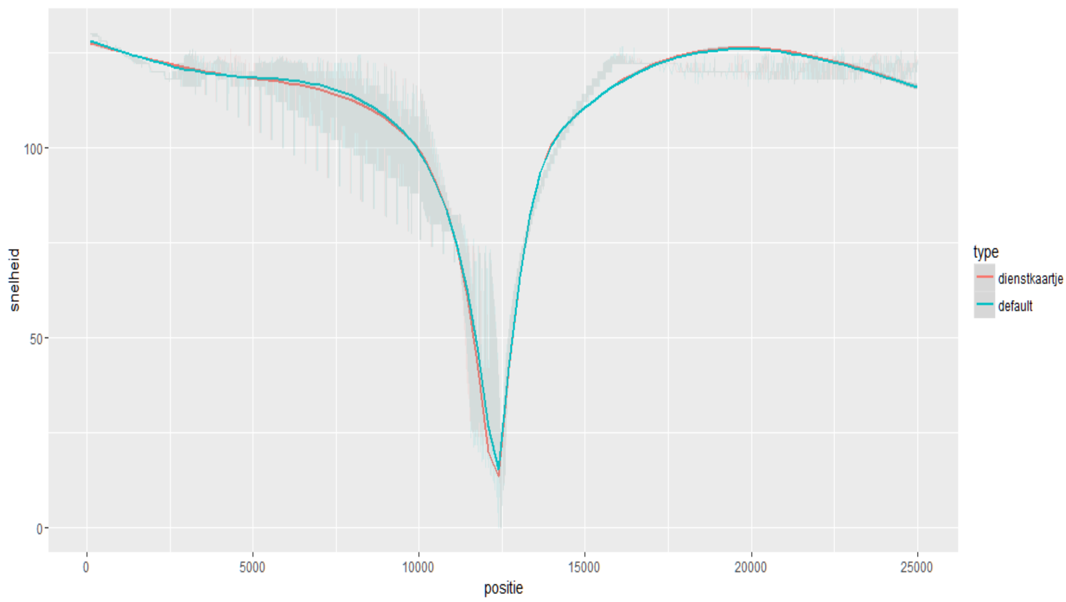

Figure 5.6: Speed distance diagram from the simulated environment based on the 3500 service showing the arrival and departing of trains with and witout dienstkaartje+.

Chapter 6

Conclusion

Following from the empirical research and the experiment, simulating data-driven operators depends highly on the actions an operator can take and if the effects are noticeable in their environment. The data-driven approach is interesting when the controls largely remain the same but the behaviour of the operator changes on new information or experience e.g. Dienstkaartje+.

In this chapter conclusions and recommendations will be elaborated for further developing a methodology simulating a train driver based on experiences through the empirical research and the experimentation done on the A2 corridor.

6.1 Data-driven modelling

A large part of this thesis involves data parsing and possibilities to enrich different data types.

How to efficiently read data from different sources like track-occupation, GPS, and simulator data to compare?

Using a standard format that holds the required information for modelling, plotting, and comparing allows using different sources. This default format is made keeping in mind the storytelling approach of a train driver. The story is in chronological order denoting information about passing signs and signals, approaching or leaving a train station, and the current location, speed, and acceleration. Combining information gives a solid representation of a train driver's journey and decisions made along the way which can be used to efficiently read the data required for modelling a train driver.

Normalising and enriching the data is a cumbersome task where inaccuracies should be omitted as explained in section 3.3. Because no known data types are created for this specific purpose, some inaccuracies will still be present. The quality of a model is improved when learning, validating, and simulating is done using the same route or even the same train service number. Trains regularly drive in the Netherlands so will still provide a sufficiently large data set.

How to define a data-driven model to simulate acceleration- and braking behaviour of train drivers?

Events are found describing different situations where a train driver has to react to changes in their environment, the actions taken defines the model. These situations are modelled using distributions describing different parameters such as distance to planned stop from where the braking manoeuvre starts. The model is constructed using real-world data of train drivers using the innovation so that the expected behavioural changes are captured within the model. It is possible that the innovation has unexpected behavioural changes during validating the model, these unexpected behaviours should also be captured and modelled in the next iteration of the model.

Validating can be done by measurable points such as passing and approaching a train station as well as speed-distance and time-distance diagrams. The simulated runs should result in a close resemblance to an actual ride. Within the data there are inaccuracies, using a large data set these inaccuracies should filter out. However, some circumstances have larger impacts such as leaves on the track or a collision. These inaccuracies can result in undesirable behaviour in the model especially comparing data sets. On validating the model the goal of the model should be kept into account. However, one should not fixate on the goal and ignore other occurring behaviours.

6.2 Behavioural changes of an innovation

The goal of this methodology is to quickly find behavioural changes using data in an environment where the actions, such as accelerating and braking, do not change. A standard data format is used so different data sources can model the driving behaviour and find behavioural changes from newly gained tracking data in any format [22]. FRISO is used to simulate several trains in a network using a model.

The effect of an innovation is validated per train however, the effect can be measured on a larger scale using a model. Simulating on a larger scale requires multiple models, preferably one for every train service and rolling stock type. Simulating on this scale enables us to validate an innovation on a larger scale with different train types, thus simulating all trains driving on a specific stretch of track.

What is the effect of Dienstkaartje+ on a larger scale using a simulation?

For this thesis Dienstkaartje+ is used as an experiment where the effect on a scale with a higher adoption of Dienstkaartje+ did not show a significant change in the behaviour of train drivers.

As explained in section 5.3 the simulation on larger scale resulted in the lack of realistic spread on the long stretches of track which in turn limits the spread in passing and arriving at a train station. However, it is still possible to indicate the relative gain of an innovation using certain measurable points such as passing and arrival times of trains. Improving the agent would increase the overall simulation and gives better insights.

What is required to generalise measuring the effects of innovations using a data-driven model?

The storyline of a train driver allows different sources to be used within this methodology. Standard train driver behaviour can be evaluated using the basic four situations; approaching signal higher speed, approaching signal lower speed, approaching planned stop, and approaching red signal. In this situations train drivers react to static signals and signs informing the train driver.

More innovations such as driver assistance systems [41, 9] are improving the information available for the train driver. Routelint is such an app which supports the train driver in its decisions, it is part of the high-frequent passenger trains and visualises the occupancy of the track ahead. A train driver can see its route for up to nine blocks of the block signalling system. Since these informal messages are not directly connected to the block signalling, additional situations are required e.g. driving behind a delayed train affecting their own schedule.

6.3 Recommendations

ProRail is a large organisation with an even larger public responsibility. The data gathering within ProRail has some challenges and possible improvements. There are some different data types with driving information listed in appendix A however each with different purposes. A proposed default format is added to use the different data types capturing the required information for simulating train driver behaviour shown in appendix G.

The infrastructure data is stored in a directional network, which makes it intuitive and easy to draw. However, there are over 117000 infrastructure items along the paths. This makes the process of finding whether a train passed a sign quite cumbersome for every new GPS location. Furthermore, the names of stretches of track are not necessarily the same, especially changes in the infrastructure, i.e. signals, signs, and switches, are not updated regularly. A third party, the maintainer of the infrastructure information, supplies the required signal and sign information to ProRail.

Some information is an approximation or has inaccuracies which diminishes the accuracy of possible conclusions. Still, these conclusions can indicate some interesting improvements or events. However for simulating the gain of an innovation, it would be recommended to gather data for the purpose of simulating, especially the moment a train driver reacts on new information. Gathering data for this specific purpose includes logging of the speeds designated to the driver by the safety mechanism ATB (in Dutch; Automatische treinbëinvloeding). Furthermore, the odometer of a train is more accurate than the derived distance from GPS coordinates and would give an accurate distance travelled instead of a GPS update every 10 seconds. Moreover the distance between infrastructure is measured on the centre of a corridor, hence in a left turn the track most left is shorter than the track on the right.

The agent used for this thesis and used within the innovation department is still in development. It has been tested on a few train services however, there are some improvements possible. Firstly the agent should verify if the braking manoeuvre it is starting is strong enough. In the real-world train drivers base their braking behaviour on prior knowledge and the scout sign. To mimic the knowledge the agent should compute if the breaking manoeuvre is strong enough, hence the agent should plan the entire break manoeuvre before starting it. Some minor adjustments are possible, but a train driver is committed to a breaking manoeuvre when started as in the real-world. The scout sign is not used within the agent but should give a better insight on the start point of braking instead of the distance to the station. The scout sign notifies a train driver to start braking for the next station if he is driving at the maximum allowed speed. The scout sign is also present in the infrastructure data.

There are different driving characteristics on the long stretch for train drivers. Currently, the agent supports no input for actions on the long stretch which would improve the overall realistic behaviour of a train driver. The parameters required on the long stretch are quite comprehensive since it depends on several parameters, such as the feasibility of the driving times between stations, the track occupancy, weather conditions, and the train driver itself.

Within the proposed format the scout sign can be incorporated as well, the situation can change once a scout has been passed. To learn from scout signs the exact time of passing is required which is not accurately available at the moment since the distance travelled is deduced from the GPS coordinates. If desired more infrastructure can be added to model the train driver behaviour such as elevation as is visible in the second rule in appendix E. Furthermore, the distance between a signal and the sensor can be used to compute the exact moment of passing a signal.

Finally, within ProRail there is a desire to model driving behaviour from a driving simulator. Unfortunately, the current simulator used for this purpose is not showing a realistic environment. Due to the unrealistic looks of the simulator, a train driver cannot orientate themselves on the track and will not give an accurate gain of an innovation. The environment consists of a large green surface without buildings and a very minimalistic way of showing a platform. Driver advisory systems could give train drivers using this innovation an unfair benefit in showing their location or accurate delay at any given moment. Such a driving simulator works fine for the purpose of feedback from train drivers. However, the data gathered and possible gain will not be representable to the real-world.

Appendix

A Data formats

The different data formats and their capabilities, first seven log formats used in the real-world, followed by three simulators with input of a train driver and finally FRISO which is used for simulating using an agent.

	interval	gps	distance	speed	acceleration	signals	signs	arrival
MTPS	10 seconds	+	-	+	+	-	- [1]	-
RTM	≈ 1 second	+	-	+	-	-	- [2]	-
QATS [9]	≈ 10 seconds	-	- [3]	+	+	-	- [2]	-
ORBIT	1 second	+	-	+ [4]	+	-	- [2]	-
RBC [5] [9]	≈ 1 - 40 seconds	-	- [6]	+	-	-	- [2]	-
DRR	≈ 2 seconds	+	-	+	-	-	- [2]	-
JRU [7] [9]								
MATRICS	1 second	-	+	+	+	+	+	+
HORTUS	1 second	-	+	+	+	+ [8]	- [8]	-
MORPHEUS	1 second	-	+	+	+	+	- [8]	-
FRISO	≈ 1 - 10 seconds	-	+	+	+	- [8]	- [8]	-

1 section identifiers are present but theoratically can skip a section on high speed.
2 without distance or section identifiers only combining option is thru gps.
3 ERTMS beacons are present, the exact time passing such a beacon is not logged.
4 Earth Centered, Earth Fixed is used to log the speed.
5 RBC is eavesdropping on other applications and logs the messages transfered thru the radio block center, at the moment the above mentioned information can be retrieved.
6 The distance is captured relative to a certain point for the tablet of the train driver, however whenever its moving towards a new point the end distance is not known.
7 Juridical recording unit data is not available for simulating purposes.
8 The signal and/or sign information can be deduced from the allowed_speed parameter in the logging
9 This format is part of ERTMS which is used on selected corridors at the moment, however will be expanded.

B MTPS format

Raw format of MTPS information, a small example is displayed with annotation of useful parameters.

treinnr [1]	materieelnr [2]	tijdstempel_gps [3]	lat [4]	long [4]	snelheid [5]	kompasrichting [6]	hdop	sat	vervoerder
3551	4071	23-3-2015 14:55:51	52,08	5,12	66	117,22	0,8	9	NS
3551	4071	23-3-2015 14:56:01	52,08	5,13	72	118,91	0,8	9	NS
3551	4071	23-3-2015 14:56:11	52,08	5,13	78	119,73	0,8	9	NS
3551	4071	23-3-2015 14:56:21	52,07	5,13	81	123,53	0,8	9	NS
3551	4071	23-3-2015 14:56:31	52,07	5,13	81	133,27	0,8	9	NS
3551	4071	23-3-2015 14:56:51	52,07	5,14	79	143,31	0,8	9	NS
3551	4071	23-3-2015 14:57:01	52,07	5,14	77	151,65	0,8	9	NS
3551	4071	23-3-2015 14:57:11	52,07	5,14	76	150,58	0,8	9	NS
3551	4071	23-3-2015 14:57:21	52,07	5,14	76	148,34	0,8	9	NS

tps_spoortak [7]	tps_kmlint	tps_kmwaarde [8]	tps_kopstaart	tps_tijdstempel [9]	tps_rijrichtingtak [10]	tps_rijrichtingkmlint [11]
HTN1847V	Asd-Zvg	36600	KOP	23-3-2015 14:55:41	T	M
HTN1847V	Asd-Zvg	37020	KOP	23-3-2015 14:56:04	T	M
HTN1847V	Asd-Zvg	37475	KOP	23-3-2015 14:56:25	T	M
HTN1847V	Asd-Zvg	37475	KOP	23-3-2015 14:56:25	T	M
HTN1847V	Asd-Zvg	37933	KOP	23-3-2015 14:56:44	T	M
HTN1847V	Asd-Zvg	37933	KOP	23-3-2015 14:56:44	T	M
HTN1847V	Ut-Btl	3165	KOP	23-3-2015 14:57:05	T	M
HTN1847V	Ut-Btl	3320	KOP	23-3-2015 14:57:13	T	M
HTN1847V	Ut-Btl	3630	KOP	23-3-2015 14:57:27	T	M

1 Train service number, unique identifier for a train along with the datetime.
2 Rolling stock number, different trains have different driving characteristics.
3 Time the gps location is recorded, not the samen as the time of the entire rule.
4 GPS coordinates of the train measured by 9 satellites in this case.
5 Speed measured by the train itself.
6 Direction according to a compass.
7 Branch of track the train is currently driving on, used for combining signals.
8 Distance travelled in this train dispatched service area, a conversion table is required to calculate the distance travelled between two areas.
9 Time of every parameter of this rule except GPS coordinates.
10 Direction driving on a branch required for filtering out signs in the other direction.
11 Direction of driving in the train dispatched area required for the conversion table.

C Train activities format

An example of train activities data, a number of columns are omitted.

basic_treinnr [1]	vkl_a_rijkarakteristiek	basic_drp [2]	basic_drp_act [3]	basic_plan [4]	basic_uitvoer [5]
3551	IC	Utma	D	23-3-2015 14:44:00	23-3-2015 14:44:17
3551	IC	Ut	A	23-3-2015 14:47:00	23-3-2015 14:46:33
3551	IC	Ut	V	23-3-2015 14:53:00	23-3-2015 14:53:41
3551	IC	Utva	D	23-3-2015 14:54:00	23-3-2015 14:55:38

vsein	infra_afgereden_seinen	mat_soort	mat_type	mat_nummer [6]
	UT$1148	ICM ICM	3 3	4071 4031
GR	UT$1230	ICM ICM	3 3	4071 4031
GR	UT$190	ICM ICM	3 3	4071 4031
	UT$214 LN$2822	ICM ICM	3 3	4071 4031

1 Train service number used for combining.
2 (in Dutch; dienstregelpunt), measure point.
3 Action performed at this point; arrival (A), passing (D), or departure (V).
4 Planned time according to the regular timetable.
5 Actual time according to sensor near the platform.
6 Train combination driving the service.

D Signal format

An example of a part of the signal logging. Some parts have been omitted for readability.

Type	Drpact	Drpact_vtg	Sein [1]	Bed. [2]	Beeld_seinbeeldrelaties [3]	Treinnr [4]	Vervoerder	Datum	T1_Start [5]	T6_Passage [6]
S	Utva D	1	LN$2822	J	GR	3551	NSR	23-3-2015	23-3-2015 14:54:31	23-3-2015 14:55:14
S	Utl D	2	LN$2864	N	GR	3551	NSR	23-3-2015	23-3-2015 14:55:05	23-3-2015 14:56:04
S	Utl D	2	LN$2882	N	GR	3551	NSR	23-3-2015	23-3-2015 14:55:55	23-3-2015 14:56:44
S	Utl D	2	LN$2918	N	GR	3551	NSR	23-3-2015	23-3-2015 14:56:35	23-3-2015 14:57:28
S	Htn D	1	LN$2938	N	GR	3551	NSR	23-3-2015	23-3-2015 14:57:19	23-3-2015 14:58:13

1 Name of the signal as known by dispatch controllers.
2 Whether a signal is a permissive signal (N) or operated by a train dispatch controller.
3 The aspect the signal is showing; green, yellow, or red. Might be added with a number GL-8, meaning yellow with 80 km/h.
4 Train service number denoting the service as well as the specific train on that day.
5 Signal is improved for the mentioned train service at the specified time.
6 Time passing the sensor for this signal.

E Infrastructure format

The infrastructure format has a lot of information; it is built on a directional network with switches or buffer stops as nodes. Hence we can locate a sign on walking back or forward to the nearest switch. The distances are denoted in areas the Netherlands are divided in and the direction the sign is facing. The data is separated by bars and contains 40 columns, hence in the example below some information is omitted, such as height.

Drp		section	section_start	richting [1]	infra_nummer	infra_type [2]	tps_rijrichtingtak [3]	tps_kmlint	tps_kmwaarde [4]	snelheid [5]
Ut	IAWISSELGEB	181	WISSEL	L	190	BED_SEIN	T	Asd-Zvg	35403	
Ut	IAWISSELGEB	181	WISSEL	L		HOOGTE		Asd-Zvg	35403	
Ut	IAWISSELGEB	181	WISSEL	L	B3-190	ATBVV_BAKEN	T	Asd-Zvg	35400	
Ut	IAWISSELGEB	181	WISSEL	L	L-190	ATBVV_LUS	T	Asd-Zvg	35398	
Ut	IAWISSELGEB	181	WISSEL	L		SNELH_BD_M	T	Asd-Zvg	35379	40

1 Direction of this section seen from the switch Ut-181; left, right, or forward (v).
2 Infrastructure type, signs starts with "SNELH_BD_". The speed is forced from this point (M), or it is notifing for an upcoming forced speed sign with an accelerate (O) or break (A) sign.
3 Direction of this sign is facing, on some tracks trains can drive in both directions.
4 Distance on this specific section, denoted in meters.
5 Speed enforced after passing a M sign or informing of upcoming speed.

From the example above, we can find the speed sign showing a maximum speed of 40 km/h by backtracking from the left side of a switch located in the Utrecht area called Ut$181. The location of sensors, signals and the elevation are denoted in this infrastructure table. The direction used in this network does not denote the possible directions trains can drive.

F Guide for validating innovations

How to validate an innovation using train driving agents

by Martijn Casteel

1. Context

What type of innovation are we validating? Before we can start, we have to figure out what effect an innovation should have on train driving. Later on, it is possible to adapt the expectations if the validation does require so. Usually, train driving can be effected in three ways; different timetables, different rolling stock, or driver advisory systems.

2. Gathering required data

Before we can start, we have to acquire the data required for this test. Depending on the real-world test done we might require location, timetable, and signalling data. First, we need to find a number of trains used in this pilot, for the comparison set we would like similar train services and rolling stock. Once we know which trains we can use.

3. Normalising data

Combining different data formats in a storyline like a format where each train driver tells their story. Within this step, outliers should be filtered out and after this step, the different data formats are no longer required. The story line within the built prototype can parse MTPS with signal and timetable data as well as the infra atlas data and the characteristics of rolling stock. This step is done with the two different data sets.

4. Optional plotting

If a visual gain of the innovation can be used, we can at this point plot the two different story lines and look for a difference. If there are no visual differences, it still might be possible that the agent can find a minute difference.

5. Creating distributions

For this step, we can use the prototype build called TANK which outputs different density list for different parameters required by the agent SMITH. The different list can plot a histogram on which a function can be fitted. These functions are required for simulating the agent from each data set.

6. Validating model

Simulate the two different data sets to compare the gain possible on a simulation. This should be done in a similar manner as the pilot is performed resulting in a train service comparable to the real-world data set. Validating the different data sets can be done on measurable points such as passing and arrival times at train stations and on comparing different plots such as time-distance diagrams, the difference between these two plots is the gain of an innovation.

7. Simulating innovation

Once the model is validated, we can simulate on a larger scale to indicate the gain of an innovation. The gain at this point is an indication of an innovation, due to inaccuracies it can exaggerate the gain.

G Proposed default data format

Within this thesis we used a format for the prototype using learned steps such as the distance to an object is far more interesting than the distance travelled a default format is proposed. It is a minimalistic format required for modelling behaviour however more attributes can be added. For this proposed format comma-separated files can be used.

train_service_number

An integer denoting a unique identifier of a specific train on a day. Keep in mind that some trains start late and may end the next morning. In the Netherlands passenger trains usually consist of 4 or 5 digits and is a unique identifier reused every day.

datetime

The exact date and time of this specific rule representing the state of a train. The datetime format is according to the ISO-8601 standard, for example; 2015-03-25T12:48:31+02:00.

rolling_stock

In the Netherlands, there is a number of different rolling stock with each their characteristics. Within ProRail the different braking parameters are known and should be used to improve the behaviour of a train.

acceleration

The acceleration is important to classify the action a train driver is currently performing but can be deduced from travelled distance and speed. A lot of other factors can affect this attribute such as a hill or the weather. The acceleration is denoted in m/s^2

speed

Speed is required and in almost every logging available as a decimal, it this proposal meters per second is used.

allowed_speed

Allowed speed is affected by a number of observations by a train driver. On passing a green signal, the train driver should have remembered the maximum speed denoted on signs. If a signal is not green other restrictions are in order. The allowed speed is used for changing situations such as approaching signal higher speed and approaching signal lower speed, which is used for signals as well as signs and departure at train stations.

current_aspect

Denoting on what condition a train driver is driving on, not all variations are required since the allowed speed is also present. However, green(GR), yellow(GL), green blinking(GRFL), and yellow blinking(GLFL) should be present. A train driver drives to obtain a speed on green but expects a red signal while driving on a yellow signal.

distance_next_planned_stop

To learn the distance a train driver interacts with a new situation we can deduce the travelled distance using this attribute in meters. For approaching a planned stop it is readable but for other signals and signs it should be deduced. Therefore the moment a signal or sign is passed there should be a new log rule with a new allowed speed.

current_action

To learn from these rules a classification is added depending on the acceleration and situation; accelerating, braking, coasting, cruising, or stationary. Because a train driver sometimes has small adjustments, one acceleration change alone is not sufficient for a proper classification. For example on acceleration due to weather conditions, a train can spin it wheels, a train driver will stop performing traction however the decrease of the acceleration does not result in a new action.

H Default train model

Approaching signal higher speed

	estimate	Std. Error
shape	1.4765345	0.18270212
rate	0.4746377	0.06972739

	estimate	Std. Error
shape	1.1347564	0.036848141
rate	0.0567824	0.002299309

First the model of the model without Dienstkaartje+ on the 3500 service from Heerlen to Schiphol. The two tables above are the fitted function on the situation approaching signal higher speed, on the left is the moment of accelerating relative to passing the signal. And on the right is the target speed relative to the allowed speed.

Approaching signal lower speed

	estimate	Std. Error
shape	5.5399648	0.78494612
rate	0.5741737	0.08515508

	estimate	Std. Error
shape	0.81973725	0.0387722879
rate	0.01554086	0.0009863464

On the left relative speed to allowed speed once the braking manoeuvre has ended, and the table on the right shows the moment of braking relative to the emergency braking curve.

Approaching planned stop

	estimate	Std. Error
mean	35.28241	0.3956579
sd	5.81496	0.2797724

	estimate	Std. Error
mean	10.47685	2.591004
sd	38.07983	1.832117

	estimate	Std. Error
shape	0.43470546	0.034046919
rate	0.01736935	0.002240967

	estimate	Std. Error
shape	0.440025354	0.0342113638
rate	0.006433459	0.0008024902

First table on the left is the speed entering the train station on a normal distribution. The upper table on the right is the start of the first braking manoeuvre relative to the emergency braking curve. The lower left table is the target speed relative to the allowed speed after the first braking manoeuvre, and the lower right table is the start of the final braking manoeuvre to the emergency braking curve.

Approaching red signal

	estimate	Std. Error
mean	34	2.857738
sd	7	2.020726

	estimate	Std. Error
shape	1.485617	0.7802742
rate	1.361815	0.8483146

	estimate	Std. Error
shape	133.01938527	34.561255903
rate	0.00957922	0.002466041

Table on the upper left is the speed starting to brake towards a red signal, the train has already encountered a yellow signal. The fitted function on the right is the time starting the final braking manoeuvre relative to the emergency braking curve. And the lower left table is the target speed relative to the allowed speed, some train drivers brake early to roll as far as possible to not come to a complete stop before the signal changes from colour again.

I Dienstkaartje+ train model

Approaching signal higher speed

	estimate	Std. Error
shape	1.4917582	0.21463530
rate	0.4469622	0.07622065

	estimate	Std. Error
shape	1.13520659	0.04524885
rate	0.0.06018757	0.00299150

The model with Dienstkaartje+ on the 3500 service from Heerlen to Schiphol. The two tables above are the fitted function on the situation approaching signal higher speed, on the left is the moment of accelerating relative to passing the signal. And on the right is the target speed relative to the allowed speed.

Approaching signal lower speed

	estimate	Std. Error
shape	5.9230392	0.9412318
rate	0.6365034	0.1055586

	estimate	Std. Error
shape	0.72607730	0.0362402633
rate	0.01027549	0.0007078734

On the left relative speed to allowed speed once the braking manoeuvre has ended, and the table on the right shows the moment of braking relative to the emergency braking curve.

Approaching planned stop

	estimate	Std. Error
mean	35.739130	0.2695279
sd	3.656054	0.1905849

	estimate	Std. Error
mean	1.320652	0.7826857
sd	10.616866	0.5534424

	estimate	Std. Error
shape	1.727425351	0.1292276822
rate	0.002789243	0.0002040194

	estimate	Std. Error
shape	-5.641304	2.359111
rate	32.000537	1.668143

First table on the left is the speed entering the train station on a normal distribution. The upper table on the right is the start of the first braking manoeuvre relative to the emergency braking curve. The lower left table is the target speed relative to the allowed speed after the first braking manoeuvre, and the lower right table is the start of the final braking manoeuvre to the emergency braking curve.

Approaching red signal

	estimate	Std. Error
mean	29.750000	0.7976746
sd	3.907791	0.5640409

	estimate	Std. Error
shape	0.546238616	0.127324259
rate	0.004214825	0.001406227

	estimate	Std. Error
shape	83.81542	10.752328
rate	52.67543	7.603044

Table on the upper left is the speed starting to brake towards a red signal, the train has already encountered a yellow signal. The fitted function on the right is the time starting the final braking manoeuvre relative to the emergency braking curve. And the lower left table is the target speed relative to the allowed speed, some train drivers brake early to roll as far as possible to not come to a complete stop before the signal changes from colour again.

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