A STABLE SPEED ADVICE FOR RELIABLE AND SAFE RAIL TRAFFIC

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Summary

The purpose of this research is to provide insight into the workings of a Traffic Management System (TMS) and how it can help improve the safety on the Dutch railways. The motivation of this research is a report by ProRail (2012), which shows that deviations from the original schedule lead to more than 11 million red signal approaches and 150 Signals Passed At Danger by drivers yearly. The deviations from the schedule are not only due to delays, but also to trains that arrive too early. This is undesirable for other reasons than safety as well. Unplanned stops cost more energy, cause further delays, reduce passenger comfort, and prevent smooth traffic flow. TMS is a tool that can support drivers and traffic controllers to keep trains on their original schedule as much as possible and make new, conflict-free, schedules in case of disruptions. Conflicts are actively detected and resolved by assigning new pass and arrival times to the involved trains, which is then translated to a speed advice to the driver. The focus of this research is to determine how this speed advice is kept as stable as possible. Stability is important in order not to distract the driver from his primary tasks, but also to motivate them to act on the advice. Figure 1 illustrates instable advices. The shown instability is the effect of not taking external factors into account in the TMS. We see that the advice is adjusted often (±25 advices) compared to the optimal speed advice (6 advices).

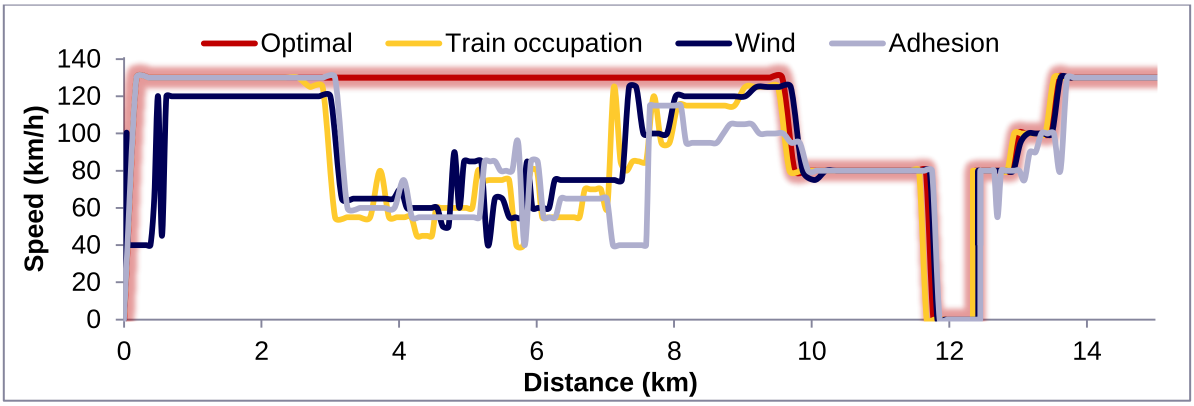


Figure 1: Examples of advised speed profiles under different conditions

From the literature, we recognize three categories of factors responsible for the instability of the rescheduling process. The first category is the quality of the input data, which determines the ability of the TMS to predict the future behaviour of the traffic when scheduling. The prediction quality depends on the accuracy of the train dynamics calculations, the accuracy of infrastructure data, and external factors which affect the train performance, such as the wind. The second category consists of time factors. These factors determine how far ahead the future state has to be predicted, how early we can detect a conflict, how fast we can solve it, and when the given advice is actually followed up by the driver. The last category consists of the choices made in the TMS model such as tolerances before initiating rescheduling, but also weights in the objective function of the TMS. For example, how many extra advices is it worth sending to the driver to prevent 1 minute of delay or to save 1 Kwh of electricity? These are of course management decisions. We examine and quantify these relationships to support these decisions.

We perform a sensitivity analysis for different factors (e.g., wheel resistance) on the minimum travel time needed. We conclude that the impact of external factors is far bigger than deviations in rolling stock specifications. The external factors are the adhesion coefficient, the wind speed, and the mass of the train determined by the number of passengers on board. Integration with the Real Time Monitor was also examined, which can deliver real time train diagnostics. We quantify the effects of TMS not taking these factors into consideration on stability and safety. Due to missing functionality in the software, we are not able to examine all identified factors in our simulation study. We investigate the following scenarios:

- Effect of the external factors: adhesion, wind, train occupation, and defect train
- Effect of different location detection methods and update intervals
- Effect of longer communication delays between TMS and the train
- Effect of driver reaction time and compliance
- Effect of different weights ratios in the TMS objective function

We quantified these effects in terms of safety, stability, traffic flow, and punctuality. We conclude that all of the factors mentioned affect at least one of the Key Performance Indicators (KPIs). For example, the location update interval affects all the KPIs mentioned while the weight ratio only affects the stability of the speed advice. The results in Table 1 illustrate the direction and magnitude of the effect. For example, the external factors affect the stability very negatively (--).

Experimental factor	Stability	Safety	Punctuality	Traffic flow
External factors	--	--	--	--
Longer location update intervals	-	-	-	-
Longer communication delays	-	-	-	-
Longer driver reaction times	--	-	-	-
Weight ratio toward energy savings	+	o	o	-

Table 1: Summary of the effects of the experimental factors

Some factors show a trade-off between KPIs, while others factors simply worsen the complete solution. The location update interval is a trade-off between stability and the other three KPIs. However, with longer driver reaction times and communication delays, all KPIs worsen. The trade-off is then between how much to invest in training drivers, for example, and the desired performance level. For the communication delay, NS should invest in better equipment, but other solutions are possible. We argue that the local speed calculation (on the train) will perform better than a central computer. This way, the speed regulation module solves minor deviations from the schedule without the need to send the current state to the central computer, and we can prevent the communication delay. Local speed calculations also simplify integration with the train diagnostic system. Thus, real time information about the status of the train is available to the speed regulation module.

The external factors add to the instability of the advice, but also safety suffers. Integrating the TMS with other information sources minimizes these effects. These information sources are already available, which reduces the cost of integration. Especially because, during the design and implementation phase, these costs are significantly lower than implementation afterwards. The potential average gains are shown in Table 2. In the first column, we see that the number of unplanned stops increases when we do not take the effect of these factors into account. The other three columns represent some stability indicators, namely: the number of advices sent per hour, and the number of acceleration advices while the train is decelerating, or vice versa.

Factor	Unplanned stops	Advices/hour	Against Current
Adhesion	54%	14%	59%
Wind	14%	2.0%	3.1%
Train Occupation	3.9%	0%	3.1%
Defect train	0.3%	0%	1.5%

Table 2: Potential savings through integration

We show the full results of the simulation study in Chapter 6. In Chapter 7, we present the conclusions and recommendation from these results. Our main recommendations are:

1. Integrate the information systems already available at NS into TMS. We recommend including the adhesion coefficient and wind speed in the calculation of the train dynamics since these two have a significant impact on the number of unplanned stops. Integration with the Real Time Monitor and passenger count systems mostly affect stability of the advice. But we argue that these will become more important in the future and integration in the design phase will be the most economical choice. Additional uses for the data integration can be thought of, such as priority rules for the TMS based on the number of passengers on board.
2. We recommend investing in GPS systems with update intervals of at most 10 seconds. We also recommend to not only use the GPS, because even the best GPS-modules have some errors due to other radiations and signals. TMS should use the current detection method, which uses physical detection of passing trains, to verify the GPS positions.
3. We recommend investing in communication equipment with a maximum transmission time of 5 seconds. Faster communication allows longer computation times for TMS, which can be used for more sophisticated algorithms than the current heuristic methods.
4. For optimal performance, drivers should react to the given advice within 8 seconds. We recommend training, motivating, and involving the drivers in the design to achieve this.
5. Overestimation of the reaction time is better than underestimation. Especially when it is consistently underestimated. We recommend starting with a worst-case reasonable value for the reaction time (8 seconds) and collecting data after the actual implementation to adjust this value to individual drivers.
6. The weight ratio in the cost function of the TMS should be set toward punctuality. We conclude that driving faster from the start leaves flexibility to the TMS to prevent more unplanned stops. The energy saved by driving with reduced speed is offset by the extra energy needed to re-accelerate after an unplanned stop. We recommend using a coasting strategy similar to UZI, which is an effective trade-off between punctuality and energy efficiency. This will also be easier to understand for the drivers of NS, who are already familiar with coasting strategies.
7. The cost function to penalize speed changes and energy usage is currently only evaluated in the speed regulation module. However, this module is only considered after the conflict resolution algorithm has determined the new schedule. We recommend considering the changes to the speed advice and the energy usage in the rescheduling algorithm.
8. Additional to recommendations 1, 2, and 7, we recommend calculating the speed advice on the train. This makes integration with the train diagnostic system easier (1), avoids

the communication delays (2), and skips the rescheduling algorithm in cases where a speed change is enough to keep trains on their original schedule (7).

The recommendations above are the results of the simulation study, during the research. We also mention other points of improvement, which should also be considered during implementation of TMS, namely:

9. The parameters of the TMS scheduling algorithm should be adjustable, not hard-coded. This allows further testing, but also to adjust the objective of the TMS to fit the situation. We argue that different situations need different objectives in terms of punctuality, energy efficiency, and stability of the speed advice. Also, the planning horizons could be valuable to adjust, because during disturbed situations, high uncertainty exists. A long planning horizon costs extra computation time while the situation is unpredictable.
10. We recommend involving drivers in the design phase for maximal motivation. NS should take drivers view on what information is useful, in the trade-off between instability and performance, and provide them with insight into their role in the performance. Driver motivation is directly linked to the performance of TMS.
11. There should be a feedback loop in the Driver Advisory System to allow drivers to provide feedback to traffic controllers in a standardized way. Examples of feedback are slippery tracks, reduced sight, people walking next to the tracks, or unrealistic new schedules. This prevents communication errors and appropriate measures can be taken quickly.
12. Use TMS to centralize the communication between all involved parties such as traffic control, drivers, and personnel planners. We recommend positioning TMS in such a way that all parties involved in the real time operations have access to the most recent and accurate state of the system concerning the exact location of personnel, material, but also exact delay to passenger information.
13. Due to the complexity of such a huge project a big bang approach would certainly lead to mistakes. We recommend a phased implementation of TMS to allow users to become familiar with the support tools available (RouteLint). This facilitates acceptance and prevents users from being overwhelmed by the extra information. Also, each step can be used to calibrate the data needed for optimal performance and adjust the TMS where needed. In our opinion, it is very important to make no mistakes, especially in the rail sector where the visibility to the public opinion is high. One accident due to a wrong advice can fail the whole project.

ACKNOWLEDGEMENT

My time at the NS was one of the most educative of my time as a student. Working with real data, which is not always readily available or in the right form, working with prototype software, and working with people of so many different backgrounds has been a great experience. I have seen the complexity of day-to-day problems at a company where more than 1.2 million people rely on to get to their destination daily. My special thanks goes to my supervisors at NS and University of Twente: Erwin Abbink, Martijn Mes and Marco Schutten, for sharing their views and providing useful and constructive feedback after endless proofreading. I want to thank Freddy Veldhuizen and Audry Wiltink for giving me insight in the work of a driver. Without their view and judgement as end-users, many factors that are part of the driver's duties would have never crossed my mind. The three hours we had to wait for mechanics to repair our broken train were very educative. I witnessed the chaos and pressure drivers experience during disruptions, how complex the operations are, and how many different people are involved in the process. I thank Douwe de Vries for all his time explaining the exact workings of FRISO-TMS and helping me set up my simulations. Without his expertise, many underlying reasons, which explain the results, would have stayed hidden. I thank Gábor Maróti for his help programming. Without his help in automating the simulation process, only a third of the scenarios would have been possible. I thank the whole innovations department of NS for the fun moments and great learning experience. Finally, I want to thank my friends and family for their support throughout the process.

Mohammad Sadegh Sabbaghian

TABLE OF ABBREVIATIONS

AGF	-	Alternative Graph Formulation
AHP	-	Analytical Hierarchical Process
ATP	-	Automatic Train Protection
B&B	-	Branch and Bound
CR	-	Conflict resolution
DAS	-	Driver Advisory System
DIS	-	Driver Information System
FRISO	-	Flexible Rail Infra Simulation Environment
HLA	-	High Level Architecture
KPI	-	Key Performance Indicator
LHS	-	Latin Hypercube Sampling
NS	-	Netherlands Railways
RTM	-	Real Time Monitor
SPAD	-	Signals passed at danger
SR	-	Speed regulation
STS	-	Stop showing Signal
TC	-	Traffic Control
TMS	-	Traffic Management System
TO	-	Train occupation
TSR	-	Temporary speed restrictions
UZI	-	(Universal Energy-efficient driving Idea

1. PROBLEM IDENTIFICATION

In this first chapter, we introduce the reader to the context of this research in Section 1.1. Then, we define the problems and research questions, the goal of this research, and our approach in Sections 1.2-4. Finally, we identify the stakeholders of this research in Section 1.5.

1.1 INTRODUCTION

Amsterdam 2012, Westerpark, two passenger trains collide head-on due to a missed stop signal by one of the drivers. 190 people were injured, of which 24 severely. One of the severely injured passed away the next day due to her injuries. Even though the rail is one of the safest transport modes, accidents still occur (Thunissen, 2009). Investigation pointed out that the driver was distracted during the approach of the signal. In addition, one part of the infrastructure was unavailable due to construction, so trains in both directions had to use the same track. One of the trains was delayed due to a freight train, and on top of that, Traffic Control (TC) missed the passing of the red signal. Because the train was driving below 40 km/h, the Automatic Train Protection (ATP) did not intervene. The Nederlandse Spoorwegen (English: Netherlands Railways, NS) and ProRail, the train and the infrastructure operator respectively, were criticized for taking insufficient measures to prevent red signals (Onderzoeksraad, 2012). In a letter on the first of July 2013 (Gout-van Sinderen and Meerstadt, 2013), management of ProRail and NS jointly informed the minister about the measures that will prevent such events in the future. This last part is the objective of this research: to prevent trains from approaching red signals to minimize the risk of accidents. Drivers and traffic controllers need tools which provide more situational information and decision support to help them take the proper measures, especially during disruptions. We define the risk of an accident as:

$$Risk = Exposure * probability\ upon\ exposure * Consequences$$

In this research, we address the exposure to the risk, by minimizing the number of red signal approaches. If drivers do not approach red signals, they cannot pass them either (Abma, 2013).

With more than 5000 trains and 1.2 million passengers daily, the Dutch railways are one of the most heavily used railways in the world. This results in high interdependence between trains, and delays propagating through the network quickly. Primary delays are unavoidable or would be extremely costly to do so. The railway system is open and consists of many interacting people and systems, such as crew, rolling stock, and infrastructure, which work in series. This makes the rail-system vulnerable to incidents and secondary delays (Mattsson, 2007). With the growing complexity of the rail network, these problems call for decision support systems to help traffic controllers (see Section 2.2) solve conflicts and take the full consequences of decisions into account. We propose a Traffic Management System (TMS) to actively detect conflicts and give speed advices to the involved trains as a solution to this problem. We can advise one train to speed up and the other to slow down during a conflict. Both trains can keep driving, and no one approaches a red signal.

Many studies approach this problem on the tactical planning level by adding time-slack to prevent small deviations to propagate through the network (Fischetti et al., 2009; Kroon et al., 2007; Liebchen and Stiller, 2009). Other researchers focus of the online operational level by real time rescheduling. These methods solve conflicts by re-routing, re-ordering, and re-timing (Albrecht et al., 2011; Caimi et al., 2009b; Corman, 2010; D'Ariano et al., 2007; Hansen, 2010;

Kecman et al., 2013; Luethi et al., 2007; Mazzarello and Ottaviani, 2007). Most of them focus on improving energy efficiency and punctuality and disregard the safety perspective. Very few papers address the stability of the advice given. An instable advice is one which changes frequently over time. The speed advice to drivers must be stable in order to be effective; a stable advice will gain acceptance and increase safety by providing situational information. Instability could distract the driver from his primary task, looking at the track and signals ahead. Our contribution to the existing literature is identifying which factors are responsible for the instability, quantify these effects, and find the relationship between instability and performance. We summarize the identified problems and their relations in Figure 1. This chart shows the relationship between problems and their causes. It helps to identify and target the core problem (Heerkens, 2005). The causes are on the bottom and eventually lead to the final goal: improving the safety and efficiency of the operations.

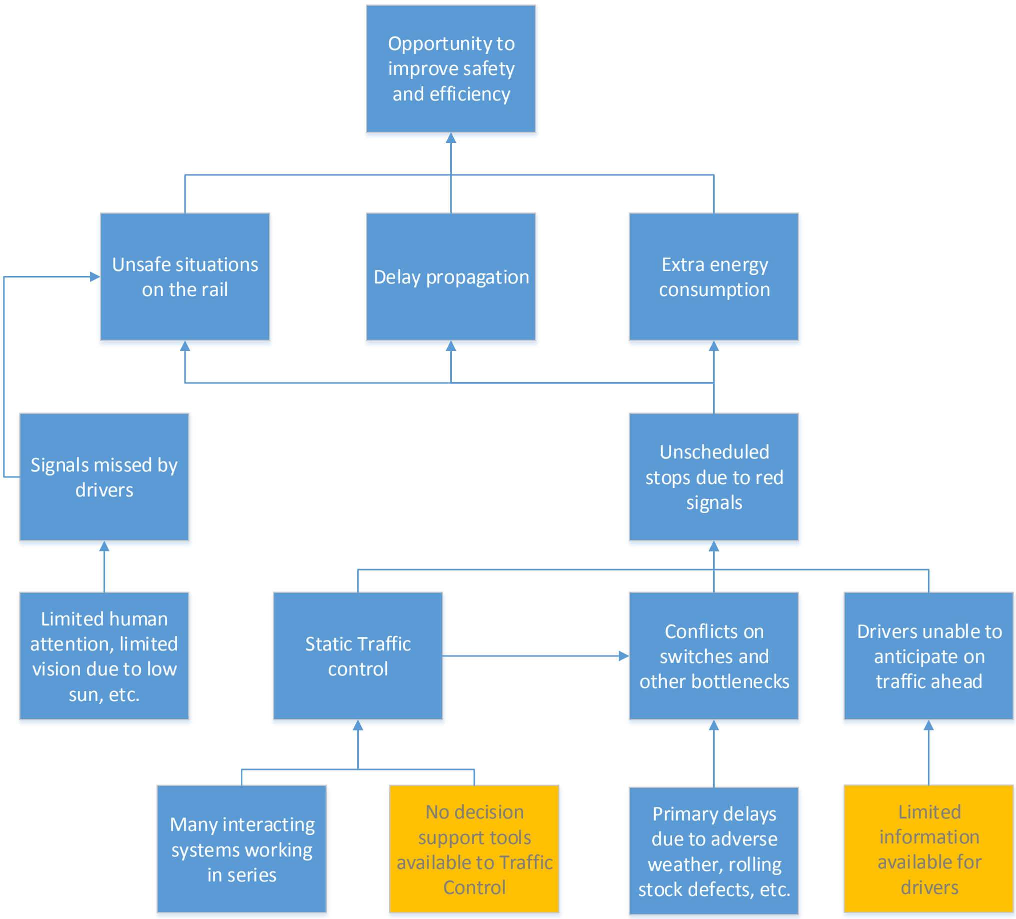


Figure 2: General problem tangle

We choose the definition given by Corman et al. (2009b) for the online traffic management problem (the two yellow blocks) :

Given a railway network, time horizon of operations, a set of train routes and scheduled event times at the relevant points in the network, and the actual position and speed of each train at the initial time, find a conflict-free and deadlock-free schedule for the trains in the network, with feasible speed profiles respecting the signalling system, no early departures, and trains arriving at the relevant points with the smallest delay.

Section 1.2 covers the problem context and its background. First, we define the problem statement and the following research questions. The problems shown in Figure 2 are the subject of this research and represent the need for a TMS. However, implementing a TMS will not automatically resolve the problems. Initial tests with the TMS developed at ProRail show promising results in terms of punctuality and energy usage. Still, the advice given to the drivers is changing frequently over time. As shown in Figure 3, the effectiveness of the TMS is offset by an instable advice, which changes often within a short timeframe. In Chapter 3, we review the literature to find the main causes of instability, which we represent by the yellow blocks.

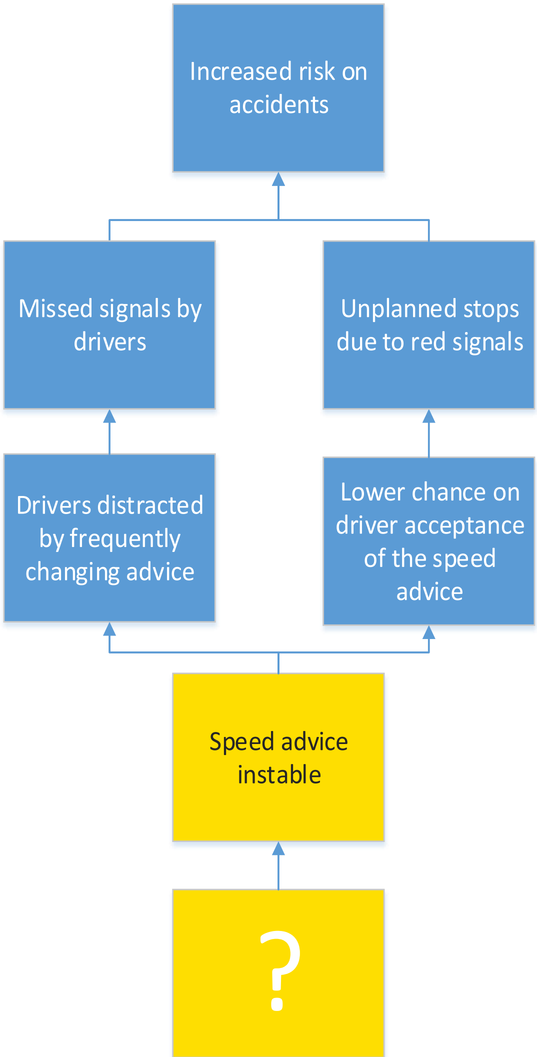


Figure 3: Problem tangle

In summary, the core problem is the frequently changing speed advice. The exact causes of instability are unknown at this moment. In order to get the desired results, without distracting the driver from his primary tasks, research is necessary before we can give stable speed advice to the drivers. Section 1.2 defines the exact problem at hand and research questions. Then, we define the goals, describe the methodology, and identify the stakeholders in the following sections. We answer each research question consecutively in the subsequent chapters. Finally, we give recommendations regarding the implementation of an effective and stable Traffic Management System.

1.2 Problem definition and research questions

In order to give a stable speed advice, we review different rescheduling techniques and identify factors which affect stability. We also quantify the effects and find ways to prevent the instability caused by these factors. The problem definition for this research is:

Which different online traffic management methods are currently available for speed advising, which factors affect the stability of the speed advice, what is the magnitude of these effects, and how can these be minimized to maximize rail safety?

The main objective of this research is to identify the factors that cause instability and quantify them. We classify these factors into three categories: the input data, time factors, and the TMS methodology. An example of the first category is the non-uniformity of the rolling stock leading to different traction and braking forces. The second category includes factors such as the planning horizon when solving conflicts and the reaction time of the drivers to the speed advice. Example of the third category is the chosen rescheduling initiation method. Finally, we want the optimal parameters for the TMS for performance and stability. These parameters include the location update interval and the objective function of the TMS. To solve the stated problem, we divide it into the following research questions:

1. How is the rail network organized and the traffic controlled in the current situation?
2. What information is currently available in the literature on online traffic control regarding different methods and rescheduling stability?
3. How significant are the effects of factors that influence the driving behaviour of the trains and should be included in the simulation study?
    a. What is the effect of imperfect rolling stock data on the driving performance?
    b. What is the effect of external factors on the driving performance?
4. What are the effects of the factors that influence the train performance on rescheduling stability and the number of unplanned stops?
5. How much communication is necessary between the trains and TMS to maximize stability and minimize the number of unplanned stops?
    a. What is an appropriate location update interval of trains to TMS?
    b. What is an acceptable communication delay between the train and TMS?
6. What are the effects and magnitudes of driver reaction time and compliance on rescheduling stability and the number of unplanned stops?
7. What are the effects and magnitudes of TMS parameters on rescheduling stability and the number of unplanned stops?

The answer to the first question provides insight into the current organization and operations at NS in order to identify current control methods and available systems. Second, we review the literature on online operational planning to get a full understanding of the current insights and industry best-practices regarding this subject. We also review available research regarding instability of the speed advice and rescheduling in general. Next, we explore which variables directly influence the stability he driving behaviour of the trains, and quantify their effects. Subsequently, we analyse the necessary input data for the simulation study, such as disruption types and their probability distributions. We examine these factors in a simulation study to quantify their effects on stability and safety. Finally, we discuss some implementation issues regarding the communication of the advice to the drivers. Rescheduling every second, with the most up to date information, and adjusting the speed of all trains to a precise level would deliver optimal performance. However, this would require immense effort from drivers, which is unacceptable in terms of safety and workload. Another problem might be that drivers lose confidence in the advice and stop following the advice completely. We will provide insight in the trade-off between the rescheduling frequency and performance to enable informed decision making during the implementation of TMS. We illustrate this trade-off in Figure 3, where the goal is to find the tangent of the effective performance.

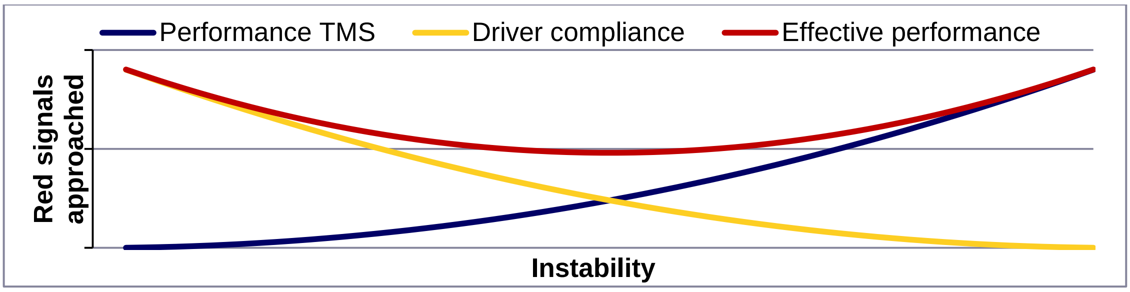


Figure 4: Trade-off between performance and instability

1.3 Goals

The goal of this research is to examine the design and parameters of the TMS in order to maximize stability and safety. We provide some parameters such as the location update interval and the factors that should be taken into consideration when calculating the speed advice. The choice of such parameters is not arbitrary due to the trade-off between costs and computation time, on the one hand, and increasing uncertainty into the prediction on the other. Speed advices resolve minor disruptions quickly, and trains will follow their original schedule as much as possible, which is highly desirable. The primary goal is, as mentioned earlier, increasing the safety on the rail by preventing trains from approaching red signals and unplanned stops. There is a trade-off between preventing red signals and minimizing driver distraction (advice stability). However, this goal is related to many other objectives of the NS. Less unplanned stops will also lead to time savings. Currently, some trains drive at maximum allowed speed until they encounter a red signal, which forces them to stop completely. Due to the high inertia of the rolling stock, anticipation can save time, which we illustrate in Figure 7.

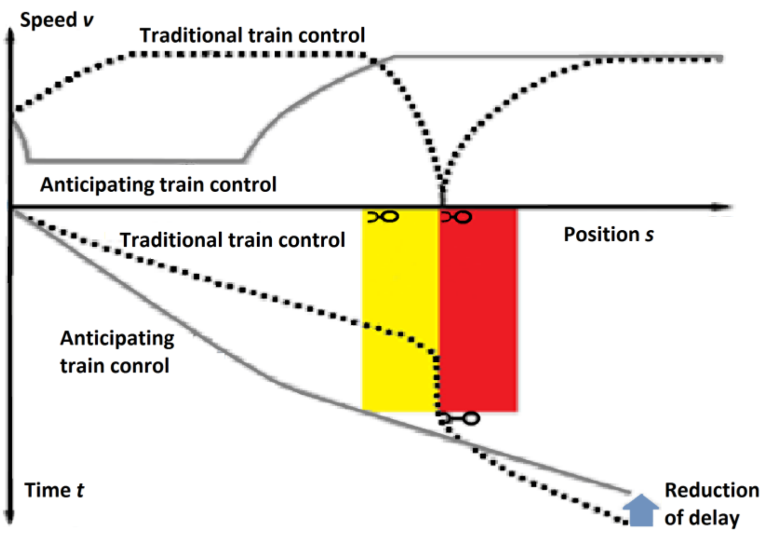


Figure 5: Principle of anticipating train control (Albrecht, 2009)

Another benefit is the reduction in operational costs. Lower driving speeds and less braking lead to energy savings and reduction of the material wear and tear. A better traffic flow results in more available capacity on the network, which is especially desirable in bottleneck areas. The final benefit is higher customer satisfaction. The passengers will not notice when the train is driving somewhat slower over the whole trajectory, but a sudden stop just before the destination, without obvious reason, might lead to annoyance and discomfort. We mention the following benefits from a stable TMS:

- Maximize safety by reducing the probability of encountering red signals
- Minimize information quantity to the driver while maximizing the quality
- Minimize waiting times/delays for the passengers
- Minimize operation costs by saving energy and material wear
- Maximize rail capacity
- Maximize customer travel comfort

Models are available for rescheduling and to advice the drivers on their speeds to stay on schedule. A potential problem lies in the fact that predictions of the future state of the system could be inaccurate, leading to new conflicts or another rescheduling iteration. This could be due to rolling stock specific limitations that might not permit the driver to follow the speed advice. Another cause could be the driver that might not be able to or willing to follow the speed advice accurately. The planning horizon of the conflict resolution software and the tolerance bandwidth, which initiate the rescheduling process are other factors. This research aims to determine these factors, quantify their effects through a simulation study with the TMS software, and finally make recommendations for the design of TMS in order to gain maximum acceptance and performance.

1.4 Methodology

In this section, we give the outline (Figure 6) of this research and the method that we use to answer the research questions mentioned in Section 1.2.

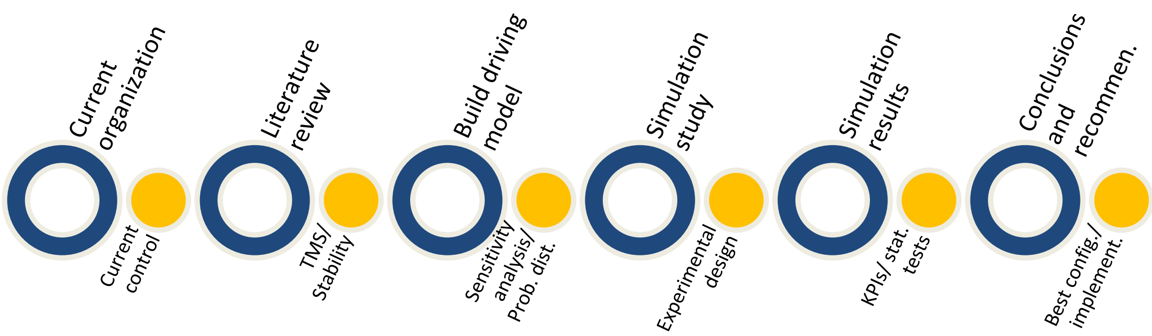


Figure 6: Research outline

First of all, we describe the current situation at the NS and the current driving and traffic control methods. Second, we review the literature to get insight into the most recent developments in the field. We explore different TMS versions and Driver Advisory Systems to compare different approaches. We review the literature on schedule stability in order to get a clear impression of the possible *sources of variation*. Next, we develop our own driving model and analyse the data to quantify the effects of several factors on the driving behaviour of trains. We use this model for the simulation study to provide a deeper understanding of these factors on the schedule stability. We quantify stability by the number of changes of the speed profile over a given time-window. We also consider other indicators for instability, which we define in Chapter 5. Whether the advice is stable or not is subjective, so we aim to create insight into the exact causes and effects of instability. We consider several options to approach this problem.

Option 1: Use the simulation software of ProRail, FRISO (Flexible Rail Infra Simulation environment), which includes many details regarding the infrastructure and rolling stock, the timetables, and is also already connected to the TMS software. This option reduces the time investment to redesign these features, but, has the disadvantage that adding own code is not possible, and the TMS is only partially adjustable.

Option 2: Designing an own simulation, which would allow a higher level of customization at the expense of detail, time and the level of real world representation. This option allows other TMS alternatives to be implemented, such as ROMA (D'Ariano, 2008).

Option 3: Make use of the current HLA (High level Architecture, a communication program) between TMS and FRISO to intercept and modify the messages between FRISO and TMS, by our own algorithm for speed advising.

We compare the 3 options and choose the most appropriate one. The scores are subjective and reflect the opinion of the author of this research. In the rest of this section, we argue this choice.

Criteria	Option 1	Option 2	Option 3	
Flexibility	0	++	+	++ = Very high + = High o = Neutral - = Low -- = Very low
Validity	++	0	++	
Detail	++	0	++	
Time consumption	++	--	-	
Future value	++	+	+	

Table 3: Comparison between the three options

Table 3 shows the criteria used and the scores of all 3 options. **Flexibility**: the level of adjustability and experiments possible. **Validity:** how well the model represents the real world. **Detail:** the level of detail in the model. **Time consumption:** time spent in modelling vs. experimenting. **Future value:** whether the models can be used in the future. We prefer option 1 because it scores very high on all criteria except flexibility. Many years of validation and the level of detail available and the fact that we save time, which we use to experiment instead of modelling, are the advantages over the other options. Improving the current TMS also has the highest future value, since it is closer to implementation. The limitation, however, is the level of flexibility. Some flexibility is available, i.e.: the input data describing trains and their disturbance. Other adjustable parameters are the priority rules to select train sequence, driver reaction time, communication delay, and location update interval (Middelkoop, 2013). However, we cannot examine some factors that may be important with this method. We identify these factors, but leave them for future research.

After the literature review, we perform a sensitivity analysis to find the most influencing factors on train performance. Because we have chosen to use the current FRISO-TMS, we cannot experiment with the rolling stock specifications and external factors. For this purpose, we model the train movements. In this model, we introduce the effects of several factors which could affect the train performance. These factors are rolling stock specifications and external factors. We analyse real world data to find the probability distributions of these factors. We use the distributions as input for our driving model to calculate the time-optimal speed profiles under these circumstances. From these results, we derive which factors have the biggest impact on the performance of the train and how big these effects are. From this model, we deduce the distribution of the effects of rolling stock specifications and external factors on train performance. Because these distributions are possible to enter in FRISO, we can still quantify their effects on network level on the stability of TMS and the corresponding safety issues. We give an example for clarification of this method.

Example: the wind speed has a significant effect of the performance of the trains, but TMS does not take this into consideration when calculating the speed advice. We cannot enter the wind in the simulation (FRISO) to quantify the effect of wind on the performance of. So, we enter *the effect of the wind* on the driving behaviour in FRISO. We do this by entering wind in our own model and calculate the effects on the acceleration performance of the train. It is possible to enter this effect in FRISO as an acceleration disturbance. In this way, a difference arises between what TMS expects the trains do and what happens in the FRISO. This method makes it possible to see how the TMS then will react and what the effect will be on the stability of the speed advice and safety.

We also combine all the disturbances using Latin Hypercube Sampling to see the interaction between different external factors (McKay et al., 1979). Moreover, we try different settings for the FRISO-TMS such as the location update intervals, driver reaction times, and communication delays to see how the TMS reacts in terms of the predefined KPIs that reflect stability, punctuality, traffic flow, and most importantly, safety.

1.5 Stakeholders

This project has many stakeholders namely, the passengers, drivers, management of NS and the Dutch government. The benefits for the *passengers* are the highest. This project prevents delays, opens the possibilities for more frequent trains, adds to passenger comfort, improves safety, and possibly lower fares due to reduced operational costs. *Management* shares the benefits of the passengers. They aim for higher punctuality, higher customer satisfaction, reduced costs, and maximized safety. The mentioned benefits are in line with the goals of the long term vision of the government (Structuurvisie, 2013). The *drivers* will have more information available to them than in the current situation. This will enable them to anticipate on their surroundings. Moreover, drivers know why they have to wait, which could otherwise be frustrating (Susskind, 2004). Finally, many of the physical complaints of drivers and conductors are about their knees, which can be reduced by more comfortable trips and no sudden brakes (Ruitenburg et al., 2009). Disadvantages are that they lose some freedom and cannot perform their own driving style. Advantages for *traffic control* are better insight into the effects of different scenarios, and that they are able to take informed decisions during disruptions. Disadvantages, drivers get insight into the work of TC through the Driver Information System, such as unnecessarily reserved block-sections. This introduces a level of control, which can be experienced as undesirable and can be used for naming and blaming. On the other hand, it provides insight into which party, train operator or infra manager, is responsible for delays and measures can be taken accordingly. Finally, Kroon et al. (2009) estimates that the direct benefit to the Dutch economy is €8 million per year for every percentage-point increase in punctuality.

The rest of this thesis follows the steps described in Section 1.4. We discuss our research questions in the presented order. We explain the current situation and review the literature in Chapter 2 and 3 respectively. In Chapter 4, we introduce our driving model and analyse the data. Chapter 5 describes our simulation study and we present the results in Chapter 6. We draw conclusions from the simulation study and provide some recommendations in chapter 7. Finally, we discuss some topics for future research.

2. Current organization and operations

In this chapter, we give an overview of the structure and organization of the Dutch rail network and NSR, the travellers department of the NS and the sponsor of this research. Also, we describe the current traffic control and signalling system and some insight in given into how often red signals are approached, and passed. This chapter answers the first research question: *"How is the rail network organized and the traffic controlled in the current situation?".*

2.1 Background NS

For 177 years, the Nederlandse Spoorwegen has been the main passenger rail operator of the Netherlands. During the last years of the last century, the NS stopped receiving subsidies and had to become more commercial according to EU directives for the railway deregulation. In 2003, this resulted in the separation from ProRail, the infrastructure operator. Furthermore, NS is divided into the six divisions. The position of NS Reizigers (NSR) can be seen in Figure 7. In Appendix I, we present the Dutch network and the terminology for the pieces of the track used in this research.

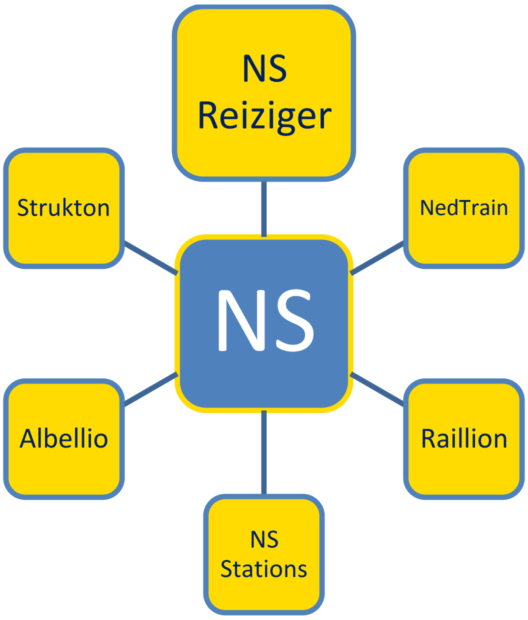


Figure 7: Different departments of NS (NS, 2013)

- NS Reizigers, responsible for the passenger transport.
- NedTrain, responsible for the rolling stock maintenance.
- Railion, responsible for the freight transport.
- NS Stations, responsible for the exploitation of the real estate.
- Albellio, responsible for the abroad activities in Great Britain, Germany, and Poland.
- Strukton, responsible for developing, constructing, and maintaining the rail.

The train is one of the best means of intercity transport, especially with the congestion around cities such as Amsterdam and Utrecht. Still, the rail is not the most popular transport modality. One of the reasons is the perceived unreliability of the trains caused by delays for passengers (Corman, 2010). To obtain a bigger share in the modal split, the government set the long term goal of quicker, more frequent, more comfortable, and reliable train services (Hijum and Dijksma, 2006). In 2003, the goal was set to improve the punctuality (percentage of trains that arrive with less than three minutes delay) from less than 80% to 95% in 2015. This should be achieved by better utilization of the current infrastructure under increasing traffic volumes (NS et al., 2003). The ministry of infrastructure concludes that, although punctuality is increasing (89% in 2013), the current way of working, planning and systems (ICT, safety, etc.) will not be sufficient to cope with the expected growth. The vision is to achieve higher perceived attractiveness of the railway by improving reliability, capacity, safety, and sustainability (Structuurvisie, 2013).

Since the rail is an open system, delays can be caused by many factors. Infrastructure failures cause approximately 17 disruptions daily, which are technical failures and third party accidents. Approximately another 17 disruptions occur daily due to operations. Research allocates these disruptions to passengers who block the doors, rolling stock problems, and drivers who are too late. Delays can spread over the network in space and time called the *knock-on effect* leading to major disruptions (Goverde, 2010; Jespersen-Groth et al., 2009). NS has to cope with these effects and still achieve the goals set by the ministry without increasing the rail capacity, which is very costly (30 million €/km for the Betuwelijn). Planners add time reserves to the timetable to minimize the knock-on effects (Carey and Kwieciński, 1995). These reserves are *recovery time* and *buffer time* that are respectively, adding time-slack to the technically fastest possible travel time and adding time-slack between consecutive trains at the expense of capacity (D'Ariano et al., 2008). The European Commission began a project called COMBINE to involve suppliers and users of Traffic Management Systems, software companies and universities to work together to realize the moving block signalling standard called ERTMS (European Rail Traffic Management System). ERTMS enables online control of the operations. This is a proactive approach to disruptions to realize a higher utilization of the available tracks (to allow a higher frequency) and to reduce red signals approaches (to increase punctuality and safety as explained earlier). As a result, developers and researchers developed several TMSs (Mascis et al., 2008), which could help TC to solve conflicts by advising drivers on speed.

Motivated by these developments, and maybe even more important, the goal of providing an even safer service, NSR explores the TMS options. NSR believes that accidents, such as the one in 2012, can be prevented by reducing the exposure. Reducing the number of red signals approaches by the drivers will lead to fewer drivers missing them and thus a reduced risk of accidents and damage. Eleven million red signals (STS) are approached annually, and 173 signals passed at danger (SPAD) in 2012 alone. Research revealed that in most of the cases drivers missed or did not have enough time to respond to the red signal (Inspectie Leefomgeving en Transport, 2013). We elaborate on these subjects in Section 2.5. The next section describes the current traffic control practice and driver information.

2.2 Traffic Control

Traffic Control, part of ProRail, is one of the controllers of the system. Traffic Control is decentralized into 13 different posts across the country and one Operations Control Centre Rail (OCCR) to coordinate on the network level, especially during major disturbances. The responsibilities are as follows: *Traffic Controllers (TC)* monitor traffic safety, release track sections to trains, make the new process plans when the requested and available track sections capacity do not match, and intervene in case of disruptions. The OCCR assigns capacity in the operational phase, communicates them to TC, and evaluates the measures taken during disturbances afterwards (ProRail, 2013).

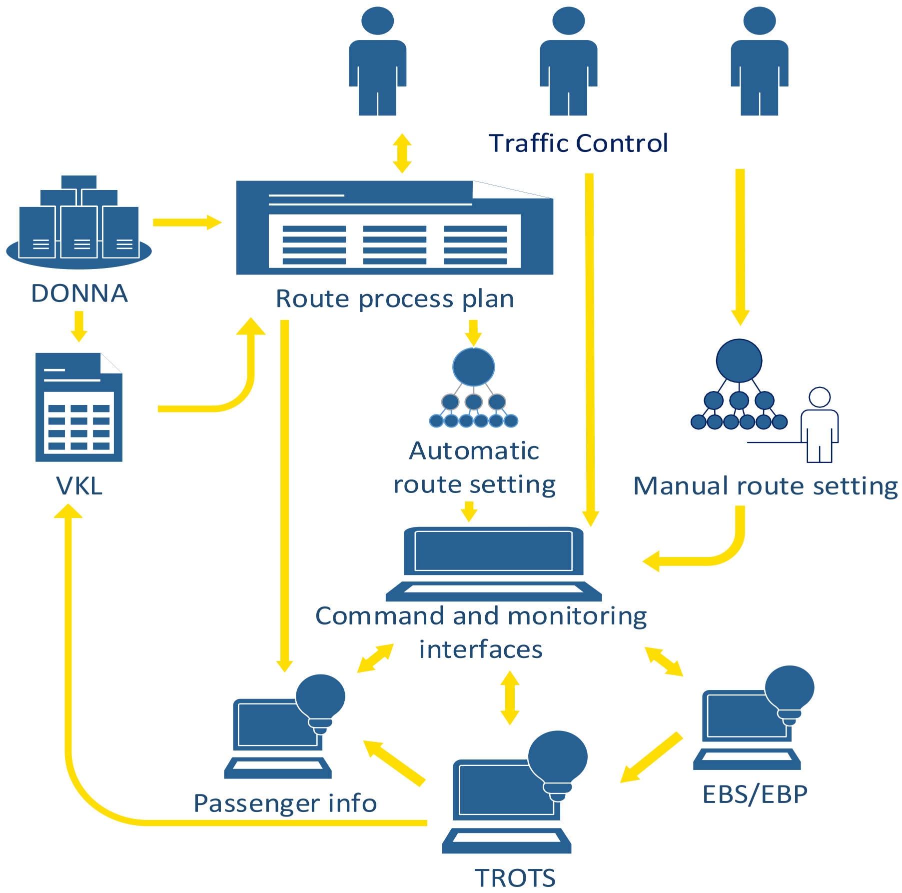


Figure 8: Dutch Traffic Control

Figure 8 represents the current traffic control process. DONNA is the system used by the NS and ProRail for the timetable and includes all the information about the origin, destination, rolling stock, and scheduled times. This information is sent to VKL (the traffic control system), which also includes up to date information about the position of the trains. This information is received from TROTS, which detects and logs train movements. A system called Automatic Route Setting (ARI) handles smaller disturbances. ARI applies changes to the Route Process Plan according to the following predefined rules (Figure 9):

- If there is a route-conflict between trains running toward the same track (if Train 2 switches to the green path): ARI maintains the original sequence.
- If there is a route-conflict between trains running toward different tracks (both trains follow their own path): the train that arrives first will go first (FCFS).

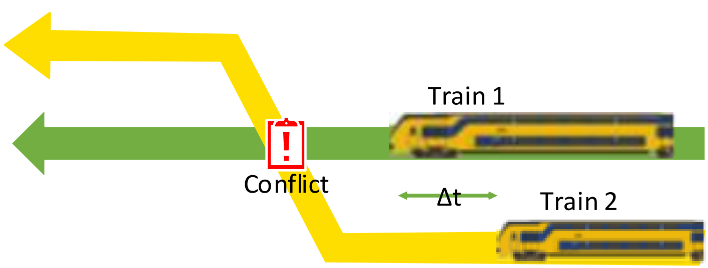


Figure 9: Example of a conflict between trains at an intersection

Traffic controllers can change routes and sequences manually according to predefined rules and scenarios as well as experience and expertise. However, only when trains are further apart (Δt >

threshold) than a predefined time-window. All this information is sent to the command and monitoring interface by the EBS/EBP system, which actually changes the switches. All this information is also sent to the passenger information system. Conflicts are difficult to recognize manually due to the complexity of the network and the huge number of trains. The lack and uncertainty of information make it hard to predict the future trajectory of the trains and potential conflicts. At Schiphol, the most intensively used junction in the network, traffic control uses another system called Dynamic Traffic Management (DVM). TC uses this system to assign tracks to arriving trains just before arrival and according to the arrival order, instead of a predefined plan. The assigned track is always on the same platform, only the side (track) is chosen last minute in order to keep some flexibility for smooth operations.

2.3 Drivers

The second controller of the system is the driver. However, they have minimal information about the current state of the system. The only information drivers have about the current traffic are the signals that are either green, yellow or red. These signals show the status of the block-sections, pieces of track, ahead. A green signal means that, at least, the next two block-sections are free, and the normal speed limit applies. If only the next block-section is free, the signal is yellow, and safety speed (40km/h) is required. Otherwise, the signal is red, and the train has to stop completely. So, only one train can be in on a block-section at a time. We illustrate the signal aspects and the resulting train speed in Figure 10 and Figure 11.

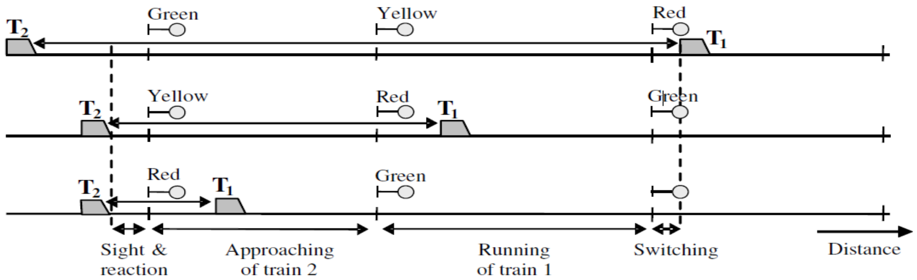


Figure 10: Three-way signalling system (D'Ariano, 2008)

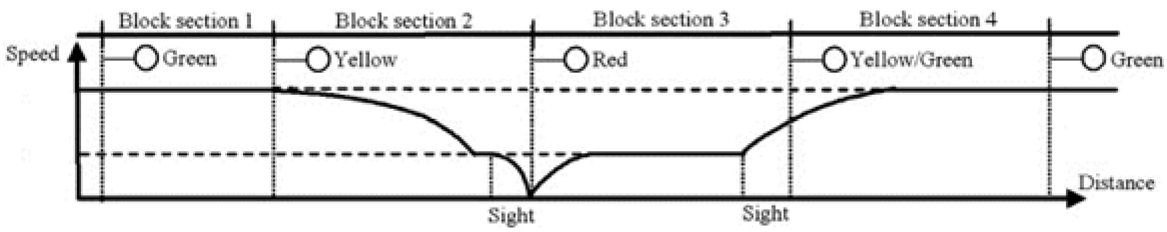


Figure 11: Train speed adjustments according to signals (Corman et al., 2009a)

A new timetable can be sent to the RailPocket (PDA) of the drivers. TC and drivers use spoken communication in case of emergencies, but only in exceptional cases (via GSM-R, a dedicated GSM-band for the rail). So, the drivers have limited real time information about the traffic ahead and behind them, until they see the signal and have to brake.

Currently, drivers are instructed to use a method called UZI (Universal Energy-efficient Idea) that is invented by a driver (Freddy Veldhuizen). The UZI method allows drivers to use the time-slack available, which is a buffer against disturbances, for energy savings. The UZI specialists safe more than 10% energy compared to uninstructed drivers. Drivers using UZI on long sections (>8 min) accelerate to maximum allowed speed, then based on the time available they start coasting at a set point in time depending on the speed. On short sections, the driver has to accelerate to a certain speed and then start coasting until arrival. The speed depends on the time available for a section. These speeds and times are shown in Figure 12.

Kort traject (rijtijd 2 t/m 8 minuten)

Rijtijd (in minuten)	Uitschakelen bij
2	80 km/u
3	90 km/u
4	100 km/u
5	110 km/u
6	120 km/u
7	130 km/u (SGM n.v.t.)
8	140 km/u (SGM n.v.t.)

Lang traject (rijtijd meer dan 8 minuten)

Baanvaksnelheid	Uitschakelen (mits baanvaksnelheid bereikt is)
140 km/u	8 min. voor aankomst (SGM n.v.t.)
130 km/u	7 min. voor aankomst (SGM n.v.t.)
120 km/u	6 min. voor aankomst
110 km/u	5 min. voor aankomst
100 km/u	4 min. voor aankomst

Punt	Rijtijd	Type	Referentie	Advies	Bijzonderheden
Ut	4		1x60		Geef ruimte aan IC naar Amf
Uto	5	+		1x110	
Bhv	4	+		1x80	
Dld	7	+		1x130	
Amf	4	AV		40- 1x80	
Amfs	3	+		1x80	
Avat	5	+		1x110	
Nkk	5	+		1x110	
Pt	4	+		1x100	
Eml	5	+		1x110	
Hd	8	+		1x140	
Ns	6	+		1x120	
Hde	6	+		1x120	
Wz	10	+		1x130	
Zl					

Figure 12: UZI method (left) and UZI speed advice between Utrecht and Zwolle (right)

To illustrate the method, the driver has 6 minutes to reach the destination; he should accelerate to 120 km/h and then switch off the power and start coasting until the speed limit or station. If the travel time is more than 8 minutes and the maximum speed is 120 km/h, the driver has to switch off power 6 minutes before arrival. These times are based on an uniform time-slack of 5-10%, but the slack is not uniformly spread along the route. The most slack is set near the end of the route, which is usually a point where the punctuality is measured. The reason is to let the drivers hurry at the start of the journey. This way, the time-slack is available for future disruptions and trains are on time on the points where NS measures the punctuality. For example, between Utrecht and Zwolle the trains have 5% on the total travel time as slack between Wezep (last station before Zwolle) and Zwolle, as opposed to 5% slack on the travel times of intermediate sections. These scenarios show the two extremes, yet in practice planners have the freedom to allocate time-slack differently. This makes it difficult for the drivers to apply UZI, and only experienced drivers know whether slack is available on a certain section (Weeda and Zeilstra, 2010). Drivers share this experience through a booklet with “speed advice”, which is shown in the column “Advies” in Figure 12. This advice means that, for example, when departing from Amersfoort (Amf) the driver has to accelerate to 40 km/h (because of the speed limit), then speed up to 80 km/h. After reaching this speed, switch off the power and start coasting until the next station.

UZI is a simple and static method, but also very effective to safe energy. Still, drivers cannot use this method everywhere on the network because planners do not distribute the slack uniformly across the network, so drivers need track familiarity. The power of this method lies in its simplicity and ease of implementation without the need for extra investments. However, UZI ignores interaction between trains. Another difficulty of UZI arises from the fact that the timetable communicated to the drivers is always in full minutes. For example, some short sections that will only take 20 seconds to traverse are shown as a full minute and others are rounded down to compensate. This leads to drivers being hurried on the first part of the trip and approaching a red signal because they arrive too early at the final destination. This is because drivers have limited information about how the slack is spread across the sections, and leads to a high variance of travel times. The exact departure/arrival and crossing times are known to planners and are currently being examined for implementation at 15 seconds detail instead of rounding to full minutes. Other shortcomings of this method are that no distinction is made between different rolling stock material types, temporary speed limitations, slopes, or signals ahead that could impact the travel time.

2.4 Disruptions

Disruptions involve many parties and need many communication lines. Communication is decentralized and occurs mainly through the telephone and GSM-R. As can be seen in Figure 13, the driver has to communicate with many parties and these parties have to communicate further in order to get all the information to the involved parties and eventually the passenger. We give an example of a defect train to illustrate the impact of a disruption on operations. The driver detects a malfunction and calls the guard to announce some delay, who in turn informs the passengers in the train about some delay. Next, the driver calls maintenance to ask for advice and has to call traffic control to inform them about the nature of his delay. If the driver can solve the, he will ask TC permission to drive again, and all is well. But many other scenarios can be thought of. The problem can be bigger, and the train may not be able to drive further. A mechanic needs to come on site for reparations and other trains have to be re-routed. Material and personnel planning has to be adjusted, because the train, driver and guard will not be at the expected location in time to switch to their next shift.

Figure 13: Communication lines driver during disruptions

2.5 STS approaches and passed

After the incident in 2012, the Ministry of Infrastructure started a research on Stop Showing Signals (STS) approached in the past 5 years (Transport, 2013). The objective of this research was to find the causes of Signals Passed At Danger (SPADs) and their risks. They found that, in 85% of the cases, the consequences are only delays, but in 10% of the cases it leads to damage to the tracks and in 5% even to collisions and derailments. 10 primary and 59 secondary causes exist, which lead to SPADs. The most important causes are too early departure signal of the guard, wrong expectations (surprised by signal), distraction by the environment, and wrong observation of the signal. Figure 14 illustrates the risk-model. For more details and the exact definitions, we refer to the original report (Transport, 2013).

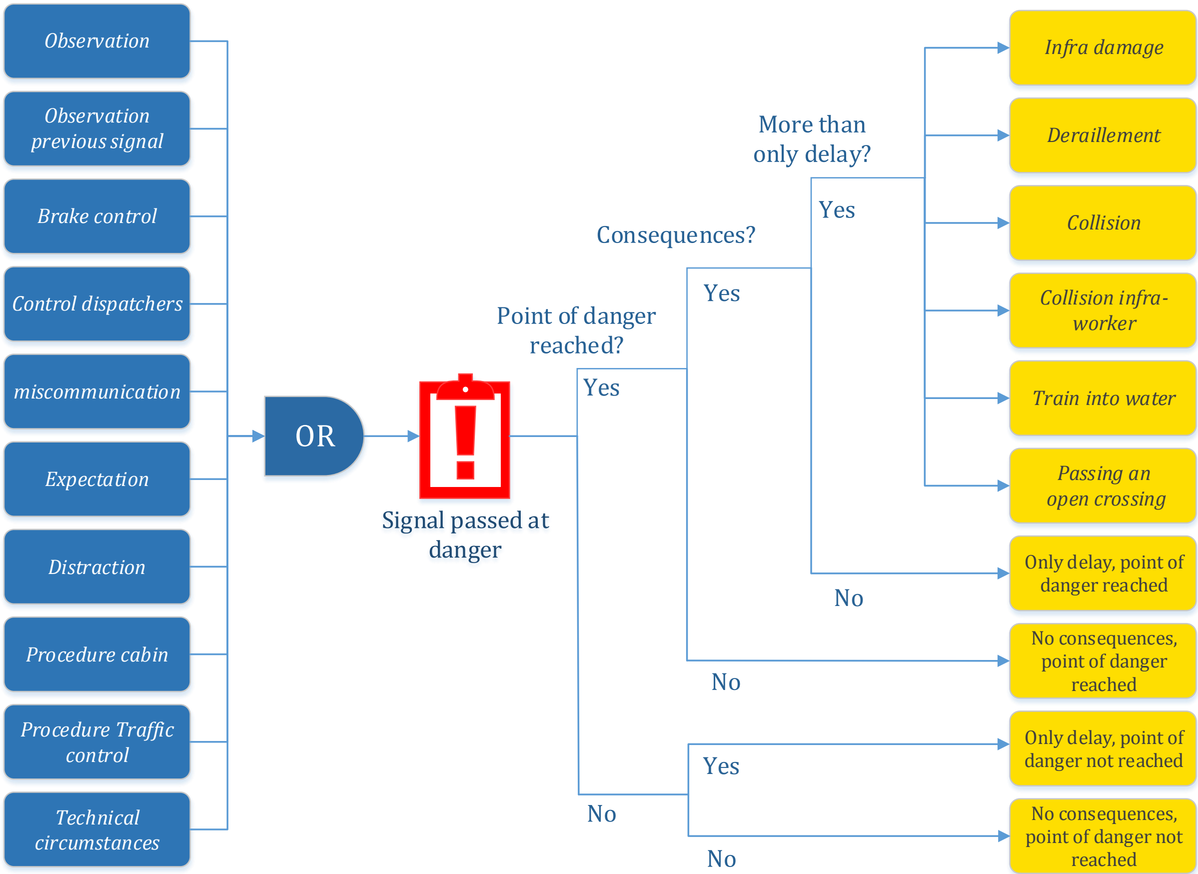
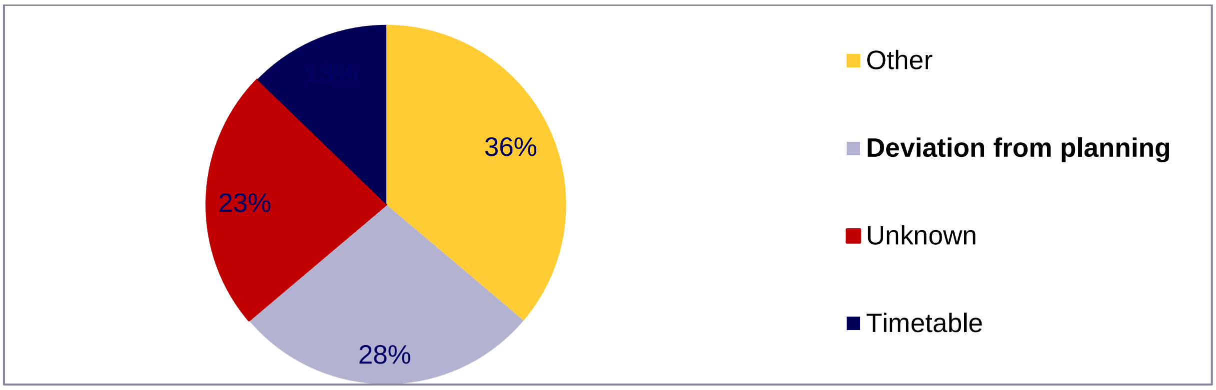


Figure 14: Main causes and consequences of SPADs (Transport, 2013)

ProRail did a similar research to identify why the signals that led to SPADs in 2012 were red when approached. We define an STS as an event in which a train passes a yellow signal; because the next signal will be red (see Figures 10 and 11). An STS is the only measurable variable in such an event. The disadvantage of this measure is that the signal may have been green at actual arrival at the signal. The report (ProRail, 2012), makes a distinction between three phases to which the red signals can be attributed to: the tactical planning (>36h before execution), offline operational planning (<36h before execution), and deviations from the planning. Another category has been found that is not related to planning, such as people walking on the tracks or infrastructure failure. The attributions of the red signals are shown in Figure 15. The bold variables are due to deviations in operations. Most of the STS approaches, which eventually led to SPADs, are outside the planning phase and are attributed to deviations from the planning. However, they can be prevented by online (on the spot) operational control to at least slow the trains down in advance.



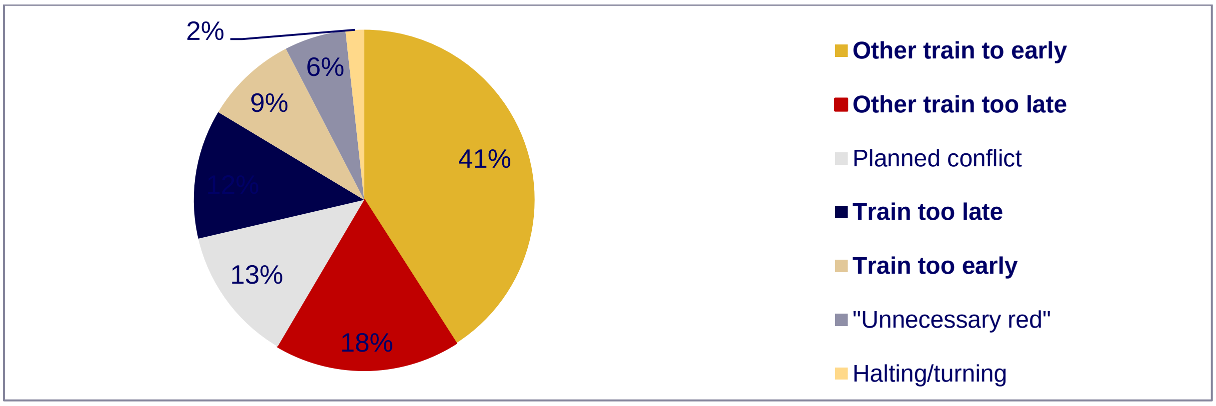


Figure 15: Causes of STS approaches (up) and main causes of SPADs (down) (de Goffau, 2013)

In conclusion, we see that more and more is required from the NS. The current systems and methods used for traffic control are static and rely on the expertise of traffic control and drivers. The information available to the controllers (drivers and traffic controllers) is minimal while problems are complex. We allocate this lack of information to the used communication methods and data available to the decision makers. This problem leads to unsafe conditions on the rail with many STS approaches and even SPADs. To reach the goals expected from the operators by the government, NS and ProRail need new control methods. We describe these new methods in Chapter 3 where we discuss the current literature on the subject of real time traffic control by means of driver information and advisory systems.

3. LITERATURE REVIEW

In this chapter, we discuss the current literature on real time traffic control to answer our second research question: *"What information is currently available in the literature on online traffic control regarding different methods and rescheduling stability?"* We describe different levels of solution sophistication, ranging from providing context information in Section 3.1 to drivers to active rescheduling techniques and speed control in Section 3.2. Finally, we discuss the literature on factors that affect the stability of the rescheduling process in Section 3.3.

A large body of research has been made in the past years regarding the railway scheduling. Hierarchy of planning exists because the complete planning problem is very complex. Starting from generating Origin-Destination-matrices for line planning, to train schedule generation, and scheduling of rolling stock and personnel. This decomposition into sub-problems makes them manageable (Bussieck et al., 1997). The steps are classified into the classical strategic, tactical and operational procedures (Anthony, 1965). The strategic planning entails, for example, resources acquisition and spans a period of 10 to 15 years. The tactical level allocates these resources to a general schedule and timetables over a period of 1 to 5 years, while the operational level, which can be divided into online and offline planning, manages the day-to-day planning (offline) and problems solving (online). This research concentrates on the rescheduling of trains during disruptions, the online operational level.

Researchers develop Operations Research techniques to support decision making and optimize the timetables, rolling stock and crew planning (Kroon et al., 2009). The focus of this research and the following literature review is handling conflict situations arising from disruptions in operations. Ashby's Law of Requisite Variety states that: "Only variety destroys variety" (Ashby, 1956) meaning flexibility must be available to the system controllers to cope with disruptions. To provide the controllers of the system (drivers and traffic controllers) with means to cope with variance (disruptions), two phases are foreseen by the management of NS. The first phase is to introduce a Driver Information System (DIS) for the drivers. A DIS provides information about the occupation of the block-sections ahead and behind the train and allows the driver to anticipate on signals ahead. This project, called RouteLint, is the first step toward better communication between the traffic control (TC) and drivers and is currently being implemented. This project will be fully operational in 2014. We explain RouteLint further in Section 3.1.

To provide TC with more means, we evaluate Traffic Management Systems (TMS) that are able to 1. detect conflicts, 2. resolve conflicts by determining time-windows for trains to reach bottlenecks in the network, and 3. giving speed advice how to reach them within a given time. In this way, conflicts are resolved, and trains can pass each other without having to stop for a red signal. This is achieved by re-ordering, re-routing and re-timing, which is the subject of Section 3.2. The plan of the NS is to first focus on minor disruptions that can effectively be solved by re-timing (Quaglietta et al., 2013). Re-timing means changing the speed of the trains involved in conflicts. RouteLint will eventually be replaced by a Driver Advisory System (DAS) as part of the TMS to advise the driver on the optimal speed. In theory, these measures will not only improve safety, but also traffic flow, punctuality, energy efficiency, and passenger comfort. Results are higher overall satisfaction of passengers and safety, at lower operating costs, without the need for capacity expansion by infrastructure investments. These savings are, among others, realized by avoiding unplanned stops whenever possible.

Our objective is to give speed advice that is accepted and followed up by the driver and also contributes to safety. The advice should not distract the drivers from looking outside, so the speed advice should be as stable as possible (Tschirner et al., 2013a). For TMS to be able to calculate a stable speed profile, this report identifies what the possible causes for instability are in Section 3.3.

3.1 Driver Information and Advisory System

In a railway case study, Hale (2003) illustrates the control-loop and show how the current communication protocols are largely open loop operations, which are vulnerable to deviations from operations. Hale (2003) suggests that the lack of communication is very undesirable from the safety perspective and identifies which rules have a high violation potential. The most interesting finding is that the safety rules are mostly violated when pressure is high, and information lacks. Poor communication protocols and methods are responsible for the lack of information. To this mean, a few commercial Driver Information Systems (DIS) are currently available. A DIS provides context information to the driver. Others include speed advices, which are Driver Advisory System (DAS). Some are already implemented such as, for example, GreenSpeed in Denmark, CATO in Sweden, and EnergyMiser in Australia. All claim energy savings ranging from 8% to 20%. However, these systems calculate the speed advice based on the current timetable and independent of other trains. In Appendix II, some of these systems are shown. The basic functions are all the same, only the amount and type of information presented differs. van den Top et al. (2009) emphasize the importance of such systems. The authors describe Ashby's Law of Requisite Variety: "*The variety of action available to the system's controllers must be at least equal to the variety of disturbances that must be compensated*" and show how the current control systems fail to pass this test. They offer a tool to overcome this problem, namely RouteLint. They argue that both drivers and TC are controllers and, therefore, should work together and share information in order to cope with disruptions. It is the duty of TC to calculate the time-windows within which the driver must reach certain scheduled point and set the route. It is the duty of the driver to adjust his driving behaviour according to the information available to him. RouteLint provides the driver with information to give him more *variety of action* to cope with the *variety of disturbances.* In Table 4, some small disturbances, the possible actions with information of RouteLint, and the results are shown.

Event	Action	Result
There is a disturbance	RouteLint lets the driver anticipate	Which leads to return to normal operations
Train ahead is running late	Coast	Driver will encounter less restrictive signals, save time and energy
TC has decided to delay your path	Coast, inform passengers, inform transport controller	Save energy, no conflicts with other trains, passenger announcements can be given
TC does unusual switching to protect track workers ahead	Speed up	Make up for time that would otherwise be lost, stay closer to ultimately planned path
TC has forgotten to set the route	Call TC to ask about the situation	Route is set before running into restrictive signals
Unplanned stop at a red signal	Driver can see reason for stop and tell passengers	Communications channel of the TC less burdening
Driving ahead of schedule	Coast	Return to schedule, save energy

Table 4: Examples of situations in which RouteLint helps to make better decisions. (Source: Top et al., 2009)

RouteLint in its current form is merely a DIS, without any advice and provides drivers with information about the decisions of TC. The interface of RouteLint is simple and contains only the block-sections (itinerary), other train ahead/behind/crossing and their delays as can be seen in

Figure 16. The train-number indicates what type of train it is (Intercity/sprinter/cargo), the colours indicate the status of the block-section, and the arrows the direction of a crossing train.

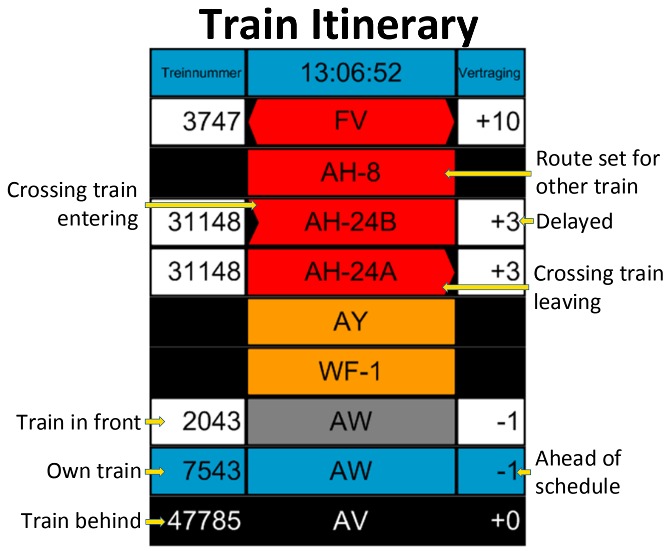


Figure 16: RouteLint (Hansen, 2010)

Two experiments were carried out at NS to examine RouteLint, one in practice and one with drivers in a simulator (Lentink, 2013). The number of STS approaches was observed and in the simulator study the heartbeat and eye-movements of the drivers were monitored to measure the workload and attention of the driver. The results of the practical research show that STS approaches decrease by 5-7%. In the simulator, the number of yellow signals was reduced by 30%, there was no significant increase in heart rate, and the attention of the driver was directed at RouteLint and their timetable up to 10% of the time. The author claims that this percentage is acceptable because he expects this percentage will fall as drivers become more familiar with the system. Drivers indicated that a speed advice and the speed of the other trains would be valuable additions (Lentink, 2013). The primary responsibility of the driver is to ensure the safety, by observing the signals outside and possible obstructions on the track. Therefore, a DIS/DAS should require minimum attention from the driver. Piechulla et al. (2003) argue that the interface should be adaptive and adjust the information availability based on the assessment of traffic conditions. For example, no updates should be sent when signals or stations are approached. In the UK, tests are carried out with Head up Displays (HUDs), which shows that the workload of drivers decreases by 5-10%. This is due to the visual representation in the field of vision of the pilots, instead of an extra display in the cabin. Although popular with all drivers, the results show no significant changes in time-keeping, speed limit observance or signal compliance. The authors expect that, with the increased information quantity from a TMS, the effects become more significant (Roden, 2008; Tschirner et al., 2013b). The discussed systems in this section do not take interaction between trains into account. These kinds of systems are the subject of Section 3.2.

3.2 TMS

When delays exceed the time reserves, knock-on delays are inevitable, and online measures must be taken by the TC. Currently, traffic controllers solve this problem by heuristics and judgement, which are suboptimal due to bounded rationality (Fransoo et al., 2011; Simon, 1972; Tversky and Kahneman, 1974). To accommodate the controllers, We need dynamic traffic management to reduce the knock-on delays and energy usage (D'Ariano, 2008). Before all else, the detection or prediction of conflicts must be timely. Deviation from the original schedule could be detected, and rescheduling could be initiated for instance when trains step outside a certain *tolerance bandwidth.* This partly depends on the train detection method, which is currently based on physical detection of passing trains at set points in the tracks. The worst-case update interval could be 3 minutes while the authors recommend intervals of 2-5 seconds (van den Top et al., 2009). GPS solutions would allow the desired time intervals, but lack accuracy. D'Ariano (2008) emphasizes that all models are as good as the input data. In complex networks with large disturbances, the successive approximations on estimating travel times can accumulate errors, leading to poor solutions and instable schedules. A typical system architecture of a TMS is shown in Figure 17. CDR is the conflict detection and resolution module and SPG is the speed regulator. In the following sections, we discuss the literature on these main components of the TMS.

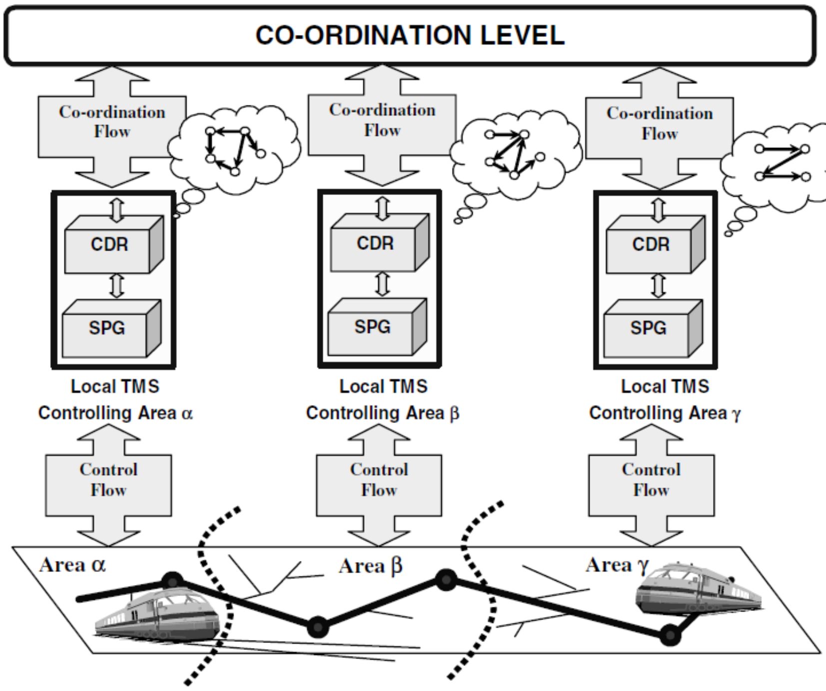


Figure 17: System architecture of TMS (Mazzarello and Ottaviani, 2007)

3.2.1 *Conflict resolution*

After conflict detection, the next step is to resolve the conflict. This is the real time railway traffic optimization step in Figure 17. Many different approaches are proposed in the literature based on Mixed-Integer Linear Programs (MILP), Branch and Bound (B&B), and the Alternative Graph Formulation (AGF). Also, different levels of abstraction are proposed. This problem could be either solved at macroscopic level, including the whole network, or a microscopic level, with details including train dynamics and infrastructure characteristics. The problem exists that the entire network is too complex to solve in real time, but local solutions need to be globally feasible. To align the two methods and ensure globally feasible plans, Kecman et al. (2013) offer a method to decompose the problem. The authors represent the railway traffic on a timed event graph to compute delay propagation on the total network. Next, they convert this graph into smaller alternative graph models, which they solve with the B&B algorithm of D'Ariano (2007). Mazzarello and Ottaviani (2007) propose another method, which is the foundation of the TMS examined in this research. Their method also decomposes the TMS into two separate modules.

First, the conflict detection and resolution module determines the optimal order of trains and the starting time of each operation. Mascis & Pacciarelli (2002) model this problem as a classical Job Shop Scheduling problem with a no waiting constraint. This results in specific time-windows for all trains and the total delay or lateness of the new schedule. Second, the speed regulation algorithm calculates the corresponding speed profiles for the involved trains to reach the time-windows calculated in the previous step. We explain the speed regulation module in Section 3.2.2. These methods rely on the Alternative Graph Formulation, where nodes (machines) represent the block-sections. Setup times represent the follow-up times and the starting times correspond to the times trains enter a block-section. This algorithm solves the problem with a heuristic to optimize the order of the trains. Figure 18 illustrates the alternative graph representation of the infrastructure layout.

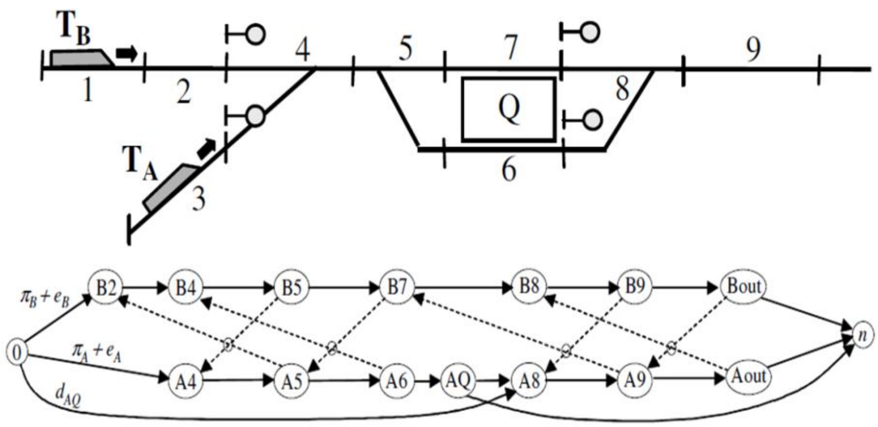


Figure 18: Alternative Graph representation of an infrastructure layout (Corman et al., 2009b)

The Alternative Graph is represented by *G = (N, F, A)* with *N* a set of nodes, *F* a set of directed arc, and a set of pairs of directed arcs A. Each arc (*i, j*) in set F has a fixed length of f_{ij} and set A contains *Alternative* arc pairs (*h, k*). The fixed arcs represent precedence in operations. To illustrate in the example of Figure 18, train B has to pass Node B2 before B4, or in other words, train B has to travel over section 2 to get to 4. The alternative pairs are the dotted lines and determine whether train A or B goes first. From each pair, exactly one arc is selected so that no positive length cycles exist, and minimizes the makespan (the longest path from node *0* to node *n*). Positive length cycles make the plan unfeasible, because they suggest that an operation should start after itself. The algorithm solves this formulation by calculating the times the starting times of all operations (t_i). Nodes represent the entry or exit of block-sections, switches, speed restrictions, and the current positions of the trains. In Appendix II, we give the exact representation of constraints and how these are modelled.

The scheduling algorithm first (1) creates a plan by generating a chain of nodes and arcs for each train operation. Then (2), pre-process the graph by considering all the precedence relations and forbidding the alternative arcs. Add the rest of the arcs to the graph, which represent the other constraints (3). Detect possible conflicts (4) by checking for pairs of alternative arcs that still need to be processed. The scheduling algorithm uses the conflict resolution heuristic to select the best of each pair. Mazzarello and Ottaviani (2007) use the so-called AMCC (Avoid Maximum Current delay) heuristic. Train A wins if the entry time of train B is higher than the exit time of A and vice versa and maintain this order in the rest of the graph by a precedence constraint (5). Finally, the algorithm checks if the graph is cyclic (6), if not, a feasible solution is found.

Otherwise steps 4 to 6 are repeated. After finishing the scheduling, the algorithm applies a post-processing task. This task checks whether the starting times of the operations are feasible before they are sent to the speed regulation module.

We briefly describe other methods for conflict resolution available in the literature in the following paragraph. D'Ariano (2008) also uses the Alternative Graph Method. The difference is that they use a Branch and Bound (B&B) algorithm instead of the AMCC heuristic. His research shows that both AMCC and B&B provide solutions that are up to four times better compared to simple heuristic methods such as FCFS. Also, D'Ariano (2008) shows that AMCC will provide near optimal solutions, but only if it finds a feasible solution in time (the computation is terminated after 120 seconds). However, AMCC finds feasible solutions in 92% of the cases while the B&B algorithm finds proven optimal schedules in 99% of the cases. The MILP (Mixed-Integer Linear Program) formulation by Törnquist and Persson (2007) minimizes total final delay and associated costs using CPLEX. To reduce computation time they provide 4 strategies under the assumption that, because the original timetable will be leading, many options can be ruled out. All strategies are examined to see differences in performance. The strategies are:

1. Allow re-routing but maintain order
2. Allow re-routing and implicit change of order
3. Allow X number of order swaps for specific segments
4. Allow all changes

After examinations, with different levels of disturbance and planning horizons, they conclude that strategy 3 has the best results, considering computation time, in all cases. These results confirmed the research of Lawrence and Sewell (1997) who compared static, heuristic and optimal methods for rescheduling policies under uncertainty and show that static methods deteriorate highly when variance increases. They show that heuristic methods perform nearly as good as and sometimes even better than optimal solution methods. A model is inherently a simplification of the reality, while optimal solution methods can become very complex and lose their practical use due to their long computation times. So, the solution might be optimal, but the problem could change during the calculations. Albrecht (2009) provides a method that is similar to that of Törnquist and Persson (2007) to minimize the weighted delay. They introduce the concept of “time losses”, which allows calculating the optimal order of trains in conflict situations. The time lost consists of the duration of operating switches, passing and release times, difference is occupation time of each train, and time needed to re-accelerate. The order of trains that minimize this lost time is the best solution. Dorfman and Medanic (2004) suggest a method called Travel-Advance Strategy (TAS) by means of a discrete event model. It is an efficient way for rescheduling trains in case of disruptions. At the so-called *Meet and Pass* points, the departure times, speed, and block-section length are taken as input and the arrival times are computed at the next critical point in the network. They claim near optimal solutions in a fraction of the time of non-linear programming methods. This is due to among others calculating of the TAS locally while checking for deadlocks, a situation where at least one train has to move backwards in order to solve the conflict, globally. However, this model relies on a few assumptions such as fixed speeds and paths. Li et al. (2008) point out that these are unrealistic assumptions and some deadlocks can be prevented by changing train speeds. They elaborated on this method by considering the speed as a decision variable and considering acceleration and deceleration. The name of their method is the Effective Travel-Advance Strategy (ETAS) and produces better results than TAS, but also has higher computation times.

3.2.2 SPEED REGULATION

Many speed regulation methods are based on the Optimal Control Theory of Pontryagin (1962). However, these methods are computationally demanding and cannot be used for real time operations. Mazzarello and Ottaviani (2007) use a heuristic method to allow real time control. They reduce the solution space by not computing a speed advice when the difference with the current speed is less than 10 km/h and only evaluate speeds rounded off to 5 km/h. This procedure is done iteratively using constrained dynamic programming until a speed is found for which the train will arrive within the set *time-window* calculated by the conflict resolution module and *speed window* determined by speed limits and infrastructure and rolling stock characteristics. The authors formulate a cost function in order to calculate the advisory speed V_{opt}. The variables are shown in Figure 19 for clarification. The cost function consists of three parts: the *Punctuality term* C_p, *Speed term* C_s, *and Energy term* C_E. Given V_{opt}, calculate the arrival time T_{arr} and the delay *D.* However, if $T_{arr} > T_{max}$ or $T_{arr} < T_{min}$, the V_{opt} is unfeasible and must be adjusted accordingly.

$$C_P = a * max(0, T_{arr} - T_{min}).$$

If V_{fin} is in the range (V_{min}, V_{max}) no speed change is required so $C_S=0$, otherwise:

$$C_S = b * max[(V_{fin} - V_{max}), (V_{min} - V_{fin})]$$

Given V_{opt} and V_{fin}, the energy cost is given by:

$$C_E = c * [abs(V_{cur} - V_{opt}) + abs(V_{fin} - V_{opt})] + d * V_{opt}$$

With the weights *a*, *b*, and *c* determine how strict the TMS considers each factor. For example, a lower value for parameter *b* allows deviation from speeds V_{min} and V_{max} if it can improve one of the other terms.

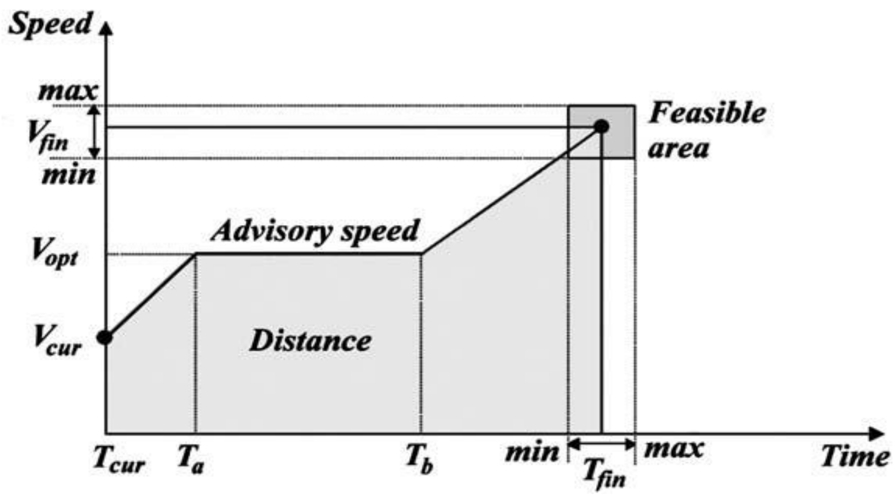


Figure 19: Speed advice calculation of TMS (Mazzarello and Ottaviani, 2007)

Mazzarello and Ottaviani (2007), as well as D'Ariano et al. (2007), point out the difficulty that when computing a speed profile, the time lag between the start of the calculation and the actual speed change by the driver. So, the future state of the train should be predicted first. This lag consists of seven different *delays* as shown in Figure 20. The delay consists of data transmission, computation, and reaction times. TMS should correct for these delays during the calculation of the speed advice. So, TMS should predict the position and speed of the train when the driver actually initiates the speed change. In the current FRISO-TMS implementation, this loop consists of three components within the algorithm: the Train to TMS delay, TMS to train delay and the driver reaction time that form the total delay-loop.

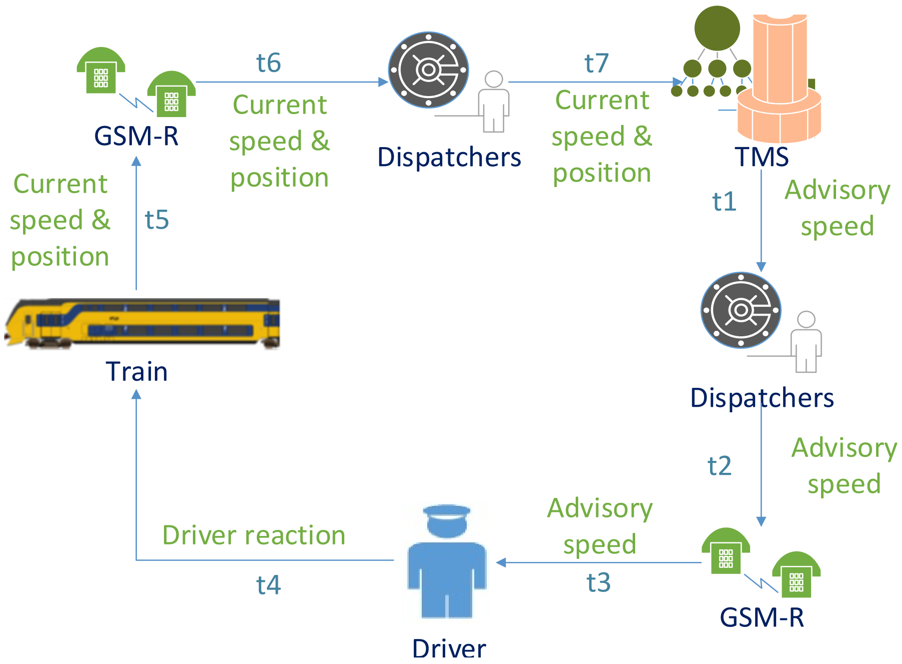


Figure 20: The TMS control-loop delay

A review of developments of the speed calculation techniques is given by Howlett et al. (2009). They present methods to apply the Optimal Control Theory principles to train control. Extensions are added to enable the original *accelerate-cruise-coast-brake* strategies to cope with gradient differences (Albrecht et al., 2011). Other simplified versions of this mathematically demanding method are designed to reduce computation time.

D'Ariano et al. (2007) use an iterative procedure for the speed calculation. First, their method calculates a time-optimal trajectory, detects the overlaps with other trains, and fixes the start and target states. Then, it gradually decreases the speed until the train reaches the target state just in time. After this step, the algorithm checks whether all signals are respected. If not, it reinitiates the loop with a shifted target state. Ke et al. (2011) present an algorithm, which takes all track and rolling stock specifications as input and delivers optimal speed profiles with multiple objectives (e.g., energy efficiency and punctuality). Their method uses Ant Colony Optimization and fuzzy PID-control, which we do not explain in detail because of the complexity. Caimi et al. (2009b) offer a model to calculate the difference between the fastest possible and the desired arrival time and distribute this slack along the trajectory to save energy. They assign some extra slack near the end to allow some flexibility to absorb disruptions. So, it should be clear that energy saving is only possible by using the time reserves allocated at the risk of needing them in the future. An internal research at NS using a MATLAB model (Scheepmaker, 2012) made a comparison of different driving strategies and their respective energy usage. The results are shown in Figure 21 where the time-optimal strategy (blue), UZI (green) and the energy optimal strategy (red) are compared. Results show energy saving around 5-6% between the UZI method (Section 2.3) and optimal speed control on this specific corridor.

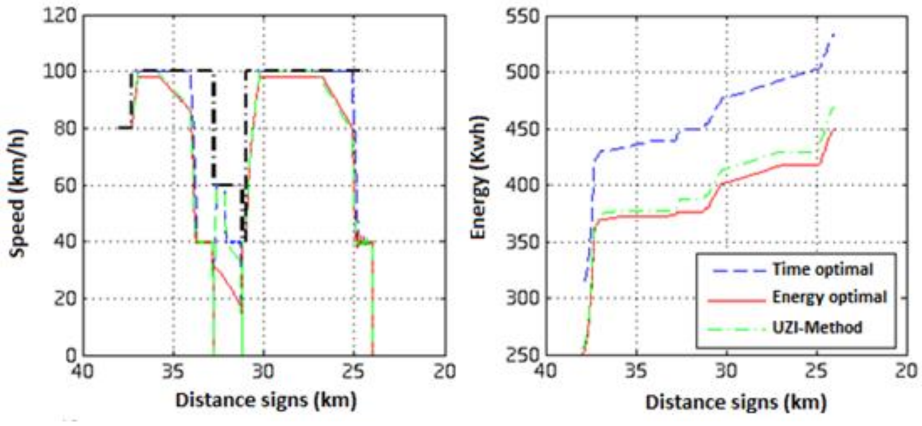


Figure 21: Different speed profiles and energy usages (Scheepmaker, 2012)

3.3 Schedule stability

The stability of the rescheduling depends on different factors according to the literature. Some of them are choices, and some are unavoidable. We classify these factors into three categories: *data quality factors, time factors,* and *model parameters.*

3.3.1 Data quality

The stability of the advice given depends on the data the TMS bases it calculations on. TMS predicts the future state of the system to detect conflicts and resolve them. The prediction of future train movements can be improved if the input parameters for the ***rolling stock specifications*** were improved. Bešinović et al. (2013) use a simulation based approach to calibrate the parameters that describe train dynamics according to the Newton dynamic motion equations. Trains accelerate with a force that is the difference between the tractive force minus the resistance at a certain speed. Their genetic algorithm minimizes the error between simulated and real speed profiles by adjusting the variables shown in Table 5. Results show that the default parameters specified by the manufacturer and used in the current models are incorrect. The data shows that these parameters have a high variance and the default specifications are neither the mean nor the upper bound. We note that their method is not 100% accurate since many more variables cloud the data than can be seen in section occupation data. These measurements are also driver dependent, but the results still proof that the rolling stock specifications are not uniform.

Parameter	**Description**
c_0	Maximum starting tractive effort due to overheating limit [N/kg]
c_1	Linear parameter of tractive effort equation [Ns/m/kg]
c_2	Hyperbolic parameter of tractive effort function [Nm/s/kg]
r_0	Constant resistance coefficient [N/kg]
r_1	Linear resistance coefficient [Ns/m/kg]
r_2	Quadratic resistance coefficient [Ns2/m2/kg]
b_{limit}	Braking to speed limit characteristic [m/s2]
$\theta_{cruising}$	Cruising performance [%]

Table 5: Speed profile decision variables (Bešinović et al., 2013)

The ***location detection method*** also has a huge impact on this prediction quality (D'Ariano, 2008). ProRail currently detects train movements by infrastructure train location detection, which detects when a train enters and leaves a block-section (section occupation data). A more accurate method is GPS, which sends the location and actual magnitude and direction of the speed (accelerating/decelerating) at fixed intervals. van den Top et al. (2009) and D'Ariano (2008) emphasize the importance of this factor. They state that the quality of the solutions of TMS depends on the quality of the input data.

The quality of predicting the future state of the system also depends on some ***external factors***. External factors such as the adhesion coefficient determine the acceleration power the train can exert on the tracks without slipping (Arias-Cuevas, 2010; Yu et al., 2006). Also, the wind has an effect on the train movement (Koetse and Rietveld, 2009). but many other factors play a role in the realized rolling stock movement such the gradient of the track, tunnels, amount of passengers on board, wind, etc. Mehta and Uzsoy (1998) give an example how statistical information can be used to develop predictive schedules by using the data available. Other extract data from the train diagnostic system in order to determine the current state of the train (Roberts and Chen, 2006). The name of this system is the Real Time Monitor (RTM). The RTM monitors variables such as the pressure on the axles of the train and the number of available engines. We can use this information to determine the exact mass of the train, but also the power available to a train. Both influence the driving behaviour of the train.

3.3.2 TIME FACTORS

Other factors which affect the stability are the time factors; they determine when the advice is received and followed. ***Driver compliance and reaction times*** are important for the performance of the TMS. If a driver does not follow the given advice, he will reinitiate another rescheduling iteration of TMS and new speed advices. Compliance seems to increase as the advice given corresponds with driver expectation, especially when the driver is familiar with the route. Bonsall et al. (1990) quantify this relationship for road traffic (Figure 22).

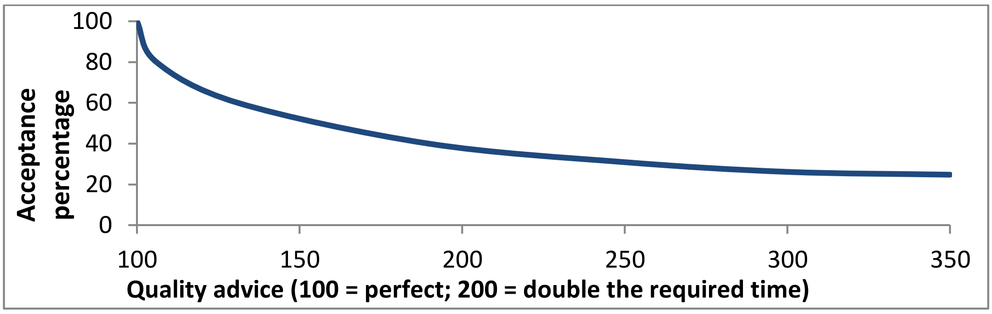


Figure 22: Acceptance of advice as a function of the quality of advice (Bonsall et al., 1990)

The ***computation time*** of the algorithm is another time factor and depends on the complexity of the problem. The complexity increases as the size of the problem and included factors grow. Oversimplified models generate unfeasible schedules and speed profiles, which lead to new conflicts, initiating another rescheduling iteration, which leads to unstable schedules. Lüthi (2009) puts forward the idea of dividing the network into condensation and compensation areas to reduce problem complexity. Condensations are areas around dense stations and form the bottlenecks of the network whereas compensation areas can be used to compensate lost time. These are the long block-sections between main stations, which have enough time-slack to drive more slowly to avoid a STS approach or to make up time when delayed. Caimi et al. (2009a) examined this method in a study on the Swiss network. They removed time reserves from condensation areas and add them to compensation zones to maximize the utilization of the bottleneck areas. This is in accordance to classic manufacturing principles (*Theory of Constraints* (Goldratt, 1990)), where buffers are kept before bottlenecks to maximize their utilization. The difference and difficulty is that due to the high inertia of the rolling stock the "buffer" must stay in motion by arriving just-in-time. The division of the network into different areas reduces the problem complexity by reducing the problem size, although this method needs some coordination between the borders of the zones (Figure 17). Other methods to reduce complexity are:

- Time discretisation
- Limited prediction and calculation horizon
- Reduced routing possibilities
- Fixed speed profiles and headways
- Pre-calculated solutions
- Multi-level approach (gradually increased solution space)

The heterogeneity of train speeds is restricting the capacity at the condensation areas (Mattsson, 2007; Vromans et al., 2006). This effect can be avoided by the Pulsing method (Roos, 2006). First, assign homogenous speeds to all trains in the condensation area and then calculate arrival times for the so-called *portal* (the border with compensation area).

The ***planning horizon*** of the TMS is also an important factor for the performance, but also the complexity of the TMS. We mention the research of (Luethi, 2010) and the impact of early detection of conflicts on the quality of the solution. Figure 23 illustrates this effect and in Table 6 we show the options traffic control has at four different points in time.

Figure 23: rescheduling point of time and impact on energy consumption (Luethi, 2010)

Possible measures	T1	T2	T3	T4
Speeding up trains	Yes	No	No	No
Conflicts prevented actively	Yes	yes	No	No
Delaying trains	Yes	Yes	Yes	No
Re-ordering trains	Yes	Yes	Yes	No
Re-routing trains	Yes	Yes	Yes	No

Table 6: Possible measures available to traffic control (Lüthi, 2009)

D'Ariano (2008) especially emphasized the increase in the computation time in ROMA due to longer planning horizons. He introduces *Static implications,* which are implied choices of arcs by past decisions to reduce the problem size. This reduces the computation time and gives a higher probability of finding the optimal solution. The results reported by D'Ariano (2008) are shown in Table 7. We list other possibilities to reduce complexity or computation time below:

Static implications	Time horizon	Iterations		Time		# Optimal solutions	# Feasible solutions
		Best	Total	Best	Total		
Yes	1h	7.3	15.1	0.66	0.74	100%	100%
Yes	2h	17,2	34,6	16,15	18,11	100%	100%
No	1h	112,3	7317	25,45	67,76	47%	83%
No	2h	0,0	21	117,7	119,4	13%	63%

Table 7: Comparison of the solutions of ROMA with and without static implications (D'Ariano, 2008)

3.3.3 MODEL PARAMETERS

These are factors which are part of the TMS model and are design choices. In Figure 24, we show how the ***rescheduling initiation method*** affects the stability. This depends on two factors, namely the *tolerance bandwidth* and the approach when these deviations are detected. An event-driven approach leads to fast new schedules in case of disruptions. One can choose to interrupt the rescheduling when new disruptions occur at the expense of waiting a long time before generating a new schedule. The danger is not finding a solution in time or sending suboptimal solutions at the cost of schedule stability. Another approach is periodic rescheduling, which after each sampling period starts rescheduling if disruptions have occurred. Lüthi (2009) proposes a hybrid method that differentiates between low and high priority events. High priority events will initiate the rescheduling process while low priority events have to wait until the next rescheduling round. We illustrate these effects in Figure 24. Green and red represent low and high priority events respectively.

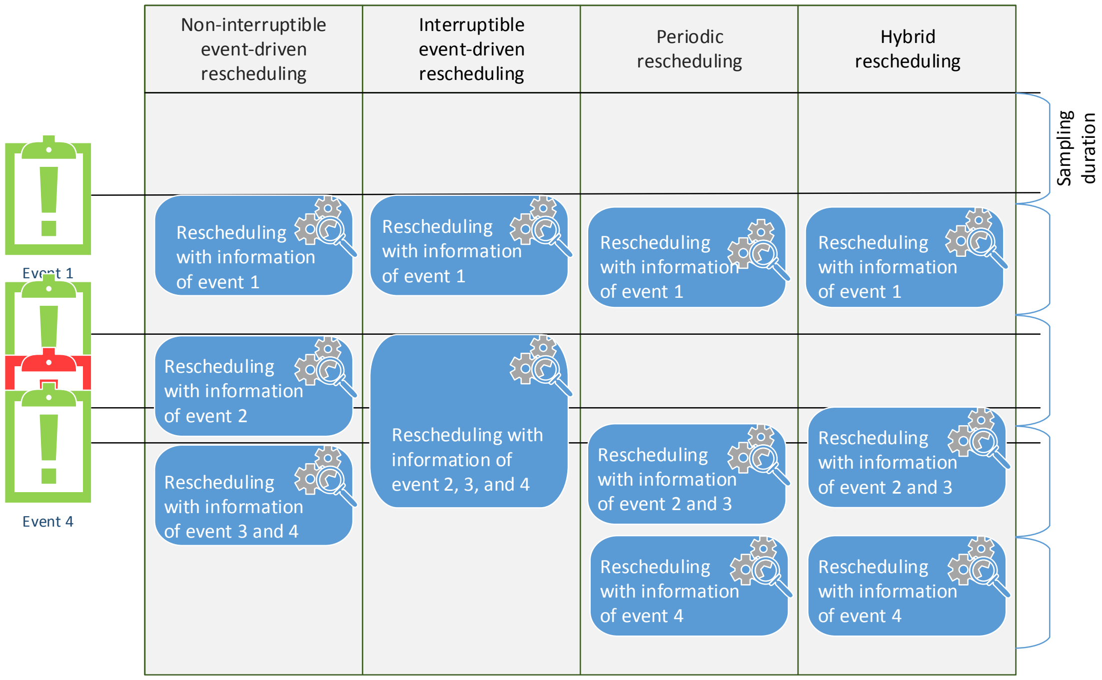


Figure 24: Representation of different initiation procedures (Lüthi, 2009)

The ***tolerance bandwidth*** has a direct effect on the rescheduling. Wider bandwidths initiate the rescheduling less often, but conflicts are also detected later, and there is less time to react. The same is true for the planning horizon. Samà et al. (2012) examine the effects of different rolling horizon periods and schedule stability. Results show that longer planning horizons do not guarantee better nor more stable solutions. It is a parameter that has to be chosen carefully, taking into account the solution quality and the computation time. A *safety cushion* when rescheduling could also help stabilize the generated solution (Van de Vonder et al., 2007). McKay et al. (2000) argue a similar solution by *under-capacity* scheduling in order to bring the operations back to normal as soon as possible before optimizing again. Figure 25 illustrates the tolerance bandwidth and the follow-up time (green arrow). The narrower the bandwidths and follow-up times, the more situations become conflicts.

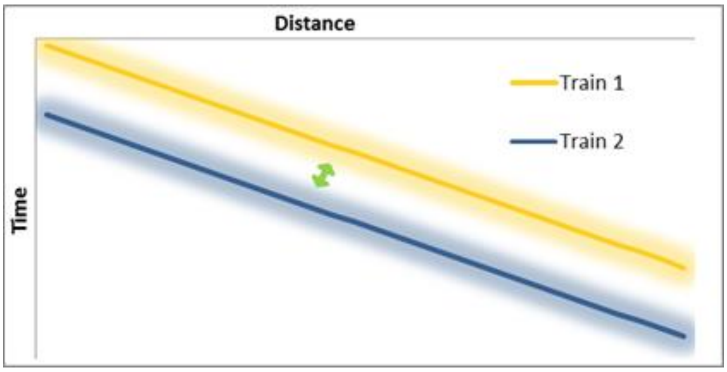


Figure 25: Representation of the tolerance bandwidth and safety cushion

Some of these decisions, such as the tolerance bandwidth, show the trade-off that has to be made between maximum performance and schedule stability when rescheduling (Church and Uzsoy, 1992; Sabuncuoglu and Karabuk, 1999). Lüthi (2009) further emphasizes the importance of proper communication channel between the driver and TC for effective realization of the solutions. For example, uncertainty about the nature of the delay can lead to instability. For example, lower adhesion on a particular block-section has other implications than a jammed door of a single train. More information enables better prediction of future behaviour of the system by the TMS, and more robust solutions. Currently, only the driver knows the exact nature of the delay, and it is rarely communicated with TC. A two-way communication is, therefore, recommended (Sandblad et al., 2002). Black et al. (2004) provide an algorithm called Adverse that incorporates the experience of human traffic controllers to improve the prediction of the system. In a full factorial design experiment, they present results that are significantly better than neglecting the knowledge of traffic controllers. Traffic controllers can make an *educated guess* about the following factors to improve rescheduling:

- Event time - The predicted start time of the event
- Event duration - The predicted duration of the event
- Impact magnitude - The initial magnitude of the impact
- Impact decay rate - The rate at which the machine recovers from the impact

For a more comprehensive literature review on the subject of TMS, we refer to D’Ariano (2008), Corman (2010) and Kecman (2013). For a general review on the subject of rescheduling under uncertainty, we refer to Aytug et al. (2005). Finally, we argue that the advice is comparable to a goal for the driver. To maximize their effect one widely used method is the SMART principle (Doran, 1981) to make objectives easier to understand, easier to do, and give a higher confidence about the goals being followed. This means that the goals, speeds advices in this context, should be: *Specific, Measurable, Attainable, Relevant, and Time-Bound.* Although the first four are true, the advice is not Time-bound. While we know the time-window within which the driver has to reach the speed advice before the current schedule becomes infeasible.

3.4 Conclusion

The literature review has shown that a multitude of solutions is available for real time traffic scheduling. Different techniques are available for conflict resolution and speed regulation. The goal of this research is not to find the best combination of the two, but to provide a background to the rescheduling process and the factors that can disturb this process. Models for train movement provide further insight into the prediction of future train travel times. Several (optimal) speed algorithms are available that take into account energy savings, but also punctuality and robustness have to be considered. The choice is how to use the travel time-slack that is available: use it uniformly during the trip or save the reserve until the last moment and use it just before arrival, as the currently used method: UZI (Section 2.3).

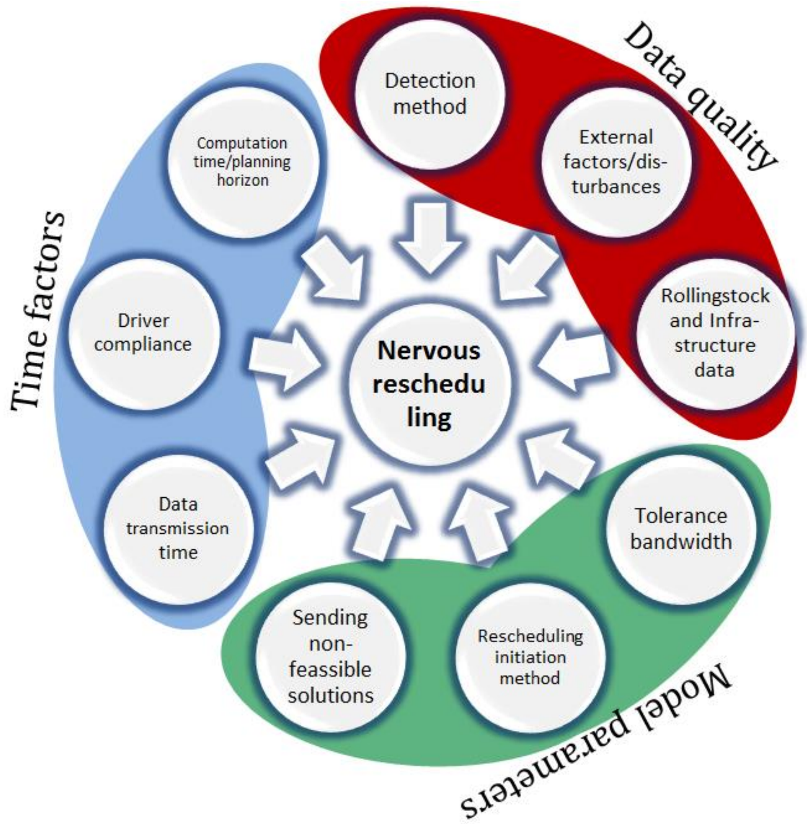


Figure 26: Influencing factors of schedule instability

Finally, from the literature we recognize a number of factors, which affect the stability of the rescheduling. We illustrate these factors in Figure 26, which are the subject of the rest of this research. We will optimize the model parameters and find solutions to cope with the effects of the others. We look for a balance between performance of the TMS and the stability of the advice. The literature on the robustness of the solution, however, is scarce. Almost no literature is found during our review about the stability of a speed advice, which emphasizes the value this research. We show the effects of a stable rescheduling process in Figure 27. These two figures together illustrate the cause and effect relationship from the literature. Some of the factors are direct relationships, while others are indirect. For example, higher driver motivation because of the reliable speed advice also adds to a better compliance and, therefore, reduced unplanned stops. In Chapter 4, we first develop a model to quantify factors that influence the driving behaviour of the trains. In Chapter 5, we design our experiments and explain how we examine the factors shown in Figure 26.

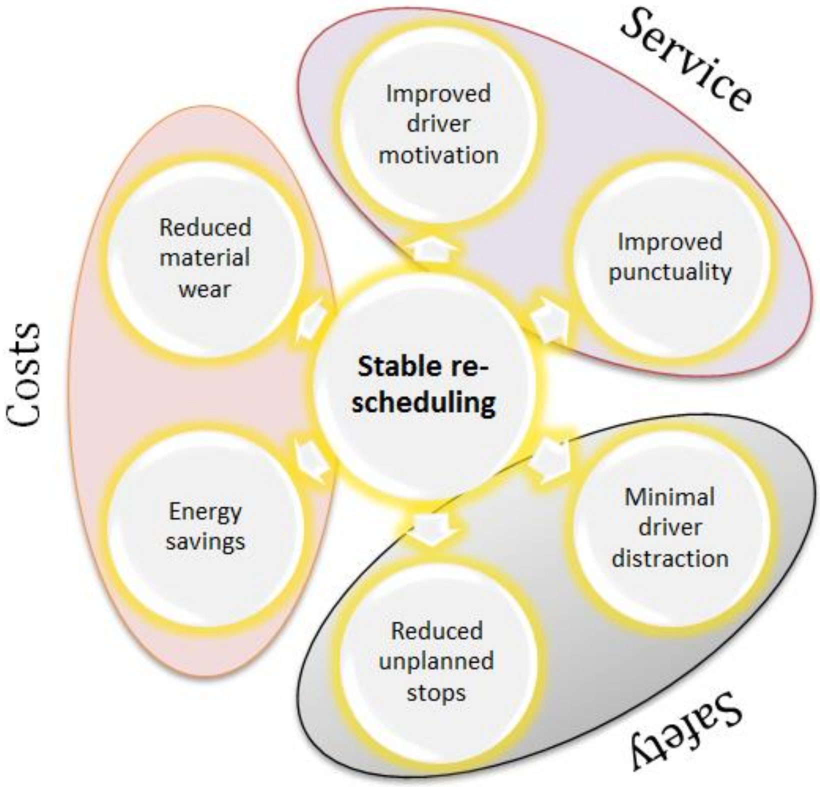


Figure 27: Effects of a stable schedule

4. Driving model and sensitivity analysis

The purpose of this chapter is to answer our third research question: *"How significant are the effects of factors that influence the driving behaviour of the trains and should be included in the simulation study?"*. In this chapter, we develop a model to analyse the effect of rolling stock specifications and external factors on the driving performance of the train. We describe the model in Section 4.1. We use this model to see which factors influence the driving performance the most in Section 4.2. Finally, we use this model to quantify the effects of these factors into probability distributions in Section 4.3. We enter these into FRISO (Chapter 5) to quantify their effect on the stability and safety on the network level, as explained in Section 1.4.

4.1 Model description

To find the sensitivity of the driver performance to the rolling stock specifications and the external factors, we develop a model for train movements. We use this model to calculate the total travel time of the train under different circumstances such as reduced adhesion, fully occupied trains, or damaged wheels with increased rolling resistance. We use the formulas (1 and 3) for train movement as given by Van Gigch and Kouijzer (1996):

$$F_{acc} = F_{Tr} - R_{tot} \tag{1}$$

With:
F_{acc} : the power available to accelerate [N]
F_{Tr} : the power delivered by the traction unit of the train [N]
R_{tot} : the total resistance consisting of the air and rolling resistance of the train [N]

The adhesion between the track and the wheels limits the F_{Tr} (from Lloyds register) according to the following equation:

$$F_{Tr} \leq \mu \, . \, m \, . \, g \tag{2}$$

With:
μ : the friction coefficient [-]
m : the mass of the train [kg]
g : the gravitational constant (9.81 average in the Netherlands) [m/s^2]

We describe the total resistance as a function of the speed by the following formula:

$$R_{tot}(v) = (A + N \, . \, B)\,(v + \Delta V)^2 + m(C + D \, . \, v) + N \, . \, E(v + \Delta V) \tag{3}$$

With:
$R_{tot}(v)$: The total resistance [N]
A : head/tail aerodynamic/air resistance coefficient [$N/(m/s)^2$]
B : length dependant air resistance coefficient [$N/(m/s)^2$]
C : Rolling resistance coefficient [N/kg]
D : Speed dependant rolling resistance [N/(kg . m/s)]
E : Internal air resistance coefficient [N/(m/s)]
N : Number of train units [#]
ΔV : Wind speed [m/s]
v : Current speed [m/s]

We retrieve the traction power (discrete data at intervals of 2 km/h) and the resistance coefficients from Lloyds register. We implement these formulas in MS Excel for a SLT VI Unit (Sprinter Light Train with 6 carriages, see Appendix X) train to calculate the F_{acc} at each speed.

From Newton's second law of motion we calculate the corresponding acceleration and the corresponding time and distance for each Δv by the following formulas:

$$a_v = F_{acc}(v)/m \tag{4}$$

$$\Delta t = \frac{\Delta v}{a_v} \tag{5}$$

$$\Delta d = v_{initial}.\Delta t + \int_{v_{initial}}^{v_{target}} a_v.t_v \tag{6}$$

With:
a_v : acceleration rate at speed v [m/s²]
Δd : distance travelled [m]
m : Mass of the train [kg]
Δt : time passed before reaching target speed [s]
t_v : time passed before next speed step is reached [s]

We use these parameters together with the infrastructure data from the InfraAtlas to calculate travel times with different values as input. The input parameters that we examine are: air resistance, rolling resistance, wind speed (ΔV in the resistance formula), train occupation (Mass empty train + mass maximal train load * Train occupation), and adhesion level of the tracks (minimum of given traction force F_{Tr} and Equation 2). The model flowchart is shown in Appendix X. First, the default parameters are set (resistance coefficients from Lloyds register, no wind, no passengers, and normal adhesion conditions) and from Equations 1-6 we calculate the traction characteristics of the train. We do the same for the deceleration, except that a constant factor is taken since it is not a function of speed and depends on the braking percentage chosen by the driver. We take a constant factor for which the train would stop over a distance of 1200 meters from 140 km/h (speed limit on the trajectory). We substitute Equation 5 into 6. We replace a_v with a constant deceleration rate a_{dec} , so we do not need the integral of Equation 6. Furthermore, $v_{initial}$ now becomes the end speed, which is zero. So we get:

$$\Delta d = \frac{1}{2} a_{dec}.\left(\frac{\Delta v}{a_{dec}}\right)^2 \tag{7}$$

We rewrite equation 7 to get Equation 8 for a_{dec}:

$$a_{dec} = \frac{\Delta v^2}{2\Delta d} \tag{8}$$

We fill in Δd= 1200 m and Δv= 38.9 m/s (140/3.6) so we get $a_{dec} = 0.63\ \frac{m}{s^2}$, which is a normal service brake. For some sections driving the maximum speed is not reachable, because then the train would not be able to stop in time. For these sections we rewrite Equation 8 to calculate the maximal reachable speed:

$$v_{max} = \sqrt{2a * \Delta d - v_{exit}^2} \tag{9}$$

In Table 6, we show the section between Utrecht and Bunnik and the in-between speed limits. We use the acceleration and deceleration data to calculate the time and distance that the train has to accelerate, brake and cruise to determine the total travel time. First, we calculate the acceleration and braking distances. If this distance is smaller than the distance to the next node, the train has to cruise the rest. This process is shown in Appendix VIII. Example:

1. From Speed limit 3 to Bunnik the current speed is 90 km/h, and the train has to accelerate to 140 km/h. To reach his speed, it takes 1668 m and 51 seconds.
2. The next node is a station, so braking distance is the distance from the current target speed of 140 km/h to a complete halt. This will take 1200.3 meters and 61.7 seconds.
3. Total distance from Speed limit 3 to Bunnik is (6871-2676=) 4195 meters, so the cruising distance is: 4195–1668–1200=1327m and cruising time= 1327/(38.9)=34.1 s

Node	Distance (m)	Speed limit (km/h)	Phase	Travel distance (m)	Travel time (s)
Utrecht	0	40	A	65.1	11.7
			C	176.9	15.9
			B	0.0	0.0
Speed limit 1	242	70	A	203.5	13.0
			C	1500.5	77.2
			B	0.0	0.0
Speed limit 2	1946	90	A	287.9	12.9
			C	442.1	17.7
			B	0.0	0.0
Speed limit 3	2676	140	A	1668.1	51.0
			C	1326.6	34.1
			B	1200.3	61.7
Bunnik	6871	140	A	2224.6	88.6

Table 8: Travel time calculation (A=acceleration, C=Cruise, and B=Brake)

In the case that in step 3 the cruising length is negative, an extra step has to be made because it would mean that the train would not be able to come to a halt in time if the train accelerates to the maximum speed limit. In which case, we calculate the maximum reachable speed (Equation 9), and repeat the procedure.

We validate our model by comparing the calculated speed profiles with actual speed profiles calculated from GPS data. In Figure 28, we show the time-optimal speed profiles of between Utrecht and Rhenen for a fully occupied train, an empty train and a profile of an actual GPS data (Provided by Scheepmaker (2012)) to validate the model. We calculate the distance between two GPS positions with the great circular distance formula:

$$Distance = \cos^{-1}(\sin(Lat1) * \sin(Lat2) + \cos(Lat1) * \cos(Lat2) * \cos(Lon2 - Lon1)) * R$$

With Lat en Lon the latitude and longitude respectively and R the radius of the earth. A correction factor has been used to fit the distances to the distances from the InfraAtlas. We expect higher errors at higher speeds, so we divide the difference in total distance to the station across the trajectory with speed as weights. Also, we validate the model with actual drivers to check whether the model corresponds with their perception of reality about deterioration of train performance by, for example, adverse weather conditions. From the red line in Figure 28 (the GPS-tracking data) we see that our model to describe the train dynamics corresponds to actual speed profiles. The biggest discrepancy is at the departure from Utrecht, which in reality is not as smooth as desirable due to the presence of other trains and signal states. Other graphs for we used for validation are shown in Appendix IX.

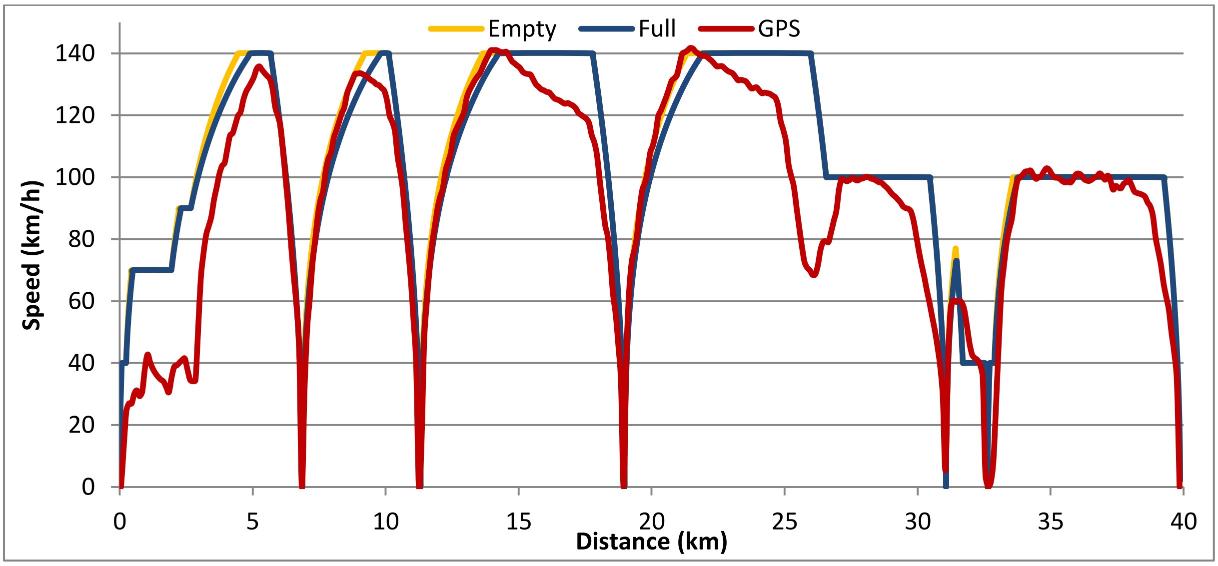


Figure 28: Speed profiles with an empty train, a full train, and an actual train run (GPS)

4.2 Sensitivity analysis

We use our model to answer the research question: "*What is the effect of imperfect rolling stock data on the driving performance?*" by changing the values for the train resistance coefficient and available power, and answer *"What is the effect external factors on the driving performance?"* by changing the adhesion coefficient, the wind speed, the train occupation, and available traction power (to represent a train with a broken engine). For all these factors, we chose 20 different values from worst-case to best-case real scenarios found in the literature and from experts such as drivers and system engineers.

Parameters	Default value	Range		Unit	Steps
Adhesion	0.3 N/kg	0.5	1.0	Factor	0.04
Wind speed	0 km/h	-50	100	Km/h	5
Train occupation	0%	0.0	1.0	Factor	0.05
Air resistance	6.425 N/(m/s)^2	1.0	3.0	Factor	0.025
Rolling resistance	0.0162 N/kg	1.0	3.0	Factor	0.05
Defect train	100 %	0.5	1.0	Factor	0.04

Table 9: Ranges of values for each factor of the sensitivity analysis

For each value of these factors, we recalculate the acceleration and deceleration table and calculate the new travel time using our model. We adjust one parameter at a time and keep the rest at the default values. For all the different values of the factors, we show the results in Figure 29. The flowchart in Appendix VIII shows the exact process. We verify the model by checking that the travel time is accumulative when conditions become worse (e.g., less adhesion). We emphasize that the speed profiles we calculate with our model are time-optimal, which means the fastest possible travel time. The minimal travel time from Utrecht to Rhenen is shown in Figure 29 on the y-axis. The x-axis is for all parameters best-case (left) to worst-case (right) and the exact values are found in Table 9.

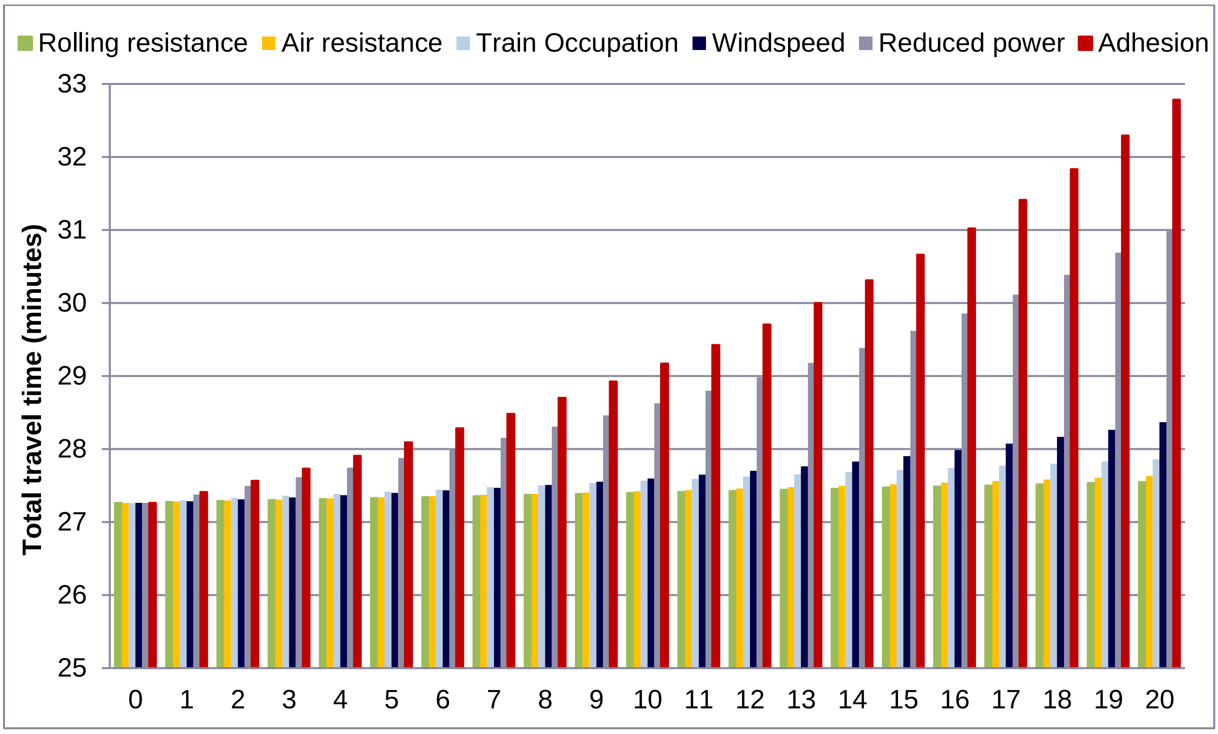


Figure 29: Results sensitivity analysis for the travel time from Utrecht to Rhenen

From the sensitivity analysis, we conclude that the three most influencing factors are the adhesion coefficient, the wind speed and the train occupation. These values are in line with findings of Koetse and Rietveld (2009) that report reduction of speed of 10 to 50% due to adverse weather. The other factors, air and rolling resistance, have relatively little effect on the total travel time. We choose to only take into account the wind, adhesion, train occupation, and defect trains in the rest of this thesis. In Section 4.3, we derive probability distributions for these factors. The extra travel time is also shown in Table 10. We compare them to respectively, empty train for the train occupation, default specifications for the air and rolling resistance, no wind, and perfect adhesion conditions.

Train Occupation		Air resistance		Rolling resistance		Wind speed		Adhesion		Reduced power	
Value	Effect	Increase	Effect	Increase	Effect	Speed	Effect	Reduction	Effect	Reduction	Effect
25%	0.6%	**50%**	0.1%	**50%**	0.2%	**25 km/h**	0.5%	**12.5%**	3.0%	**12.5%**	1.7%
50%	1.1%	**100%**	0.2%	**100%**	0.3%	**50 km/h**	1.2%	**25%**	7.0%	**25%**	3.9%
75%	1.6%	**150%**	0.3%	**150%**	0.5%	**75 km/h**	2.4%	**37.5%**	12.5%	**37.5%**	7.0%
100%	2.2%	**200%**	0.5%	**200%**	0.6%	**100 km/h**	4.0%	**50%**	20.2%	**50%**	11.6%

Table 10: Extra travel time due to external factors

4.3 Probability distributions

In this section, we define probability distributions of the significant factors. This part is necessary because we cannot enter these disturbances in FRISO (see Section 1.4). We use our model to calculate the effect of each factor on the acceleration power compared to the default values, which are: perfect adhesion, no wind and 60% train occupation. For the defect trains, we do not calculate probability distributions, because no data is available about the exact defect. Also, FRISO allows entering defect trains directly and there is no need to “translate” the effects into disturbance.

4.3.1 ADHESION

Adverse weather conditions are responsible for approximately 10-20% of all disturbances, which is why this is a very important factor (Koetse and Rietveld, 2009). These disturbances are very seasonal, but occur throughout the year because tracks can be slippery due to the presence of oil and other filth. Traffic control uses the reporting system ISVL to register slippery tracks when drivers report them. The data, however, is in PDF format. Since analysing thousands of PDF files is very time consuming, we make an approximation based on the data available. We use the total number of report and calculate the average duration of the disturbance. We come to the conclusion that 2070 of the daily 5200 trains encounter a slippery track during the fall, which is 60% of all trains. During the rest of the year, this percentage is approximately 2%. The lower bound for the adhesion coefficient is chosen at 0.03, because at lower coefficient trains are cancelled completely (Arias-Cuevas, 2010; Koster, 2007). The probability density function found in the literature has similar results (Popovici, 2010). During the fall period, the adhesion coefficient was measured with a tribometer. We show the probability distribution and the fitted Gamma distribution in Figure 30. According to this research 66% of the observations were below the critical point where trains cannot use their maximum tractive effort. This distribution is shown in Figure 30. We enter each possible value of the adhesion coefficient in the model of Section 4.1 and calculate the reduction in acceleration power. This results in the probability distribution for the disturbance due to adhesion shown in Figure 31. This is the Gamma distribution with shape parameter 0.135 and scale parameter 3.37.

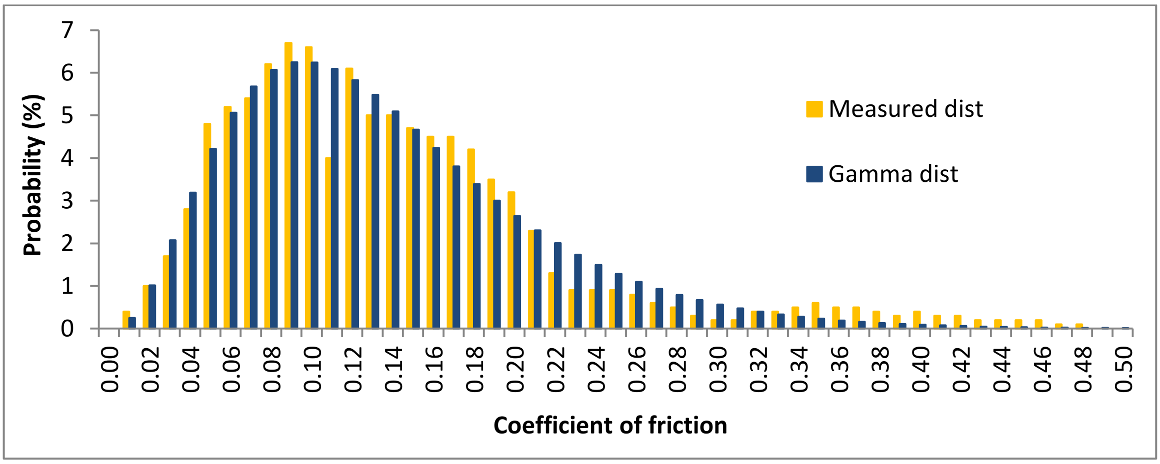


Figure 30: Probability density function of the coefficient of friction (Popovici, 2010)

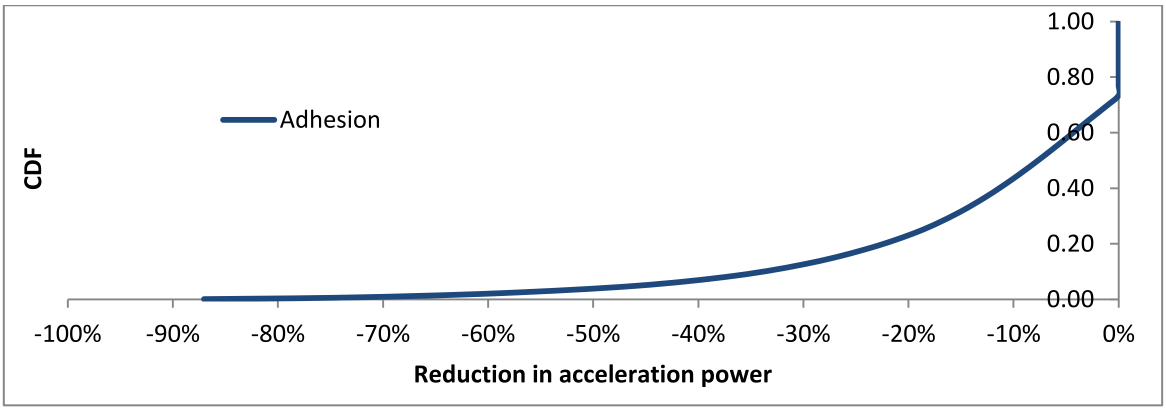


Figure 31: Cumulative density function of disturbance due to the adhesion

4.3.2 WIND SPEED

To quantify the effect of the wind, we collect weather data from the KNMI over the past years. The data consists of the average wind speed and direction measured at 22 weather stations across the Netherlands. We assume that the direction of the wind is not important because of the fact that trains make roundtrips, so for every train that has the wind from one direction there is another where the wind is coming from exactly the opposite direction. The effect of crosswind is bigger than the head wind due to the much larger side area (Lukaszewicz, 2001). To model these forces, we need sophisticated software and mathematical models that are beyond the scope of this research. To not completely neglect this effect, we estimate the disturbance to be twice as big as the head wind with a 50% probability on having crosswind, 25% head wind, and 25% chance on having back wind. This effect is in agreement with driver experience. From theory, the wind has a Weibull distribution with shape factor k and scale factor c (Seguro and Lambert, 2000). We fit the empirical data using the least squares method with MS Excel solver, using k=2 suggested by Seguro and Lambert (2000) in Figure 32.

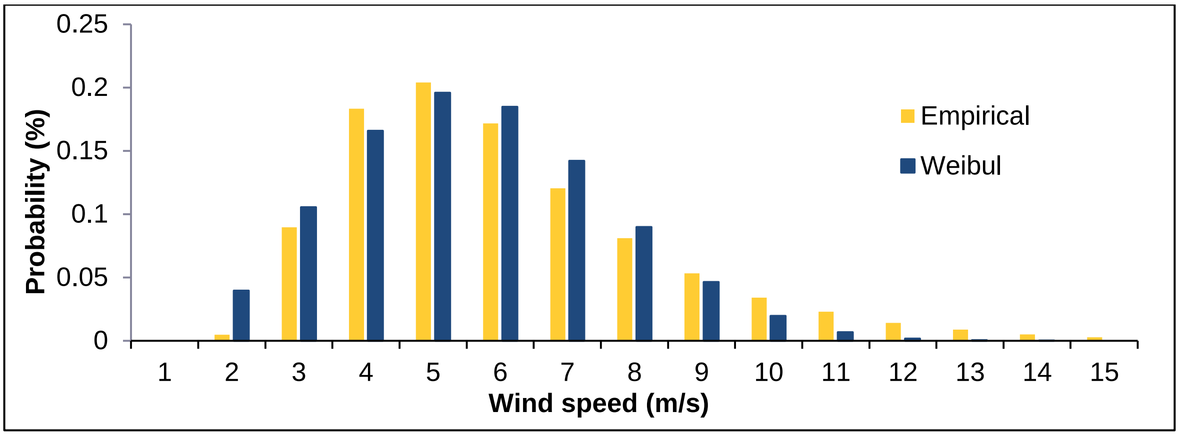


Figure 32: Probability density function of wind speed

In the same way as the adhesion coefficient we translate the disturbances due the wind by entering each possible speed of the wind in our model and calculate the corresponding disturbance of the acceleration power caused. We calculate the disturbance is the percentage difference in acceleration force relative to the acceleration force when there is no wind. For the distribution, we use the Logistic distribution with a mean of -0.267 and standard deviation of 0.187 (Figure 33), because of the lower RMSE (root mean square error).

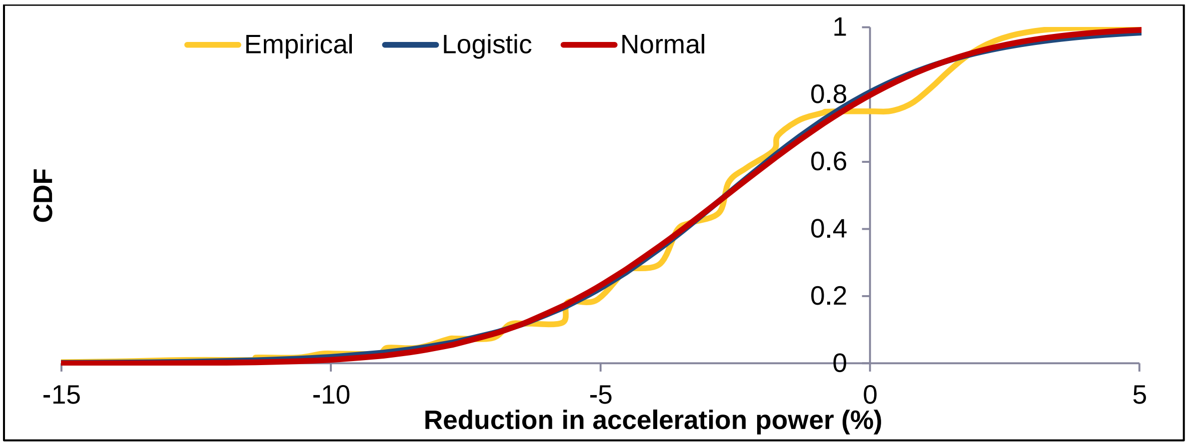


Figure 33: Cumulative density function of disturbances due to wind

4.3.3 *Train occupation*

The train occupation (TO) has a significant effect on the acceleration rate of the train as seen in Section 4.2. As input for the distribution, we use passenger count numbers and the planned rolling stock capacity. We note that these numbers are based on the 90th percentile and are an overestimation of the real values. Distinction is made for planning between the summer and the fall period where the demand is significantly higher. However, the effects are very similar, so we ignore this distinction in our simulation study. We calculate the TO by dividing the passenger count by the total capacity. Since the trip consists of different passenger counts on different parts of the trip, we weight these by the length of the sub-trip. So, for example, if a trip goes from station A to B and then to C and the distance AB=20 and BC=40, and the TO between AB=0.7 and BC=0.4 then the TO= 0.5 ((20/60)*0.7+(40/60)*0.4). The data can be seen in Figure 34.

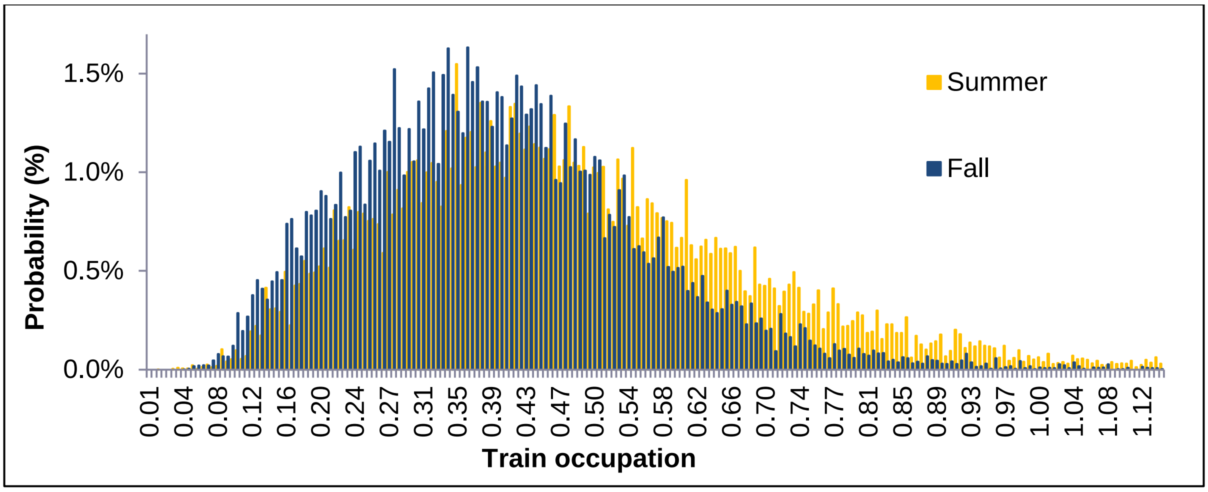


Figure 34: Probability distribution of the TO

We repeat the same procedure as with the wind and adhesion disturbances to get the following distribution for the disturbance in the acceleration power. These disturbances are the effect of a deviation in mass due to a different TO. The normal distribution is chosen because of the lowest RMSE, with a mean of 1.04 and a standard deviation of 0.04 (Figure 35).

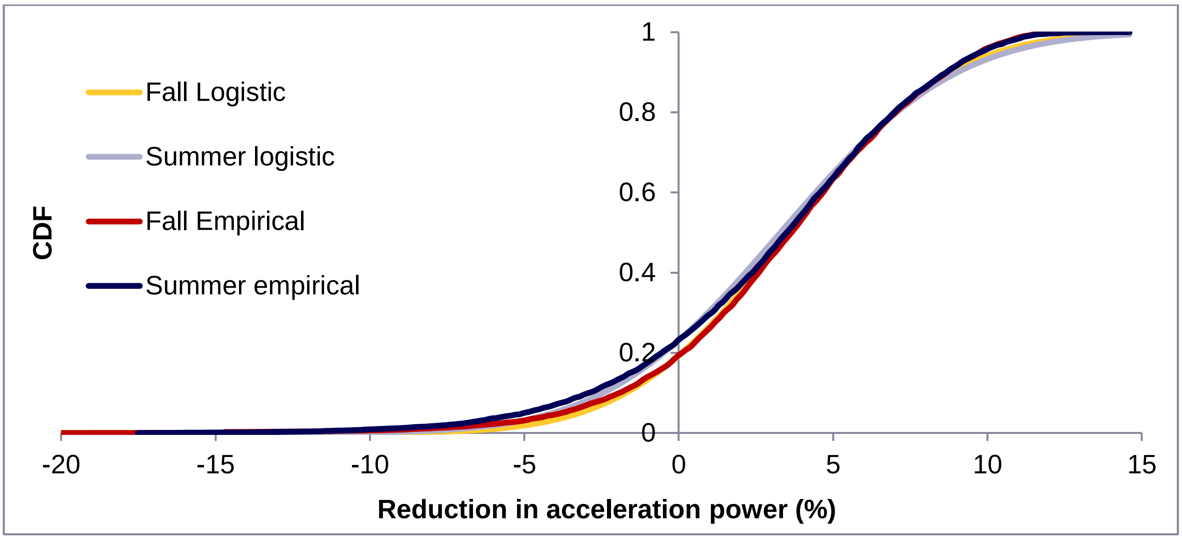


Figure 35: Cumulative density function of disturbance due to train occupation

4.3.4 COMBINED EFFECT OF THE EXTERNAL FACTORS

We also evaluate combinations of the external factors (adhesion, wind, and train occupation) to see how they contribute to divergence from expectations. We use this experiment to find interactions between the external factors. For example, a fully occupied train has fewer problems with the reduced adhesion since the maximal force that the train can exercise is proportional to its total mass. To reduce the number of experiments, we use Latin Hypercube Sampling (LHS). We prefer this method above random sampling to reduce the variance and to make sure all possibilities are equally represented (McKay et al., 1979). The LHS divides each input parameter X_k into N strata of equal probability. From each interval, one value is drawn at random, which we then match at random with values of the other parameters. We have 3 parameters and divide each parameter into N strata and take 1 value from each interval. Then we match one value of each parameter with one value of the other parameters. So, we create 1000 different inputs, which consist of 3 different values each. We determine sample values [1=occupation, 2=wind, 3=adhesion] by:

$$X_n = F_{Xn}^{-1}\left((j-1+\varepsilon_{Xn})/N\right)$$

Where X_n is the sample value, $\varepsilon_n \in [0,1]$ is a random number, and F_{xn} is the cumulative probability distribution of X_n (Cheng and Druzdzel, 2000). We used this method to draw sample values from the fitted distributions of Sections 4.3.1-3. The next step is to randomly combine the sample values from each parameter with each other. This is done by making two columns, one with sample value *[1,..,N]* and one with random numbers for each parameter and then ordering the random numbers ascending. We use the LHS method to get the sample values for occupation, wind, and adhesion. Next we enter these values into the driver model to calculate the weighted acceleration disturbance relative to the default parameters. So, for each sample we have the corresponding disturbance, which we enter into FRISO as acceleration disturbances (Figure 36).

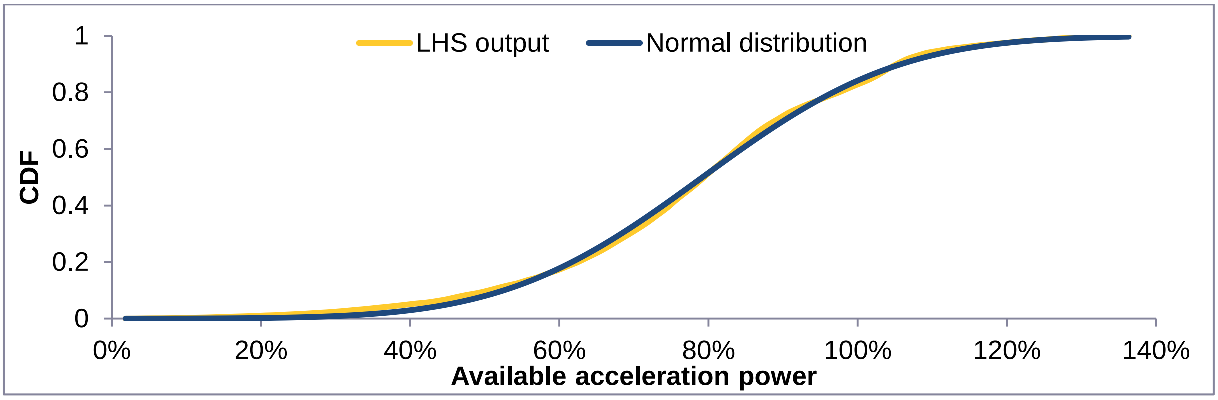


Figure 36: Cumulative density function of disturbance due to the combined disturbances

4.3.5 WEIGHTS

The disturbance in FRISO consists of one value and counts for the whole acceleration phase while the acceleration rate and the disturbance dependents on the speed. Therefore, we weight the disturbances to get exactly one disturbance factor for each wind speed. We determine the weight of each disturbance at speed v, called W_v, by running reference simulation runs (undisturbed situation). So, for example, if two trains would accelerate from 0 to 40 km/h and another train from 40 km/h to 130 km/h then the total number of different velocities would be: 2*(40-0)+(130-40)=170 and W_1=2/170, W_2=2/170,...,W_{130}=1/170 and $\sum_{v=1}^{130} W_v = 1$. Let the disturbance at speed v by wind speed x be D_{vx}, then the weighed disturbance of wind speed is given by x=$\sum_{i=1}^{130} W_v * D_{vx}$.

4.3.6 Computation time

The final disturbance that we need to calculate is the computation time of TMS. This is necessary because, in the current architecture, the simulation (FRISO) will freeze while the TMS is rescheduling. This is not realistic and so we calculate the computation time from the CPU utilization time. We log the CPU utilization with the Windows Performance Monitor for each TMS module (Speed regulator, conflict resolution, etc.). The most time consuming process, in this case the conflict resolution module (blue), is the "bottleneck" since the processes run in parallel. The result is shown in Figure 37. The computation time is between 2 and 5 seconds. We examine this parameter as part of the delay-loop in the simulation study.

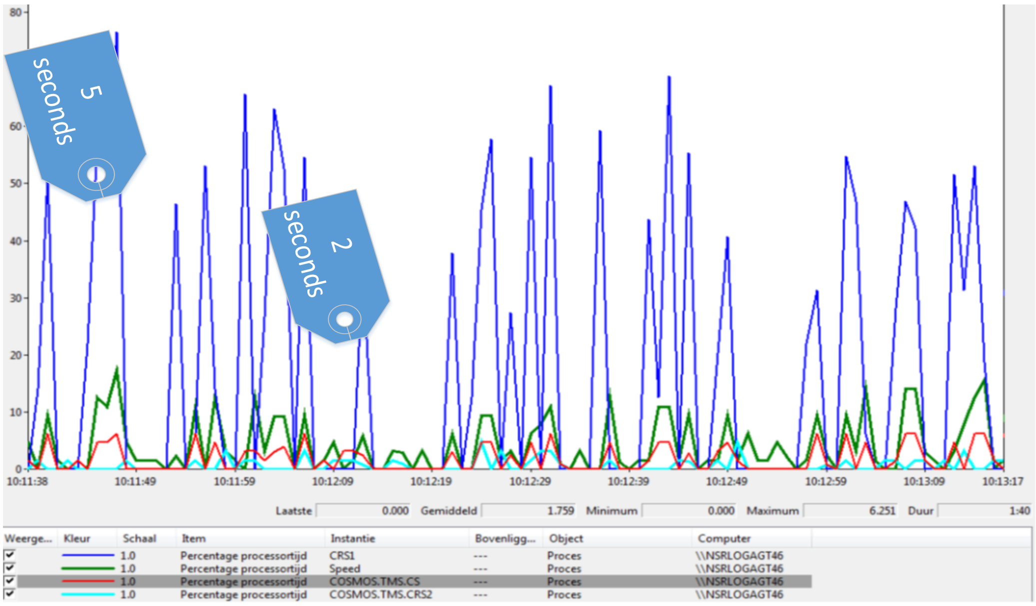


Figure 37: Processor time of all TMS components

4.4 Conclusions

From the sensitivity analysis, we conclude that four factors (adhesion, wind, train occupation, and defect trains) influence the driving performance the most. For example, the minimum travel time rises with 20% if the adhesion coefficient decreases with 50%. The TMS could make more accurate predictions of the future state of the system if these factors were known. This is possible by integrating TMS with other innovations currently examined at NS, such as the Real Time Monitor for real time information about available power to a train. Also, passenger count systems are currently examined, which allow accurate estimations of the train mass. To examine whether integration would significantly add to the performance of the TMS and the stability of the speed advice, we add these effects to the simulation study. We cannot add these variables to the TMS calculation for train movements, but what we do is introduce their effect on the train performance to see their effect on the stability of the advice and the safety if these factors are NOT taken into account by TMS. The exact simulation study and experimental factors are the topics of Chapter 5.

5. Simulation study

In this chapter give the outline for the simulation study, which we use to answer the rest of our research questions. These research questions are to quantify the effect of the factors found in the literature and found in the sensitivity analysis of Section 4.2 on the stability of the advice and the safety. First, we specify the exact FRISO-TMS model and define the experimental factors identified from the literature and our sensitivity analysis in the experimental design. We calculate the number of replication and warm-up period needed for the simulation. Finally, we define the exact KPIs we measure and how we assess the outcomes of each experiment in Section 5.2.

5.1 Model specification

In our simulation study, we use the existing simulation package available at ProRail, called FRISO. The benefit of using FRISO is the appropriate level of detail in the model (e.g., infrastructure and rolling stock characteristics) as we argue in Section 1.4. We design the experiments to quantify the effect of the factors identified in Chapters 3 and 4. Since some of these factors are not present in the current model, we model their impact on the driving behaviour as a disruption to see how the TMS reacts on difference between the predicted and simulated driving behaviour. The rest of this chapter provides the outline of the simulation study where we search for the most stable and safest model settings, instead of optimal in terms of punctuality alone. The model contains the Den Bosch area with only the passenger trains included. We describe the train-series in the area and the detailed model infrastructure layout in Appendix XII. We respect the following restriction during our simulation study:

- We allow no changes to the current timetable. The method, such provided by Caimi et al. (2009b), fall outside the scope of this research.
- The design should keep the current rail infrastructure, limitations and signalling system.

FRISO-TMS is currently not fully documented. So, most of the information about the model is given by the tester and FRISO expert at ProRail, D. de Vries. The simulation software FRISO has limited adjustability and supports the following disturbances to be modelled (Steneker et al., 2009):

- Driver compliance: interval between and period that drivers ignore the speed advice.
- Acceleration power: percentage or absolute difference between the acceleration power from Lloyds Register and realization in the simulation.
- Braking power: the uniform deceleration rate.
- Halt time: halt time at stations corresponding to passengers entering and leaving.
- Entrance time: deviation from the planned entry time of the train into the simulation.
- Departure time: deviation from the planned departure time after a halt, corresponding to waiting for the departure signal of the guard.

Furthermore, the user is able to adjust the following parameters:

- Driver reaction time: time between receiving an advice and following it.
- Location update interval that FRISO sends to TMS. Also, section occupation data instead of GPS can be sent to resemble the current train location system.
- The communication delays between the location update sent by the train and the moment the driver start to follow the speed advice (Figure 20).

From initial test runs with FRISO-TMS, we conclude that since the software is still in the testing phase, the TMS will crash when the location update interval or the communication delays become too high (>20). Also, the driver compliance disturbances will lead to a software crash. We consider these limits in the design phase of the simulation study as restrictions on the upper bounds of these parameters. The reason that the TMS crashes is that some trains will stop to react to the speed advice and block the whole route. This will overload the speed regulation module. We identified and logged several different scenarios where this problem occurs. However, no clear reason has been found. Our hypothesis is that it is a bug in the communication software (the HLA) and the way it stores the yet to follow advices in memory. However, we cannot say this with certainty without access to the code. TMS needs further testing, and we discard the simulations where this problem occurs.

5.2 Experimental design

First, we narrow down the experimental factors based on the model specifications of Section 5.1. We determine the factors that we cannot include in the simulation study. Then, we define the remaining factors as experimental factors and define the range of different values for each factor (levels) for which we examine them. Next, we describe the scope en the underlying assumptions of the model and determine the number of replications for statistically significant results. Finally, we present the objective function and the definition of all the performance indicators we use to assess the results.

5.2.1 Factors not included

Some of the factors that could affect the performance and stability of the TMS remain for future research because both FRISO and TMS are propriety software. We are not able to adjust the parameters that are “hard-coded” in the software. We exclude others because no data is available or because they are found insignificant in our sensitivity analysis. We briefly describe these factors in this section.

The **rolling stock specifications** are the characteristics that can influence the driving behaviour. However, from our sensitivity analysis we conclude that these effects are insignificant. This is also in accordance to the expert opinions of system engineers of NedTrain (responsible for the maintenance of the rolling stock), and drivers. We exclude this factor from our simulation study.

The **infrastructure data** has to be accurate before we are able to give stable speed advices. However, no data is available about the errors in the infrastructure data. Most of the errors consist of wrong platform lengths and the exact location of the signals. From experience, the Performance Analysis Bureau of ProRail estimates the deviations to be of the order of magnitude of a hundred meters, however, no estimates are available about how often this problem occurs. Since the deviations are near stations, we consider the effects for the advice stability small. Also, we cannot enter these disturbances into FRISO-TMS and exclude this factor from our research.

The **planning horizon** has a big influence on the computation time of TMS, and the conflicts detected. However, the current implementation of TMS takes the complete planning horizon into account. This means that TMS calculates the complete schedule from the moment the train enters the scenario until the moment the train exits the experiment. This is not an adjustable setting, so we cannot design experiments for this, very important factor.

The **tolerance bandwidth** is a parameter that is found in the literature, which influences the stability and performance of the TMS significantly (Luethi, 2010), but we cannot adjust this tolerance in FRISO-TMS. The speed advice is rounded to 5 km/h, which acts as a kind of tolerance. Another tolerance is build in the scheduling algorithm. This tolerance allows the new schedule only if it is significantly better than the current schedule (de Vries, 2013). This is also shown in Figure 19, where the size of the feasible area show the tolerances in the arrival time and speed, which depend on the weights in the cost function. Since both parameters are hard-coded in the TMS and not adjustable, we cannot analyse the effects of different tolerances. However, from the literature and practice we know that rounding off to 5 km/h is commonly accepted (Edinger, 2013; Weeda and Zeilstra, 2010).

The **rescheduling initiation method** cannot occur event-driven (Figure 24) because FRISO sends the location updates in discrete intervals. New disruptions cannot interrupt the rescheduling process because the simulation is frozen while the TMS is rescheduling. Also, events cannot initiate TMS because the HLA interchanges messages with discrete intervals.

Sending infeasible solutions is also not an option in FRISO-TMS for the same reason as the rescheduling initiation method. No new disturbances can occur that would make the current solution obsolete or infeasible. So, we cannot model this effect in the current simulation study.

5.2.2 EXPERIMENTAL FACTORS

All factors which could affect the stability are shown in Figure 26. We discuss the three categories *data quality, time factors and model parameter* and how we design our experiments in order to quantify the effect of these factors with FRISO-TMS. The experimental factors X_1 to X_{12} are the different simulation scenarios and we discuss the results in Chapter 6. We define the following experimental factors to quantify the effects of *data quality.*

The **external factors** that we take into account are the wind, train occupation, and adhesion. TMS is able to calculate more accurate estimates for the travel time by integration with other systems. Integration allows the TMS to predict the future state of the network more accurately, which leads to better performance and stable speed advice. Methods are available in the literature to calculate travel times based on track conditions, with the help of a sensor (Yu et al., 2006). From the results of our sensitivity analysis of Section 4.2 we conclude that the adhesion, wind, train occupation, and available engine power have a significant effect on the driving performance. We cannot introduce these factors into FRISO-TMS, but we can introduce their effects in terms of acceleration disturbances. We enter the disturbances of Section 4.3 into FRISO-TMS for each of the external factors. We include the combined effect of the external factors (X_4) using the method we describe in Section 4.3.4.

$\boldsymbol{X_1} = Adhesion\ \{Incorporated, not\ incorporated\}$

With this experimental factor, we quantify the effects of integrating TMS with a tribometer (Section 4.3.1) in the trains and taking the exact adhesion coefficient into account during rescheduling.

$\boldsymbol{X_2} = Wind\ speed\ \{Incorporated, not\ incorporated\}$

With this experimental factor, we quantify the effects of taking the wind speed (Section 4.3.2) into account during rescheduling.

$\boldsymbol{X_3} = Train\ occupation\ \{Incorporated, not\ incorporated\}$

With this experimental factor, we quantify the effects of integrating TMS with a passenger count systems (or similar) in the trains (Section 4.3.3) and taking the exact mass of the train into account during rescheduling.

$\boldsymbol{X_4} = Combined\ disturbances\ \{Incorporate\ all, incorporate\ none\}$

With this experimental factor, we quantify the combined effect of experimental factors 1-3 (Section 4.3.4).

$\boldsymbol{X_5} =$ Defective train (reduced available power) $\{60, 80\}$ (% of total power available)

With this experimental factor, we quantify the effect of integrating the Real Time Monitor with TMS, which could report when a train has reduced power (Section 4.1).

We examine the following *time factors* in our simulation study:

For the **detection method,** two possibilities are available. Currently, the section occupation data is available for train positioning. In the future, NS will replace this method by GPS. The location update interval, however, is a choice only limited by the technical specification of the trackers. Common Trackers have a three second update interval as a minimum interval, so this is the lower bound of this parameter. The maximum deviation from the expected position occurs when the driver starts accelerating/decelerating right after the signal has been sent. This deviation in location grows quadratic with the time because of the relationship $\left\{\Delta s = \frac{1}{2} a * \Delta t^2\right\}$. Since the update interval is adjustable and we can use section occupation data in FRISO-TMS, we include this factor in our simulation study.

$\boldsymbol{X_6} = Location\ update\ interval\ \{1,3,5,7,9,10,11,13,15,17,19, \text{and}\ section\ occupation\ data\}$ (s)

With this experimental factor, we adjust the time interval between location updates to find the optimal parameter for TMS in terms of the defined KPIs.

The **communication delays** vary depending on the connection coverage, the amount of data that has to be transmitted and the distance to the phone post. For this reason, the magnitude of this delay varies between different trains. This delay is an adjustable parameter in FRISO-TMS and represents the delay-loop (Section 3.2.2). TMS allows adjustment of two parts of the delay-loop separately, namely: the communication delay from the train to the TMS and the delay from the TMS back to the train. These two represent the t1-t3 and t5-t7 of Figure 20 respectively. The driver reaction time is also part of the delay-loop. Because communication delays are technical factors and driver reaction times are human factors, we treat them as a separate factor. The **computation time** is also part of the delay-loop, however, the simulation stops while the TMS is computing the advice (de Vries, 2013) This does not resemble reality. In Section 4.3.6, we quantified this factor and our findings to determine the range for which we examine the TMS to Train delay. We increase this value to see what the effect of longer computation times. These parameters cannot be higher than 20 seconds, because TMS will crash.

$\boldsymbol{X_7} = Train\ to\ TMS\ delay\ \{1, 5, 10, 15, 20\}$ (s)

With this experimental factor, we adjust the communication delay from the Train to TMS to find the optimal parameter for TMS in terms of the defined KPIs.

$\boldsymbol{X_8} = TMS\ to\ Train\ delay\ \{1, 5, 10, 15, 20\}$ (s)

With this experimental factor, we adjust the communication delay from the TMS to the train to find the optimal parameter for TMS in terms of the defined KPIs.

The **driver reaction time** is an important for the TMS to work. However, no data is available to determine the driver reaction time. If drivers react late to the advice given, the solution can become infeasible. This has an impact on the performance and the stability of the TMS. The value for the reaction time parameter is set to 4 seconds (de Vries, 2013). We are able to adjust this value and measure the effects from the output of FRISO-TMS. There are two different scenarios that consider the driver reaction time. One is the expected reaction time, and the other is the unexpected reaction time of the driver to the given speed advice. The difference is that TMS already has a static parameter for the reaction time. TMS will use this value when calculating the speed advice. We examine this parameter by adjusting this parameter and FRISO will change the train speed exactly after this time. For the unexpected reaction time, we give a static parameter to TMS, but change the reaction time performed in the simulation. This is not a setting in FRISO-TMS, but since both use their own database, we can set the values separately. The driver reaction time set in TMS is the default value of 4 seconds, so TMS expects the trains to adjust their speed after 4 seconds. However, the simulated driver reaction times by FRISO deviate from the 4 seconds. For example, an unexpected driver reaction time of -2 seconds means that TMS expects 4 seconds, but FRISO already follows the speed advice after 2 seconds.

$\boldsymbol{X_9} = \ Expected\ reaction\ time\ \{1, 4, 7, 10, 15, 20\}$ (s)

With this experimental factor, we quantify the effect of longer, expected, driver reaction time to the given speed advice by TMS in terms of the defined KPIs.

$\boldsymbol{X_{10}} = \ Unexpected\ reaction\ time\ \{-3, -2, 2, 4, 6, 8, 10, 15\}$ (s)

With this experimental factor, we quantify the effect of driver reacting times that differ from the expected reaction time of TMS, in terms of the defined KPIs.

Driver compliance is how often the speed advice is followed, instead of late reaction. Driver compliance is an adjustable disturbance in FRISO. We point out that the compliance is related to the quality of the advice. So, we also examine this factor in our simulation study. We choose the disturbance in discussion with drivers and FRISO ignores the speed advices for 30 seconds once every 15 minutes.

$\boldsymbol{X_{11}} = \ Driver\ compliance\ \{\text{Full compliance, partial compliance}\}$

With this experimental factor, we quantify the effect of drivers who periodically ignore the given advice by TMS, and keep their current speed, in terms of the defined KPIs.

We cannot adjust the *model parameters* found in the literature because these are "hard-coded" in the software. However, one setting exists, which we can adjust. This is the weight ratio of the cost function of the speed regulation module. The exact formulation is given in Section 3.2.2. This ratio determines the objective in the speed optimization step and can be either set to optimize for punctuality (weight 1) or optimize for energy efficiency (weight 0).

$\boldsymbol{X_{12}} = \ Weight\ ratio\ cost\ function\ \{0, 0.2, 0.4, 0.6, 0.8, 1\}$

With this experimental factor, we quantify the effect of different ratio of the weights in the cost function on TMS perform in terms of the defined KPIs (Section 3.2.2).

For a full factorial design, to also study interactions between the factors, we have to examine all possible combinations. A total of 3.8 million possible configuration combinations exist for these experimental factors. Because we need 20 replications (see Section 5.2.6) and one replication takes around 30 minutes, 215 years of computation time would be required. We choose for the *one factor at a time* approach to find solutions within the available time for this research. As the name suggests, we modify one factor and set the other factors on their default values (see Table 11). Therefore, we exclude the interaction between the different factors in this research. We only examine the interactions between the three external factors (Section 4.3.4). The *one factor at a time* approach requires 18 days of continuous computation time to complete all scenarios. We automate this procedure as shown in Appendix XIII.

Experimental factor	Location update interval	Train to TMS delay	TMS to Train delay	Expected reaction time	Unexpected reaction time	Weight ratio
Default values	5	5	5	4	0	1

Table 11: Default TMS parameters

5.2.3 Reports

We define the outputs of the simulation under investigation in this section. These are the performance indicators of the system. The most important output is the safety report with the number of unplanned stops. More safety indicators are the number of the yellow and red signals approaches that do not lead to a full stop. We also measure the stability of the advice given, which is the main topic of this research. Other Performance indicators are the punctuality and traffic flow, which are common KPIs (Key Performance Indicators) in the rail sector. The main categories are the following:

- *Safety* indicators, such as the number unplanned stops
- *Stability* of the speed profiles, such as the number of advices given
- *Punctuality* indicators, such as the maximum delays
- *Traffic flow*, such as the average driving speed

These categories consist of several KPIs whose definition and how we calculate them is given in Section 5.2.7. The output is spread over many directories and files, so we automate the analysis of the defined KPIs in VBA (see appendix XIV for the pseudo code). This is necessary to convert 6 GB of data spread over 3.000 directories and 30.000 files into 2000 usable replications and more than 60.000 performance indicators. After this process, we remove the outliers manually from the results. This is necessary because extreme outcomes are due to errors in the software where trains stop reacting to the speed advices and come to a complete halt. This problem can only be repaired by the software providers. We finally report significant differences in performance with the help of QQ-plots, the Shapiro-Wilk, Sign, and paired t-test. These methods are suitable for small samples (Shapiro and Wilk, 1964). We take the average of each KPI over each scenario for scoring, which we explain further in Section 5.2.8. Furthermore, we use correlation matrices to see the relationship between the experimental factors and the measured KPIs.

5.2.4 Scope and level of detail of the model

Simulating the entire rail network does not provide the necessary level of detail to illustrate the effects of our experimental factors on the speed advice. Also, it would require too much computation time and power. For our purposes, we use FRISO (Flexible Rail Infra Simulation environment) for a microscopic view of several important block-sections of the railways with many conflicts. The area consists of the ´s Hertogenbosch area and the surrounding stations. The complete representation of the simulation area is shown in Appendix XII. The level of detail is on the micro level to incorporate our experimental factors such as the effects of the external factors on train movements and the driver reaction time. The amount of work is significantly decreased by the pre-modelling of the network and the connection to databases containing the timetables, geological data, infrastructure, and safety requirements (e.g., required time between consecutive trains). Extensive validation and verification studies have taken place, and the model is continuously improved to represent the real infrastructure and rolling stock. We exclude extreme disruptions such as total rolling stock failure and collisions in this research because these extreme scenarios need custom measures taken by traffic control that fit the situation. The task of the TMS is to prevent the smaller disruptions into propagating through the network and reducing the spread in driving behaviour.

5.2.5 Assumptions

We make several assumptions during the design of our experiments. Our first assumption is that not using the specific values of adhesion, train occupation, and wind speed will lead to traction disturbances only and will not affect the driving behaviour. We expect drivers to be more careful when trains are fully occupied or drive on tracks with reduced adhesion. In case of implementing the external factors, we assume the optimal case where accurate calculation would be possible, and driver adjust their driving behaviour perfectly to the circumstances. These assumptions are common for simulation studies to find estimates for the effects. FRISO cannot simulate real driver behaviour (yet), and a simulator, rather than simulation study is the tool to find these effects. Another assumption is perfect driver compliance regardless of the quality of the advice. This assumption is necessary because this effect has not been quantified, and FRISO-TMS does not offer the option to conditionally accept speed advices. We base the "normal" disturbances in the simulation study, such as the entrance and departure delays, on the disturbances during 2013. To simulate the situation where the TMS is already implemented, we decrease the magnitude of all disturbances by 20%. This is the expected reduction in delays from TMS, based on the initial potential estimations on the Dutch network (de Vries, 2013). Finally, we compare the output of the simulation scenarios with the paired t-test. For these KPIs, we assume that the differences in the output are normally distributed.

5.2.6 Replications and warm-up period

Since the simulation covers a limited area of the network and starts with no trains, a warm-up period is necessary before interactions between trains start to matter, and the TMS is really tested. The warm-up period is exactly 1 hour of simulated time because of the cyclic timetable, each hour the trains follow the exact same schedule. One replication is a period of four hours simulated time and represents one rush period. This takes 30 to 40 minutes to complete on average. We determine the number of replications with the sequential method (Law and Kelton, 1991). The more replications, the better the estimation of the real mean of the output. The number of replications cannot be too large because of the long computation time. So, we choose a relative error to the real mean of 10%. We use the sequential method to determine the number of replications necessary. The sequential method determines the minimal number of replications to ensure, given a confidence level, the simulation mean does not deviate more than the relative error from the real mean. After performing this procedure for each KPI, 13 replications are sufficient to get the desired confidence level (95%) with the relative error of 10% for all KPIs. We decide to perform 20 replications to leave room for removing failed runs due to crashes (see Section 5.1).

5.2.7 PERFORMANCE INDICATOR DEFINITIONS

We classify the Performance Indicators (PIs) into 4 categories, namely: safety, punctuality, traffic flow and stability. We calculate these PIs for each replication using the output of FRISO-TMS, which we define in Table 12. We present an example to demonstrate how we calculate them.

	#	Performance Indicator	Definition
Safety	1	Next signal red	The number of trains that pass a yellow signal.
	2	Start braking for red	The number of trains that start braking for a red signal.
	3	Unplanned stops	The number of trains that come to a complete halt due to a red signal.
	4	Total stops	The sum of indicators 1, 2 and 3.
Stability	5	Advices/hour	Average number of changes to the given speed advice per hour per driver (see Figure 44).
	6	#excl. halts/hour	Same as indicator 7 only excluding the arrival and departure process.
	7	Against current	Number of advices that are against the current direction of acceleration. E.g., advice is to decelerate while the train is accelerating or vice versa.
	8	Against previous	Number of advices that are against the direction of last given advice.
	9	MAXMIN20	Number of advices that are either higher or lower than the begin current speed and the speed given speed advice in 20 seconds.
	10	MAXMIN30	Same as 9 only with interval T=30.
	11	MAXMIN60	Same as 9 only with interval T=60.
	12	MAXMIN90	Same as 9 only with interval T=90
	13	MAXMIN120	Same as 9 only with interval T=120.
Punctuality	14	Min delay	The earliest train.
	15	Max delay	The latest train (maximum delay).
	16	Early	The total time trains arrive too early
	17	Convergence	The total time the exit delay compared to entry delay has converged to zero (See Table 9).
	18	Divergence	The total time the exit delay compared to entry delay has diverged from zero (See Table 9).
	19	Total convergence	The difference between convergence and divergence.
Traffic flow and energy efficiency	20	Total run time	The total travel time of all trains from entry until exit, excluding planned stops.
	21	Energy	Total energy usage during the 4 hours represented by the Work ($Work(Joule) = Force(Newton) * \Delta distance(meter)$).
	22	Distance travelled	Total distance travelled by all the trains during the 4 hours of simulated time.
	23	Kwh/km or Kwh/v	Total energy usage divided by the travelled distance or the average driving speed, when we intentionally slow down the trains (weight ratio experiment).
	24	Average speed	Average speed of all trains.
	25	Avg. Duration	Average duration of the unplanned stops.
	26	Tot Duration	Total duration of the unplanned stops.

Table 12: Definitions of all performance indicators

To illustrate PIs 5-13 of Table 12, we use the example in Figure 38. The numbers in the figure show when an advice is given. The blue line is the advice speed profile and the red line is the simulated speed profile.

5. The number of advices given to this train is 11 during 900 seconds. So 11/900*3600= 44 advices per hour.
6. Same as 5, except that we exclude advice 1 and 11, so 9/900*3600= 36 advices per hour.
7. At point 8 an advice is given to accelerate and while the train is still accelerating an advice is given to decelerate. This would count as 1.
8. For this PI, we count how often the direction of the advice changes. So at point 3 the advice is to accelerate, at point 4 to decelerate, at point 5 to accelerate, at 6 to decelerate, 7 accelerate, 8 decelerate. So the advice is alternating in direction from point 4 to 8 and the PI is 5. From the data, we cannot make a distinction between advices given due to

speed restrictions and due to TMS decisions, so we count them all. Since we use the same infrastructure in all experiments and compare the KPIs relative this is not a problem.

9. This PI is the same as PI 10-13 and all of them measure the peaks in the speed advice for different time horizons T. For example, for T=120 we consider an advice instable when the current advice V_b=80 km/h at point 7 and 120 seconds later the advised speed is still 80 km/h (V_e). During the 30 seconds, however, the advice is given (point 8) is higher than either V_b or V_e. The same is true for advice 5. So, this indicator is 2 for this train.

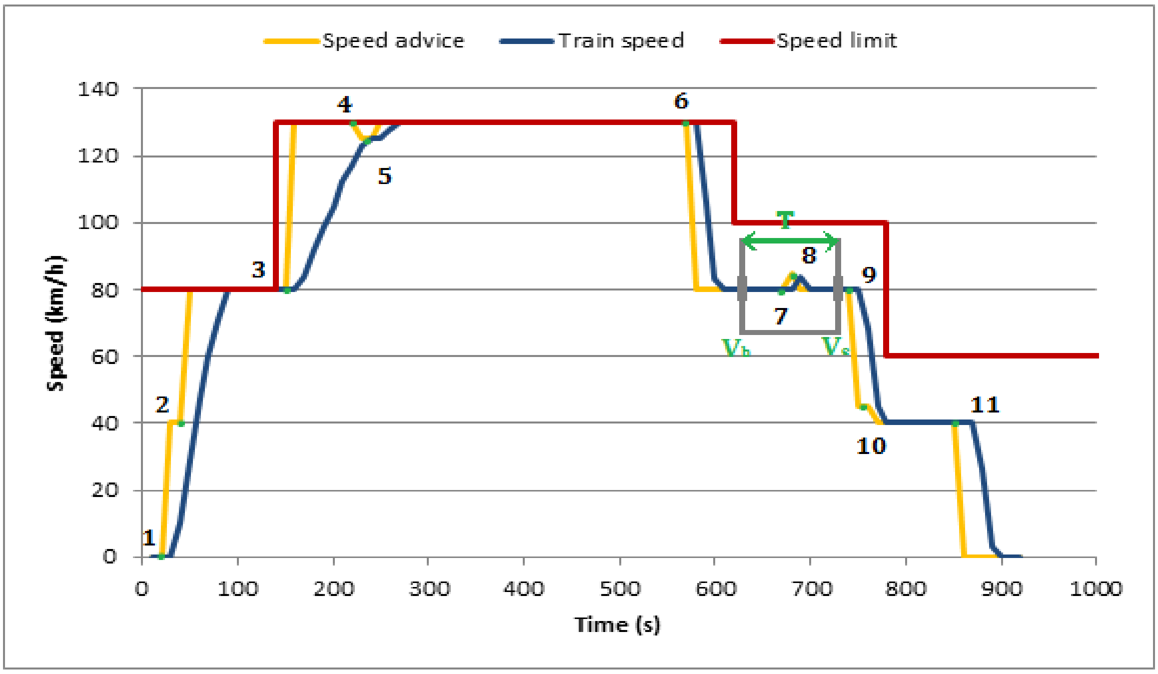


Figure 38: Example of instability of speed advice

Furthermore, we calculate convergence (PI 17) in the following way: if a train enters the simulation area with a delay of 40 seconds, but leaves the simulation with a delay of 10 seconds, we say the delay has converged 30 seconds to its original schedule. However, if a train enters the simulation area exactly on time, but leaves the area with a delay of 20 seconds, the train has diverged 20 seconds from his schedule (PI 18).

5.2.8 OBJECTIVE FUNCTION

The objective of this research is to find the experimental setting for which the TMS performs the best. We translate this objective in the following objective function for each experiment *i* with *n* replications:

$$\textbf{Objective} = \underset{i}{\textbf{Min}} \propto/n \sum_{i=0}^{n} SA_i + \beta/n \sum_{i=o}^{n} ST_i + \gamma/n \sum_{i=o}^{n} PU_i + \delta/n \sum_{i=o}^{n} TF_i$$

In the formulation above, the objective is to minimize the weighted score of the KPI scores. The KPIs concern *Safety, Stability, Punctuality* and *Traffic flow* of run *i* respectively. α, β, γ, and δ are the relative importance of the categories. We determine these weights using the Analytical Hierarchical Process (AHP) (Saaty, 1988) to translate the expert opinions of project leader, a driver, and the managing consultant of the innovation department of NS. Each of the KPIs consists of several sub performance indicators (e.g., number of unplanned stops as an indicator for safety, see Section 5.2.7). We use the AHP method to weigh these scores and get one final score for each category. We aggregate these scores into a single score for each category and eventually into the final score. This hierarchy is shown in Figure 39. We calculate the scores for the indicators from the simulation output. We normalize the scores in order to prevent indicators with small weights but high values to dominate. See Section 5.2.7 for the definitions of all indicators.

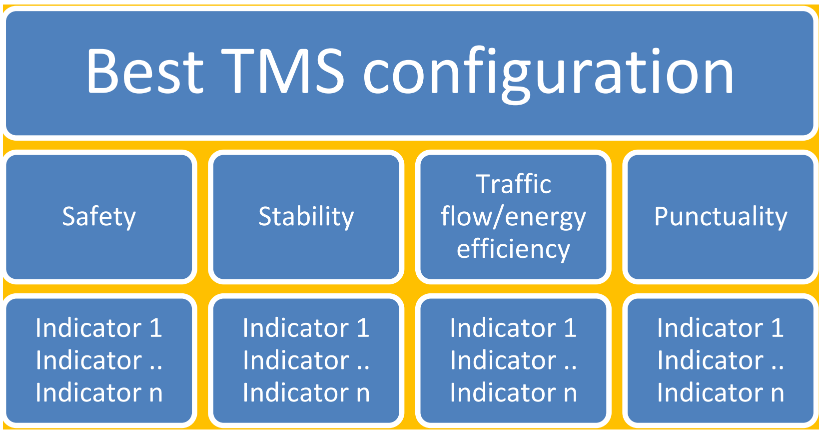


Figure 39: Hierarchy of criteria

It is important to note that this version of the TMS the objective is to minimize the cycle time. This means that if a train can go faster without delaying other trains, it will. The cost function in Section 3.2.2 shows that the objective function only punishes delayed trains. This is against intuition since the early trains are responsible for many unplanned stops in the current situation (Section 2.5). In this case, however, shorter cycle times mean capacity gains in the network, because trains release the tracks earlier, and other trains can follow faster.

In this chapter, the simulation scenarios and experimental design are given. The experimental factors are defined as well as the reports and indicators to assess the different scenarios in order to find the best set of parameter for the TMS. Furthermore, we determined the number of replications we need to get statistical significant results and analysis methods. Finally, the model assumptions and scope are described. We implement these scenarios into FRISO-TMS and discuss the simulation results in the next chapter.

6. Simulation results

In this chapter, we first perform the Shapiro-Wilk test for normality before we can compare the different scenarios in Section 6.1. We perform an experiment with the default parameter values and no extra disturbances due to external factors in Section 6.2. We use these results as a benchmark to compare the rest of the settings. Next, we describe the results of the scenarios designed in Section 5.2.2 and perform statistical tests to compare different parameter settings. We present the effect of the *data quality* in Section 6.3 and 6.4, the *time factors* in Section 6.5-7 and the *model parameters* in Section 6.8. We check whether the differences in performance are statistically different. We use the paired t-test and the sign-test with a confidence interval of 95%. Finally, we use the method described in Section 5.2.8 to score each replication in Section 6.9. For the exact definitions of the performance indicators, we refer to Section 5.2.7. We use the performance indicators that drivers and practitioners consider important, but also represent the effect of the experimental factors the most.

6.1 Shapiro-Wilk test

From this test, we deduce that, with a 95% confidence, the differences between the performance indicators are normally distributed. The KPIs that did not pass the Shapiro-Wilk test are:

- *Safety*: start braking for a red signal.
- *Punctuality*: min delay and max delay.
- *Traffic flow and energy efficiency*: energy/km, average speed, average and total duration of unplanned stops, and the total run time.

We use the sign-test for the KPIs that did not pass the Shapiro-Wilk test and the paired t-test for the remaining KPIs. We use these tests to see whether the differences in performance are statistically significant due to the experimental factor (e.g., the driver reaction time). Otherwise, we attribute the differences to the high variance in the output of the simulations. We present these results for each experiment and KPI in Appendix V. In the rest of this chapter, we briefly discuss the results of the experimental factors described in Section 5.2.2. In each section, we will identify what the major effects of the experimental factors are and the significantly changed KPIs compared to the default settings. In the results tables, blue cells are the default settings, green cells are significantly different, and red cells are not.

6.2 Default settings

This experiment is the benchmark for the rest of the scenarios. The settings are the default parameters chosen by the developers of the TMS. The disturbances are, as described in Chapter 5, the daily entrance and halt delays. The disturbances due to the external factors are not implemented, so as if TMS considers the exact effect of the external factors during rescheduling. We show the results of the performance indicators with the highest weights in Table 13.

Settings (s)					Results								
					Safety (#)	Stability (#)				Punctuality (min)		Traffic flow	
Train to TMS delay	TMS to Train delay	Driver reaction time		GPS interval	Unplanned stops	Advices / hour	Against Current	Against Previous	MAXMIN T=30	Conver-gence	Max delay	Kwh/ km	Avg. Speed (km/h)
		Expected	Unexpected										
5	5	4	0	5	3.0	50.2	3.1	10.5	4.3	58.7	5.0	72.8	92.1

Table 13: Results of the default settings of FRISO-TMS

6.3 EXTERNAL FACTORS

In Table 14, we summarize some of the mostly affected performance indicators due to the external factors (experimental factors $X_{1\text{-}5}$ in Section 5.2.2). We compare these results with the default settings, which represent perfect information about these factors to TMS during rescheduling. We present the results of the defect trains in Table 15. We choose to leave the KPIs on punctuality and traffic flow out of the comparison for the experimental factors which concern acceleration disturbances. This is because they reflect the performance decrease to the slower trains, and we cannot compare them to normal conditions. For example, the amount of energy usage is lower; however, this does not mean better energy efficiency, but only lower average speed. This is a disadvantage of our chosen method. A better comparison is to compare the outcomes with the scenario in which the TMS also uses the reduced acceleration power in the speed calculations. However, this is not possible in the current TMS version. However, we allocate the differences in the stability and safety KPIs to the difference in TMS expectations and simulated behaviour.

Settings	Results				
	Safety (#)	Stability (#)			
Experimental factor	Unplanned stops	Advices/ hour	Against Current	Against Previous	MAXMIN T=30
Default	3.0	50.2	3.1	10.5	4.3
Adhesion	5.6	63.0	6.4	15.0	6.4
Difference	87%	25%	106%	43%	49%
Wind	3.4	50.9	3.4	11.5	4.4
Difference	13%	1%	9%	10%	3%
Train occupation	3.1	50.5	3.4	11.2	4.3
Difference	3%	1%	9%	7%	0%
Combined effects	4.6	64.7	4.4	13.3	6.4
Difference	53%	29%	41%	27%	49%

Table 14: Results of the external factors on safety and stability indicators

6.3.1 ADHESION

As explained before, we translate the reduced adhesion (X_2) into disturbances in the acceleration performance of the train (Section 4.3.1). We enter these disturbances in FRISO while TMS still uses the original acceleration power, with good adhesion conditions, to predict the driving behaviour. From the results in Table 14, we see that these disturbances significantly add to the instability of the advice, but TMS also performs worse on safety. The average number of unplanned stops almost doubles and the instability indicators increase with 25-106%.

6.3.2 WIND

We enter the power of the wind (X_2) in the simulation in the same way as the adhesion coefficient (Section 4.3.2). We compare these runs with the undisturbed situation, which would be the case if perfect information would be available to the TMS during speed calculations. In the paired t-test, statistically significant difference in performance is found in the stability of the advice and the number of unplanned stops. These effects, however, are much smaller than the adhesion disturbances. The number of unplanned stops increases 13% and the stability KPIs perform up to 10% worse than the default conditions.

6.3.3 TRAIN OCCUPATION

The train occupation disturbances (X_3) occur when TMS uses a static occupation rate during rescheduling (Section 4.3.2). From the results, we see that this factor has no significant effect on the safety. There is a significant effect on some of the stability indicators. However, the effect of this factor is the smallest of the external factors. These results are in line with our expectations because the mass of the passengers is partially accounted for by the TMS, while the wind and adhesion are not. TMS uses a 60% occupation during calculations and the average occupation from our data is 47%.

6.3.4 COMBINED EFFECT OF ADHESION, WIND, AND TRAIN OCCUPATION

For this experiment (X_4), we use the combination of the disturbances with Latin Hypercube Sampling to reflect the underlying relation between the three factors (Section 4.3.4). For example, higher mass increases the force before the wheels start to slip since the friction force is higher. From the results, we conclude that the main effect remains the adhesion. The stability and the safety both deteriorate significantly to highly undesirable values.

6.3.5 DEFECT TRAINS

In this scenario (X_5), we examine the effect of a single train with 60% and 80% of its original traction power to see the effects on the total system. We adjust the acceleration power of a Sprinter (13600 series) in one experiment and of an InterCity (3500 series) train in another. We see that the influence of an Intercity train is slightly less than that of sprinter train. During the departure process, the train experiences the most trouble from the reduced acceleration power. So, we explain the higher effect on sprinters by the higher number of stops. None of the experiments shows significant differences in the number of unplanned stops. Still, some performance is lost in terms of stability, due to the fact that TMS does not receive information about the current status of the train (defect engine). We present the results of these experiments in Table 15.

Settings	Results				
	Safety (#)	Stability (#)			
Experimental factor	Unplanned stops	Advices/ hour	Against Current	Against Previous	MAXMIN T=30
Default	3.0	50.2	3.1	10.5	4.3
Defect InterCity 80%	3.0	50.3	3.3	11.1	4.3
Difference	0%	0%	5%	6%	1%
Defect Sprinter 80%	3.0	50.3	3.3	11.1	4.3
Difference	0%	0%	6%	6%	1%
Defect Sprinter 80%	3.2	51.0	3.5	11.4	4.5
Difference	8%	2%	11%	8%	5%

Table 15: Results of one defect train compared to the default settings

In Figure 40, we show the relative scores of all the external factors. We normalize the values by dividing them by the maximum value. Since the indicators are all undesirable, higher values are worse. It is interesting to see that the combined effects are not as bad as adhesion alone. We explain this effect by, for example, fully loaded trains, which help increase the friction of the wheels with the tracks. We present the other performance indicators in Appendix V.

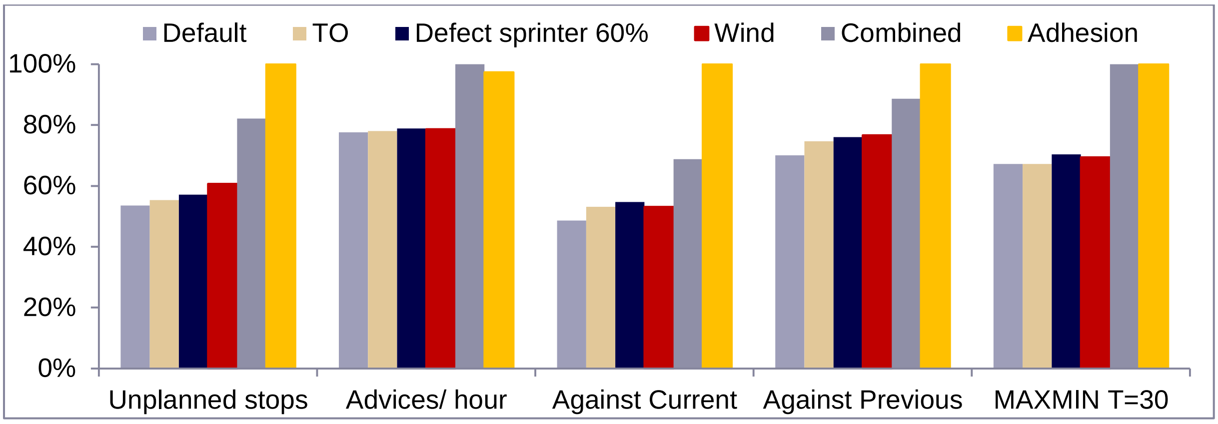


Figure 40: Relative results of some relevant KPIs due to external factors

6.4 Location update interval

The location update interval (X_6) has a significant effect on the most indicators. The most interesting result is the higher instability of the advice for lower intervals. The reason is that each time the train sends location updates; TMS will check for conflicts and tries to solve them. If the rescheduling algorithm finds a better schedule, new speed advices are sent. The results for different location update intervals are given in Table 16.

Settings	Results								
	Safety (#)	Stability (#)		Punctuality (min)				Traffic flow	
GPS interval (s)	Unplanned stops	Advices/ hour	Against Current	Against Previous	MAXMIN T=30	Conver-gence	Max delay	Kwh/ km	Avg. Speed (km/h)
1	3.8	83.2	3.5	21.2	10.1	46.5	12.2	15.3	85.8
3	2.6	58.4	2.9	12.9	5.6	60.8	4.9	15.9	92.3
5	3.0	50.2	3.3	11.1	4.3	62.2	5.0	15.6	91.2
7	3.7	47.8	2.4	10.1	3.2	61.0	4.9	15.4	90.3
9	4.6	46.9	2.1	10.1	3.2	59.4	5.0	15.3	87.9
10	3.9	50.0	3.7	10.6	4.0	59.8	5.2	15.6	87.8
11	4.6	46.3	1.7	9.5	3.2	58.3	5.4	14.9	87.0
13	4.5	45.3	1.1	8.7	2.1	57.1	5.8	14.8	85.4
15	5.4	46.5	1.3	9.1	2.3	56.3	5.9	14.3	80.3
17	16.0	45.0	9.0	9.1	2.5	54.1	6.9	13.8	73.4
19	24.0	44.8	8.0	9.2	2.9	51.4	7.5	13.3	69.4
Section occupation data	4.6	32.2	N.A	8.1	N.A	64.3	4.9	14.5	92.4

Table 16: Results of different location update intervals

However, smaller intervals between updates do not guarantee better results. The outcomes show that an interval between 5 and 10 seconds is sufficient to get good results. Even lower intervals only add to a more instable advice without significant improvement of the other KPIs. Higher intervals, however, significantly deteriorate the TMS performance in every aspect. In Figure 41, we see that the results stay steady on the 5-13 range. However, from the pairwise t-test we conclude that the 5 second interval performs better than the higher values. Compared to a 5 second interval, the 7 second interval results in a reduction of 5% in the number of advices.

However, the reduction comes at the expense of 23% more unplanned stops. A 3 second interval reduces the unplanned stops with 12% but increases the number of advices with 16%. The number of advices stops decreasing when the interval exceeds 13 seconds, while the number of unplanned stops starts to increase rapidly. From Table 16, we see that given the initial delay of a train the TMS is better at getting the train back on schedule on the 3-10 second interval (convergence). Also, the values for the maximum delay, the highest average speed (traffic flow), and energy efficiency (Kwh driven km) are the most desirable near the 3-10 second range of update interval.

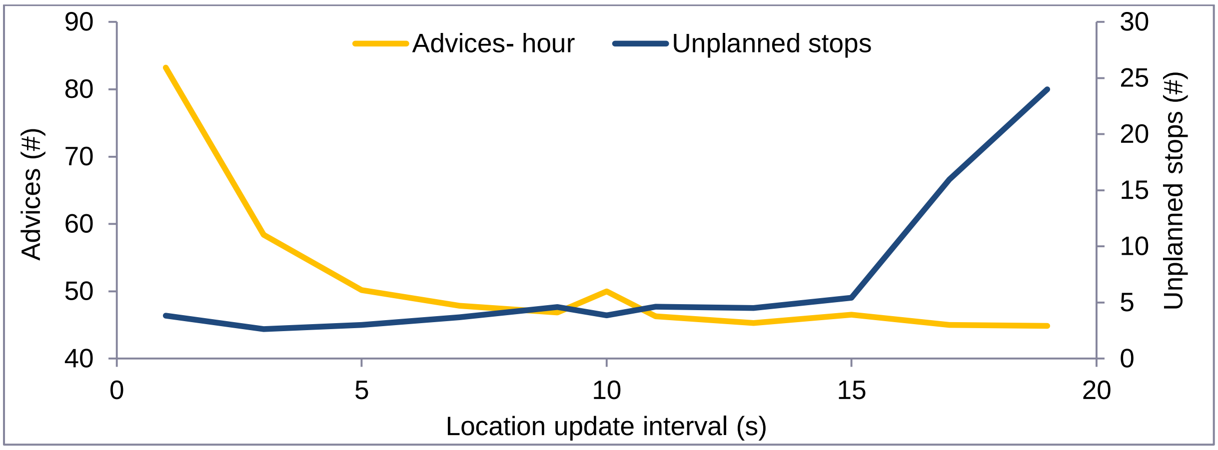


Figure 41: Location update interval effects on stability and unplanned stops

Furthermore, the difference between the section occupation data and GPS is examined. GPS data performs better than section occupation data on safety. The number of unplanned stops decreases, at the expense of more advices (50 per hour compared to 32 per hour). The performance of GPS data, however, deteriorates significantly when the intervals exceed ±13 seconds. A location update interval of 15 seconds performs significantly worse than section occupation data on all KPIs. However, not on the most important safety KPI, which is the actual number of unplanned stops. We note that the difference is not statistically significant due to the high variation in the performance, and the TMS performance is very unstable as a whole at higher location update intervals. The reason that the occupation data performs better is that the average time interval between detection points is 12 seconds on average. The intervals could be as high as 14 minutes, but those are on long block-sections where the trains drive a constant predictable speed. We do not calculate the number of advices that are against the current direction of the acceleration and the MAXMIN indicator for this detection method because TMS logs the speed only on discrete intervals which vary in length.

6.5 DELAY-LOOP

The delay-loop, from conflict detection until the driver following the speed advice, consists of several parameters. In this section, we evaluate the Train to TMS delay(X_7), the TMS to Train delay (X_8) and the driver reaction time. We discuss the driver reaction time in Sections 6.6, because, unlike the communication delays, it is not a technical factor, but a human factor. The statistical tests show that both stability and safety KPIs suffer from longer communication times between TMS and the train. These results are shown in Table 17. The relation to the number of unplanned stops and advices per hour is shown in Figure 42 for both factors. These results show that TMS is very sensitive to communication delays longer than 10 seconds. Since the computation time of TMS is 2 to 5 seconds, 5 seconds are left to actually deliver the speed advice back to the train.

Settings (s)		Results								
		Safety (#)	Stability (#)				Punctuality (min)		Traffic flow	
Train to TMS delay	TMS to Train delay	Unplanned stops	Advices/hour	Against Current	Against Previous	MAXMIN T=30	Conver-gence	Max delay	Kwh/km	Avg. Speed (km/h)
5	5	3.0	50.2	3.3	11.1	4.3	62.2	5.0	72.8	91.2
1	5	3.3	48.7	2.5	10.0	3.6	62.8	5.0	73.2	91.0
10	5	4.3	52.3	3.5	12.0	4.8	61.0	6.6	87.7	87.0
15	5	3.8	54.9	3.5	12.7	5.3	59.9	5.2	76.9	87.3
20	5	3.8	55.7	3.4	12.6	4.9	61.0	5.3	76.6	86.9
5	1	3.0	49.4	2.6	10.2	3.7	62.7	5.0	72.4	92.0
5	10	3.3	50.9	3.3	11.5	4.6	62.0	5.0	73.8	90.3
5	15	4.2	53.0	3.4	11.9	5.0	61.7	5.1	75.0	89.4
5	20	5.3	52.9	3.1	11.6	4.6	65.3	5.3	76.5	88.0

Table 17: Results of communication delays between the train and TMS

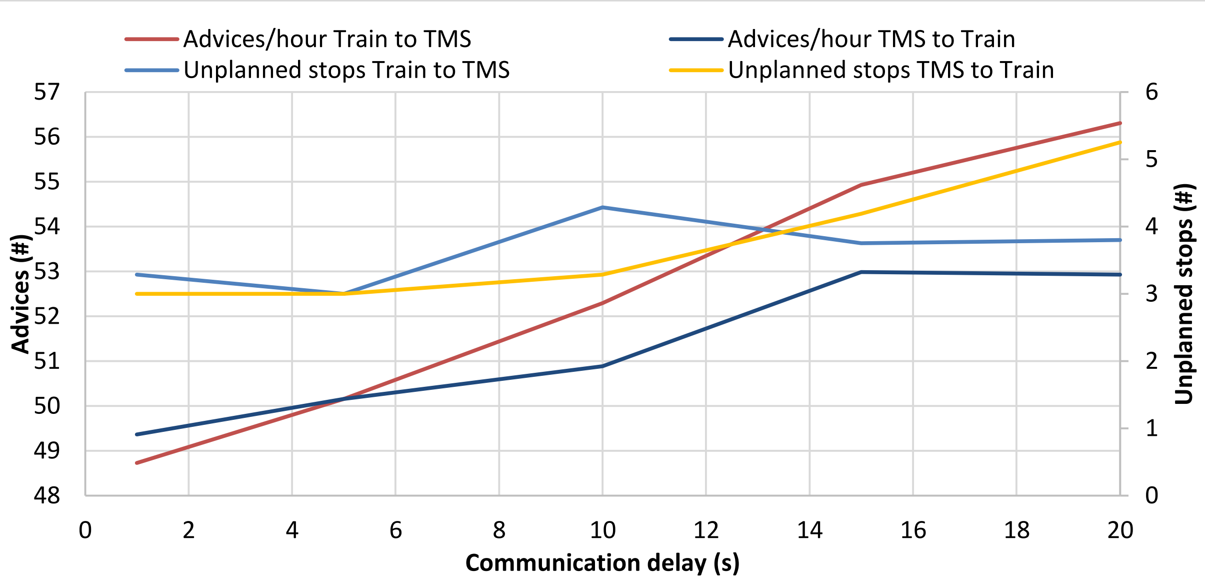


Figure 42: Effect of Train to TMS and TMS to Train delays on the stability and safety

The relative scores on all the KPIs are given in Appendix V. The results found are in line with our expectations, except the fact that the *TMS to Train* and *Train to TMS* have different effects. We would expect that no difference should exist as long as the total delay remains the same. Results show that a longer communication delay between the train and TMS is worse than the delay of the advice arriving from the TMS to the train, despite that the total loop remains the same. So, 5 seconds for the TMS to receive the message of the train and 10 seconds before the train receives the speed advice back, is better than the other way around. This is in conflict with the findings of the original authors (developers of the current TMS system. They report that: *"... different distributions of delays t1, . . . , t7 (Figure 20) giving the same sum s will produce the same results since, in any case, the TMS computes the advisory speeds based on the measure detected at time t, while these advisory speeds reach the trains only at time t + s."* (Mazzarello and Ottaviani, 2007). Further research revealed that the delays that are given as input do not represent the real delays in the simulation. Actual delays depend on the time steps of the HLA, which regulates the communication between FRISO and TMS. The Train to TMS delay is always a multiple of the HLA time step rounded up and the TMS to FRISO delay is a multiple of the HLA time step rounded down. Taking this into account, still we obtain different results for different configurations that should be rounded off to the same value. Discussion with practitioners revealed that the TMS does take the individual parameter values into account in the calculations, but FRISO rounds them off during execution. From this, we conclude that the difference in results comes from the fact that TMS uses the actual value of the parameters while FRISO rounds them off. To illustrate this, suppose we set the Train to TMS delay at 1 second and the HLA time step at 5 seconds. TMS assumes that the location data is 1 second old, whereas, in "reality", it is 5 seconds old due to FRISO rounding off to the highest multiple of the HLA time step. This is an implementation decision and should be re-evaluated to obtain more reliable results. The results in this report do not suffer from this, and the parameters are chosen such that the TMS uses the correct delays.

Another statement by Mazzarello and Ottaviani (2007) is: *"..The TMS operates in an efficient way even under severe traffic conditions and large loop delays (1 min)."* However the current implementation did not allow loops larger than 30 seconds. Experiments with loops between 25 and 30 seconds crash depending on the initial disturbances. We consider this to be an issue of the HLA architecture, which is still a prototype. Trains stop to follow the speed advices given by the speed regulator, which leads to the speed module crashing. No clear cause is found for this problem without access to the code of FRISO-TMS and further research by the developers is needed. Therefore, we only use a small portion of the simulation results in this.

6.6 Driver Reaction Time

From the results of this experiment, we see that the driver reaction time affects all the KPIs, and these deteriorate significantly as the driver reaction time increases. We divide the outcomes into two categories as mentioned earlier, the expected and unexpected driver reaction time.

Settings	Results								
	Safety (#)	Stability (#)				Punctuality (min)		Traffic flow	
Expected driver reaction time (s)	Unplanned stops	Advices/ hour	Against Current	Against Previous	MAXMIN T=30	Conver- gence	Max delay	Kwh/ km	Avg. Speed (km/h)
1	2.6	48.1	2.7	10.1	3.6	62.2	5.0	15.5	92.0
4	3.0	50.2	3.3	11.1	4.3	62.2	5.0	15.6	91.2
7	3.0	51.3	3.1	11.5	4.5	61.0	5.0	15.7	90.2
10	3.7	51.5	2.9	11.5	4.6	62.3	4.9	15.9	90.6
15	5.3	61.3	3.0	15.2	6.5	47.9	13.5	17.0	80.2
20	6.6	64.3	2.8	16.1	6.6	58.1	15.7	17.3	73.1

Table 18: Results of the expected driver reaction time

The **expected reaction time** (X_9) is when both FRISO and TMS get the same value for the driver reaction time. From the simulation runs, we see that higher driver reaction times add to the instability of the advice. In Table 18, the results of the expected driver reaction time are shown. We see that the KPIs concerning safety, punctuality and traffic flow perform worse when reaction times rise above 7 seconds. Driver reaction times lower than the default value (4 seconds) will lead to a more stable advice and possibly a reduced number of unplanned stops. Due to the high variance in the simulation results, we need more replications before we can proof the latter with certainty. The trend in the number of advices and unplanned stops is shown Figure 43. For the complete list of relative scores on all KPIs we refer to Appendix V.

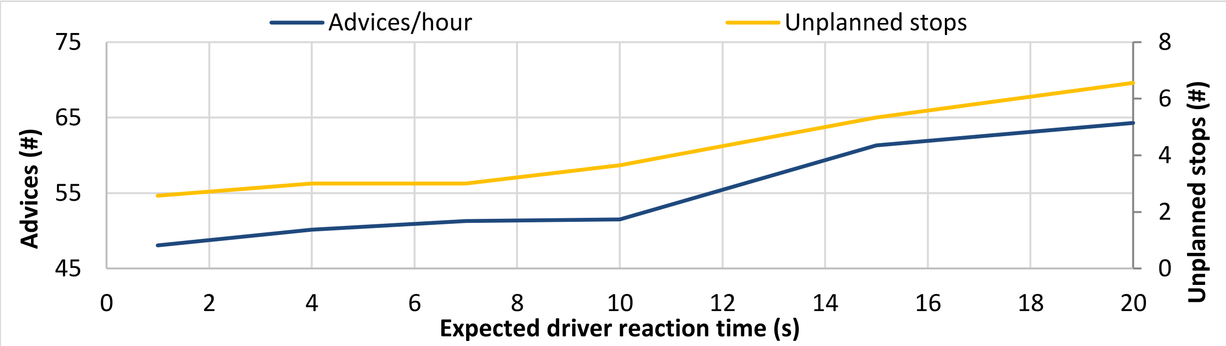


Figure 43: Effect of longer reaction times on the stability and safety

Settings	Results								
	Safety (#)	Stability (#)				Punctuality (min)		Traffic flow	
Unexpected driver reaction time (s)	Unplanned stops	Advices / hour	Against Current	Against Previous	MAXMIN T=30	Conver-gence	Max delay	Kwh/ km	Avg. Speed (km/h)
-3	3.0	50.5	3.2	11.3	4.3	62.5	4.9	15.7	91.7
-2	2.7	50.5	3.4	11.2	4.2	62.2	4.9	15.6	91.8
0	3.0	50.2	3.3	11.3	4.3	62.2	5.0	15.6	91.2
2	3.3	50.9	3.1	11.4	4.2	62.6	5.0	15.9	90.3
4	3.9	52.2	3.4	11.5	4.3	62.1	5.0	15.9	89.3
6	4.0	53.7	3.4	11.9	4.4	61.8	5.2	16.4	88.3
11	7.0	65.8	3.5	17.3	7.1	50.6	13.8	17.3	78.0
15	7.0	63.7	3.3	17.2	6.7	47.6	16.1	18.5	81.2

Table 19: Results of the unexpected driver reaction time

The unexpected reaction time (X_{10}) is tested by setting different values for the driver reaction time in FRISO and TMS. For example, an unexpected driver reaction time of -2 seconds means that TMS expects the trains to follow the advice after the default 4 seconds, while FRISO already changes the speed after 2 seconds. These effects are shown in Table 19 and Figure 44. The results show that small deviations from the expectation have small effects. Reaction times that deviate 4 seconds or more from the expected value start to perform worse on every KPI, including safety. These differences in performance are statistically significant. We also see that reacting faster than the expected value performs better. More than 2 seconds, however, leads to high variance in the simulation results, and we cannot draw conclusions.

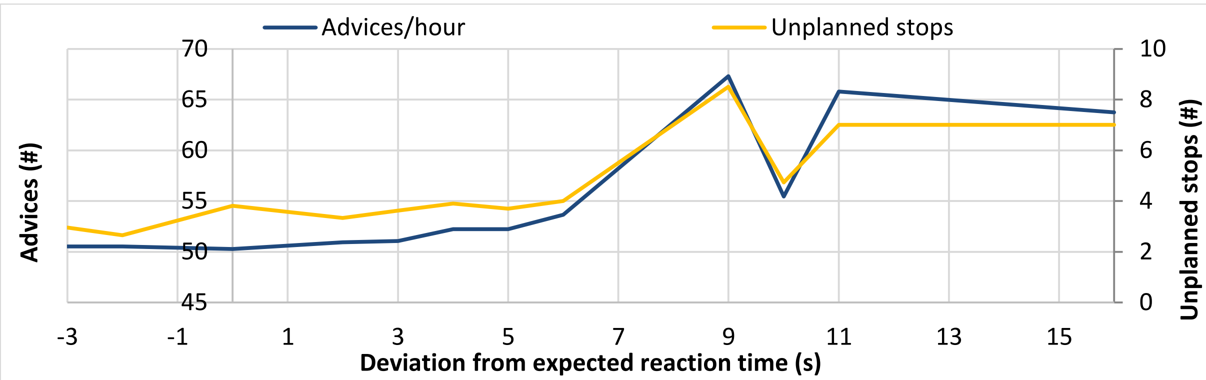


Figure 44: The effect of unexpected driver reaction time on the stability and safety

In Figure 45, we compare the expected and unexpected driver reaction times relative to each other and normalized (both divided by the highest value). In Figure 45, lower values are better for the first ten KPIs, but for the last three KPIs a higher value is better.

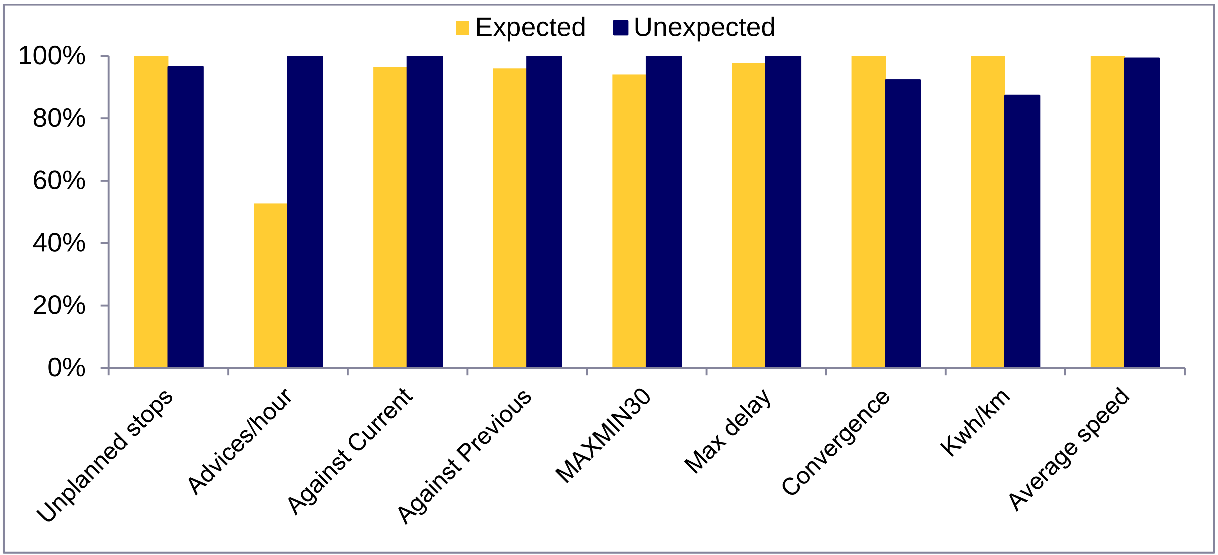


Figure 45: Relative results between expected and unexpected driver reaction time

6.7 DRIVER COMPLIANCE

We examine the **driver compliance** by letting FRISO ignore some of the advices given by TMS with a random interval (15 minutes on average) for a random period (30 seconds on average). So every 15 minutes, the drivers ignore the advices for 30 seconds. From the results, we find that driver compliance is a very important factor for the TMS performance. The impact on the number of unplanned stops is significant. Also, the advice stability, punctuality and the traffic flow are negatively influenced. The number of unplanned stops compared to full compliance almost triples. Instability indicators, such as the number of times the advice given is against the direction of the current acceleration during one replication, deteriorate with 8%. Other factors also deteriorate, but we could not complete enough successful replications to attribute the reduced performance to the noncompliance. The reason for this is that TMS crashes in many replications, depending on the initial disruptions. We consider this to be a problem of the current TMS version, which is a prototype and not due to the magnitude of the initial disruptions only. From several experiments, we see that the trains stop responding completely, but the exact reason could not be found. So, the results that we mention here are only preliminary and need further investigation before conclusions can be drawn with certainty. Still, the results emphasize that the compliance is important to fully benefit from the TMS.

Settings	Results								
	Safety (#)	Stability (#)				Punctuality (min)		Traffic flow	
Compliance	Unplanned stops	Advices/ hour	Against Current	Against Previous	MAXMIN T=30	Conver-gence	Max delay	Kwh/ km	Avg. Speed (km/h)
Full	3.0	50.2	3.3	11.1	4.3	60.7	5.0	15.6	91.2
partial	8.5	48.9	3.5	11.5	4.5	54.6	5.0	18.1	84.6

Table 20: Result due to driver compliance

6.8 COST FUNCTION WEIGHTS

The current TMS-FRISO implementation allows distributing the ratio between the punctuality and energy cost function. The default value chosen by the developers is 100%, which corresponds to all the weight on the punctuality term and the changes to the speed are unimportant. To investigate at what costs the energy savings would come, we examine several different ratios. The results are shown in Table 21 and show that the number of unplanned stops increases if we move the ratio toward energy efficiency. The best choice is to use a ratio of 80% since it performs better on stability. Even lower ratios lead to a higher number of advices, but perform better on other instability indicators that are more desirable from drivers' perspective (AHP weights in Appendix XV). On average, 4 unplanned stops occur at a ratio of 60% compared to 3 at an 80% ratio during one rush hour. The extra energy expenses would be € 15 on average during the simulated 4 hour rush period (at the current price 0.10 €/Kwh (Scheepmaker, 2012)). If we extrapolate this number to a year and assume this number is representative for the entire network, the extra relative costs would be € 400,000 yearly. We see that all factors have some sort of effect on the performance, may it be the safety, punctuality, stability or traffic flow. But we need to emphasize the state that the current TMS version is in. So, we argue that these numbers should be seen as relative scores rather than absolute values.

Settings	Results								
	Safety (#)	Stability (#)				Punctuality (min)		Traffic flow	
Weight Ratio	Unplanned stops	Advices/ hour	Against Current	Against Previous	MAXMIN T=30	Conver-gence	Max delay	Kwh/ km	Avg. Speed (km/h)
0	4.2	64.7	4.4	13.3	6.4	56.2	5.2	15.2	87.8
0.2	3.8	51.1	3.1	10.6	4.5	58.6	5.3	15.6	89.4
0.4	4.0	50.8	3.1	10.5	4.4	58.7	5.1	15.7	89.3
0.6	3.9	50.4	3.1	10.5	4.2	59.3	5.1	15.7	89.9
0.8	3.3	50.5	3.1	10.6	4.1	60.1	5.0	15.7	90.5
1	3.0	50.2	3.3	11.1	4.3	60.7	5.0	15.6	91.2

Table 21: Differences in performance for some weight ratios

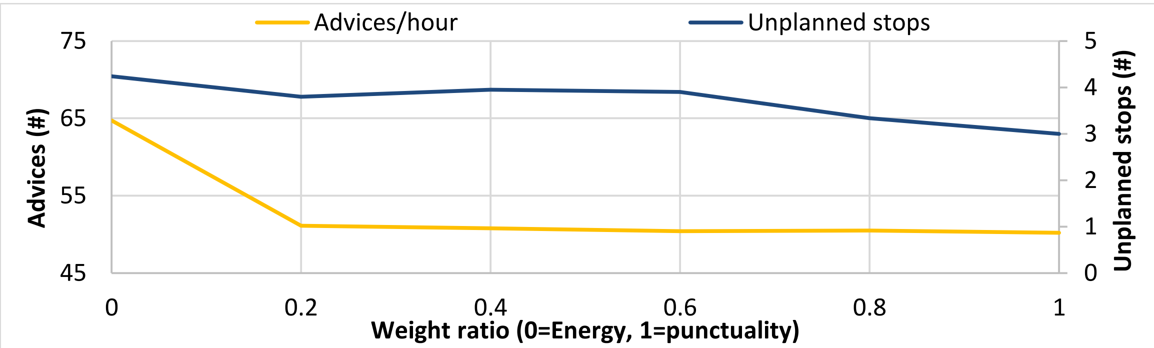


Figure 46: Effect of different weight ratios on the stability and safety

In Table 21, we present the differences in performance. The most interesting values are the average energy usage per driven km, the energy efficiency does not increase, and less delayed trains converge to their original schedule. We allocate the higher energy usage due to the higher average number of unplanned stops. So we see that using the slack in the timetable from the start to save energy will not always have the desired effects. In this case, we save no energy and get more unplanned stops.

6.9 AHP SCORES

The complete list of scores and ranking using the AHP method (Section 5.2.8) is shown in Appendix XV. However, we like to make some notes when interpreting the results. This method uses the averages of the KPIs over the replications. This leads to some parameter settings scoring high while these differences are not statistically significant due to the high variances. For instance, if we only look at the scores of the AHP method the final score of weight ratio 1 is better than the score of weight ratio 0.8 (Section 6.8). However, we see from Table 21 that the KPIs where ratio 0.8 scores better are statistically significant, while the KPIs where ratio 1 scores better are not. The AHP computes the scores using the average results and ignores the significance of the difference. We recognize this shortcoming of our scoring method; therefore, we use the final scores only as an indicator. We group the rankings per experiment, or comparable experiments. The best 3 parameter settings are given in Table 22. We rank the disturbances include all the external factors from most disturbing to least disturbing. So, integration with tribometers to measure the adhesion delivers the most performance gains. For the other factors, the first rank is the best performing value for the parameter. The unexpected driver reaction time is the difference with the default reaction time of 4 seconds. So, -2 means that the TMS expects a reaction time of 4 seconds, but the driver (FRISO) follows the advice after only 2 seconds. The driver compliance (X_{11}) is not shown in this table since only one scenario finished successfully. We conclude that the simulation results correspond to intuition. Fast communication and reaction times and accurate information about the external factors lead to more stable and safer traffic. Lower location update intervals, however, are beneficial to a certain level. Intervals below 5 seconds increase the instability significantly without improving the other KPIs. It is also interesting to see that TMS is better able to optimize punctuality than energy efficiency.

Scenario	Integration ($X_{1\text{-}5}$)	Location update interval (s) (X_6)	TMS to Train delay (s) (X_7)	Train to TMS delay (s)(X_8)	Driver reaction time (s)		Weight ratio (X_{12})
Rank					Expected (X_9)	Unexpected (X_{10})	
1	Adhesion	5	1	1	1	-2	1
2	Wind	7	5	5	2	-1	0.8
3	Defect train	3	10	10	4	0	0.6

Table 22: Ranking of the different experiments using AHP

In this chapter, we identified which factors affect which performance indicators and the magnitude of these effects. We see that each factor influences at least one KPI, and we see for which values the FRISO-TMS performs the best. Finally, we ranked each experiment in order of best performing setting. In Chapter 7, we draw conclusions from these results and make some recommendations for testing and implementing TMS regarding model parameters, but also regarding driver motivation. Finally, we provide some topics for future research in Section 7.3.

7. Conclusions and recommendations

The goal at the start of this research was to find which factors influence the stability of the speed advice. From the results of Chapter 6, we draw conclusions about the effects of the identified factors on the performance of the TMS and answer our research questions in Section 7.1. In Section 7.2, we make recommendations to improve the current prototype to a fully functional system, which improves the operations without overwhelming the driver with information. Finally, we discuss some topics for further research in Section 7.3.

7.1 Conclusions

In this section, we repeat the research questions stated in Section 1.2 and draw conclusions from our research to answer them.

Question 1: How is the rail network organized and the traffic controlled in the current situation?

The goal of this question is to get insight into the current organization of traffic control at NS, which is the subject of Chapter 2. We have seen that the operational control is mainly offline and does not prevent delay propagation actively. Traffic controllers and drivers are part of different companies and have different goals. However, our biggest concern is the communication between TC and drivers, which is mostly through the signalling system. Verbal contact is possible but is inconvenient and prone to errors. Many different parties are involved during bigger disruptions. They all need to cooperate to resolve the problem and inform the passengers correctly. Small disruptions and non-transparent allocation of time-slack in the timetable results in huge variations in driver behaviour and travel times. Experienced drivers know that there is slack and adjust their speed, while others will drive as fast as possible to be on time. This is highly undesired, because if drivers do not use the time-slack available, they arrive too early. This in turn leads to millions of red signal approaches yearly that are undesirable from the perspective of safety. Red signal approaches are also undesirable from the perspective of punctuality, operational costs, passenger comfort, and rail capacity.

Question 2: What information is currently available in the literature on online traffic control regarding different methods and rescheduling stability?

Nearly all the literature reviewed in this research points toward some method of providing additional information to the driver. We found three levels of sophistication. First, Driver Information Systems, then Driver Advisory Systems, and finally Automated Train Control. This seems to be the correct evolutionary path in a conservative environment. We focussed on the advisory systems, which recognize three possible measures are possible during disruptions, namely re-ordering, re-routing and re-timing. From the rescheduling methods proposed, the Alternative Graph Formulation is the one most widely discussed. Researchers divide the online traffic management problem into two parts to reduce complexity and provide solutions in real time. First, the conflict resolution module determines the optimal order of trains and the corresponding starting times of the operations. Second, the speed module calculates the speed profile in order to reach these goals. For the speed regulation, several degrees of sophistication are available, but most researchers prefer heuristic methods over the optimal solution for the sake of computation time. The scarce literature on the robustness of the speed advice provides three factors which are responsible for the instability. The first factor is the ability of the TMS to predict the future state of the system, which depends on the available data. The second factor is the time between detection of a conflict and the eventual actual changes completed. The third factor concerns the scheduling algorithm itself, such as the implemented tolerances and weights. We refer to Chapter 3 for the full discussion of this topic.

Question 3: How significant are the effects of factors that influence the driving behaviour of the trains and should be included in the simulation study?

The prediction of the future state of the system is very important, since deviations lead to new rescheduling iterations and changes to the existing speed profiles. The classic saying garbage in, garbage out applies to this part of the problem. We divide the factors that influence the driving behaviour of the train into two categories: static rolling stock specifications and external factors. Errors arise from wrong input data about the static rolling stock specifications, which are considered to be uniform among all trains. We also considered external factors, such as the adhesion and wind. To quantify these effects, we model the train movements and incorporate these factors in the calculations to see how sensitive the performance of the train is to them.

Question 3a: What is the effect of imperfect rolling stock data on the driving performance?

We conclude from the sensitivity analysis that even if the rolling resistance doubles, the extra time needed is only 0.3%. The effect of the air resistance is even less as shown in Table 23. We discuss the complete results in Section 4.2. Also, drivers and engineers were questioned about these effects. Both share the view that these effects are very small, and other factors have a much bigger impact. These factors are driver behaviour and weather conditions. We conclude that imperfect rolling stock data has no significant impact on the performance, and we exclude them from our simulation study.

Question 3b: What is the effect of external factors on the driving performance?

The external factors have a high impact on the travel times. The extra travel time needed is shown in Table 23. We exclude interaction with other trains and driver behaviour. So, all travel times are theoretical minima. The examined external factors are adhesion, wind, train occupation, and possible defects in either the train or power supply. In most cases, the extra travel time could be absorbed with the time-slack in the timetable. However, no additional flexibility is left, and any other small disruption will propagate through the network. Therefore, we include the external factors in our simulation study to examine the effects. To quantify the effect of the external factors on the performance of TMS we use the available data about these factors as input in our driving model. We fit the probability distribution of the effects of these factors on the driving performance, which we use as input for the simulation.

Train Occupation		Air resistance		Rolling resistance		Wind speed		Adhesion		Reduced power	
Value	Effect	Increase	Effect	Increase	Effect	Speed	Effect	Reduction	Effect	Reduction	Effect
25%	0.6%	**50%**	0.1%	**50%**	0.2%	**25 km/h**	0.5%	**12.5%**	3.0%	**12.5%**	1.7%
50%	1.1%	**100%**	0.2%	**100%**	0.3%	**50 km/h**	1.2%	**25%**	7.0%	**25%**	3.9%
75%	1.6%	**150%**	0.3%	**150%**	0.5%	**75 km/h**	2.4%	**37.5%**	12.5%	**37.5%**	7.0%
100%	2.2%	**200%**	0.5%	**200%**	0.6%	**100 km/h**	4.0%	**50%**	20.2%	**50%**	11.6%

Table 23: Extra travel time needed due to external factors

Question 4: What are the effects of the factors that influence the train performance on rescheduling stability and the number of unplanned stops?

The performance of the TMS is negatively influenced by these external factors. In the simulation study, all external factors affected the stability of the advice. For the train occupation and the defect train, the extra advices are sufficient to maintain the same number of unplanned stops. However, TMS cannot prevent extra unplanned stops for the wind and adhesion disturbances, and the unplanned stops increase with 13% and 100% respectively. We conclude that integration with current systems available would improve the performance of the TMS in terms of stability and safety. Especially the adhesion coefficient and wind speed should be included in speed regulation module of the TMS. Data about the number of passengers on board and the reduced power affect the stability of the advice, so including these factors in TMS will be valuable. However, if we assume that instability of the speed advice does not affect driver compliance, the effect on the safety is negligible. This assumption is necessary because we do not know the exact effects of the instability on the driver compliance.

Question 5: How much communication is necessary between the trains and TMS to maximize stability and minimize the number of unplanned stops?

The communication between the train and the TMS consists of location updates from the train to the TMS and the speed advice back to the train. We also examined what the effect of the communication delay is on the performance of TMS. We conclude that more frequent communication does not necessarily provide better performance. For example, we see that an update interval of 1 second for the location and speed increases the number of advices to the drivers without performance gains. We discuss these factors in sub-questions 5a and 5b.

Question 5a: What is an appropriate interval for location updates of the trains to TMS?

One of the most important factors for the performance of TMS is the location update interval. We compared several GPS update intervals and the current detection method (section occupation data). Results show significant differences in performance between different GPS location update intervals. We conclude that with an update interval between 5 and 10 seconds overall performance will stay steady. Still, the 5 second update interval performs the best in our simulation study when we take all KPIs into account with the AHP method. Better performance, in terms of unplanned stops, can be achieved with even lower intervals (3 sec) at the expense of the stability of the advice significantly decreasing. Another benefit of lower location update intervals is a higher average train speed. This is a measure for traffic flow and possible capacity gains on the tracks without the need for infrastructure investments. We compared implementing GPS to the current detection method, and we conclude that we can reduce the number of unplanned stops with 35%. Not using GPS data also has a negative impact on the traffic flow, energy efficiency and punctuality. However, the advice changes less frequently since only the infrastructure detection points initiate rescheduling. Location update intervals of 15 seconds and higher perform significantly worse in every aspect than the current detection method, which updates every 12 seconds (on average). From these results, we conclude that short intervals are not necessary on longer block-sections where the speed is constant and predictable. Finally, we conclude that each location update initiates the rescheduling process. This leads to the instability of the speed advice because each time TMS can reduce the total delay the speed algorithm will recalculate the speed advice. Stability of the speed advice is only considered in the second (speed regulation) step of the rescheduling process and the first step (conflict resolution) only considers delays. Thus in the current design of TMS the location update interval is also the rescheduling interval.

Question 5b: What is an acceptable communication delay between the train and TMS?

The delay-loop and the individual components are also a significant factor for the stability as well as the safety, punctuality, energy efficiency, and traffic flow. Although the effects are not as large as the factors discussed before, these effects are still significant. We conclude that the communication delay will not be an issue for the safety since the performance of TMS does not suffer significantly from delays up to 10 seconds. It is possible to keep the actual transmission time of the communication delays low with current GSM-technology. We conclude that the Train to TMS delay affects the performance more than the TMS to Train delay. For this reason, a longer computation time might be allowed if the solution found by the scheduling algorithm is better. A more sophisticated method, such as the Branch and Bound algorithm of D'Ariano et al. (2007) is, therefore, possible. This method is an alternative for the AMCC heuristic (current method) and finds the optimal solution more often in the conflict resolution phase (Section 3.2.1).

Question 6: What are the effects and magnitudes of driver reaction time and compliance on rescheduling stability and the number of unplanned stops?

Driver reaction times, whether expected or unexpected, affects the performance of the TMS significantly. An expected delay of 8 seconds has a significant negative impact on nearly all KPIs. An unexpected delay performs even worse. This is only a problem when the discrepancy between what TMS expects, and drivers really do, is consistently wrong. We conclude that driver reaction time should remain below 8 seconds while the input parameter for the TMS should not be more than 2 seconds longer from the real reaction time. The most undesirable results are from drivers who ignore some of the given advices completely. From these results we conclude that TMS alone is not sufficient, but also the stability of the advice is very important. We argue that the stability of the speed advice is a measure for the quality, which is directly related to the compliance of the drivers.

Question 7: What are the effects and magnitudes of TMS parameters on rescheduling stability and the number of unplanned stops?

This question remains partly unanswered. We identified many factors in our literature review, which could affect the rescheduling stability. The magnitudes, however, cannot be quantified because we cannot adjust these factors in the current FRISO-TMS version. These factors are, for example, the tolerance bandwidth, the rescheduling initiation method, and the planning horizon. We discuss these in Section 7.3 where we provide recommendations for future research. One factor, which we could examine, is the weight ratio in the cost function of the speed module (Section 3.2.2). We conclude that TMS does not perform well with a low ratio. A low ratio means more weight on energy efficiency than on punctuality. The energy savings through lower train speeds are offset by extra energy needed for acceleration due to more unplanned stops. From the increased number of unplanned stops, we also conclude that TMS performs better when the trains do not start to use the time-slack available in the timetable immediately after departure. This time-slack gives TMS additional flexibility in case new disruptions occur.

We summarize the results of the experiments in Table 24 to give an overview of the effects. In the recommendations column, we summarize the recommendations and refer to the number of the recommendation in Section 7.2 for elaboration. The values in the summary column are upper bounds of the parameter before performance starts to deteriorate very fast. The optimal values for the parameters are shown in Table 22. We give a range of values in Table 24 for the settings of TMS since, for example, an unexpected driver reaction time of -2 is found to be the best performing setting. This is hard to achieve, and therefore, the given boundary is more useful. The scores in the table are on a 5 point Likert scale relative to the original default settings (Table 11) and no disturbances due to external factors.

Factors \ KPI	Stability	Safety	Punctuality	Traffic flow	Recommendation	
					Summary	#
Adhesion	--	--	--	--	Integrate	1, 10
Wind	-	-	o	o	Integrate	1, 10
Train occupation	-	o	o	o	Optional	1, 10
Combined effects	--	--	--	--	Optional	1, 10
Defect train	o	o	-	o	Optional	1, 10
Location update interval	-	-	-	-	≤13 sec	2
Train to TMS delay	-	-	-	-	≤10 sec	3, 10
TMS to Train delay	-	-	-	-	≤10 sec	3, 10
Expected reaction time	--	-	-	-	≤8 sec	4
Unexpected reaction time	--	--	--	--	≤2 sec	5
Driver compliance	--	--	--	--	Maximize	6, 7
Weight ratio cost function	+	o	-	+	≥0.8	8, 9, 10, 11

Table 24: Summary of the influences of the different experimental factors

7.2 RECOMMENDATIONS

We considered many different scenarios and factors, and come to the conclusion that all the examined factors influence the performance of TMS to some extent. We were not able to examine some of the parameters and could not get a full resolution of the effects due to software limitations. However, we developed a good understanding for how TMS works and reacts in different scenarios. This allows us to make some recommendations to improve the performance of the TMS. Table 24 can be used as a reading guide for the recommendations. Recommendations 12 and 13 concern the implementation phase.

1. *Integrate the information systems already available at NS with TMS.*

The conditions and the rolling stock are neither uniform nor static. Using static values for strategic and tactical planning is sufficient, but we need accurate data for online operational control to provide feasible and stable schedules. We recommend including the adhesion coefficient and wind speed in the calculation of the train dynamics since these two also have a significant impact on the number of unplanned stops. Integration with the Real Time Monitor and passenger count systems mostly affects the stability of the advice. So we consider them less important than other external factors. However, from the literature (Bonsall et al., 1990) we conclude that the quality of the advice is related to the compliance with the advice. Since the driver noncompliance has negative effects on the safety, we also recommend considering integration with the Real Time Monitor and passenger count systems in the future. We argue that when the amount of traffic increases, these will become more important and integration in the design phase will be the most economical choice. If not available or needed now, they will be in the near future if NS pursues operational excellence. The recommendation is to, at the very least, consider these factors during the design phase to prevent future costs. Other possible benefits of integration are:

- Dynamic priority rules for the TMS based on the train occupation.
- Detection of the actual train combination, which deviate from the planned combination 20% of the time (Prompt, 2012).
- Reduced adhesion is directly known to all drivers and traffic control.

2. *We recommend investing in GPS systems with update intervals of 5 seconds.*

Real time control needs real time data, so we recommend investing in GPS systems for all trains. According to our results 50% additional unplanned stops occur with the current detection method compared to GPS. We argue that GPS should not replace the current detection method, but both methods should be complementary to one another. Even the best GPS-modules are prone to errors due to radiation and signals in the air. TMS should use the current detection method, which relies on physical detection of the trains, together with the GPS to verify the exact location. This is even more important as GPS location and speed are not completely accurate. To illustrate this effect we visualize some speed profiles in Google Earth (Figure 47). We see that some trains do not appear to be running on the tracks, and one train is even driving through the headquarters of NS. In Figure 28, the (in)accuracy of the speed sent by the GPS-module is shown (Section 4.2).

Figure 47: GPS locations of actual trains in Google Earth

In the current implementation of FRISO-TMS, each time location updates initiate rescheduling algorithm and TMS checks whether a better solution exists. Thus, a location update interval of 1 second gives highly instable speed profiles. We argue TMS performs better if TMS uses the location data differently. The measured data should be aggregated to make a better estimation of the location, speed and acceleration. Better estimation of these parameters allows better extrapolations of the location of the train instead of initiating the conflict resolution algorithm based on one measurement.

3. *We recommend investing in communication equipment with short transmission times.*

Our results show that communication delays up to 10 seconds are acceptable. However, TMS can use the reduced communication delays for longer computation times. This allows more sophisticated algorithms than the current AMCC heuristic. For example, we can implement the Branch and Bound algorithm of D'Ariano et al. (2007), which provides the optimal solution more often than the AMCC heuristic. Especially combined with the *static implications* to reduce the problem size. Other possibilities to use the extra computation time are:

- Consider a longer planning horizons
- Take the stability of the advice into account during conflict resolution
- Take more factors into consideration for the speed advice such as adhesion
- Optimize the speed advice using optimal control theory.

These methods are computationally more demanding, but provide better solutions.

4. *For optimal performance, drivers should react to the given advice within 8 seconds.*

We recommend to train, motivate, and involve drivers in the design to achieve this goal. It is very important to make drivers aware of the effects of their behaviour, and show that the TMS is not very useful without their effort. The trust of drivers in the system depends on the performance of the TMS, and vice versa. So, it is important that drivers are aware of their own influence and the other factors that affect the stability. If they are aware, they can compensate for these factors by relying on their own craftsmanship and expertise. For example, if the wind speed is not taken into account by the TMS, it will take the train longer to reach the advised speed. If drivers are aware of this, they can decide to accelerate to a higher cruising speed to compensate for lost time. This way, drivers know what to expect from TMS and what is expected from them. Furthermore, we recommend to not only show the current advice, but also the next. This is common in navigation equipment, which announce the next advice and driver can prepare to react quickly. See Figure 48 for an example.

5. *Overestimation of the reaction time is better than underestimation.*

Especially when the reaction time is consistently underestimated the performance of the TMS decreases significantly. We recommend starting with a worst-case reasonable value for the reaction time (8 seconds). It is possible to adjust this value to the level of individual drivers based on empirical data when TMS is actually implemented. This is necessary because driver behaviour is not uniform, and their reaction times depend on several factors such as age, motivation, and circumstances. From our perspective, it is wrong to consistently expect a driver to react, for example, after 4 seconds when he normally reacts after 8 seconds.

6. *We recommend involving drivers in the design phase for maximal motivation.*

The end-users should be in charge of what information is useful to successfully anticipate on the surrounding traffic. Their perspective should be included on the trade-off between instability and performance, but also to provide them with insight in their role in the performance. Driver motivation is directly linked to the performance of TMS.

To determine the exact layout and the available information we need the opinion of the drivers, since only they know what they need and what works for them. In our opinion, there is also no "one size fits all" in this age of mass customization. More than one layout and functionality should be available to drivers to choose from, a layout or functionality that fits best to their personal needs and preferences. A conservative driver might prefer to see a single advice, while others might want to have maximal information available to perform the best they can. This personalization will support the acceptance of the system by the drivers. The level of sophistication can be gradually increased to allow the drivers to first get used to the basic functions. Other additions such as crossings and altitudes could be added later.

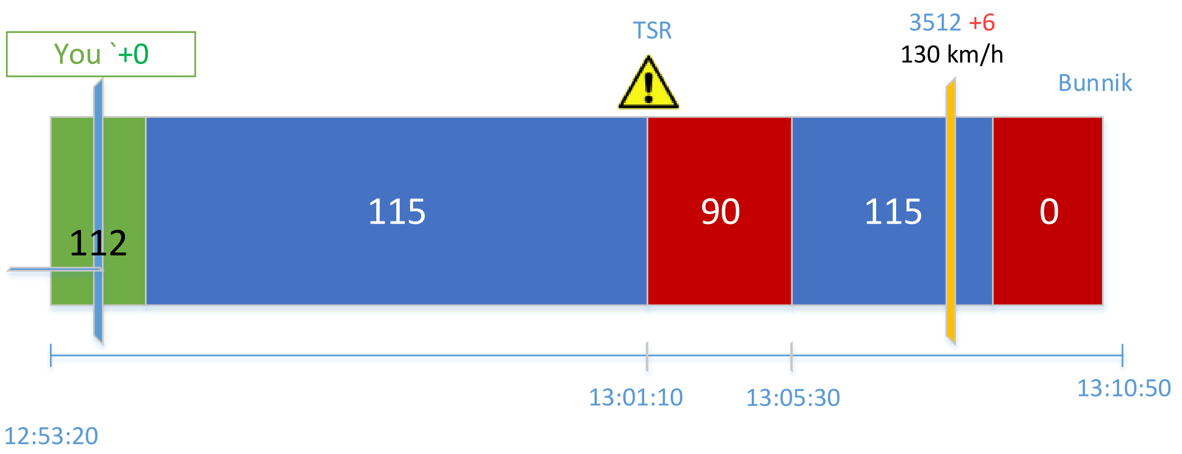


Figure 48: Example of a possible visualization fo the speed advice on a DAS (Driver Advisory System)

To improve the compliance as well as the reaction time, we also recommend announcing new speed advices beforehand. A similar approach as navigation systems is possible. Announce directions and when they should be followed beforehand to allow the driver to anticipate. In our opinion, it is also a matter of presentation of the advices that determines how effective they are. Minimal information should have maximal content. We give the following example in Figure 48, which combines the information available in RouteLint (Section 3.1), the timetable, temporary speed restrictions (TSR), and the speed advice, including tolerances. This way, the driver has all the information he needs in one place. On the left, the current speed of the train is given (112 km/h), and the width of the bar is the tolerance. As long as the driver stays within this tolerance, he will not disturb other trains, and he will be on time. Of course, this margin becomes narrower if he keeps driving 112 km/h instead of 115 km/h and eventually initiates the rescheduling algorithm. Also, the tolerances should be dynamic: narrow on critical points of the network, while less critical sections should allow autonomy of the driver. This distinction and, more importantly, the communication of these critical points to the driver, can increase driver satisfaction and compliance when it is most needed.

7. *The interface of the TMS should allow feedback from the driver back to traffic control.*

Many researchers emphasize the importance of communication between the controllers of the system. The TMS helps traffic control to make new schedules and translates these to speed advices to the drivers. Drivers should be able to provide feedback about the quality of these decisions. If the advice is unrealistic or cannot be followed for any reason that might affect the system for a longer period, such as fog or people walking next to the tracks. The DAS can facilitate the communication in a standardized manner by giving the option to report back to all traffic controllers and close the communication loop (Hale, 2003).

8. *The weight ratio in the cost function of the TMS should be set toward punctuality.*

We conclude that driving faster from the start provides flexibility to the TMS to prevent additional conflicts. Driving with a reduced speed from the start leads eventually to more unplanned stops. Therefore, energy savings due to the lower driving speed is offset by the extra energy needed to re-accelerate due to more unplanned stops. The stability of the speed advice does improve when we move the weight toward energy efficiency. This is because the speed regulation (SR) module of TMS penalizes speed changes. If NS decides to use the current TMS, we recommend setting the ratio between punctuality and energy efficiency to 0.8 (toward punctuality). This ratio performs better than the current ratio of 1 in terms of stability, while no significant loss in punctuality or safety is found. An alternative is a coasting strategy similar to UZI (Section 2.3). As the research of Lüthi (2009) points out, when a conflict is detected too late the option to speed up the train is no longer effective or feasible. The UZI strategy starts with speeding up to maximum speed, and therefore maintains the slack in the travel time. When the driver is certain that he does not need the slack anymore, he can start coasting to save energy. This strategy is a very good trade-off between punctuality and energy efficiency. The shortcomings of UZI are that it is static and only works in undisturbed situations. These shortcomings can be overcome with TMS. Another benefit of such a strategy is that drivers are already familiar and trained with it, so adapting will be easier.

9. *The stability of the speed advice should be part of the objective function in the scheduling algorithm.*

We expect the stability and overall performance of TMS to increase if the conflict resolution (CR) module penalizes speed changes. The reason is that the current objective of the TMS during rescheduling is to reduce the total amount of delay. The SR module only allows two speed changes to achieve the time/speed goal that the CR module calculates. However, this means that the SR can give two speed advices each time the CR determines new goals. So, the stability is only considered after the rescheduling process, while it is already affected by the CR. We recommend considering stability already during rescheduling instead of the AMCC heuristic, which only considers maximum total delay. We argue that the delay is not the most important factor, and the cost of avoiding delay must be considered as well. The exact formulation and weights still need further investigation since these parameters are hard-coded in the current TMS. We think that these optimization goals are not a static choice, and different situations and parts of the network need different approaches. This could be the decision of the traffic controller who can assess the situation and determine the objective. For example, during big disruptions one might consider giving more advices and higher energy usage are a reasonable cost to return to the original state as fast as possible. However, the decision might be the exact opposite in less pressing circumstances.

10. *We recommend calculating the speed advice locally on the train as an addition to recommendations 1, 3, and 9.*

This makes integration with the train diagnostic system easier (1), avoids the communication delays (3), and skips the rescheduling algorithm in cases where a speed change is enough to keep trains on their original schedule (9). Due to the modularity of TMS, the speed optimization algorithm is independent of other trains. Calculating the speed advice locally avoids the location of the train to be sent to the TMS first, for the CR module to check whether conflicts exist, solve them, calculate speed advices, and send them back to the train. The SR module should be on the train or on the mobile device of the driver. The CR module can independently calculate new schedules and send new time goals to the SR module. This reduces the delay-loop considerably, and the SR module solves minor deviations from the current schedule locally by adjusting the speed instead of going through the whole rescheduling loop.

11. *The parameters of the TMS scheduling algorithm should be adjustable, not hard-coded.*

This would allow for further examination, but also to adjust the objective of the TMS to be adjusted as needed. We argue that different situations need different objectives in terms of punctuality, energy efficiency, and stability of the speed advice. Also, different planning horizons could be valuable to adjust, because during disturbed situations, high uncertainty exists. A long planning horizons then costs extra computation time to calculate solutions for unpredictable situations.

12. *TMS can be used to centralize the communication with all the involved parties such as material and personal planners.*

TMS does not only need data from other systems; it can also provide valuable data to other systems and parts of the organization. We recommend positioning TMS in such a way that all parties involved in the real time operations have access to the most recent and accurate state of the system with regard to the exact location of personnel, material, and passenger information about exact delays. The TMS will enable NS and ProRail to gather enormous amounts of useful data about the infrastructure, rolling stock, and driver behaviour. We can use the data about the length of sections, platforms, available Voltage, altitude differences, rolling stock characteristics, and driver behaviour to calibrate the TMS. These are not TMS specific advantages, but still a welcome bonus. The calibration should be done in the pilot studies to ensure accurate data at the final launch of the system. Furthermore, TMS can provide accurate data to inform the passengers about delays, actual train composition and location to material planners, and the position and situation of drivers and guards to personnel planners. We argue that the TMS is an opportunity to create a platform which unifies the entire operational chain. TMS can centralize data about the current state of the system and provide feedback to all relevant stakeholders during disturbances (Section 2.4). In Table 25, we summarize our recommended information flow from and to TMS as a central component. We illustrate this position in the operational chain in Appendix VII. The biggest benefactors of the system, even though not directly connected to the TMS, are management and most importantly the passengers. The benefits for the passengers have been mentioned sufficiently in this report, but management will have new tools and data to steer very accurately with the valuable data that the TMS will collect. The current reports on red signal approaches and unplanned stops are only estimations, extrapolated from the data. The same is true for driver performance and energy efficiency. Accurate and detailed management dashboards will enable the NS to continuously improve operations with the focus on the most important problems.

Unit	To TMS	From TMS
Traffic Control	• Cancelled trains • Special priorities • Broken connections • Mass messages to drivers	• Decision support • Real-time status system • Disruption reports
Driver	• Material type/combination • Disruptions encountered • Standardized messages (signal unnecessarily red) • Driver and guard number	• Speed advice • Context information • Infra status • Current schedule • Temporary restrictions • Current disruptions
Material and infra Database	• Rolling stock characteristics • Infra information	• Calibrated data on Infra and rolling stock
Train	• Current position • Current speed * Current power status * Adhesion coefficient * Capacity utilization * Actual material type/length	
Passenger info		• Real-time arrival times • Real-time status trains
Material and personnel planners		• Real-time location and predicted arrival times • Actual rolling-stock used • Possible connections
Maintenance	• Real-time status of train	

Table 25: Recommended information flow between all units involved

13. *We recommend a slow and phased implementation toward full TMS.*

According to Kotter and Schlesinger (1979), change strategies are a continuum between fast and slow. The implementation of a full TMS is very complex. Attempts to implement advice systems failed in the past due to resistance of drivers. This points toward a slow implementation, with flexible planning, lots of involvement of stakeholders and resistance should be minimized by early end-user involvement. A big bang approach would certainly lead to mistakes in a project of this size. Gradually introducing full TMS allows users to familiarize with support tools available (RouteLint), which will help acceptance and prevent them from being overwhelmed by all the extra information. Also, each step of the implementation can be used to calibrate the data needed for optimal performance of TMS. In our opinion, it is very important to make no mistakes. Especially in the rail sector where the visibility to the public opinion is high. One accident which can be blamed on distraction, or even worse, wrong speed advice, and the whole project will encounter large setbacks. It is better to begin with a stable advice by for instance planning more time-slack between trains. This might not lead to the maximum performance, but it does help to gain the trust of the drivers first. As drivers become more familiar with, and accept the system, the focus can be shifted toward performance.

The initial planning with the intermediate steps is shown in Figure 49. The individual steps recommended in this section are highly advised for a successful implementation. First, RouteLint has to be implemented. This is a huge step forward and paves the way for speed advising (DAS). Pilot studies have to be conducted in order to identify implementation issues such as missing data, integration possibilities, potential studies, and driver opinions. The next step is the implementation of the DAS. This can be a local, on the train, speed regulation module similar to GreenSpeed (Figure 54 in Appendix III). The modularity of the system is very appealing, because the implementation can be phased. Data requirements and calibration can be initiated with the gathered data from pilot studies. Also, feedback from the drivers can be gathered. In this way, a robust and stable TMS is designed and implemented, while drivers get used to working with a DAS. The next level of support will be the coordination of multiple trains in the network with the full TMS. Again, a pilot study should be initiated, but lessons can also be learned from the previous steps. Continuous improvements by adding features and system integration can start until the next big step, such as Automated Train Control (ATC).

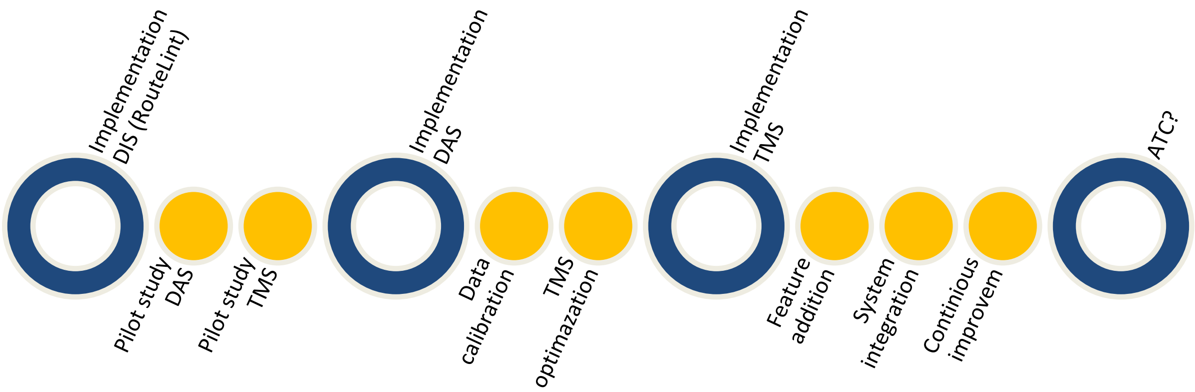


Figure 49: Implementation phases toward full TMS

The final recommendation is to continue working on the current prototype TMS-FRISO. Despite the huge potential of this project, only a few people are working and testing the software. During this research, we encountered some shortcomings in the software in its current state. Unlike what the name FRISO suggests (Flexible Rail Infra Simulation Environment); it is only flexible for the developers. Simulation studies are a powerful tool when the testers have the flexibility to experiment. This is one of the biggest advantages of such studies. We understand that the source code remains hidden because it contains intellectual property. However, from the perspective of progress, we urge to at least add the option to implement custom scripts to determine conditional events. For example, if two speed advices are given within *t* seconds of each other, ignore the speed advice or longer reaction time if the speed advice is poor, which can be defined in many possible ways. These kinds of conditions are very specific and depending on the developers each time researchers think of a scenario is not the way to go.

7.3 FUTURE RESEARCH

In this research, we experimented with many different scenarios and configurations. However, these do not cover all the factors which add to the instability of the advice. We lack data to examine some of the factors and other factors are either hard-coded in the current TMS or not implemented at all at this phase. Also, new questions arise from the results found, which have not yet been answered. A great amount of data is gathered, which can be analysed more in depth. Before these steps can be taken, the inner workings of TMS need to be stabilized, tested, and most importantly, documented. One factor which remains a question for future research is the planning horizon under consideration during the conflict resolution algorithm.

The current implementation considers the entire path of the train, from the entrance until the exit of the area. This means that during each rescheduling iteration, TMS calculates the speed profiles of all trains from the moment they enter the simulation until the moment they leave the simulation. It is interesting to log all speed profiles calculated instead of only the advices that are actually sent. From analysing this data, we can see how much in advance the final advice, which is actually sent to the driver, was calculated. This data is currently available in the message logs kept by the HLA, but these messages are unstructured and need further processing before analysis is possible. This can help to quantify the predictive capacity of TMS. For example, we could determine how far ahead the speed advice is shown to the driver based on this factor.

Methods to handle or correct for drivers who do not respond to the advices also need further investigation. For instance, one possibility would be to first warn the driver and then treat that particular train as autonomous. In this way, TMS can try and steer the other trains around it, instead of continuing to expect the non-complying driver to follow the advice.

Other factors which could affect the stability are the initiation method and the choice of interrupting the rescheduling iteration if new information becomes available (Section 3.3). The impact of these factors remains unknown at this moment.

Many other priority rules come to mind that could be more important than the one AMCC currently provides. Does priority depend on train type, number of passengers on the train, most passengers waiting on destination, most connections, delay, slowest accelerating train, or importance of the destination (e.g. airport)? What about personnel or material cost for rescheduling? How much extra delay is acceptable to prevent an extra unplanned stop when choosing the weights in the cost function? What are the benefits of data calibration, such as the method discussed for the rolling stock by Bešinović et al. (2013), which is also interesting for future research. We also recommend comparing the performance of different TMSs, such as ROMA, with the current TMS using the same scenarios and infrastructure for a fair comparison. Finally, research should focus on designing agent based systems to coordinate between traffic control, material, and personnel planners with TMS as a central component.

Appendices

I. The rail network 2013

This Figure displays the Dutch railway service and their frequencies. These are the lines that are currently serviced. A list of names of different tracks is given for better understanding of the terminology.

- **Sections/trajectory/route/corridor** are used interchangeably, and all mean the track that starts and ends at a timetable point and consist of more timetable points and open tracks.
- **Timetable points** are the stations, stops, connections, and bridges.
- **Open track** is the track that connects two major timetable points with no branches or operated switches and signals.
- **Block-sections** are the piece of track between two operated signals; a block-section cannot be occupied by more than one train at a time.

II. Constraint representation AGF

The *blocking constraint* has to be added to ensure that only one train at a time can enter a block-section. We represent these constraints by the dotted lines in Figure 50 and have a length (q_i) is such a way that safety norms are met considering the train length and speed. In this example operation *j* can start after *s (i)* or vice versa.

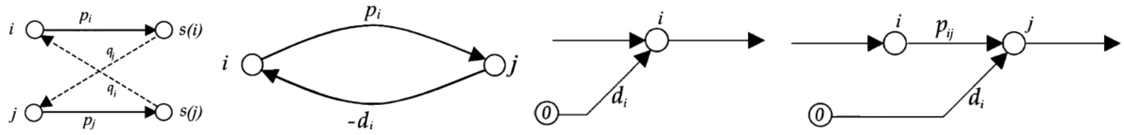


Figure 50: from left to right; Blocking, minimum speed, passing, and stop and departure constraint (Mazzarello and Ottaviani, 2007)

The *minimum speed constraint* is determined by the maximum travel time d_i for a train to be on time and is denoted by the negative maximum travel time, so if $p_i > d_i$ a positive length cycle occurs. This would make the solution infeasible because it would mean that the operation can start only after itself. The *passing constraint* ensures that a train can pass node *i* only after d_i. The authors call these kinds of arcs *Target Arcs* because they represent a requirement for the scheduling algorithm. The *stop and departure constraint* is represented by the two nodes, one for each operation and the length of the arc is p_i, the minimum dwell time at the station. The *connection constraint* (Figure 51) is similar to the previous constraint only that the arc is now connected to the stop of another train, with the length of the arc representing the minimum connection time. The *out of order constraint is* represented by two arcs with lengths $-d_i$ and b_i, the start and end time of the unavailability period of the section. The *Precedence constraint* is directly handled during the graph building stage by selecting all arcs from A to B if train A has to pass before B and to forbid the paired arcs.

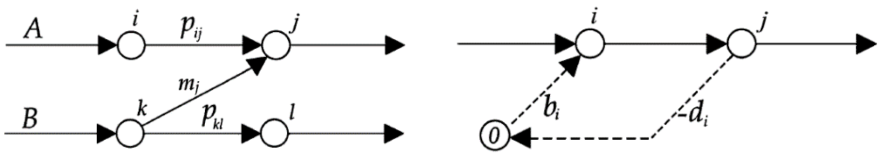


Figure 51: Connection and out of order constraints

III. Examples of DIS/DAS interfaces

Here we give a few samples of information and advisory systems currently available on the market for drivers. Most of them are for energy saving purposes (EnergyMiser), but some provide context information and try to replace all the current paper sheets drivers need (EBuLa). Scan the QR-codes in **Fout! Ongeldige bladwijzerverwijzing.**, Figure 54, and Figure 53 for more information and demonstrations.

Figure 52: RouteLint

Figure 54: GreenSpeed

Figure 53: CATO

Figure 55: EcoScout, by Voith

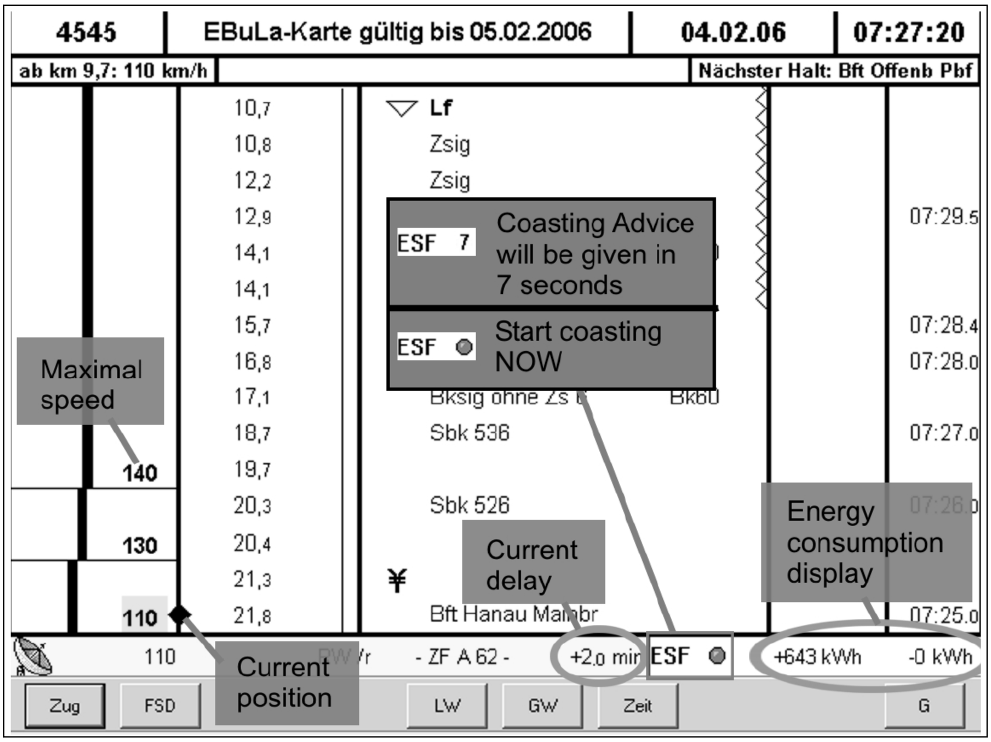


Figure 56: EBuLa by Systel

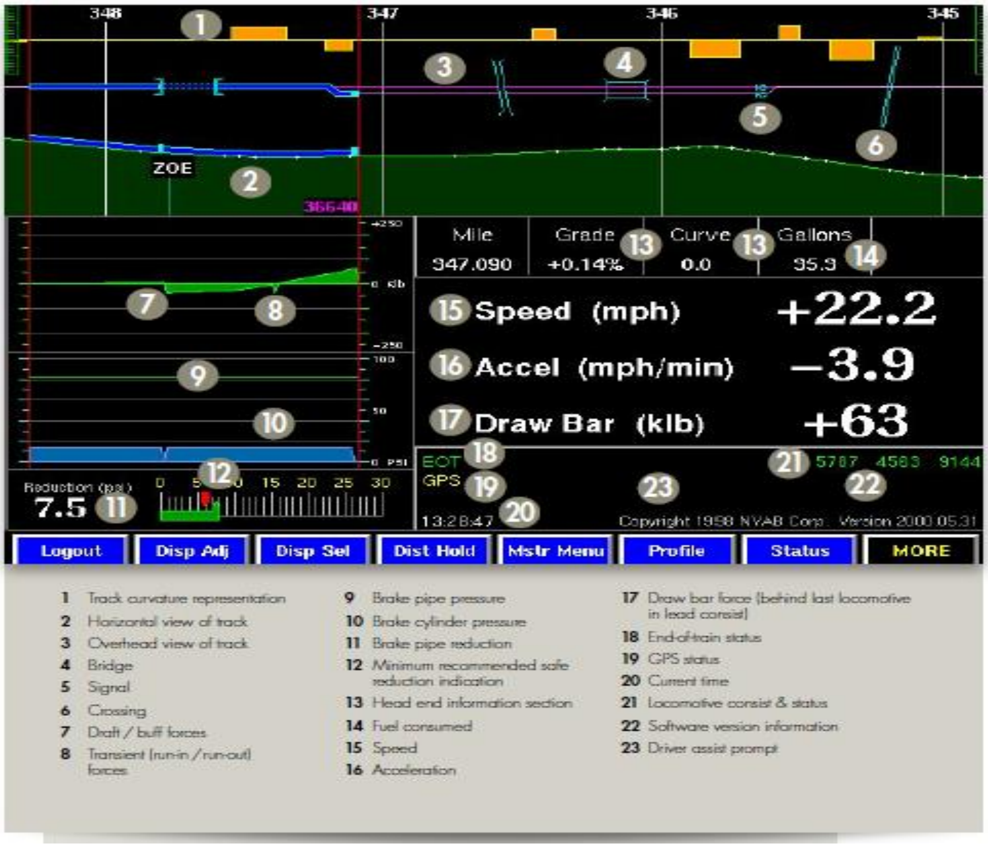


Figure 57: LEADER by Knorr-Bremse

IV. Examples KPI calculations

To illustrate KPIs 5-13 of Table 12, we use the example in Figure 58. The numbers in the figure show the advices given, the blue line is the advice and the red line the actual train speed.

10. The number of advices given to this train is 11 during 900 seconds. So 11/900*3600= 44 advices per hour.
11. Same as above except that we do not count advice 1 and 11, so 9/900*3600= 36.
12. At point 7 an advice is given to accelerate and while the train is still accelerating an advice is given to decelerate. This would count as 1. The same occurs at point 4, but the previous advices speed was not reached yet, which is considered so this one is not counted.
13. For this KPI we count how often the direction of the advice changes. So at point 3 the advice is to accelerate, at point 4 to decelerate, at point 5 to accelerate, at 6 to decelerate, 7 accelerate, 8 decelerate. So the advice is alternating in direction from point 4 to 8 and the KPI would be 5. From the data no distinction can be made between advices given due to speed restrictions and due to TMS decisions, so we count them. This should be no problem since the KPIs are used relative to other trains that use the same infrastructure and should have the same number of "Instability" due to speed limits.

9-13 These KPIs are the same except for different horizons T represented in the graph at

Point 8. For example for T=30 an advice is considered instable when the current advice V_b =80 km/h at point 7 and 30 seconds later the advised speed is still 80 km/h (V_e). During the 30 seconds however an advice is given (point 8) that is higher than either V_b or V_e. The same is true for advice 4. So this KPI would be 2 for this train.

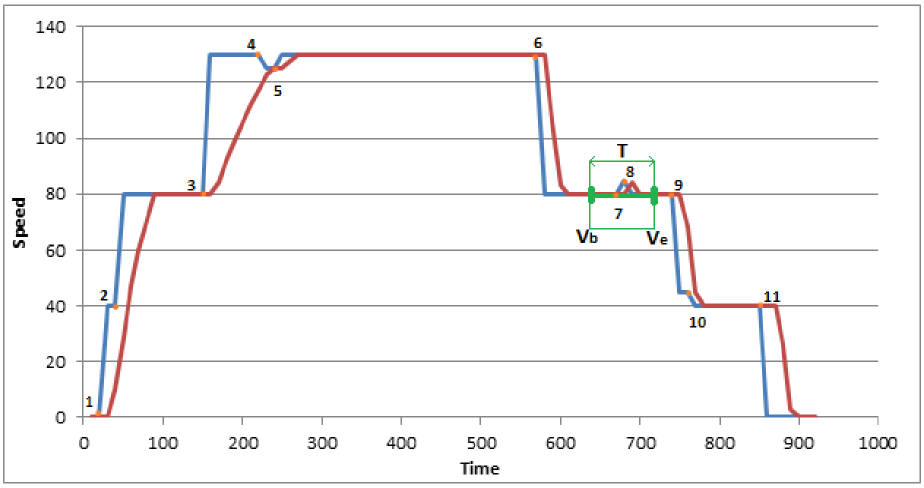


Figure 58: Example of instability of speed advice

In contrast to the example above Figure 59 shows the desired advice stability. In Table 26, we compare the stability KPIs of both examples.

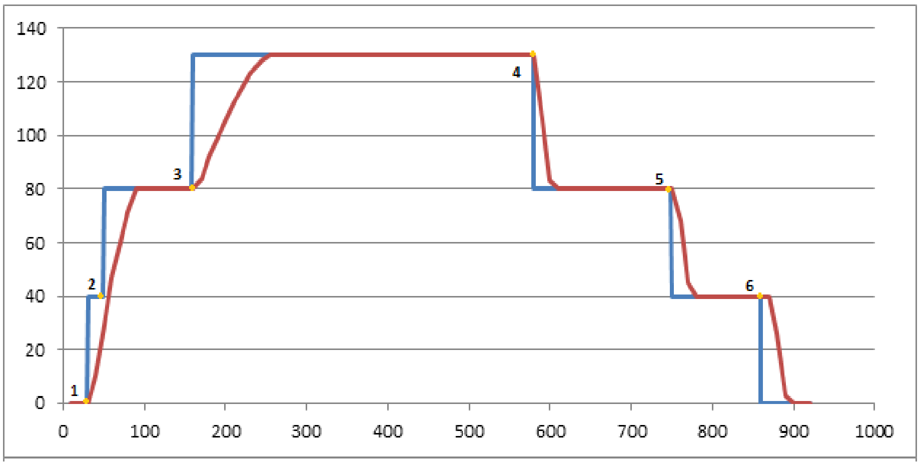


Figure 59: Example of a smooth speed advice

KPI	Situation 1	Situation 2	Difference
5	44	24 (6/900*3600)	-45%
6	36	16 (4/900*3600)	-56%
7	1	0	-100%
8	5	1	-80%
9-13	2	0	-100%

Table 26: Comparison of the two speed profiles

In Table 27 we show how we calculate convergence and divergence for the delays. The values for the entry and exit can be either positive, negative or zero. These are used to calculate KPIs 17 and 19.

Entry	Exit	Value
-	-	Entry - Exit
-	+	Exit - Entry
-	0	-Exit
0	-/+	- ABS(Exit)
+	0	Entry
+	-	ABS(Entry) - ABS(Exit)

Table 27: delay divergence en convergence

The energy KPI is not the actual energy usage, but an estimation that can be used relatively. This method is chosen to reduce the calculation time of the huge amount of data. The Energy KPI represents the difference in Kinetic energy which is the *Work. Work* represents the difference in Kinetic energy over a distance and is the product of force and distance travelled (W=F.Δd). From the TrainState log the acceleration and the distance over which this acceleration force is exerted are used to calculate the total Work done. The cruising phase is neglected.

V. Relative scores on all KPIs

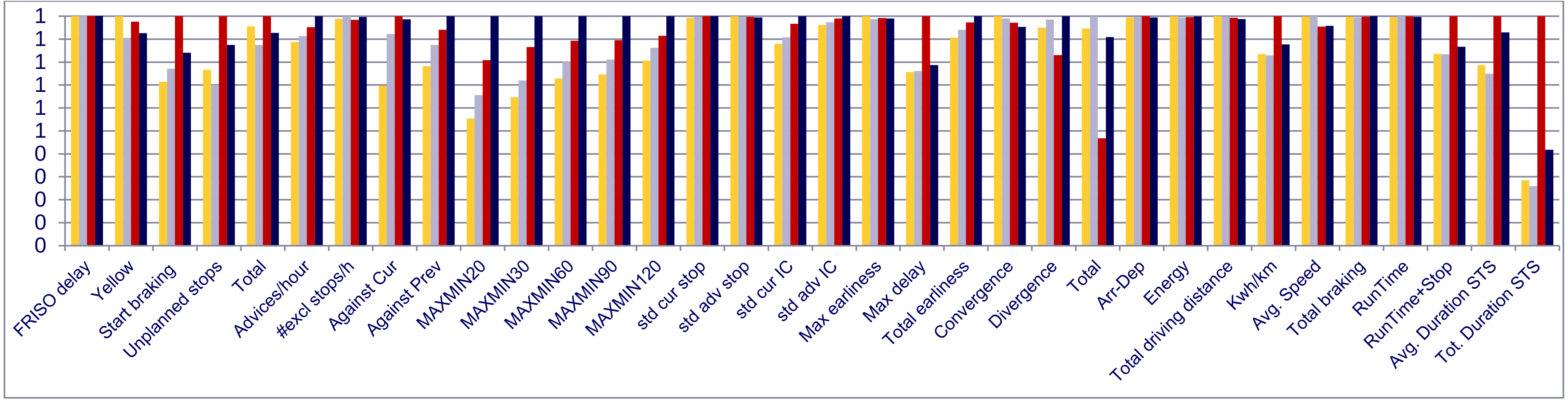


Figure 60: Effects of the Train to TMS delay (FRISO delay)

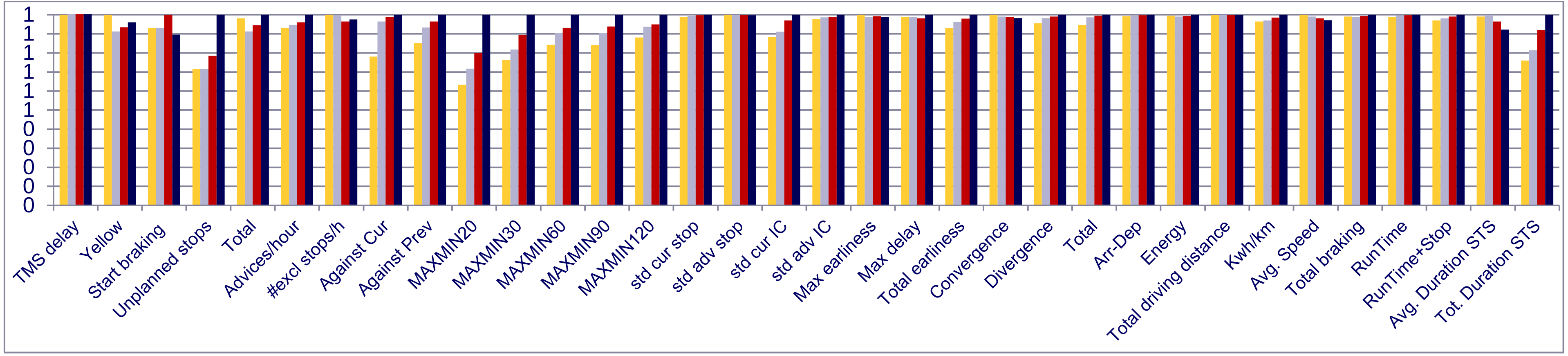


Figure 61: Effects of the TMS to Train delay (TMS delay)

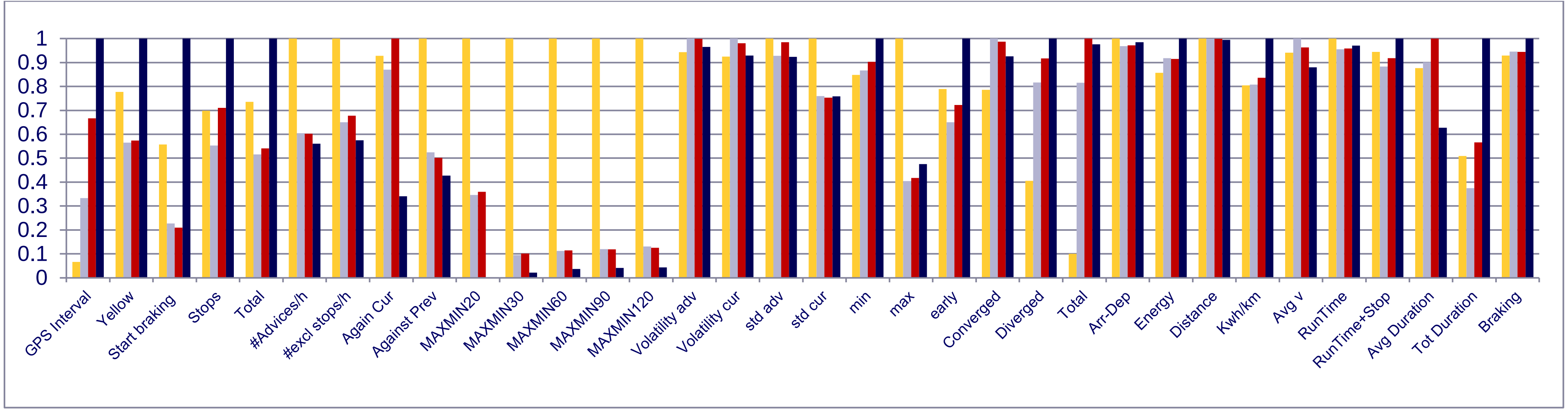


Figure 62: Effects of the location update interval

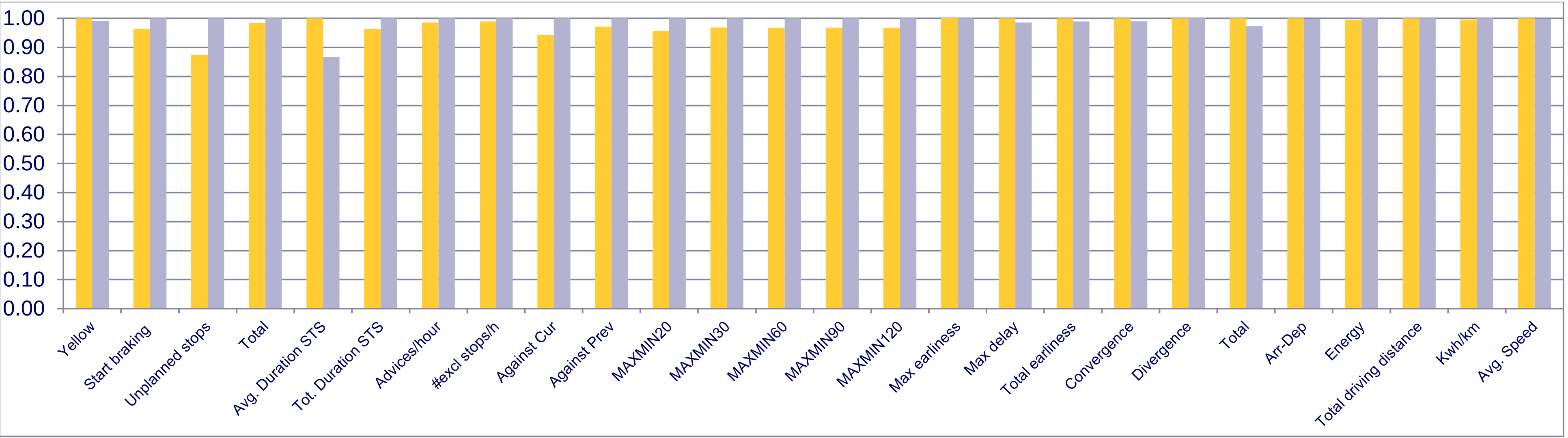


Figure 63: Effects of disturbances due to the wind

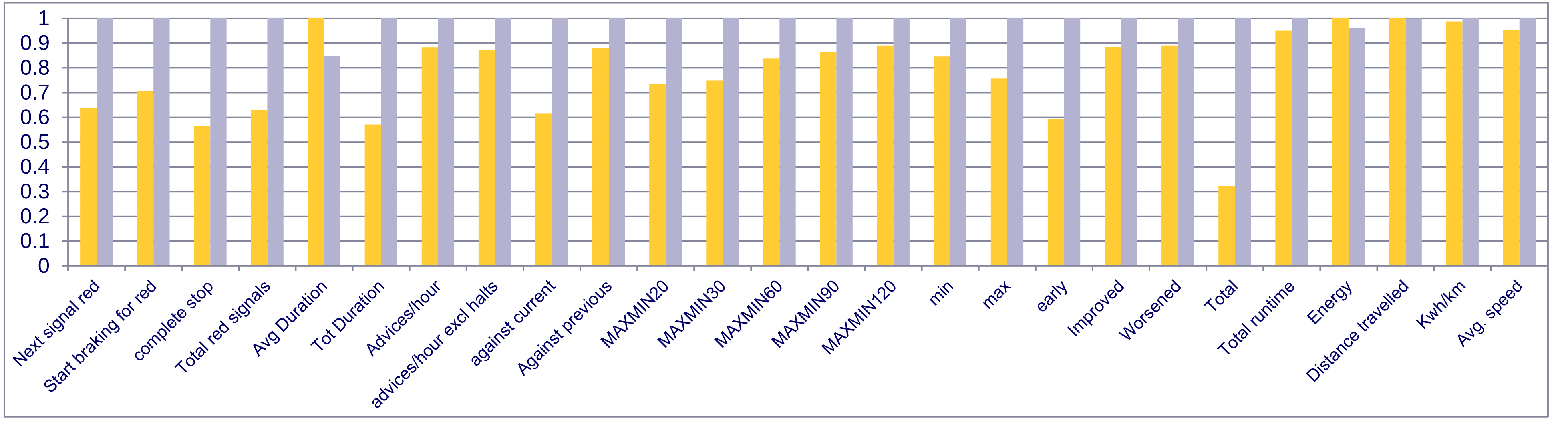


Figure 64: Effects of disturbances due to adhesion

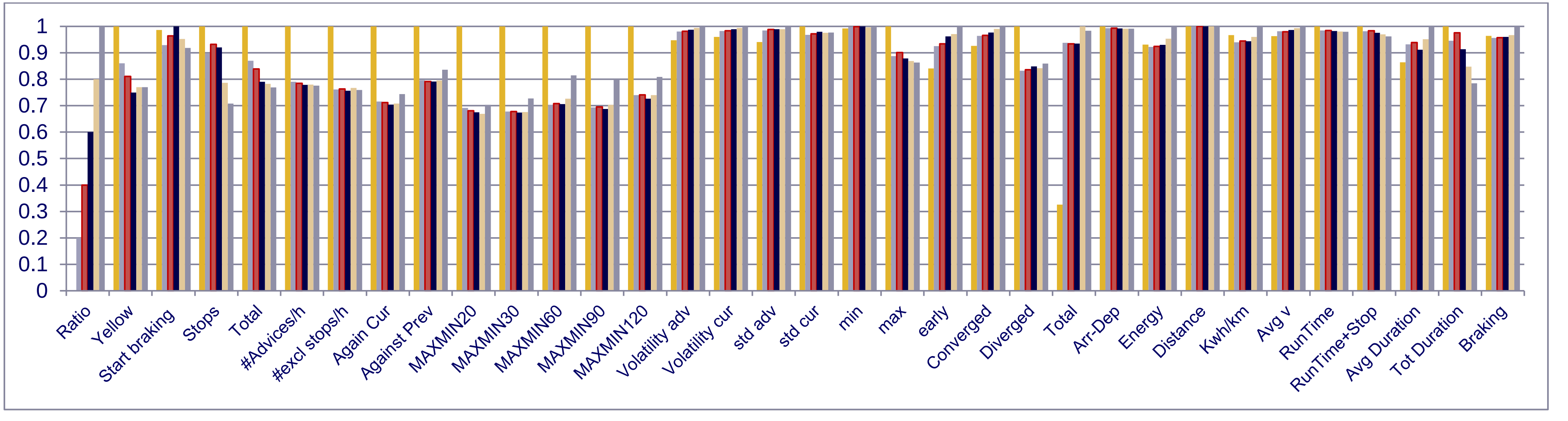


Figure 65: Effects of different weight ratios between punctuality and energy usage

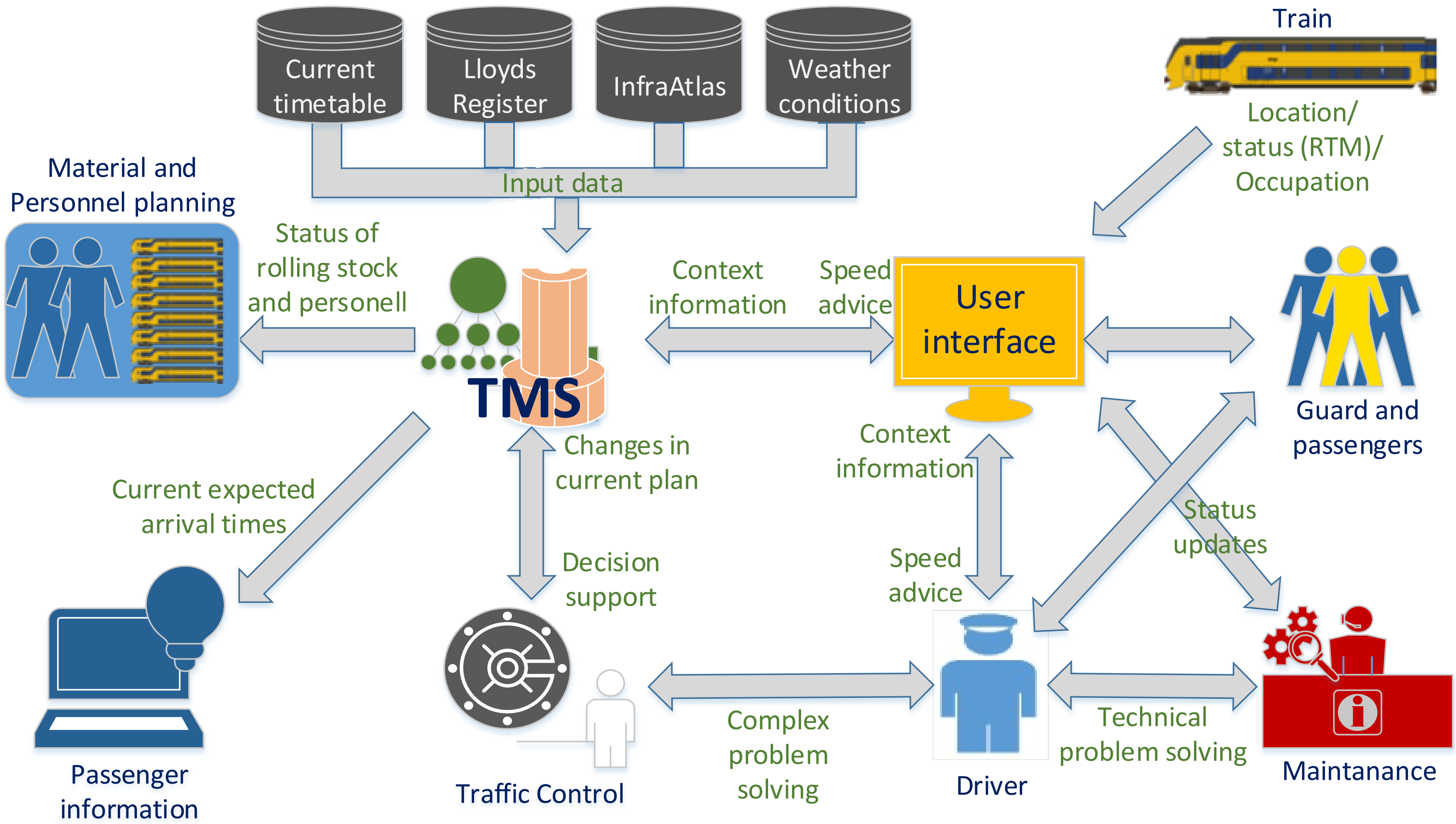
VI. Significance test of the performance

In the following table the results are shown of the paired t-test (orange KPIs) and the sign-test (yellow KPIs). For the full results and magnitude and direction of the differences we refer to the Excel file "Compare Means". The used values for GPS, TMS, and FRISO are in seconds and "rt" is short for reaction time.

KPI	Safety				Stability												
	Yellow	Start braking	Stops	Total	#Advices/h	#excl stops/h	Again Cur	Against Prev	MAXMIN 20	MAXMIN 30	MAXMIN 60	MAXMIN 90	MAXMIN 120	std cur stop	std adv stop	std cur IC	std adv IC
Adhesion	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Wind	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Capacity utilization	No	Yes	No	No	Yes	No	Yes	No	No	No	No	No	Yes	No	No	Yes	Yes
Defect train	No	No	No	No	Yes	No	Yes	No	Yes	Yes	No	No	No	No	No	No	No
Ratios	No	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Compliance	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No
Unexp. Rt	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	No	No	Yes	No	Yes	No
Expected rt	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes
exp. vs unex. Rt	No	Yes	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	No	Yes
GPS 5 vs 10	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes
TMS 5 vs 10	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No
FRISO 5 vs 10	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	No

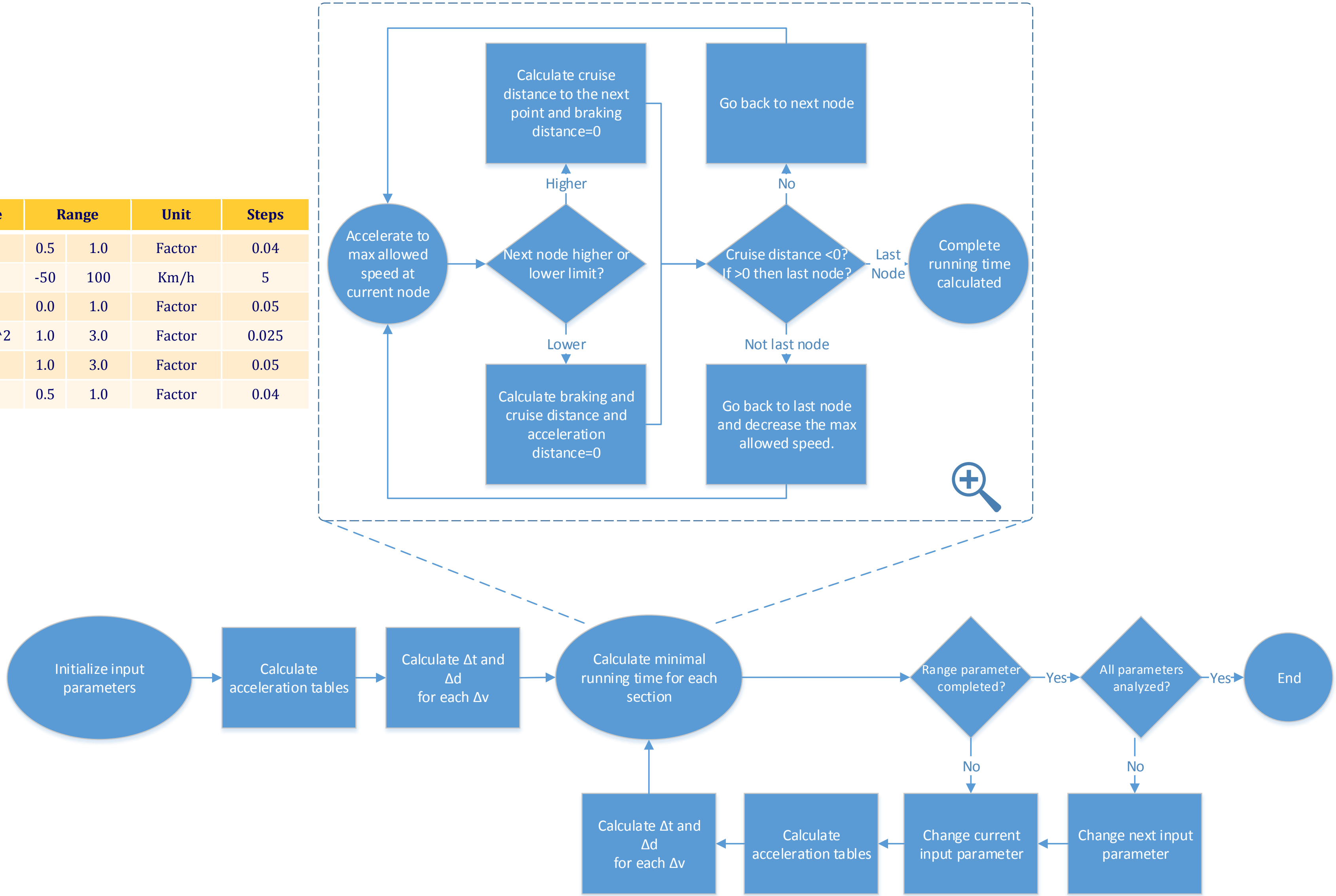
KPI	Punctuality						Traffic flow									
	Min delay	Max delay	Total early	Converged	Diverged	Total	Arr-Dep	Energy	Distance	Kwh/v	Avg v	Run time	Run time + Stop	Avg Dur	Tot Dur	Braking
Adhesion	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes
Wind	No	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Capacity utilization	Yes	No	Yes	No	Yes	No	No	Yes	No	Yes	Yes	No	No	Yes	Yes	No
Defect train	Yes	No	Yes	No	Yes	No	No	Yes	No	Yes	Yes	No	Yes	No	No	Yes
Ratios	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	No	No	Yes	No	Yes
Compliance	Yes	No	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	No	No	Yes	No	Yes
Unexp. Rt	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	No	Yes
Expected rt	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes
exp. vs unex. Rt	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
GPS 5 vs 10	Yes	Yes	Yes	No	Yes	Yes	No	Yes	No	No	Yes	No	Yes	No	No	No
TMS 5 vs 10	Yes	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes
FRISO 5 vs 10	Yes	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No

VII. Suggested position of TMS within the operations



VIII. Sensitivity analysis model

rameters	Default value	Range		Unit	Steps
ion	0.3 N/kg	0.5	1.0	Factor	0.04
speed	0 km/h	-50	100	Km/h	5
occupation	0%	0.0	1.0	Factor	0.05
sistance	6.425 N/(m/s)^2	1.0	3.0	Factor	0.025
g resistance	0.0162 N/kg	1.0	3.0	Factor	0.05
: train	100 %	0.5	1.0	Factor	0.04



IX. Speed profiles sensitivity model

These graphs show the time/speed and time/distance graphs of the travel time model used for the sensitivity analysis. The actual travel times are much longer because the model delivers minimum travel time and in reality more factors come into play such as other trains and the fact that driver's coast to save energy as can be seen in the graph. We remove the halting times at the stations for clarity.

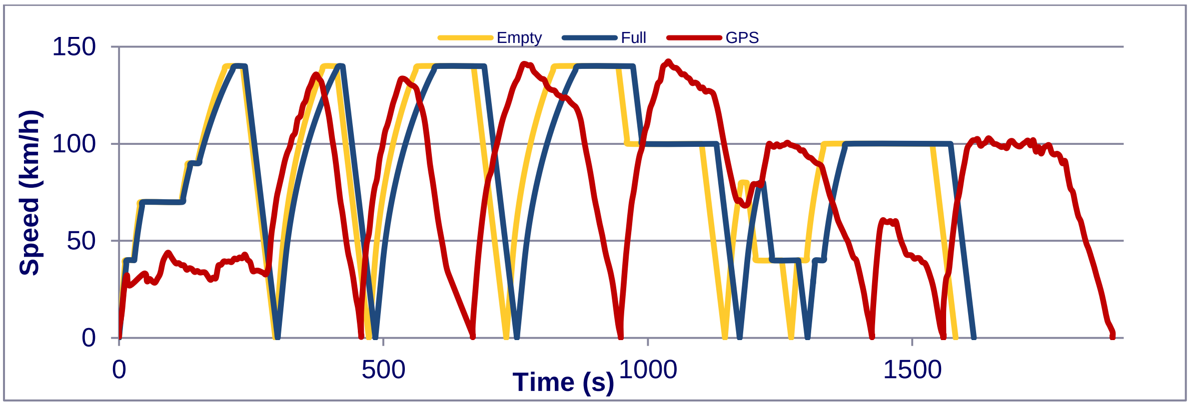


Figure 66: Speed/time profile

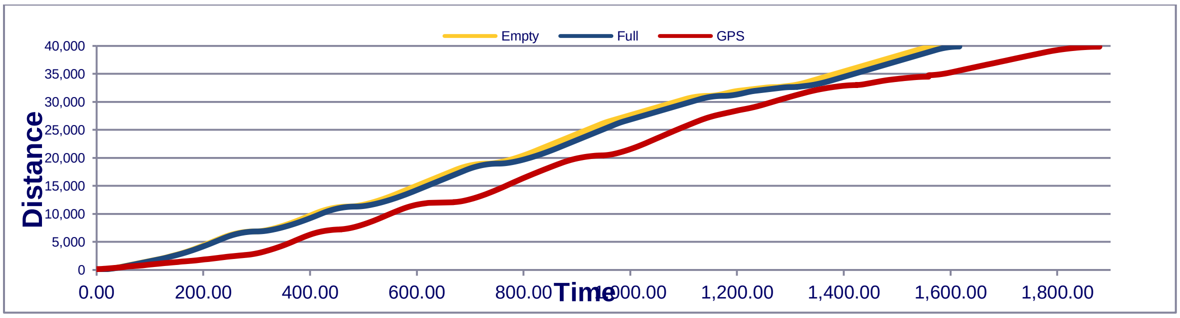
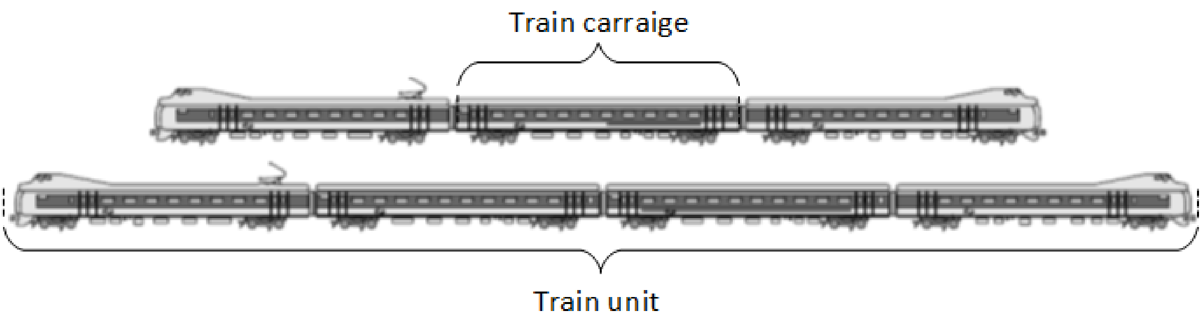


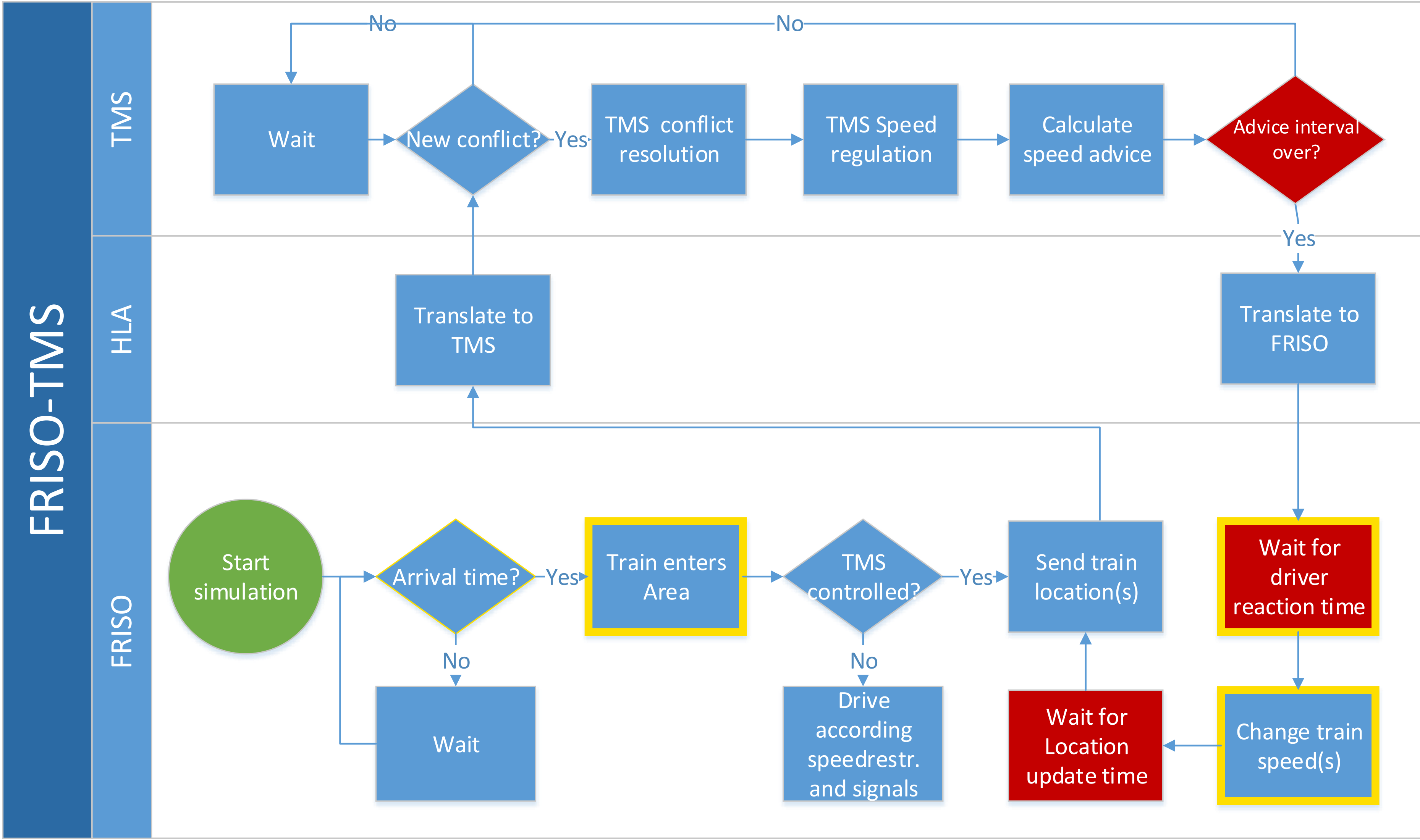
Figure 67: Time distance profile

X. Train compositions

A train can consist of multiple units, which in turn consist of multiple carriages. A unit can consist of different combination of carriages. There are limits for the amount of units and carriages that can be combined together, typically 12 to 15 carriages maximum (Kroon et al., 2009).



XI. FRISO-TMS flowchart



XII. FRISO Model layout

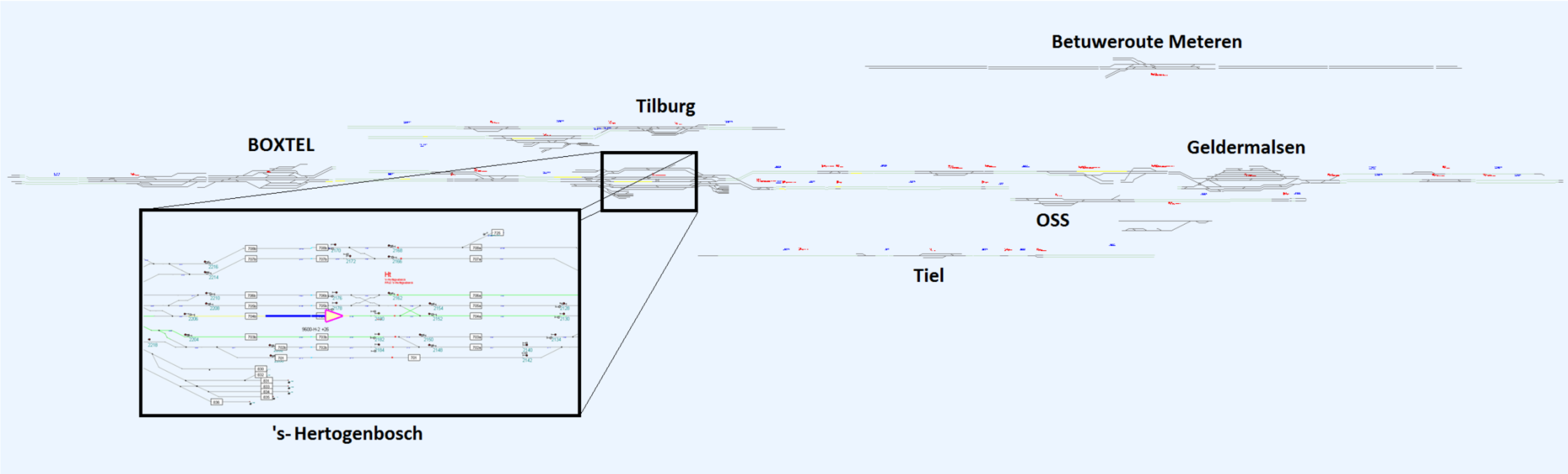


Figure 68: Area modelled

Train-series	Between		Frequency (per hour)	Material type	Type
13600	Tilburg	Den Bosch	4	SLT 10	Sprinter
16000	Den Bosch	Geldermalsen	4	SLT 10	Sprinter
3500	Boxtel	Geldermalsen	4	VIRM 8	IC
3600	Tilburg	Oss	4	VIRM 6	IC
36700(*Arriva)*	Geldermalsen	Leerdam	4	GTW2/8	Sprinter
4400	Den Bosch	Oss	4	DDM4	Sprinter
800	Boxtel	Geldermalsen	2	VIRM 10	IC
9600	Boxtel	Den Bosch	4	SGM2 6	Sprinter

Table 28: Trains modelled

XIII. Simulation automation

This peace of code is implemented in Eclipse (Java) to automate the simulation process, since all the mentioned steps have to be done manually otherwise. Also this makes the process continuous and runs can be done 24/7. The productivity rises with at least 420%.

```
Sub DoSimulations()

1.  GenerateInstances (input parameters and replication number combinations)
2.  For all instances loop
    2.1.  Modify FRISO database to instance parameters
    2.2.  Modify TMS database to instance parameters
    2.3.  Set seed value that corresponds with the replication number
    2.4.  Launch FRISO_mapper and wait to start
    2.5.  Launch TMS_mapper and wait to start
    2.6.  While no output is present and all processes running
          2.6.1. IF True wait
          2.6.2. ELSEIF processes crashed, close all processes and go to next instance
          2.6.3. ELSE output folder filled, collect all different output files from output folders to
                 a new folder with instance name
    2.7.  Close all processes
3.  Loop

End Sub
```

XIV. Results processing

To analyse the output of the simulations, the following procedure is applied to convert the data into the relevant KPIs described in Appendix XIII. This is a VBA script implemented into MS Excel.

Sub GetResults

1. Search in the given path and collect all sub directories into array A.
2. For all the indices of A, search these directories for directories that contain the file: "LogAnalyseVeiligheid.txt" and fill B_{Ai} array with all directory paths.
3. Fill array C with already collected results from results tab.
4. Loop over all the indices of array A
   - 4.1. Loop over all the indices of array B_{Ai} that are not in array C.
     - 4.1.1. Get experimental settings from directory name.
     - 4.1.2. Call Safety
     - 4.1.3. Call STS
     - 4.1.4. Call Times
     - 4.1.5. Call TrainState
     - 4.1.6. Copy outcomes to results tab
   - 4.2. Loop
5. Loop
6. Calculate the averages and standard deviations of each scenario over all replications and copy to results summary tab.
7. Normalize the outcomes for relative scoring.

End Sub

The sub-procedures that actually calculate the KPIs work as following.

Sub Safety

1. Perform a query to load "LogAnalyseVeiligheid.txt"
2. Loop over all rows
   - 2.1. Check whether the same train is logged twice for same stop by comparing times
   - 2.2. If situation between hour 1 and 5 and is not true on step 2.1
     - 2.2.1.Check situation description
     - 2.2.2. Count the different situation types
3. Loop

End Sub

Sub STS

1. Perform a query to load "LogTreinstops.txt"
2. For all rows
   - 2.1. If situation between hour 1 and 5 and the stop is "Unplanned"
     - 2.1.1. Duration = TIME_START_ACCELERATION - TIME_STOPPPED
3. Loop
4. Calculate average and sum over all the durations

End Sub

```
Sub Times()

1.  Perform a query to load "LogEntryExitTimes.txt"
2.  Loop over all rows
    2.1. Convert all the negative times from string to real
    2.2. Calculate delay values according to Table 27
    2.3. Calculate run time
3.  Loop
4.  Sum over all positive delay values is convergence
5.  Sum over all negative delay values is divergence
6.  Sum over all negative arrival times is total earliness
7.  Min(Arrival times) = most early arrival
8.  Max(Arrival times) = maximum delay
9.  Sum over all run times = Total runtime
10. Calculate average and sum over all the durations

End Sub
```

```
Sub TrainState()

1.  Perform a query to load "TrainState.csv"
2.  Delete all warm-up data
3.  Sort data on train-number
4.  Loop over all rows
    4.1. Deduce train type from train-number (IC or Sprinter)
    4.2. Calculate advised and actual acceleration
    4.3. Count all advices where advised acceleration >0 while actual acceleration <0 or
         vice versa
    4.4. Count all advices where the acceleration is not zero
    4.5. Count all advices where advice and actual acceleration are both not zero
    4.6. Count advices where previous advice >0 and current adv. <0 and vice versa
    4.7. Calculate distance travelled
    4.8. Calculate Work performed (Work=Mass x acceleration x Δ distance)
    4.9. Calculate the MAXMIN T KPIs as described in appendix XIII.
         4.9.1. Calculate times step TS
         4.9.2. Current speed is cell CurSpeed i
         4.9.3. End Speed in T seconds is in cell CurSpeed i + (T/TS)
         4.9.4. IF {Max cells (i+1) to (i + (T/TS)) > Max(Current and End Speed) OR
                Min cells (i+1) to (i + (T/TS)) < Min(Current and End Speed)} AND {TrainID I =
                TrainID (i + (T/TS))} AND NotAlreadyCounted THEN
                MAXMIN T = MAXMIN T + 1
5.  Loop
6.  Update pivot table which calculates the standard deviations over all nodes for ICs and
    Sprinters

End Sub
```

XV. AHP ranking of all scenarios

The total scores and weights of the AHP method are the average weights of the respondents. All though the overall ranking can be used to get a general idea, not all scenarios can be compared due to different computers and different initial disturbances. Scenario scores do represent the relative performance of the factors. The weights are:

Safety				Stability								
Yellow	Start braking	Unplanned stops	Total incidents	Advices/ hour	Excl halts/ hour	Against current	Against previous	MAXMIN T=20	MAXMIN T=30	MAXMIN T=60	MAXMIN T=90	MAXMIN T=120
2.6%	10.5%	21.6%	10.5%	1.1%	1.4%	4.0%	4.1%	2.1%	1.6%	1.3%	0.8%	0.7%
Punctuality						**Traffic flow**						
Min delay	Max delay	Earlyness	Conver-gence	Diver-gence	Total	Avg. Dur. stop	Tot. Dur. stop	Tot. travel time	Total energy	Distance travelled	Kwh/km	Average speed
1.4%	2.5%	0.7%	1.2%	1.2%	2.2%	5.1%	5.1%	5.0%	3.0%	1.8%	4.0%	4.7%

The settings are as following: Train to TMS delay – TMS to Train delay – GPS interval – Driver reaction time – HLA time step

Experiment + settings	Total Score	Rank scenario	Rank overall	Experiment + settings	Total Score	Rank scenario	Rank overall
GPSTest\5-5-5-4-5	0.401	1	4	TrainOccupation\5-5-10-4-10	0.494	1	32
GPSTest\5-5-7-4-7	0.402	2	5	RTM\5-5-5-4-5 13600H1 60	0.501	2	34
GPSTest\5-5-3-4-3	0.403	3	6	RTM\5-5-5-4-5 3500H1 80	0.501	3	35
GPSTest\5-5-11-4-11	0.420	4	12	RTM\5-5-5-4-5 13600H1 80	0.501	4	36
GPSTest\5-5-9-4-9	0.421	5	13	TrainOccupation\5-5-5-4-5	0.503	5	37
GPSTest\5-5-10-4-10	0.422	6	14	TrainOccupation\5-5-10-4-10	0.503	6	38
GPSTest\5-5-13-4-13	0.424	7	15	TrainOccupation\5-5-5-4-5	0.506	7	40
GPSTest\5-5-15-4-15	0.477	8	29	Wind\5-10-5-4-5	0.519	8	43
GPSTest\5-5-1-4-1	0.533	9	48	Wind\5-15-5-4-5	0.532	9	47
GPSTest\5-5-17-4-17	0.668	10	62	CombinedEffects\5-5-15-4-15	0.561	10	50
GPSTest\5-5-19-4-19	0.799	11	72	Adhesion\5-5-5-4-5	0.590	11	52
DriverReaction\5-5-5-1-1	0.385	1	1	Adhesion\5-5-5-5-5	0.595	12	53
Unexp. ReactionTime\5-5-5-2-5	0.399	2	2	CombinedEffects\5-5-20-4-20	0.891	13	85
Unexp. ReactionTime\5-5-5-1-1	0.401	3	3	CombinedEffects\5-5-5-4-5	0.967	14	88
Unexp. ReactionTime\5-5-5-4-5	0.405	4	7	Ratio\5-5-5-4-5 1,0	0.814	1	73
DriverReaction\5-5-5-7-1	0.406	5	8	Ratio\5-5-5-4-5 0.8	0.832	2	77
Unexp. ReactionTime\5-5-5-6-5	0.413	6	9	Ratio\5-5-5-4-5 0,6	0.869	3	80
DriverReaction\5-5-5-10-1	0.415	7	10	Ratio\5-5-5-4-5 0.2	0.873	4	83
Unexp. ReactionTime\5-5-5-7-5	0.435	8	17	Ratio\5-5-5-4-5 0.4	0.882	5	84
Unexp. ReactionTime\5-5-5-9-5	0.439	9	19	Ratio\5-5-5-4-5 0.01	0.967	6	88
Unexp. ReactionTime\5-5-5-1-5	0.440	10	20	CombEffects LessDist.\5-5-10-6-10	0.788	1	70
Unexp. ReactionTime\5-5-5-8-5	0.444	11	21	CombEffects LessDist.\5-5-10-7-10	0.818	2	74
Unexp. ReactionTime\5-5-5-10-5	0.445	12	22	CombEffects LessDist.\5-5-5-5-5	0.819	3	76
DriverCompliance\5-5-5-1-5	0.463	13	25	CombEffects LessDist.\5-5-5-6-5	0.866	4	79
DriverCompliance\1-1-5-4-5	0.467	14	28	CombEffects LessDist.\5-5-10-5-10	0.871	5	82
Unexp. ReactionTime\5-5-5-14-5	0.499	15	33	CombEffects LessDist.\5-5-5-7-5	0.914	6	86
DriverReaction\5-5-5-15-1	0.526	16	45	GPS+Delay LessDist.\1-1-3-3-3	0.417	1	11
DriverCompliance\5-5-5-4-5	0.531	17	46	GPS+Delay LessDist.\1-1-5-7-5	0.434	2	16
DriverCompliance\1-1-1-1-1	0.541	18	49	GPS+Delay LessDist.\1-1-5-10-5	0.436	3	18
DriverReaction\5-5-5-20-1	0.575	19	51	GPS+Delay LessDist.\4-3-10-3-10	0.448	4	23
DriverCompliance\1-1-5-1-5	0.608	20	55	GPS+Delay LessDist.\1-1-5-3-5	0.449	5	24
DriverCompliance\1-1-10-1-10	0.658	21	58	GPS+Delay LessDist.\1-1-10-7-10	0.465	6	26
Unexp. ReactionTime\5-5-5-20-5	0.658	22	59	GPS+Delay LessDist.\1-1-10-10-10	0.466	7	27
Unexp. ReactionTime\5-5-5-15-5	0.663	23	60	GPS+Delay LessDist.\1-1-3-10-3	0.504	9	39
Unexp. ReactionTime\5-5-5-13-5	0.710	24	63	GPS+Delay LessDist.\1-1-15-1-15	0.490	8	30
DriverCompliance\5-5-10-4-10	0.793	25	71	GPS+Delay LessDist.\1-1-1-1-1	0.516	11	42
DelayLoop\5-1-5-4-1	0.741	1	64	GPS+Delay LessDist.\1-1-10-1-10	0.509	10	41
DelayLoop\1-5-5-4-1	0.750	2	65	GPS+Delay LessDist.\1-1-5-1-5	0.521	12	44
DelayLoop\5-5-5-4-5	0.752	3	66	GPS+Delay LessDist.\1-1-15-3-15	0.601	13	54
DelayLoop\5-10-5-4-1	0.777	4	68	GPS+Delay LessDist.\1-1-3-7-3	0.656	15	57
DelayLoop\20-5-5-4-1	0.784	5	69	GPS+Delay LessDist.\1-1-15-7-15	0.655	14	56
DelayLoop\5-15-5-4-1	0.819	6	75	GPS+Delay LessDist.\1-1-15-10-15	0.664	16	61
DelayLoop\15-5-5-4-1	0.835	7	78	GPS+Delay LessDist.\1-1-3-1-3	0.762	17	67
DelayLoop\5-20-5-4-1	0.870	8	81	-			
DelayLoop\10-5-5-4-1	0.927	9	87	-			

XVI. Correlation matrix

	FRISO	TMS	GPS	DRIVER	Total-Loop	FRISO/GPS	TMS/GPS	DRIVER/GPS	corr loop	GPS-Loop	GPS+Loop	Loop/GPS
Yellow	-0.109	-0.103	0.469	0.230	0.046	-0.024	-0.109	0.117	0.310	0.057	0.502	-0.011
Start braking	-0.062	-0.076	0.697	-0.074	-0.130	-0.026	-0.188	-0.165	0.249	0.263	0.592	-0.155
Stops	-0.047	-0.022	0.601	0.045	-0.006	-0.086	-0.194	-0.112	0.304	0.152	0.575	-0.160
Total	-0.088	-0.080	0.622	0.115	-0.012	-0.048	-0.170	-0.020	0.326	0.147	0.604	-0.099
#Advices/h	0.117	0.037	-0.584	0.341	0.330	0.768	0.768	0.869	0.183	-0.549	-0.210	0.951
#excl stops/h	-0.003	-0.060	-0.622	0.259	0.150	0.701	0.715	0.815	-0.029	-0.396	-0.387	0.882
Again Cur	0.286	0.221	-0.825	0.096	0.354	0.341	0.525	0.366	0.015	-0.571	-0.474	0.495
Against Prev	0.145	0.065	-0.605	0.401	0.405	0.737	0.763	0.887	0.244	-0.614	-0.178	0.944
MAXMIN20	0.177	0.093	-0.790	0.321	0.382	0.683	0.746	0.805	0.097	-0.616	-0.395	0.885
MAXMIN30	0.157	0.112	-0.692	0.347	0.399	0.716	0.795	0.846	0.207	-0.642	-0.257	0.935
MAXMIN60	0.100	0.079	-0.660	0.398	0.385	0.692	0.776	0.883	0.207	-0.621	-0.237	0.932
MAXMIN90	0.108	0.089	-0.699	0.419	0.410	0.661	0.772	0.882	0.217	-0.655	-0.253	0.918
MAXMIN120	0.024	0.032	-0.701	0.444	0.349	0.586	0.704	0.877	0.127	-0.581	-0.320	0.859
std cur stop	0.001	-0.037	-0.190	0.598	0.408	0.349	0.357	0.730	0.375	-0.444	0.162	0.564
std adv stop	0.165	0.122	-0.418	0.535	0.543	0.317	0.399	0.638	0.395	-0.614	0.042	0.535
std cur IC	-0.018	-0.040	-0.144	0.676	0.451	0.352	0.362	0.788	0.450	-0.476	0.244	0.590
std adv IC	0.108	0.095	0.034	-0.263	-0.074	-0.046	-0.064	-0.280	-0.080	0.090	-0.038	-0.153
min	-0.208	-0.207	0.552	-0.287	-0.438	0.104	-0.261	-0.201	-0.274	0.603	0.125	-0.153
max	0.127	0.091	-0.407	0.666	0.599	-0.087	0.166	0.477	0.467	-0.667	0.101	0.224
early	-0.197	-0.203	0.448	-0.201	-0.368	0.114	-0.244	-0.122	-0.268	0.528	0.069	-0.112
Converged	0.210	0.221	-0.534	0.141	0.343	-0.095	0.263	0.097	0.187	-0.518	-0.178	0.118
Diverged	-0.154	-0.143	0.422	-0.548	-0.559	0.241	-0.085	-0.279	-0.416	0.635	-0.055	-0.056
Total	0.052	0.081	0.182	-0.683	-0.414	-0.223	-0.257	-0.721	-0.380	0.442	-0.170	-0.471
Arr-Dep	-0.067	-0.017	0.071	0.578	0.366	0.135	0.154	0.539	0.437	-0.319	0.360	0.324
Energy	-0.209	-0.208	0.491	-0.289	-0.441	0.119	-0.242	-0.183	-0.309	0.592	0.064	-0.132
Distance	-0.181	0.044	-0.216	-0.004	-0.081	-0.042	0.111	0.079	-0.192	0.015	-0.267	0.063
Kwh/v	-0.203	-0.209	0.573	-0.278	-0.430	0.110	-0.258	-0.194	-0.249	0.597	0.155	-0.147
Avg v	-0.009	0.047	-0.470	-0.301	-0.194	-0.001	0.128	-0.132	-0.429	0.041	-0.589	0.005
RunTime	-0.083	-0.024	0.028	0.709	0.447	0.171	0.198	0.674	0.497	-0.398	0.379	0.408
RunTime+Stop	0.043	-0.033	0.214	0.154	0.116	0.018	-0.060	0.070	0.229	-0.047	0.293	0.007
Avg Duration	0.119	-0.035	-0.219	0.170	0.169	0.053	0.047	0.156	0.059	-0.198	-0.086	0.100
Tot Duration	0.054	-0.031	0.215	0.074	0.066	-0.001	-0.084	-0.006	0.175	-0.001	0.254	-0.040
Braking	-0.024	0.000	0.752	-0.225	-0.175	-0.185	-0.335	-0.425	0.192	0.348	0.583	-0.377

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