Short-turning Trains during Full Blockages in Railway Disruption Management

Ghaemi, Nadjla

DOI
10.4233/uuid:a5a85092-4bd5-429d-b227-ba23a75b9793

Publication date
2018

Document Version
Final published version

Citation (APA)
Ghaemi, N. (2018). *Short-turning Trains during Full Blockages in Railway Disruption Management*. [Dissertation (TU Delft), Delft University of Technology]. TRAIL Research School. https://doi.org/10.4233/uuid:a5a85092-4bd5-429d-b227-ba23a75b9793

Short-turning Trains during Full Blockages in Railway Disruption Management

Nadjla GHAEMI

Delft University of Technology, 2018

This thesis has been funded by the partnership programme ExploRail of technology foundation STW and the Dutch railway infrastructure manager ProRail in the project SmartOCCR under grant number 12257.
The Netherlands Research School for Transport, Infrastructure and Logistics TRAIL is greatly acknowledged.

Short-turning Trains during Full Blockages in Railway Disruption Management

Dissertation

for the purpose of obtaining the degree of doctor

at Delft University of Technology

by the authority of the Rector Magnificus, Prof.dr.ir. T.H.J.J. van der Hagen,

chair of the Board for Doctorates

to be defended publicly on

Wednesday 4, July 2018 at 10:00 o'clock

by

Nadjla GHAEMI

Master of Engineering and Policy Analysis,

Delft University of Technology

born in Tehran, Iran.

This dissertation has been approved by the promotor:
Prof. dr. R.M.P. Goverde

Composition of the doctoral committee:

Rector Magnificus	Chairman
Prof. dr. R.M.P. Goverde	Delft University of Technology, promotor

Independent members:

Prof. dr. ir. S.P. Hoogendoorn	Delft University of Technology
Prof. dr. ir. A. Verbraeck	Delft University of Technology
Prof. dr. D. Huisman	Erasmus University of Rotterdam
Prof. dr. Z. Li	Delft University of Technology
Prof. dr. F. Corman	ETH Zurich, Switzerland
Dr. P. Pellegrini	IFSTTAR, France

TRAIL Thesis Series no. T2018/4, the Netherlands TRAIL Research School

TRAIL
P.O. Box 5017
2600 GA Delft
The Netherlands
E-mail: info@rsTRAIL.nl

ISBN: 978-90-5584-234-6

Printed in the Netherlands

Dedicated to Abolfazl, Sholeh, Dorsa, and Bernat

“The only way of catching a train I have ever discovered is to miss the train before.”

Gilbert K. Chesterton

Preface

I was very lucky to have the chance of performing a research on a topic that can have a direct social impact. Yes, I believe in luck. It could only be due to good luck that I was surrounded by supportive and friendly colleagues and friends without whom I would have not enjoyed the past few years as much. Here, I would like to acknowledge and thank them.

I have a lot to thank my promoter Rob Goverde who has undoubtedly been the main support for this work. To start with, thank you for trusting me to perform this research. Critical thinking and keeping a broad perspective while having an eye for detail are examples of many lessons that I learned from you. Your constant support has played a significant role not only in achieving the result of this dissertation but also in shaping the person I am today. Thank you for being always available to help and guide me through all the steps. And again I feel lucky to be the first PhD student to have your signature on my diploma. I would also like to express my gratitude to my daily supervisor Oded Cats for his support and valuable remarks to improve the quality of this research. Oded, thank you for your enthusiasm, guidance and friendship throughout this process. Moreover I would like to thank Ingo Hansen from whom I learned a lot during the railway group meetings. I must thank the committee members; Paola Pellegrini, Francesco Corman, Dennis Huisman, Zili Li, Serge Hoogendoorn, Alexander Verbraeck for reading and assessing my dissertation.

I would like to thank the other members of the SmartOCCR group. During regular group meetings I learned a lot about the railway operation from Dirk Kes. Thank you Dirk for showing me the existing challenges within the railway sector and for being open and curious about new ideas. It was a pleasure to have you as the SmartOCCR contact person in ProRail. I'm thankful to Dorota Kurowicka for her support, guidance, and for showing me that one can be serious, funny, and to the point at the same time. I would also like to thank Aurelius Armando Zilko who performed the first project of SmartOCCR. Zilko thank you for your help during the past few years. I was fortunate to have a smart and kind colleague like you.

I'm particularly grateful for the support I got from ProRail. I would like to thank Tom van Hoorn, Dick Middelkoop, Theo Stoop, and Reinier Klein Schiphorst who helped by providing the data and the corresponding insight.

I was lucky to share the office with very nice people who are more than colleagues to

me. I would like to thank my Chinese sisters with whom I shared a lot during these years. Fei thank you for joining the group slightly after me and did not let me to be the only girl in the group. You know that I very much appreciate your effort in our collaboration. We share a lot of happy moments together. Pengling thank you for all your kind support. You are a symbol of a knowledgeable and down to earth person for me. Yongqiu thank you for being a caring and supportive friend. I enjoyed and learned from our discussions. Gerben, although you were spending limited time in the office, I received a lot of positive energy and support from you. Thank you.

I do not forget the nice colleagues that warmly welcomed me upon my arrival in the railway group. First of all I would like to specially thank Pavle Kecman. Besides all the support, I would like to thank you for showing me a paper (by Paola Pellegrini and others) that became the basis for the microscopic rescheduling model. Daniel Sparing, thank you for encouraging me to pursue my dreams. I should say your weirdness is always being missed! Thank you Egidio Quaglietta for kindly welcome me as the first female PhD student in the group. Thank you Nikola for preparing the input data.

I am sincerely grateful to Siamak from whom I learned the alphabet of programming. Siamak thank you for all the time and effort you spent to help me dealing with problems very often. No matter how annoying a problem was, you made sure that you find a solution. Thanks to you I also learned how to look for a solution. I would like to specially thank Samaneh for her limitless kind support. Samaneh thank you for always giving me positive energy, motivation and courage. Thanks to your company I did not feel alone in my PhD years. I would like to thank my close friends Ghazaleh, Nazgol, Behnaz for all the sweet moments we shared together. Thank you for your never-ending support and friendship.

I enjoyed a lot the time I spent with my friends. Saba, Nami, Pejman, Pantea, Armin, Mahtab, Zahra, Shahob, Ario, Behzad, Delaram, Dena, Rad, Leila, Mana, Anton, Ale, Antonio, Ale, Luzma, Pheadra, Tommi, Tele, I would like to thank you for your support and friendship. I was lucky that I made such nice friends in the department; Azita, Solmaz, Yashar, Xavi, Montse, Paul, Haneen, Niharika, Flürin, Gema, Silvia, Lin, and many others. I would like to specially thank Siswa and Daniel for translating the summary of this dissertation and many thanks to Pedro for designing the cover of this book.

Meanwhile I received a lot of love and support from my family. Here I would like to thank Anvarjoon, dai Shahram, khaleh Shashar, Monirjoon, Shamsijoon, Nasrinjoon, Mònica, Sevi, and Aurora. Special thanks to my sister, Dorsa and my brother-in-law, Amir for their constant support.

Here I would like to thank my partner Bernat. Bernat being your partner is the best side effect of my PhD, and I owe it to the department of T&P. Your love, patience, endless support made this mission accomplished. Before you, I thought I'm probably a lucky person, but after knowing you I became sure. Thank you for being there and as you always say, being my "biggest fan".

Finally I would like to thank my parents Sholeh and Abolfazl for their love, encouragement, and all kinds of support. You remind me of this quote "There are only two lasting bequests we can hope to give our children. One of these is roots; the other, wings." Thank you for giving me both.

Delft, April 2018

Nadjla Ghaemi

Contents

Chapter 1

Introduction

1.1 Background

During railway operations, unplanned events may occur (e.g. switch or signal failure) that hamper the traffic. If the impact of the event is not limited to minor changes in the timetable but also require a new schedule for crew and rolling stock, then the event is defined as a disruption (Cacchiani et al., 2014). In such cases, traffic controllers are responsible for rescheduling and rerouting the affected trains to prevent a drop in quality service. Currently, the traffic controllers are not using any decision support system to handle disruptions. This thesis aims at developing support to the traffic controllers to deal with disruptions.

With a steady growth in Dutch railway traffic, and less steep growth of railway construction, the railway infrastructure needs more maintenance due to its increased utilization. Even though maintenance has increased over the past few years, the statistics of the Dutch railway operation show an increased number of disruptions in recent years. Figure 1.1 shows the number of disruptions (in blue bars) and the total duration of the relevant disruptions (in red circles) in the Dutch railway network from 2011 to 2017.

From the same source, Figure 1.2 shows the proportions of different disruption causes. It can be observed that the top three frequent causes of Dutch railway disruptions are infrastructure failure, rolling stock problems and accidents. Many times such events can lead to a complete blockage where no train can use part of a track for several hours. The economic impact of disruptions can vary depending on the severity of the disruption. Directive 2009/149/EC (European Commission, 2009) defines methods to compute measures for quantifying the economic impact of accidents, such as the costs of delays, damages to the environment, material damages to rolling stock or infrastructure, et cetera. Figure 1.3 shows the economic impact of the time spent for the door-to-door journey (Nederlandse Spoorwegen, 2016). This Figure shows that the delays in the Dutch railway network costed 200 million euros in 2016.

Unplanned events such as infrastructure failure and rolling stock breakdown can have

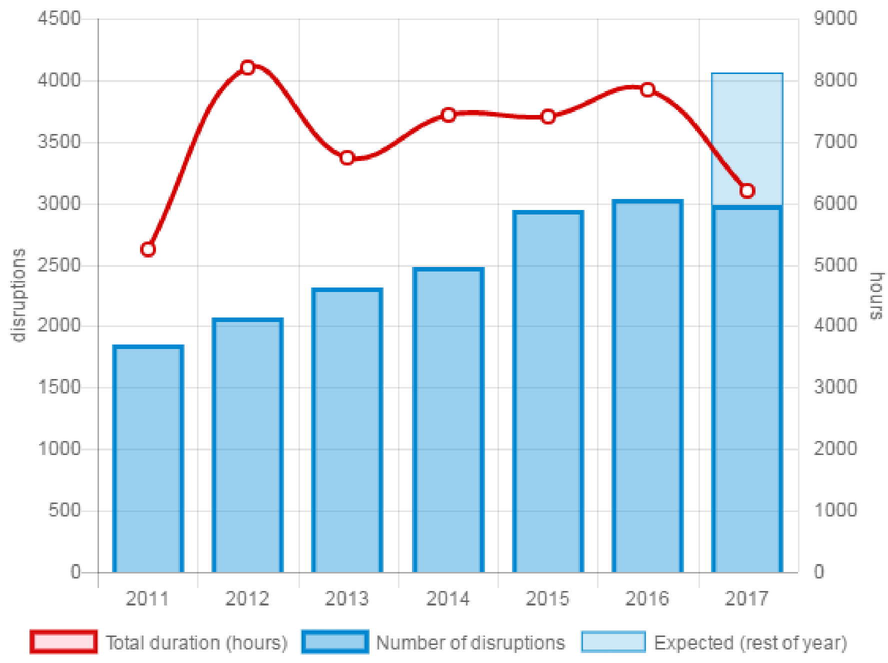


Figure 1.1: The number and duration of disruptions in the Dutch railway network. Source: https://www.rijdendetreinen.nl/en/statistics (accessed September 25, 2017)

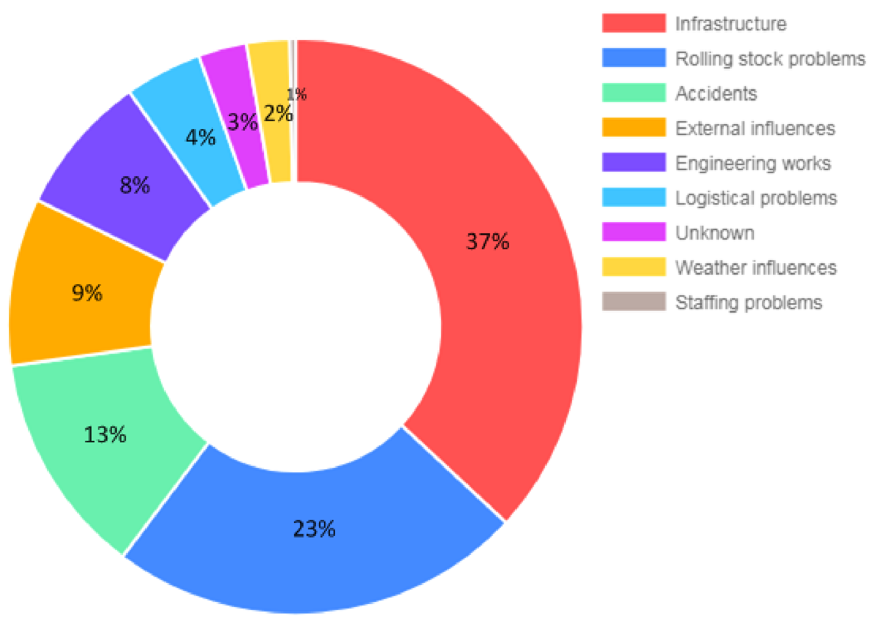


Figure 1.2: The causes of Dutch railway disruptions. Source: https://www.rijdendetreinen.nl/en/statistics (accessed September 25, 2017)

a tremendous negative impact if they are not handled efficiently. In this context, efficiency refers to finding a solution with the least adverse consequences within the shortest time. This becomes of greater importance with the constant increase in rail-

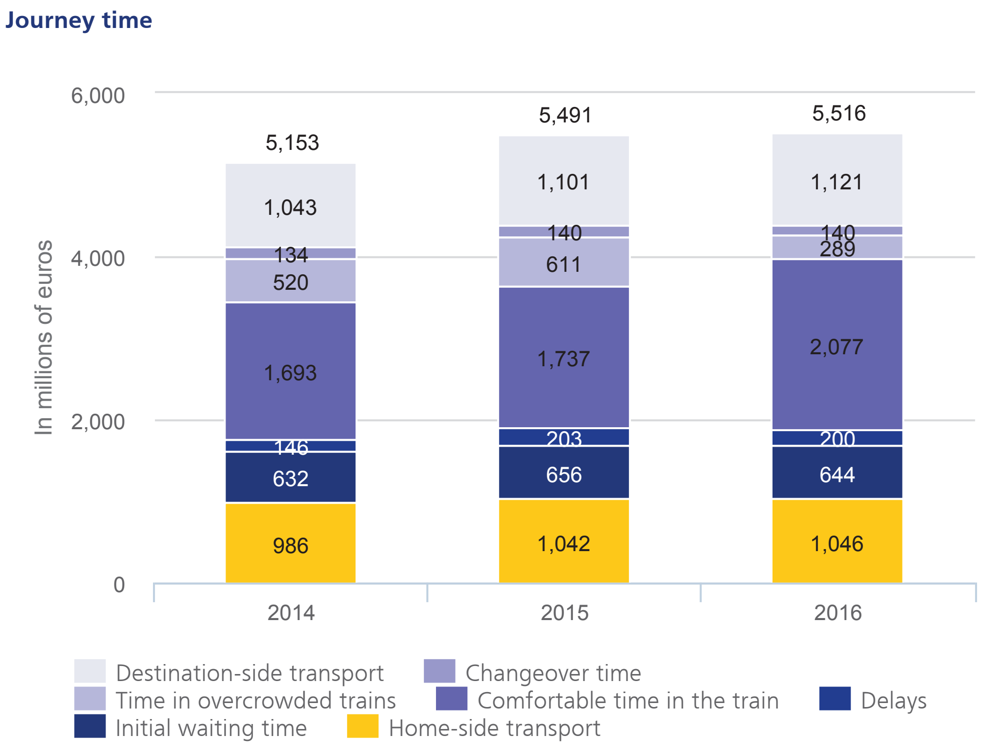


Figure 1.3: The economic impact of journey time. Source: NS Annual Report 2016

way operations. A dense network is more vulnerable to disruptions than a network with less traffic. This is not only due to the increase of the use of the resources (railway infrastructure and rolling stock) but also to the fast delay propagation to the rest of the network.

During a disruption, the level of service decreases and remains low until the cause of disruption is removed and the original timetable can be operated again. This decreased level of service is illustrated in Figure 1.4 by means of a bathtub model. Disruption period can be divided into three phases. When a disruption happens, the railway traffic cannot operate corresponding to the original timetable. Thus the traffic is decreased (first phase). The traffic remains decreased during the time the problem is being handled (second phase). When the problem is solved, the traffic can return to the original timetable (third phase).

1.2 Disruption management in practice

One strategy to handle a disruption is to isolate the disrupted area in order to confine the propagated delays to the neighboring stations. A well-known measure applied specially in cyclic operation in case of complete blockages is to short-turn services that cannot proceed due to the disruption. These trains then short-turn and perform the services in the opposite direction for which the trains could not pass through the blockage and perform these services.

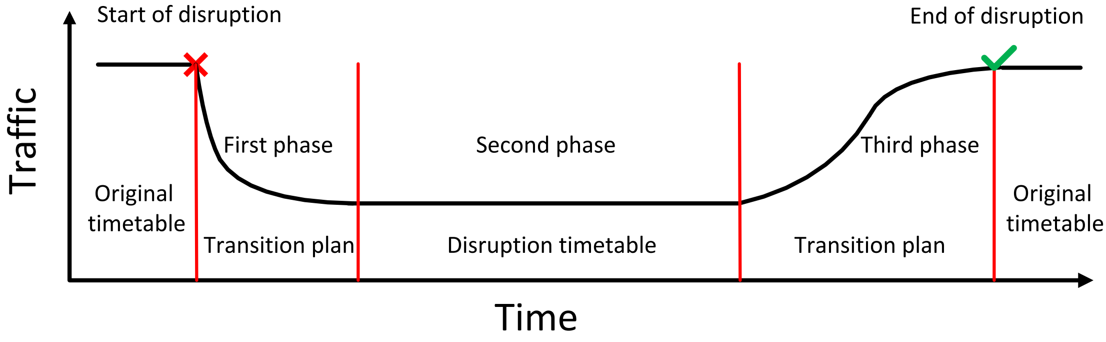


Figure 1.4: Bathtub model

Corresponding to the bathtub model, the first phase starts as soon as a disruption takes place and traffic controllers start to prepare the area to implement a new plan. This phase will continue till the area is free of traffic and ready to be operated by the disruption timetable. Considering the ongoing flow of traffic, switching to the disruption timetable through the transition phase might not be straightforward. The second phase starts when the disruption timetable begins to be operated. Due to the capacity drop, the traffic will be lower than the original timetable as is shown in the bathtub model. The third phase starts when it is known to the traffic controllers that the disruption cause is resolved and the traffic can be operated again based on the original timetable. This phase ends when the original timetable resumes in the operation.

In the remaining of this chapter the contingency plans are described in Section 1.2.1. Section 1.2.2 explains the organization of the railway traffic control centers in the Dutch railway sector. The processes of the disruption management are described in Section 1.2.3 and the challenges are pointed out in Section 1.2.4.

1.2.1 Contingency plans

Traffic controllers generally handle disruptions by using pre-defined solutions. These static pre-defined plans are called contingency plans (VSM or ”Versperringsmaatregelen” in Dutch). They suggest how to operate the traffic if a certain part of the network is disrupted. These if-then scenarios depend mainly on the location of the disruption and the timetable. An example of such contingency plans are shown in Figure 1.5.

Besides the visualisation of the disrupted part of the infrastructure, the contingency plan suggests the disruption timetable which indicates the decreased level of traffic corresponding to the second phase of the bathtub. The contingency plans are designed by experienced traffic controllers based on the timetable (basic hour pattern) and the infrastructure capacity of the disrupted area. The provided solution for each specific if-then scenario includes the services that need to be cancelled, those that can still operate and the services that have to short-turn or reroute. For the short-turning services, the arrival, departure and platform are indicated.

ProRail **Maatregel 87.050**

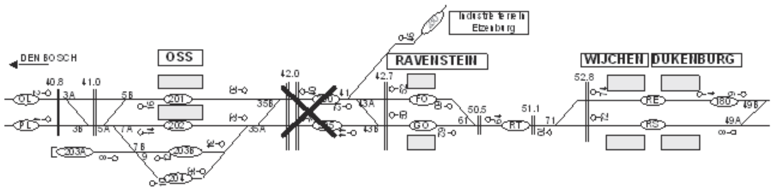
Traject: **Nijmegen - Den Bosch**

Baanvak: **Ravenstein - Oss**

Status: Definitief
Ingangsdatum: 27 apr 2014
Einddatum:

Situatie

Situatie: **Beide sporen Ravenstein - Oss zijn versperd.**



Gestremde sporen

Reizigerstreinen

Serie	*richting*	*bijzonderheden*	*werkverdeling*
Opheffen			
3600	Oss - Nijmegen v.v.		Keuze LVL-DVL
4400	Oss - Wijchen v.v.		Keuze LVL-DVL

Goederentreinen

Goederentreinen omleiden in overleg tussen Prorail LVL en de Transportcontroller DBS of de wachtdienst van de betreffende vervoerder.

Treinkeringen

Serie	*A.tijd*	*A.spoor*	*keert op*	*V.tijd*	*V.spoor*	*oorspr.*	*bijzonderheden*
Nijmegen							
3600	-.12	4a	3600	-.18	4a		
3600	-.42	4a	3600	-.48	4a		
Oss							
3600	-.24	1	3600	-.36	1	1	
3600	-.54	1	3600	-.06	1	1	
4400	-.14	2	4400	-.17	2	1	
4400	-.44	2	4400	-.47	2	1	
Wijchen							
4400	-.02	1	4400	-.26	2	2	Omrijden via Maasbrug.
4400	-.32	1	4400	-.56	2	2	Omrijden via Maasbrug.

Spoorwijzigingen

Serie	*A.tijd*	*A.spoor*	*keert op*	*V.tijd*	*V.spoor*	*oorspr.*	*bijzonderheden*

Bijzonderheden ProRail

Omroepberichten

Dames en Heren,
Door <oorzaak> rijden er geen treinen Nijmegen en Oss.
Reizigers met bestemming 's Hertogenbosch worden geadviseerd via Utrecht te reizen. U extra reistijd is ongeveer 30 minuten.

Afgedrukt op: 2-9-2014 09:15 *12 van 30*

Figure 1.5: An example of a contingency plan for a specific disruption in the Dutch railway network. Source: ProRail

1.2.2 Traffic control centers

Based on the European regulation (European Commission, 2001), railway transport is mainly divided into two separated responsibilities: the infrastructure manager is responsible for providing and maintaining the railway infrastructure, and the railway undertakings are responsible for providing train services. The two parts need to collaborate closely to operate services. In the Dutch railway network, the infrastructure manager has 13 and the main train operator has 5 local traffic control centers in the network.

To improve the operation, a central control room called Operation Control Center Rail (OCCR) was established in 2010. In the OCCR different actors within the railway sector gather, such as the traffic controllers from the infrastructure manager and the train operators, the contractors and experts in ICT. In case of disruptions, the OCCR has the main responsibility to handle the traffic. Having the traffic controllers from different sectors together, improves the process of communication while handling disruptions.

1.2.3 Processes of handling disruptions

Upon a disruption the signaller that is in the local traffic control center receives a notification. Then s/he informs the back office in the OCCR. If the disruption requires inspection at site, the inspection is performed by an inspector appointed by the OCCR. The OCCR receives the information update through this person. At the same time, the back office that is responsible to deal specifically with disruptions makes a new notification within a system called ISVL (stands for ”Informatie System VerkeersLeider” in Dutch), so all the controllers within the whole network are informed. The decision about the contingency plans is agreed between the traffic controllers and train operators. If for a given disruption, there is no contingency plan available, the decision regarding handling the disruption is made by the traffic controllers.

1.2.4 Challenges in case of disruptions

When a disruption occurs, it is usually unknown how long the disruption might take. Having a reliable disruption length can help the traffic controllers to reschedule the plans for the rolling stock, crew and the timetable efficiently.

Since the disruption length can vary considerably, the contingency plans in its current structure neglect the disruption length and provide a general solution that only corresponds to the second phase of a disruption while the transition phases are not addressed.

The advantage of the contingency plans is that they provide a general guideline as the base plan, and then traffic controllers can further develop a feasible solution. Having a general guideline reduces the complexity of making decision during the critical time upon the occurrence of disruption.

The disadvantages of contingency plans are that they are static predefined solutions that cannot take into account the inherent uncertainty of the real-time operation. For example, the contingency plan might not take into account a specific train that is running on a specific day, as these contingency plans are designed based on a certain timetable that is in operation for most of the days. Moreover, these plans need a yearly update which is due to changes of the timetable or the infrastructure.

It is possible that for a specific disruption case there is no existing contingency plan. In any case, the contingency plans need adjustments before they can be implemented. The adjustments should be performed by the traffic controllers. Thus, the traffic controllers are usually subject to considerable pressure to communicate the problem and collaboratively decide on a solution plan.

It has been observed that the solution provided by the contingency plans sometimes does not meet all the operational constraints, such as the minimum short-turning time that can result in infeasible platform track assignment and conflicting routes. Besides the feasibility of these plans, their optimality has not been investigated. Since the contingency plans are manually designed, the suggested solution might not be optimal. The disadvantages of the contingency plans are summarized in the following points:

- Static and inflexible
  - No transition plan
  - Regular manual update
  - Many missing disruption scenarios
- Possibility of infeasible solution due to ignoring the process times
  - Infeasible platform track assignment
  - Conflicting routes
  - Sub-optimal short-turning choices

1.3 Rescheduling models in literature

There are several surveys and literature reviews on rescheduling models. Cacchiani et al. (2014) divide real-time rescheduling models into four categories. Any rescheduling model handles disturbances or disruptions and is developed either at a macroscopic or microscopic level of detail. If any service has to be cancelled, and the resources such as rolling stock and crew need to be rescheduled, the event is categorized as a disruption. In case the problem can be resolved by only rescheduling the timetable, and the impact is limited to delays for some services, then the event is referred to as disturbance. Figure 1.6 shows a macroscopic representation of the Dutch railway network (on the left side) and a more detailed microscopic representation of station Utrecht which is located in the middle of the network (on the right side). In microscopic models, not only the infrastructure is represented in large detail (e.g. track circuits, switches, etc.), but also the operations are considered at a similar level of detail, including signalling constraints. Consequently, microscopic models are often applied to smaller areas due to the large magnitude of the detail as opposed to the macroscopic models that can include larger areas.

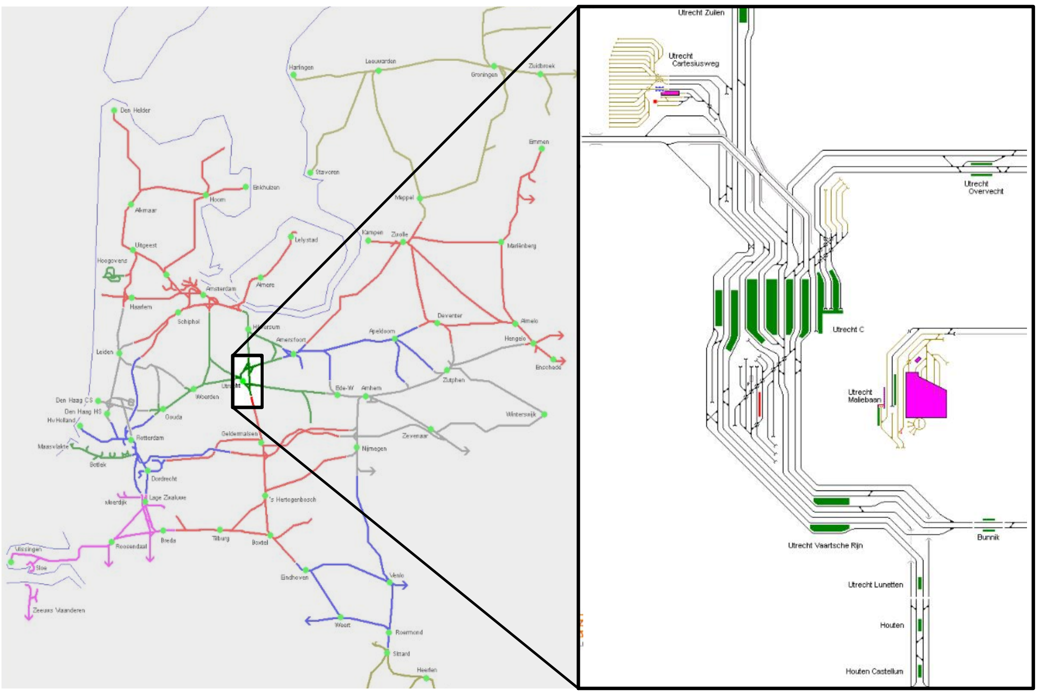


Figure 1.6: The macroscopic and microscopic representation of the Dutch railway network. Source: http://www.sporenplan.nl/(accessed September 25, 2017)

The macroscopic approaches often use graph theory for modelling the railway operation, representing the stations as nodes and the tracks between them as the arcs. This level of aggregation is suitable for providing a network wide solution but it can miss some essential detail that could lead to infeasibility at the local level. The macroscopic approach is used widely for rescheduling models to handle disturbances (Acuna-Agost et al., 2011a,0; Dollevoet et al., 2012; Kecman et al., 2013; Schöbel, 2009; Törnquist and Persson, 2007). Recently the focus has shifted to handling disruptions, which affect the network on a larger scale. Consequently there are fewer studies that address disruptions (Groth et al., 2006; Louwerse and Huisman, 2014; Narayanaswami and Rangaraj, 2013; Zhan et al., 2015), and none of them takes into account short-turning as a rescheduling measure. The literature mostly addresses either the first, second or third phase of disruption. Only Veelenturf et al. (2016) include short-turning and implicitly takes into account the first and third phases. Thus, the optimality of short-turnings is not thoroughly investigated.

The microscopic approaches can entail different level of details. If the signals and block sections are included then the model is classified as microscopic. There is a rich literature on microscopic rescheduling models that handle disturbances (Caimi et al., 2012; Corman et al., 2009; Lusby et al., 2011). Few studies include a deeper level of details which take into account the operation at the track circuit sections of a block section (Pellegrini et al., 2014; Rodriguez, 2007). Microscopic approaches for handling disruptions have hardly been investigated with some exceptions (Corman et al., 2011b;

Hirai et al., 2009). A common approach is to have a macroscopic view to model disruptions due to its large impact to the network. At the same time, short-turning is a rescheduling measure that is applied locally and reduces the negative impact on the network. However the existing literature of microscopic models does not offer any insight into the feasibility and optimality of the disruption rescheduling measure.

1.4 Research objective and research questions

The objective of this research is to develop algorithms that can compute an optimal solution for short-turning trains in case of complete blockage. Thus, the main research question is formulated as:

How to optimize short-turnings of train services in case of complete blockages?

To answer the main research question, the following sub questions are defined:

1. What measures can be considered for railway disruption management in practice and literature? (Chapter 2)
2. How to apply the short-turning measure to minimize the negative impact to the rest of the network? (Chapter 3)
3. How can the optimal short-turning solution depend on the disruption period? (Chapter 4)
4. How can the short-turning measure be modelled to address conflict-free routes at the microscopic level? (Chapter 5)
5. How can different disruption length predictions impact the short-turning solution and consequently the passengers? (Chapter 6)

1.5 Research approach and scope

In order to develop a model that can answer the main question, a series of incremental steps is performed to gradually build a short-turning model that can provide a feasible solution for the three phases of disruption. The steps are explained in section 1.5.1 and the research scope is described in section 1.5.2

1.5.1 Research approach

First, a macroscopic short-turning model is developed based on a Mixed Integer Linear Program that assigns the arriving trains to scheduled departures in the opposite direction and can select the optimal short-turning station.

Then the macroscopic short-turning model is extended to both sides of the disrupted area to analyze the impact of the disruption period on the optimal short-turning solution entailing the transition phases. However, the macroscopic model does not take into account the infrastructure detail of the short-turning stations. Thus, the solution cannot accurately define the conflict-free routes in the station for short-turning.

In order to incorporate this detail in the third step, a microscopic rescheduling and rerouting model (also in Mixed Integer Linear Program formulation) from the literature is extended with short-turning variables and constraints.

Finally, the model is integrated withing a framework to analyze the impact of the disruption length estimations on the short-turning solutions and consequently on the passenger delay.

1.5.2 Research scope

The models developed in this research are applicable to railway disruption cases with a complete blockage and a cyclic timetable (the timetable pattern repeats in each period.) The models do not include partial blockage, where some train services can still operate in the disrupted area using different tracks.

The operational processes such as running times, dwell times, short-turning times and the original timetable are given as input and are not computed in this research.

The output of the macroscopic model includes the choice of short-turning trains and stations. The extended microscopic model computes the optimal platform allocation and conflict-free local routes within the short-turning stations.

Both macroscopic and microscopic models can be applied to similar transport modes such as metros.

1.6 Main contributions

1.6.1 Scientific contribution

The scientific contributions are listed in correspondence to the order of the chapters.

- *A thorough analysis of the processes during disruptions and classification of the relevant models is provided.* Each phase of the disruption is characterized by different processes that can be improved by implementing the methods developed in the literature. This requires a thorough understanding of the problems in each phase and how the traffic controllers can benefit from the developed algorithms.

- *A macroscopic short-turning model is developed to analyze the impact of considering multiple short-turning stations.* In case the short-turning station does not have enough capacity for short-turning services on time, the services can short-turn in an earlier station. The possibility of short-turning in an earlier station can result in less propagated delay.

- *The macroscopic short-turning model is used to analyze the impact of the disruption period on the optimal short-turning solution.* Besides considering the traffic on both sides of the blockage, including the transition phases requires a reliable disruption length prediction. To analyze the impact of the disruption period on the optimal solution, the traffic on both sides of the disrupted area is taken into account. Moreover based on the defined indicators, the transition phases are defined and measured.

- *A microscopic short-turning model is developed to compute the optimal platform allocation and routes in the short-turning stations.* To guarantee the feasibility of the solution in the short-turning stations a microscopic level of detail for the infrastructure and operation is included. The variables and constraints from the macroscopic short-turning model are integrated into a microscopic rescheduling model in order to make it applicable to disruptions.

- *The macroscopic short-turning model is integrated into a framework to analyze the impact of the disruption length on the short-turning solution and the passenger generalized travel time.* The disruption length is not known in advance and yet it is essential to have a reliable prediction to compute a new schedule and accordingly measure the impact of the new schedule on the passengers. The macroscopic short-turning model is integrated in a framework to analyze the impact of different disruption predictions on passengers.

1.6.2 Societal relevance

The societal contribution of this thesis is twofold. First by providing a fast rescheduling solution, the traffic controllers experience less stress handling the disruption. Secondly the computed solution minimizes the delay and number of cancelled services. From the passengers points of view, not only the implemented solution entails the least delay and number of cancelled services, but such models can speed up the decision making processes and eventually achieve shorter transition phases.

1.7 Outline of the dissertation

This thesis consists of seven chapters. Figure 1.7 illustrates the outline and the order of the chapters that can be followed by the arrows. The relevant chapters are grouped together. Chapter 1 and 2 are grouped as they provide an introduction to the challenges and possible solution directions in railway disruption management. Chapters 3, 4 and 6 consider the macroscopic short-turning models and thus they are jointly grouped.

Chapter 3 presents the initial macroscopic short-turning model which is applied on one side of the disrupted area. In chapter 4 the macroscopic short-turning model is applied to both sides of the disruption and the transition phases are measured based on the defined indicators. Chapter 5 presents the extension of a microscopic rescheduling model with the possibility of short-turning in multiple stations. Chapter 6 integrates both researches of SmartOCCR (the disruption length prediction model and short-turning model) and passenger assignment model to develop a framework for analyzing the impact of the disruption length prediction on the passengers. Finally chapter 7 concludes with the main findings and recommendations. Moreover the limitation of this research and possible future research directions are discussed.

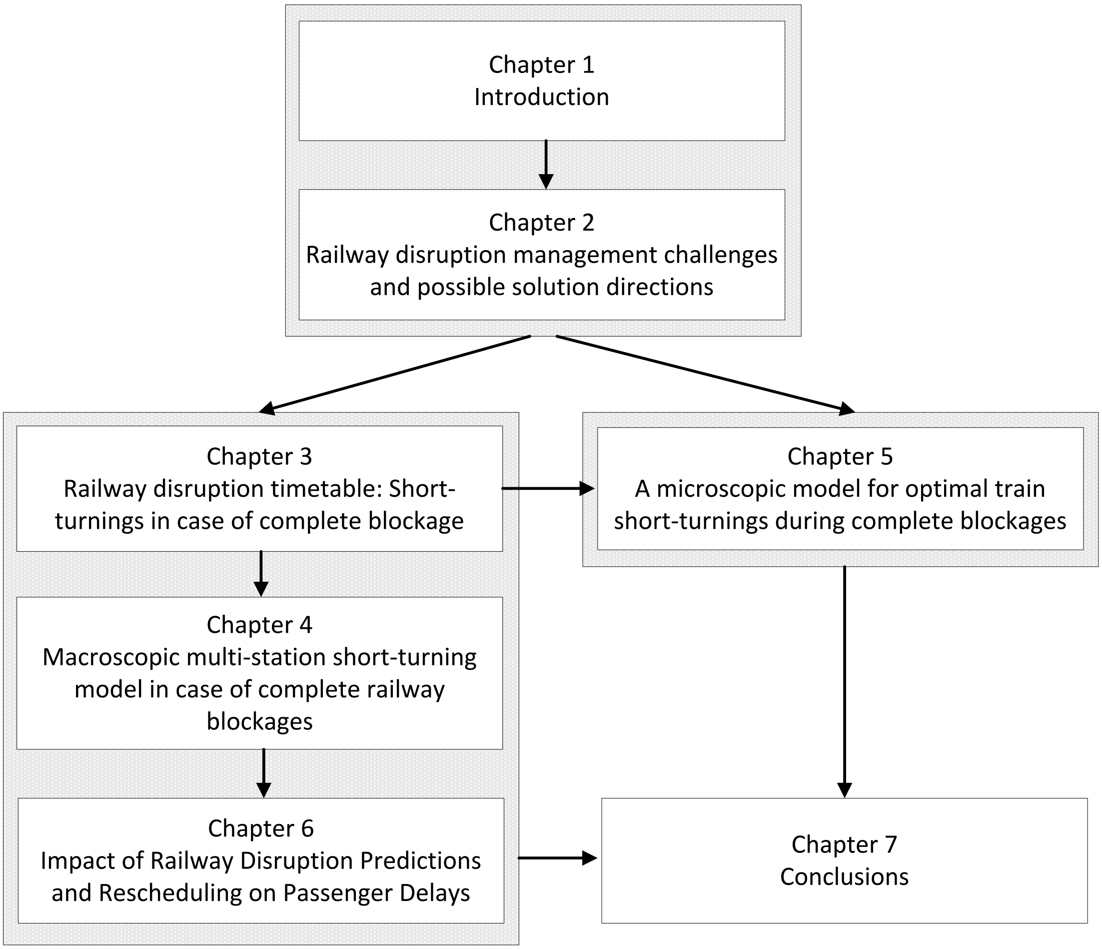


Figure 1.7: Flowchart of the thesis structure.

With the exception of chapters 1 and 7, the remaining chapters are based on the following published or submitted articles:

- Chapter 2: Ghaemi, N., Cats, O., Goverde, R.M.P., 2017. Railway disruption management challenges and possible solution directions. *Public Transport* 9 (1): 343 –364.

- Chapter 3: Ghaemi, N., Goverde, R.M.P., Cats, O., 2016. Railway disruption timetable: Short-turnings in case of complete blockage. 2016 *IEEE International Conference on Intelligent Rail Transportation (ICIRT)*, 210 –218.

- Chapter 4: Ghaemi, N., Goverde, R.M.P., Cats, O., 2018. Macroscopic multiple-station short-turning model in case of complete railway blockages. *Transportation Research Part C: Emerging Technologies*, 89:113 –132.

- Chapter 5: Ghaemi, N., Cats, O., Goverde, R.M.P., 2017. A microscopic model for optimal train short-turnings during complete blockages. *Transportation Research Part B: Methodological*, 105:423 –437.

- Chapter 6: Ghaemi, N., Zilko, A. A., Yan, F., Kurowicka, D., Cats, O., Goverde, R.M.P., 2018. Impact of Railway Disruption Predictions and Rescheduling on Passenger Delays. Accepted in: *Journal of Rail Transport Planning & Management.*

Aurelius Zilko contributed in sections 6.3.1 and 6.3.4 about the disruption length model and the interaction between the models, in section 6.4 about the application and in section 6.5 about the main findings. Fei Yan contributed in section 6.3.3 about the dynamic passenger assignment model under disruption and its application in section 6.4.

Chapter 2

Railway disruption management challenges and possible solution directions

Apart from minor updates, this chapter has been published as:

Ghaemi, N., Cats, O., Goverde, R.M.P., 2017. Railway disruption management challenges and possible solution directions. *Public Transport* 9 (1): 343 –364.

2.1 Introduction

In case of large disruptions (e.g. infrastructure failures, rolling stock breakdown, accidents, etc.) railway traffic controllers should apply fast and proper measures to resolve the train services and prevent delay propagation to the rest of the network. Currently, predefined solutions called contingency plans are used to assist traffic controllers in dealing with disrupted traffic in the Netherlands and in other countries like Germany, Switzerland, Denmark and Japan (Chu and Oetting, 2013). Each contingency plan corresponds to a specific disruption scenario in a specific location designed manually by experienced traffic controllers. The disadvantages of these plans are that they are not worked out in detail on infrastructure allocation level and cannot cover all the disruption cases throughout the network. They are constantly getting designed and updated based on the changes in timetable and infrastructure. In practice, it might happen that no suitable contingency plan is available for a disruption case. For such cases the traffic controllers are faced with a high workload to reach an agreement about the suitable plan. Since these plans are static and inflexible, the traffic controllers need to make some adjustments before being able to implement them. Hence, an algorithm that computes a new timetable for both sides of the disruption area is needed in practice.

We believe that a feasible solution requires formulating the operation and infrastructure with fine granularity. Thus, in our research a great importance is given to methods with a microscopic level of detail.

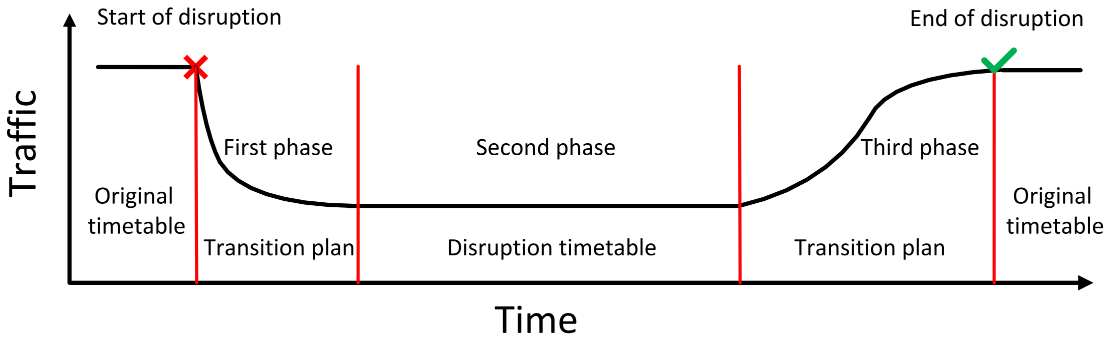


Figure 2.1: Bathtub model used for illustrating the traffic level during a disruption

The traffic level during disruptions resembles a bathtub, as is shown in Figure 2.1. This bathtub model is divided into three phases. When a disruption happens, the traffic will decrease (first phase). The traffic remains at a low level during the disruption where a disruption timetable is applied based on the contingency plans (second phase). When the disruption has been solved the traffic will be recovered to the original timetable (third phase). The first and third phases are called transition phases, since they represent transitions of the operations from the original timetable to the disruption timetable and vice versa. In transition phases the traffic is not as regular as the traffic in the second phase or in the undisturbed situation. Those services that are decided to be cancelled in the disruption timetable should be handled in the first transition phase. In the third phase the cancelled services need to resume their operations. One of the drawbacks of the contingency plans is related to the lack of any instruction on how to deal with the transition phases.

In this paper the problems that railway traffic controllers face when dealing with disruptions are investigated based on the Dutch practice. Then these problems are classified based on the three phases of the bathtub model. Next a critical review of the models and approaches known from the literature is carried out. In the following step the applicability of the models for the defined problems is investigated, and an illustrative case shows the applicability of a microscopic model to a case of a complete track blockage. The contributions of the paper are as follows:

- Identification of the challenges of traffic controllers in disruption management based on interviews with practitioners.
- Classification of the existing approaches in literature according to the bathtub model.
- Demonstration of the support provided by a microscopic rescheduling model in different phases of a disruption.

The structure of the paper is as follows. Section 2.2 describes the current disruption management practice from the Netherlands and identifies the problems that need improvements. Section 2.3 reviews relevant disruption management models from the literature. Section 2.4 provides an illustrative example on how a microscopic model could support the disruption management within the three phases. Conclusions are given in Section 2.5.

2.2 Disruption management in practice

This section describes the practice of disruption management focusing on the Netherlands, and identifies the problems encountered based on interviews with traffic controllers, contingency plan developers, and railway control staff.

2.2.1 Design of contingency plans

Contingency plans are designed by experts who used to be signallers or traffic controllers. The design of these pre-defined solutions is based on the basic hour patterns of the Dutch timetable and station track occupations. Based on these patterns and a specific disruption scenario, the planner estimates the remaining capacity and decides which trains should be cancelled or short-turned. The cancellation of services should be divided between the different railway undertakings that are operating in the area. Then the stations at which the trains should be short-turned are defined. For each corridor so-called decoupling stations are defined in advance where trains will short-turn in case of a complete blockage. Different train types (e.g. Intercities or local trains) may have different decoupling stations for short-turning. In defining the short-turning locations, it is anticipated that the short-turned trains replace the trains in the opposite direction. Based on the station track occupation, it is checked whether the trains could short-turn at the proposed time and platform. These static solutions are not able to consider the inherent uncertainties of the real-time operations and thus their realization might not be possible if the actual traffic deviates from the basic patterns.

2.2.2 Workflow of disruption management

Since 2010, the Netherlands has a centralized Operation Control Centre Rail (OCCR) to face large disruptions. The aim of having a centralized control centre is to bring different railway stakeholders such as the traffic controllers from the Infrastructure Manager (IM), the operations controllers from the Railway Undertakings (RU) and the delegates from the contractors together to achieve a higher performance by better communication. This becomes especially important with big disruptions on the network when the stakeholders have to cooperate closely. Figure 2.2 shows the workflow during a disruption. If the train traffic is hampered due to a serious failure of infrastructure or rolling stock, it is usually the driver who first notices the problem. This information is communicated to the back office (BO) of the OCCR through the decentralized control center by a signaller. Then, an inspector (a.k.a. general controller) is sent to the location of the failure to provide updates about the status of the problem to the back office. In the meantime the back office creates an announcement notification in the online traffic control information system, so the signallers, traffic controllers and other involved actors could access the announcement and get informed. In this notification, the problem, the people who should be involved, and the specific location that should be identified by the signaller are mentioned. The involved actors are able to modify and update the provided information online.

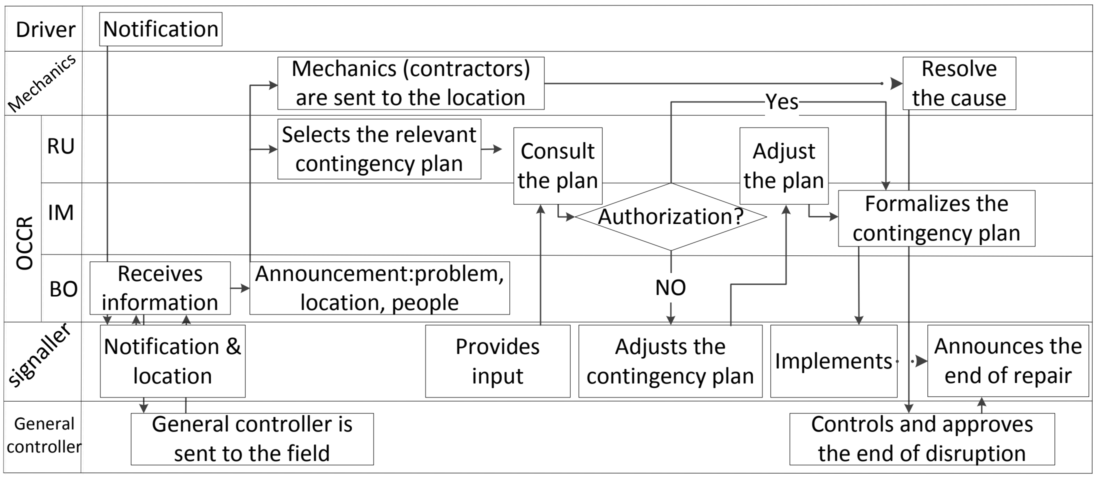


Figure 2.2: Workflow of disruption management

If required, contractors are sent to the location to repair the problem. Meanwhile the railway undertakings should deal with the disturbed trains that cannot proceed according to their original schedule. Based on the information from the field such as the location and severity of the disruption, the relevant contingency plan is selected and communicated with the traffic controllers from the infrastructure manager. Before implementing any plan, first it should be agreed between the traffic controllers of the infrastructure manager and the railway undertakings that the selected plan offers a suitable solution for the disrupted situation. Finally the traffic controllers in the OCCR should authorize the implementation of the contingency plan. In case the contingency plan requires some adjustments, this should be performed in consultation with the signallers who are responsible for route setting. Once authorized the contingency plan will be formalized by the traffic controllers and implemented by the signaller. After the repair crew solved the cause of the disruption and this has been approved by the general controller, the termination of the repair in the field will be announced in the online information system. The traffic can restore as soon as the disruption is over. However, as is shown in Figure 2.1, the third phase may take some time for the transition from the disruption timetable to the original timetable.

2.2.3 Identified problems in the OCCR

In this section the difficulties regarding the processes mentioned earlier are presented and projected on the three phases of the bathtub model. The first phase starts as soon as the traffic becomes disturbed due to an unplanned event or when an incident is communicated to the back office. It takes some time before the *precise location of the disruption* is known and communicated. The situation is communicated to the back office of OCCR where a decision should be taken. The decision about implementing a contingency plan in the first place depends on the disruption *length* estimation. If the estimated length is less than 45 minutes then it is preferred not to implement any contingency plan. Thus, it is important to have a fast and accurate disruption length estimation which is currently missing. If it is expected that the disruption lasts longer than 45 minutes, the search for a suitable contingency plan starts. This search is based on the information received from the field such as the exact location of the disruption and its severity.

In case of an existing suitable contingency plan, there is a problem regarding the implementation of these plans in the short-turning stations. The contingency plans correspond to the second phase of the bathtub model with the reduced traffic. However, since the detailed information regarding the implementation of this reduction depends on the real state of the traffic, the solution cannot be specified in the contingency plan exactly. It might happen that at the moment when the suitable contingency plan is selected, the train already left the station where it had to short-turn and the traffic controller needs to take care of the operation of this train in the following station. Thus, the traffic reduction might not be implemented as straightforward as is suggested in the contingency plan. Therefore these plans do not provide sufficient detailed information about the processes that were unplanned in the original timetable. Since these contingency plans are predefined, they may need to get *adjusted* to reflect the real traffic status. For example, if the trains do not operate according to the plan and their platform track occupation does not correspond to the planned pattern, then the specific station platform might still be occupied by another train and accordingly a suggested short-turning might not take place at the defined time or platform.

Nevertheless, the most relevant contingency plan is chosen by the RU operations controllers and then modified to a disruption timetable in collaboration with the IM traffic controllers in the OCCR. A problem might occur when the traffic controller and signaller do not agree on a decision such as cancelling a service and have *different opinions* about which decision should be taken. Then reaching an agreement might take long and moreover the final decision might not be the optimum, since it depends on the experience of the traffic controller and signaller. If no suitable contingency plan is available then the traffic controllers are in charge of providing a feasible plan based on the actual traffic state. The common practice is to *isolate* the disrupted area and prevent delay propagation to other lines. The services that are directly affected by the disruption should be identified and handled separately. This task is rather difficult, especially in the main stations with many trains. In current practice, handling the disruption directly depends on the experience and skill of the person in charge. This is the main reason of disagreements between the controllers and signallers.

In the second phase any new information about the actual state of the disruption might require some *adjustments* to the current operation. In this phase, it is also important to plan ahead to restore the original timetable. Therefore, in this phase the information about the *disruption length* plays an important role. If accurate information about the disruption length is available, the third phase could be planned to achieve a smooth and fast *transition* from the disruption timetable back to the original timetable. In the third phase, it is important to *reinsert the cancelled services* and *restore the original plan* in such a way that it does not hamper the traffic of the adjacent areas. Table 2.1 summarizes the identified challenges in each phase. Looking at the identified problems, it can be concluded that the traffic control faces most problems during the first phase where the uncertainty regarding the exact disruption and a suitable solution is the highest.

Table 2.1: Identified challenges in each phase

Phase	Challenges identified
First Phase	Receiving precise information about the disruption location Estimating the disruption length Discussing the decision & adjusting the contingency plan Isolating the disrupted area (in case of no contingency plan)
Second Phase	Adjusting and implementing the disruption timetable Estimating the remaining disruption length Preparing the transition phase
Third Phase	Reinserting the cancelled services Restoring the original plan

2.3 Literature study

There is a rich literature and overview of models and methods used for dealing with operational uncertainties. However, there are limited references addressing the large disruptions where many trains should be cancelled or short-turned. Cacchiani et al. (2014) provide an overview of models and algorithms for real-time rescheduling. In this overview, the literature is classified into two categories. The models and methods that are handling relatively small deviations from the scheduled timetable referred to as disturbances, and those which deal with large deviations that usually involve long delays and cancellation of services and rescheduling of rolling stock and crews which are referred to as disruptions. The models for disturbances and disruptions are developed based on either microscopic or macroscopic detail of the infrastructure and operations. The review concludes that the research on disruption management and especially with microscopic level of detail is surprisingly limited.

This section provides a review of the disruption literature with special attention to the three phases of the bathtub model. In this review the models are classified based on the number of different phases they are applicable to. It is also indicated whether they consider a micro or macro level of detail. Within this classification the applications of the approaches are also divided into those models that compute a new schedule and those that provide insight into any of the three phases. Note that in our review crew rescheduling is not included. The relevance of models to the different phases are determined based on the characteristics of each phase, which are as follows:

- First phase: Disruption length uncertainty, service cancellation and its impact on the operating services.
- Second phase: Disruption length uncertainty, disruption timetable.
- Third phase: Service reinsertion and its impact on the operating services.

Section 2.3.1 reviews the relevant literature and classifies them to one or more of phases. Then Section 2.3.2 presents the application of these approaches to dealing with the challenges mentioned in Section 2.2.3 per phase.

2.3.1 The disruption models

Models dealing with one phase

Despite the importance of short-turning strategies in case of disruptions, there are only limited references that investigated this topic. Coor (1997) macroscopically modelled a high-frequency single transit line to simulate short-turning trains with the objective to decrease the passenger waiting times. He concluded that a short-turning strategy is more beneficial in case of severe delays than small delays. The model provides insight about the advantages of short-turning for the second phase of the bathtub model.

Shen and Wilson (2001) developed a real-time disruption control model using mixed-integer linear programming (MILP). The macroscopic model considers a single line and formulates the route between stations as a sequence of block sections. Different control strategies such as short-turning, holding and stop skipping are tested. The authors conclude that the combination of holding and short-turning strategies reduces the mean passenger waiting time remarkably well. The model computes a schedule mainly for the second phase. Although the model could have been extended to the other phases this was not mentioned explicitly, so we disregard their relevance for the transition phases.

Jespersen-groth et al. (2009) focus on the recovery transition from a disruption timetable to the original timetable. When a disruption occurs, the trains are shunted away to the closest depots in the same direction. After the cause of disruption has been resolved, first a train should take the train drivers from the central station to the depots so that the cancelled trains can resume their operations. This recovery is modelled macroscopically as a mixed integer program (MIP) to calculate the best reinsertion of cancelled services into the network to fit the periodic timetable.

Hirai et al. (2009) used petri nets and integer programming (IP) to formalize and solve the train stop deployment problem. The model determines the stop locations for trains that can no longer operate according to the timetable and need to be cancelled. To avoid delay propagation, the focus is on isolating the disturbed area from other lines. The output of the model is a stop location for each train to clear the route for trains that are not disturbed and can still commute on other lines. The model is considered to be microscopic since the infrastructure is modelled at the level of block sections. This method partly addresses the first phase of the bathtub model with respect to the services that are cancelled due to a disruption but it does not provide any plan to the other trains or decides whether trains should be shunted or short-turned in case of a complete blockage.

Meng and Zhou (2011) used stochastic programing to incorporate the uncertainty of the disruption duration in probabilistic scenarios. The rescheduling is then performed based on a rolling horizon. The selected solution is the one with the minimum expected delay at the final station of all services. In this paper, the services resume as soon as the infrastructure is available, thus no other strategy such as short-turning or cancellations are considered and the focus is on the third phase.

Narayanaswami and Rangaraj (2013) developed a MILP for a single-track line. The only dispatching measure considered is delaying trains. The model assumes disruption length to be given, as well as the start and end time of the disruption. The decision variables of the model represent the arrival and departure of the trains in the station. The model is macroscopic and thus does not consider blocking times. Minimum process times and scheduled arrival and departure times are the inputs of the model. The objective is to minimize the weighted difference between the scheduled and actual arrival time at the final destination for all trains. The model computes the decision variables by delaying trains until the disruption is over and then defines the order and schedules of departing trains based on the weights. The disadvantage of this model is that the delay could propagate easily if the trains are not short-turned. The model is useful for the third phase of the bathtub model when the disruption cause is repaired and the operations can get back to the original timetable.

Chu and Oetting (2013) considered additional processes that are not planned but result from a disruption. The extra processes refer to communication, gathering information about the disruption, taking decisions about the suitable contingency plan and implementing the selected solution. To gain an insight about the first transition phase, they analysed the operational data of two big German urban railway networks where contingency plans were implemented. They concluded that one of the main reasons for delays during this phase was due to queuing of trains at the short-turning stations. Looking into the extra processes, they make a distinction between non-recurring and recurring processes. The first one refers to those specific processes that belongs to specific trains (e.g. giving written orders train by train) which do not repeat and the second one refers to the ones that reoccurs such as short-turnings. They highlighted the importance of these extra processes in deriving feasible contingency plans in stations using microscopic modelling of the blocking times. This research gives insight about the first phase of bathtub model.

The objective for managing large disruptions may be to maximize the service level. Louwerse and Huisman (2014) formulated the problem as a macroscopic MILP, considering both partial and complete blockages of a railway line. Their main focus is on computing the disruption timetable for the second phase. The original timetable and an estimation of the disruption duration are used as input of the model and the output of the model is the rescheduled timetable indicating which trains should run with their schedules.

Models dealing with two phases

Zhan et al. (2015) modeled a complete blockage by mixed integer linear programming. Their objective is to minimize total weighted delay and cancelled services considering headway and station capacity constraints. The output of the model is the decision about cancelled services, the stations where the affected trains need to wait until the disruption is over and the order of the departures. The model is developed for long distance services with seat reservations. In case of a disruption, the trains are not short-turned due to problems associated with rolling stock circulations. Since the model defines waiting locations for hindered services, it partly addresses the first phase. For the most part, the model deals with the third phase by computing the departure orders after the disruption cause is repaired.

Zilko et al. (2016) developed a model for estimating the disruption length. A Non-Parametric Bayesian Network (NPBN) is used to model the joint distribution between variables that characterizes the nature of the disruption. By conditioning on new information the estimation of the disruption length can be improved whenever information updates become available. Accurate estimates of the disruption length are very useful to achieve smooth transition phases. Thus, the model provides support for the first and second phases of the bathtub model.

Models dealing with three phases

Nakamura et al. (2011) developed a macroscopic model for dealing with a complete blockage on a double-track network. The model uses three predetermined factors: train group, train cancellation sections and short-turning patterns, which result in a train rescheduling pattern. The model cancels the services running in the disrupted area and connects the short-turning trains to the trains running in the opposite direction. Then it identifies those train lines that have either no assigned rolling stock or no planned route. At the final step of the algorithm, the process of matching the plans and rolling stock takes place. The main focus of the paper is to support the traffic controllers by proposing train cancellations and short-turnings. The support covers the three phases of the bathtub model.

Veelenturf et al. (2016) extend the macroscopic model of Louwerse and Huisman (2014). In the extended model, a real case of a railway network is used with more than two tracks between and inside stations, and the train services are able to use other tracks than they were originally assigned to. The objective of the model is to minimize delay and the number of cancelled services. The transition phases are implicitly addressed.

2.3.2 Applicability of models to the identified problems

This section investigates the applicability of the reviewed models to the identified problems for each phase. Within each phase the applicable literature is sorted based on the order of the identified challenges in Table 2.1. Tables 2.2 to 2.4 summarize the models over the three phases.

First phase

The traffic controllers face most challenges during the first phase. The first difficulty is to have an accurate estimation about the disruption length. Zilko et al. (2016) developed a model specifically for estimating the disruption length, which includes latency time and repair time. Knowing the approximate disruption length, the traffic controllers have to find the relevant contingency plan and implement it. Before implementing the contingency plan for the second phase, they also have to decide on a plan for the first phase which would eventually reach the disruption timetable suggested in the contingency plan. Thus, for the greatest extent, the plan for the first phase depends on the contingency plan of the second phase.

Chu and Oetting (2013) studied the effects of unplanned events that result in extended process times. The research provides a clear understanding on the capacity consumption in stations with short-turning, however it does not provide a rescheduling model to compute a solution including short-turnings. The implementation of short-turning trains still needs to be investigated more at a microscopic level of detail.

Another problem in the first phase is how to adjust a contingency plan and reach an agreement on a decision. To address this problem, the papers on rescheduling that include cancelling and short-turning trains can be used. Nakamura et al. (2011), and Veelenturf et al. (2016) provide solutions for rescheduling that implicitly include the first phase. Nakamura et al. (2011) focus on avoiding delay propagation while Veelenturf et al. (2016) focus on minimizing delay and number of cancelled services. However they do not provide microscopic insight into the station capacity consumption which is very important in the first phase.

The final problem concerns the cases where no contingency plan is available and traffic controllers should isolate the disrupted area to avoid delay propagation. Hirai et al. (2009) provide a model that can be used to calculate the stop positions for the trains that are affected directly so that the other trains could continue their trips conflict-free. The approach by Zhan et al. (2015) also defines the waiting location for trains until the source of the disruption is over. We believe that using a decision support tool can speed up the process of discussion and decision making.

Table 2.2: The identified challenges and relevant literature for the first phase

Problems	Models for the first phase
Estimating the disruption length	Zilko et al (2016)
Identifying the stop locations	Hirai et al (2009) Zhan et al (2015)
Adjusting the contingency plan & discussing the decision	Nakamura et al (2011) Chu & Oetting (2013) Veelenturf et al (2016)

Second phase

In the second phase the contingency plan might get adjusted with the updated information about the status of the disruption. For example, it might be the case that more (or fewer) routes should be cleared due to the disruption to access the tracks where the repair needs to be done. This results in the same problems of adjusting the plan and agreeing on a decision as in the first phase. Most literature available concerns the development of a disruption timetable for this phase such as Shen and Wilson (2001), Nakamura et al. (2011), Louwerse and Huisman (2014) and Veelenturf et al. (2016). Coor (1997) looked at short-turning trains as a strategy to compensate for the time loss in the second phase and the main conclusion confirms the benefits of short-turning trains in case of large disruptions. Also in the second phase a reliable estimation about the disruption length is required for which the model developed by Zilko et al. (2016) can be used.

Third phase

It is important to know when the disruption cause is expected to be resolved. This information is essential to plan for the third phase, where the train operations should

Table 2.3: The identified challenges and the relevant literature for the second phase

Problems	Models for the second phase
Estimating remaining disruption length	Zilko et al (2016)
Adjusting and implementing the disruption timetable	Coor (1997) Shen & Wilson (2001) Nakamura et al (2011) Louwerse & Huisman (2014) Veelenturf et al (2016)

switch from the disruption timetable to the original one. To give an example, if a reliable disruption length is available it can be decided earlier to stop the short-turning and operate trains based on the original plan again which shortens the second phase. The model of Meng and Zhou (2011) incorporates the uncertainty regarding this information and determines the order of trains to proceed after the disruption with the least delay. Narayanaswami and Rangaraj (2013) and Zhan et al. (2015) also contribute to the third phase, by computing the departure orders after the end of disruption. Jespersen-groth et al. (2009) focus on resuming the operation taking into account the rolling stock circulation and crew. This model can also be used to develop a plan for reinserting the services for the third phase.

Nakamura et al. (2011) and Veelenturf et al. (2016) provide a plan for cancelled and short-turned trains, which helps the traffic controllers to know which cancelled and short-turned trains should be reinserted back in the network. However the implementation of the plan in this phase requires a microscopic representation of the infrastructure and processes, especially in stations where trains were short-turned.

Table 2.4: The identified challenges and the relevant literature for the third phase

Problems	Models for the third phase
Reinserting the cancelled services	Jespersen Groth et al. (2009) Meng & Zhou (2011) Narayanaswami et al (2013) Zhan et al (2015)
Restoring the original plan	Nakamura et al (2011) Veelenturf et al (2016)

Table 2.5 gives a summary of the disruption models. The relevance of each model to each phase is shown by ✓. The column “Focus” indicates whether the model is rescheduling (R) or brings insight (I) to a particular phase. From the table we can conclude that there are limited disruption support models at a microscopic level of detail. There are two macroscopic models that address all three phases. However the feasibility of these solutions should be checked with a microscopic model. Thus, a microscopic model that is able to address all three phases of a disruption is still missing

in the literature. In the following section we will show how a microscopic model can provide support for the traffic controllers for each phase of a disruption.

2.4 Application of microscopic model for a disruption case

This section illustrates the relevance and applicability of a microscopic approach for rerouting and rescheduling trains in the different phases of a disruption. Caimi et al. (2011) developed a resource-constrained multicommodity flow model originating from the node-packing approach by Zwaneveld et al. (1996) for rerouting and rescheduling, which can be applied to resources at a microscopic level of detail. The set-packing approach developed by Lusby et al. (2011) incorporates time and place dimensions to the problem formulation by considering each resource utilization in intervals of 15 seconds. The disadvantage of time discretization is the possibility of missing any conflict that might take place between two discretized time points. In addition, both node-packing and set-packing approaches require pre-processing effort for computing resource utilization and conflict detection which eventually leads to limited rescheduling alternatives.

Pellegrini et al. (2014) proposed a Mixed Integer Linear Programing formulation for rescheduling and rerouting trains in complex junctions. The advantage of this formulation is that there is no need for pre-processing of the resource utilization to detect conflicts. Thus this formulation offers more scheduling alternatives. In this approach the conflicts are avoided by computing an order variable that prevents simultaneous resource utilization. Our rerouting approach is based on the model developed by Pellegrini et al. (2014) with the focus on short-turning services. The model computes the

Table 2.5: Summary of the reviewed disruption models

Paper	Micro	1 Phase	2 Phase	3 Phase	Application
Coor (1997)	–	–	✓	–	I
Shen & Wilson (2001)	–	–	✓	–	R
Jespersen Groth et al (2009)	–	–	–	✓	R
Hirai et al (2009)	✓	✓	–	–	R
Nakamura et al (2011)	–	✓	✓	✓	R
Meng & Zhou (2011)	–	–	–	✓	R
Narayanaswami & Rangaraj (2013)	–	–	–	✓	R
Chu & Oetting (2013)	✓	✓	–	–	I
Louwerse & Huisman (2014)	–	–	✓	–	R
Veelenturf et al (2016)	–	✓	✓	✓	R
Zhan et al (2015)	–	✓	–	✓	R
Zilko et al (2016)	–	✓	✓	–	I

blocking time (Hansen and Pachl, 2014) of each track section used by any running train and finds a conflict-free route for each train while minimizing the total delay of all trains along their routes. The model is implemented in Matlab 2016a using YALMIP (Löfberg, 2012) which is a free toolbox for fast implementation of optimization problems. Gurobi 2013 is used as solver on a laptop with an Intel(R) Core(TM) processor with 3 GHz and 8 GB RAM. The computation time for all the cases (21 trains operating between 5 stations on 100 track sections) was less than 3 seconds.

The aim of this case study is to illustrate the possible support that could be provided by a microscopic model to a traffic controller to manage the disruption during the different phases. For this case a railway corridor in the south of The Netherlands is selected. Figure 2.3 shows the corridor from station Nijmegen through Nijmegen Dukenburg (Nmd), Wychen (Wc), Ravenstein (Rvs), Oss (O) and further towards Den Bosch (Ht). This corridor is for the most part double-track, except between stations Wychen and Ravenstein where there is a single track (bridge) serving trains in both directions. The disruption occurs between station Oss and Den Bosch, thus all the arriving trains from Nijmegen have to short-turn in station Oss back to Nijmegen.

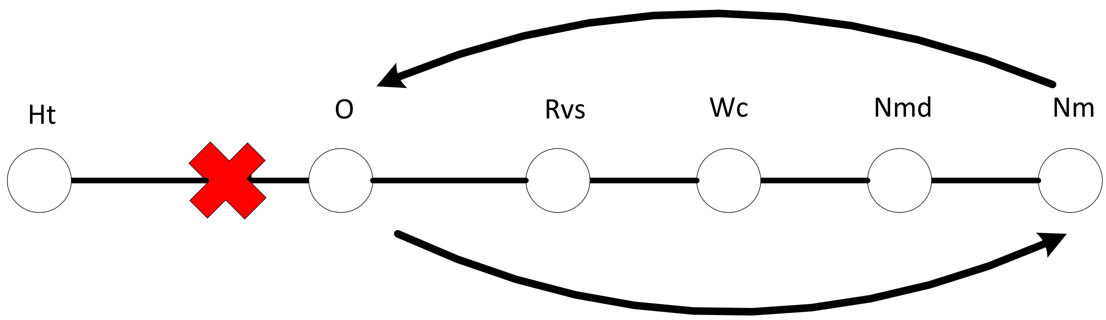


Figure 2.3: An example of a complete blockage on a Dutch railway corridor

In the original timetable, two train lines operate between stations Nijmegen and Den Bosch: an intercity (IC) and a local train line (called sprinters (SP) in Dutch). To make a distinction between opposite services of the same line odd and even numbers are used depending on the travel direction. For example the services of the lines IC3600 and SP4400 run from station Den Bosch to Nijmegen on one track, and services of the lines IC3601 and SP4401 run in the opposite direction on the other track. The last two digits of the train line numbers indicate the operation time of that line during the day. For instance IC3617 departs at 06:18:00 from Nijmegen. The next IC train in the same direction departs half an hour later at 06:48:00 as IC3619. Both lines IC3600 and SP4400 operate with a frequency of two services per hour in each direction.

Due to the obstruction, trains coming from Nijmegen heading towards Den Bosch should be short-turned in station Oss and continue running back towards station Nijmegen. This short-turning implies a changed station track utilization with adjusted routes and platform track allocations that need to be checked for conflicts, acceptable track occupation and fit in the new timetable with preferably all short-turned trains running according to the original opposite scheduled train paths. Note that the running times and blocking times change due to the changed routes. Likewise, the platform track occupation time of a short-turning train also takes longer than the minimum dwell time for a continuing train.

Figure 2.4 shows the track layout in station Oss. In the original timetable, both SP and IC services run on the upper track from Nijmegen to Oss and on the lower track from Oss to Nijmegen. As can be seen the trains are able to use both platform tracks for short-turning in station Oss.

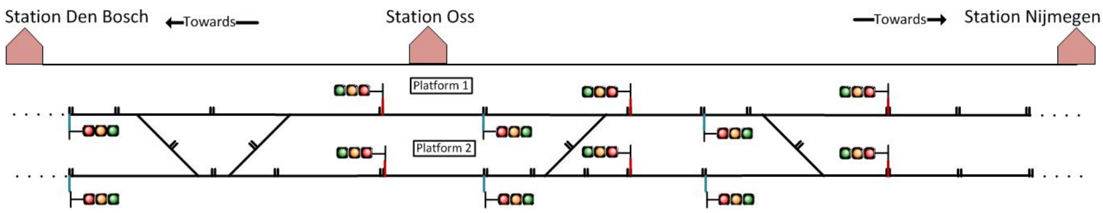


Figure 2.4: The layout of station Oss where trains have to be short-turned

Table 2.6 shows the hourly pattern of the original timetable for the two train lines SP4400 and IC3600. The actual train numbers are represented by ** as they vary each hour. The departures and arrivals are indicated by the minutes in the hour. For instance the first row can represent the train IC3617 that departs from Nm at 06:18 and arrives in O at 06:32. The microscopic rescheduling model developed by Pellegrini et al. (2014) is used to compute the blocking time diagram for the original timetable of this corridor. Figure 2.5 plots the computed blocking time diagram of the services for the route operated by train line IC3600. The lack of visual blocks for the train line SP4400 in Nm is due to the fact that their departure platforms are different from those of line IC3600.

The planned timetable is shown by red dash-dotted lines for IC3600 services and red dotted lines for SP4400. The computed rescheduled trajectories are shown by solid blue lines passing through the blocks. To distinguish between the IC3600 services from SP4400 services, the planned departures and arrivals of the IC3600 services are marked as stars. In addition, the blocks of train line IC3600 are colored in magenta and the blocks of train line SP4400 are colored in cyan.

As mentioned before, the corridor is double track except between stations Wc and Rvs. Hence, the trains from station O to Nm run on another track than those running from Nm to O (besides the mutual single-track part). Thus, the blocking stairways from O to Nm shown in Figure 2.5 are related to the single track between stations Rvs and Wc. Since all the services in both directions use the single track, the changes of the timetable including the order of services within the three phases are best understood by the single track blocking times at this location. Thus the blocking times of the single tracks are shown with different rectangles to emphasise the difference between the three phases of the disruption. The order of the operations of the train lines IC3600

Table 2.6: Original timetable

Train lines	Dep from Nm	Arr to O
IC36**	18	32
SP44**	23	43
IC36**	48	02
SP44**	53	13
Train lines	Dep from O	Arr to Nm
SP44**	14	35
IC36**	26	44
SP44**	44	05
IC36**	56	14

and SP4400 on the single track between Wc and Rvs are shown with a solid rectangle in Figure 2.5. This order represents the scheduled order of the original timetable. Two cases are defined to show how the optimal solution can be different given different disruption periods. Thus two cases are defined with a different start time of the disruption. The disruption in case 1 starts at 6:00 AM and in case 2 it starts at 6:30 AM. In both cases the disruption is over by 8:00 AM.

2.4.1 Case 1: Disruption starting at 6:00

In this case the disruption period is assumed to be between 6:00 and 8:00. In the disruption time window, there are seven services (SP4417, IC3617, SP4419, IC3619, SP4421, IC3621, SP4423) running from station Nm towards station O that arrive before 8:00. IC3623 is the first service that arrives at station O after 8:00 and is allowed to start using the restored section, after which also the services IC3623, SP4425, IC3625 and SP4427 resume their original operation. In the opposite direction, there are eight services (SP4416, IC3616, SP4418, IC3618, SP4420, IC3620, SP4422, IC3622) scheduled to operate from station O to Nm in the disruption period. Thus, in this particular case, seven arriving trains short-turn and can replace at most seven services from station O to Nm. This would mean one service from station O to Nm needs to be cancelled. The choice of cancelling a service needs to be made by the traffic controllers, and the existing contingency plans do not provide any support in similar cases. Since the microscopic rescheduling model by Pellegrini et al. (2014) does not include the possibility of service cancellation, we have to predefine the cancelled service. Thus, two variants of Case 1 are considered with the assumption of cancelling the first IC service (IC3616) in the first variant and cancelling the last IC service (IC3622) in the second variant. The resulting computed blocking time diagrams are shown in Figures 2.6 and 2.7.

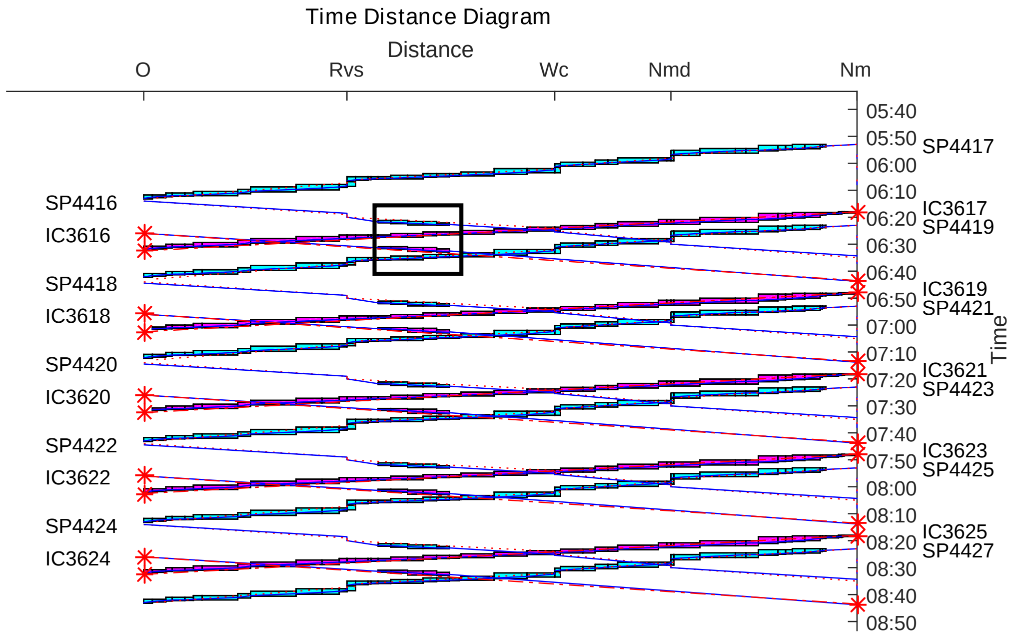


Figure 2.5: Blocking time diagram of the original timetable

Note that the services arriving from Nm to O, use the upper platform track as shown in Figure 2.4. Both time-distance diagrams shown in Figure 2.6 and 2.7 plot the blocking times for the route starting from the IC platform track in Nm until the planned platform

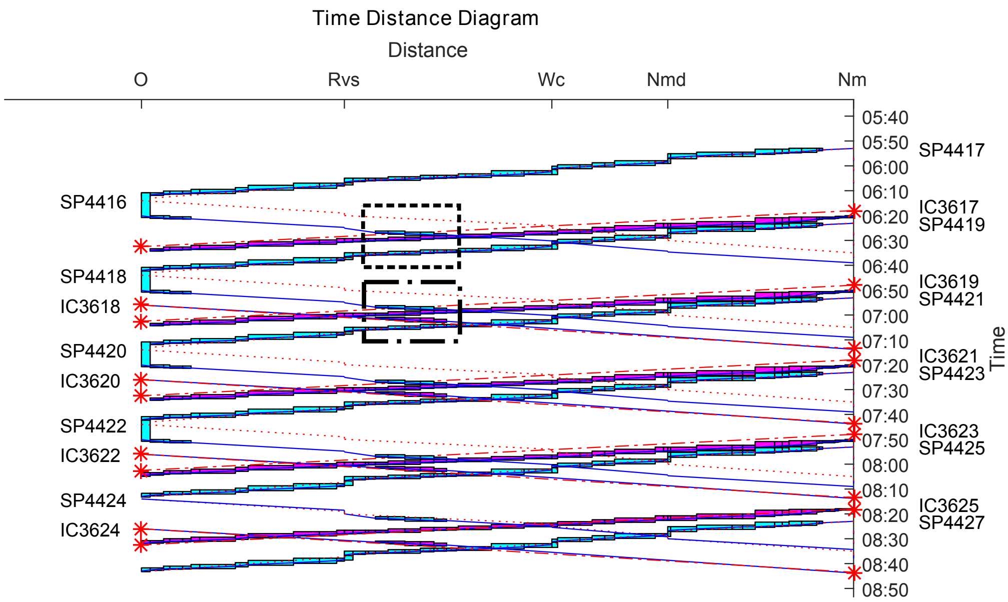


Figure 2.6: Blocking time diagram when the disruption starts at 6:00 with IC3616 cancelled

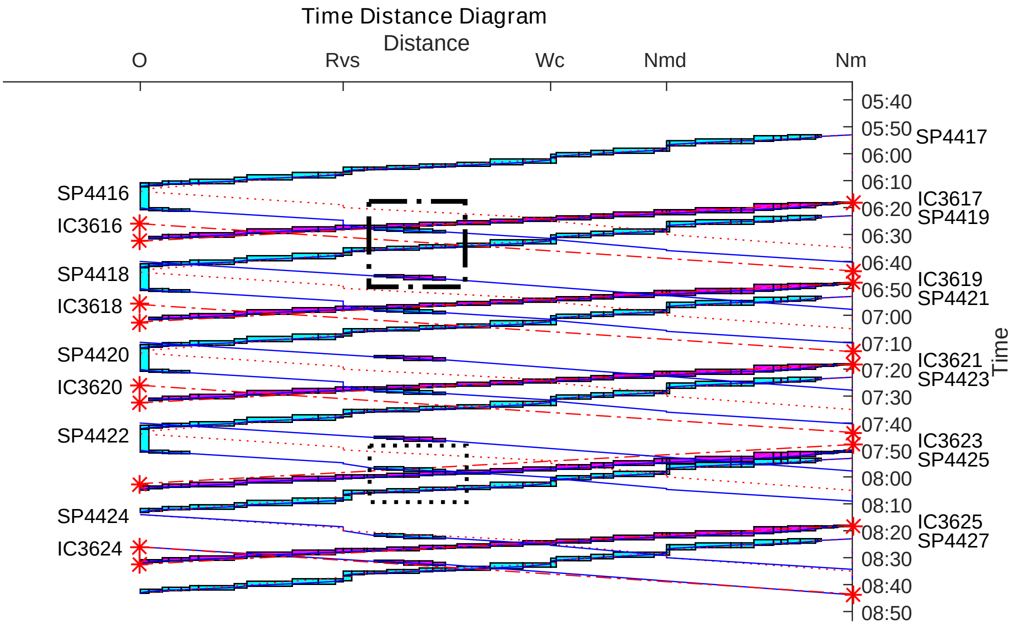


Figure 2.7: Blocking time diagram when the disruption starts at 6:00 with IC3622 cancelled

track used for the services arriving from Nm (upper track shown in Figure 2.4). As shown in both figures, the optimal solution proposes that the services from line SP4400 short-turn on the upper track in station O. These short-turnings are shown by the cyan blocks in station O. Since the services of line IC3600 short-turn on the lower track these short-turnings are not shown in the Figures 2.6 and 2.7 as the plotted blocks are related to the upper track. The computed platform choice is consistent with the existing contingency plan. Since the rescheduling is performed for the whole period, all three phases of disruption are included in the result. The differences in the phases are easiest detected by checking the blocking time diagram of the single track between stations Wc and Rvs.

Figure 2.6 shows the first variant where service IC3616 has been cancelled. In this variant, every train that arrives at station O, short-turns as the next service departing from O. The SP services arrive 1 minute before the original departures of the planned services towards Nm.

However, we assume a minimum short-turning time of 8 minutes. Thus, it is observed that the SP services are departing with 7 minutes delay. The delay is visualized by the difference between the dotted red line (the planned train paths of SP services from O to Nm) and the solid blue lines (the computed train paths). The delay of SP services from O towards Nm, introduce some delay to the IC services from Nm to O. The reason for this delay is that in our formulation the delay penalties for SP and IC services are the same. From the optimization perspective, delaying an IC service that has one departure and one arrival is more favorable than delaying the SP service that has several stops in between. However the choice of penalty can be easily changed based on the importance of the different services. The IC services arriving from Nm to O have enough time for short-turning, thus the departure delay from Nm does not propagate after the short-turning.

In Figure 2.6 the first phase is shown with a dashed rectangle, where the IC3616 has been cancelled. The second phase of the disruption with a stable and repetitive pattern is shown in the dash-dotted rectangle. In this variant, the order of operation on the single track remained the same as in the original timetable with the blocking times being closer to each other. Thus, there is a smooth transition from the second phase to the original timetable as shown by services SP4424, IC3625, IC3624, SP4427.

Figure 2.7 shows the second variant where IC3622 has been cancelled. In this variant, the SP services from Nm to O short-turn as the next service departing from O. Similar to the previous variant, the short-turned service has 7 minutes of delay. The difference of this variant from the previous one is the choice of short-turning for the IC services. In this variant, the IC services from Nm to O replace the services from O to Nm that are scheduled to depart before their arrival. Thus, there is an unavoidable departure delay. In addition, the minimum short-turning time increases the departure delay of IC services from O to Nm. In this variant, there is a smooth transition to the second phase. The dash-dotted rectangle shows the order of services operating on the single track in the second phase. In this variant, it is observed that the delay of SP4416 from O to Nm did not introduce any delay to the IC3617 from Nm to O. Instead, the SP4416 has more delay in comparison to the previous variant. This is due to the fact that, in case IC3617 is delayed, the delay would propagate through the short-turning. In this variant, the order of the operation is changed in the third phase. This is shown by a dotted rectangle. IC3623 is the first service that start using the blocked section after O and does not need to short-turn. Thus, there would be no short-turning delay propagation. However it introduces a delay from O onwards which is not included in the model.

In the first variant the total arrival delay is 101 minutes and in the second variants it is 333 minutes. The difference is due to the choice of short-turnings and the cancelled service. Hence, it is of great importance to compute the optimal choice of short-turning and cancelled services in case of disruption. Note that computing an optimal timetable for different phases of the disruption is not possible without having a reliable disruption length estimation.

2.4.2 Case 2: Disruption starting at 6:30

In this case, the disruption starts at 6:30 and ends at 8:00. Within this period, there are six services running from Nm to O (IC3617, SP4419, IC3619, SP4421, IC3621, SP4423). Note that SP4417 arrives at O before 6:30 and continues its original route. The same holds for the services in the opposite direction SP4416 and IC3616.

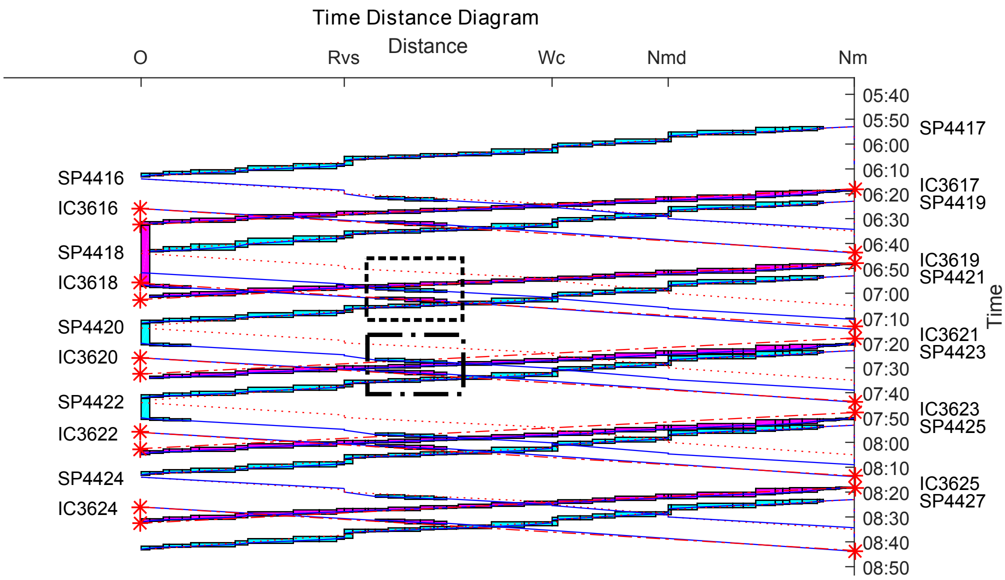


Figure 2.8: Blocking time diagram when the disruption starts at 6:30 with IC3617 short-turning on the upper track

So the services SP4418, IC3618, SP4420, IC3620, SP4422 and IC3622 need to be performed by the arriving trains to O. In this case, there are six trains arriving and six scheduled services departing from O. Thus, there is no need for service cancellation.

As mentioned earlier, the existing contingency plan suggests that the IC services short-turn on the lower track and the SP services short-turn on the upper track. In the original timetable without disruption both IC and SP services use the upper track to pass through station O. It is probable that the disruption starts when the IC service is already on the upper track although the optimal solution proposes the lower track.

Figure 2.8 shows the optimal timetable in case the disruption period is from 6:30 to 8:00. In this case, the service IC3617 is already at the upper track when the disruption starts. So it needs to short-turn on the upper track in O. This would result in a different order of operation on the single track in the first phase which is shown by the dashed rectangle. The next IC services short-turn on the lower track.

The resulting blocking time diagram on the single track for the next services are shown in the dash-dotted rectangle representing the second phase. Since the choice of short-turning in this case is the same as the first variant of the first case, the single track blocking time diagram in the second phase are the same for both cases. Similarly there is a smooth transition from the second phase to the original timetable starting from SP4424, IC3625, IC3624 and SP4427.

2.4.3 Discussion

Depending on the disruption period there are different services affected. In the first case with a disruption from 6:00 to 8:00 there are seven arriving services and eight train services in the opposite direction. Thus, one service in the opposite direction should be cancelled. Since the existing contingency plans do not take into account the disruption period, they cannot provide any support regarding the short-turning choices and cancelled services. Different choices of short-turnings and cancelled services result in different timetables. The differences can be observed by the output of the microscopic rescheduling model for the two variants of the first case. With a microscopic model we are able to compute the blocking times of each track section and determine the optimal platform tracks for short-turnings. This cannot be done unless by taking into account the microscopic infrastructure and operational data. Moreover the microscopic model provides insight about the order changes of services on the single track within the three phases. In the second case the disruption period is from 6:30 to 8:00. In this case there are six arriving services that would replace the six services in the opposite direction. The first IC service that should short-turn is already on the upper platform track when the disruption starts. However the computed optimal solution as well as the contingency plan suggest the lower platform track for the short-turning of IC services. This case shows that a static contingency plan cannot take into account such dynamic conditions and the suggested solution would not be feasible particularly in the transition phases.

2.5 Conclusion

In this paper the processes of disruption management and its relevant challenges were investigated, and the limitations of the current static contingency plans were discussed. The disruption models and algorithms in the literature were reviewed and classified based on the three phases of disruption. The literature study revealed that rerouting and rescheduling services during the transition phases are not sufficiently investigated. It was also concluded that limited microscopic models have been developed to deal with disrupted services. In the search for microscopic approaches, some relevant rescheduling models for small delays were reviewed. To illustrate the applicability of such methods for the three phases of disruption, a microscopic rescheduling model has been applied on a Dutch railway corridor. Since the microscopic rescheduling model was developed for traffic management of smaller delays and does not include the option of cancelling and short-turning train services, some assumptions were considered before applying the model to a disruption case. Two cases of disruptions were defined with different start times of a full blockage. It is concluded that depending on the disruption period, some services might need to be cancelled and different choices of short-turnings can be achieved. The results illustrated the support provided by a microscopic rescheduling model to traffic controllers for each phase of a disruption.

Currently there is no reference in the literature and no support for the traffic controllers to decide which service is better to be cancelled and which choice of short-turnings results in the least total delay. The extension of a microscopic rescheduling model with cancellation and short-turning decisions will be a next research direction. Moreover it is also interesting to investigate the possibility of short-turning the services in other stations.

Chapter 3

Railway disruption timetable: Short-turnings in case of complete blockage

Apart from minor updates, this chapter has been published as:

Ghaemi, N., Goverde, R.M.P., Cats, O., 2016. Railway disruption timetable: Short-turnings in case of complete blockage. 2016 *IEEE International Conference on Intelligent Rail Transportation (ICIRT)*, 210 –218.

3.1 Introduction

Railway operations are prone to unplanned events such as incidents. The occurrence of such events lead to unavailability of part of infrastructure for an uncertain period of time. In these situations, the traffic controllers are in charge of resolving the traffic and reduce further delay propagation to the neighboring stations.

To show the traffic level in case of disruption, the bathtub model is used. As it is shown in Figure 3.1, the operation is based on the original timetable before the disruption. The traffic level decreases with the disruption and remains decreased until the cause of disruption is removed and the original timetable is resumed. The disruption period is divided into three phases. In the second phase the operation is stable and according to the disruption timetable. The first and third phases represent transitions of operation from original to disruption timetable and vice versa.

In case of disruption, traffic controllers are facing a complicated problem of rescheduling taking into account safety restrictions, traveller demand, rolling stock and crew availability. Considering the time needed to communicate the decisions to the involved actors, the decision needs to be made quickly. To reduce the complexity of this

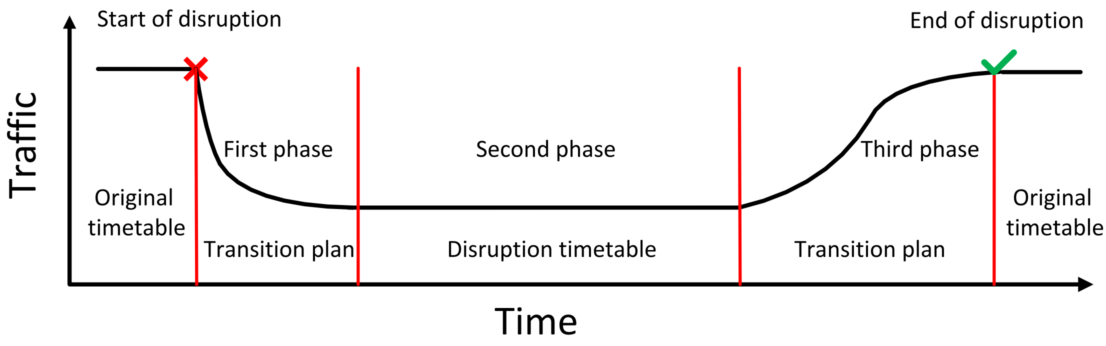


Figure 3.1: The service level during disruptions

decision in real-time operation, the Dutch railway sector makes use of predefined solutions called contingency plans. Each contingency plan represents a certain disruption scenario at a specific location designed manually by experienced traffic controllers. The solution suggested is based on the timetable (basic hourly pattern) and the capacity of the disruption scenario. These location-specific plans define which trains should continue, and which should be cancelled, short-turned or re-routed. For the trains that should be short-turned the stations where the short-turning should take place are identified, as well as the departure time and platform. These plans correspond to the second phase of bathtub model illustrated in Figure 3.1. The Dutch train operator provide bus services between the disturbed stations for the passengers that are affected by the disruption.

A service is decided to be cancelled if there are not enough resources. Besides human resources, any operating service requires rolling stock and available railway tracks between stations as well as inside the stations areas. In case the cancellation occurs due to the unavailability of tracks, the train either has to operate differently than planned (e.g. short-turn, reroute, etc.), or being shunted to a nearby depot and resume the operation when the track is available. However due to the cost associated with taking out a train from the rolling stock circulation as addressed by Nielsen et al. (2012), it is preferred to keep the train operating in the network.

The aim of short-turning trains is to replace the train that is supposed to operate in the opposite direction, but is not able to pass the disturbed area. In this way, short-turning reduces the delay propagation to a great extent. The contingency plans are however not worked out in detail at the infrastructure allocation level and they do not cover all the possible disruption cases throughout the network. In practice, it thus might happen that no suitable contingency plan is available for a disruption situation. In such cases, the traffic controllers are faced with a high workload and a lot of communication to reach an agreement about a suitable recovery plan. The available contingency plans are thus static and inflexible. Even if a suitable plan is available the traffic controllers still need to make adjustments and fill in the details to implement them. In particular, each short-turning takes some time which is not taken into account in the contingency plans. By ignoring the short-turning time, the plan becomes infeasible.

Another problem involves the platform track allocation. Since all trains need to short-turn in case of complete blockage, different platform tracks might be used in the stations. With a slightly different operation than the one suggested in the contingency plan, the platform allocations might become infeasible. Then it is up to the traffic controller to assign platform tracks for short-turning the trains.

The models developed in the literature mainly address the disturbances (Cacchiani et al., 2014) where there is usually no need to cancel or short-turn trains (Pellegrini et al., 2014; Caimi et al., 2012; D'Ariano et al., 2008). Ghaemi et al. (2017a) provide an overview of the models specifically designed for dealing with disruptions. Some of the disruption models disregard the possibility of short-turning during the disruption period and focus on rescheduling when the period is over (Narayanaswami and Rangaraj, 2013; Meng and Zhou, 2011; Zhan et al., 2015). Veelenturf et al. (2016) is one of the few references that optimizes the schedule during the disruption including cancellation and short-turning at the final station. The possibility of short-turning in earlier stations as a trade off between less delay and more cancelled services remains thereof an open question in the literature.

This paper presents a macroscopic rescheduling model to compute the disruption timetable for a complete blockage with the focus on the short-turning trains. The main contributions of the model are as follows:

- Optimal short-turning plan, considering the required time.
- Optimal platform track allocations for short-turning trains.
- Introducing the possibility to short-turn in an earlier station.

The model is a Mixed Integer Linear Programming formulation and it is applied on a part of the Dutch railway network.

In the remaining of the paper, the problem is described in more details in Section 3.2. Section 3.3 presents the mathematical formulation. The case study is reported in Section 3.4. Finally the conclusions are discussed in Section 3.5.

3.2 Problem description

As mentioned earlier, due to the complete blockage all the trains should short-turn before the disrupted area. In this problem description, each service is defined as a single trip between two stations. In other words, a single rolling stock unit performs multiple services along it's operational line.

Figure 3.2 shows an example for the short-turning problem. In this example, there is a disruption between station a and b. The services are noted as v. To distinguish between different services, sub and superscripts are used which are explained in more details later. In order to make a distinction between the services approaching the disruption area and those distancing from the disruption area, prime and double prime are used respectively.

In this example, the solid blue arrows (v'_1 and v'_2) represents the arriving trains that originally had the plan to proceed to station b and further. But due to the disruption, they have to short-turn in station a. The dashed green arrows show the original plans for the services (v''_1 ,v''_2 and v''_3). Due to the disruption the related trains could not reach station a to operate these services. Thus, the arriving trains short-turn and operate these services after performing their own services (v'_1 and v'_2).

The problem of short-turning is an assignment problem. In other words, it is the optimal assignments of arriving trains to the planned departing services while taking into account the required short-turning time. Note that each train is able to short-turn and replace only a service from the same line. In this example, to make it simple we assume that all trains are for the same line in both directions. As is shown in the figure, two trains are arriving and can short-turn and perform two departing services from station a. It means that one departing service needs to be cancelled due to lack of a train. One possible solution is that v'_1 short-turns as v''_1, v'_2 short-turns as v''_2 and service v''_3 is cancelled. Obviously both services (v''_1 and v''_2) depart with a delay. Another solution would be that v'_1 and v'_2 short-turn as v''_2 and v''_3 respectively, leaving v''_1 as the cancelled service. Depending on the demand, some services might have high priority and thus are less favorable for cancellation.

In case v'_1 short-turns as v''_3, the services arriving after the arrival of v'_1 (such as v'_2) are only allowed to use the same platform track after the departure of v''_3 plus headway time. In this way a feasible platform allocation is ensured for the optimal short-turning trains.

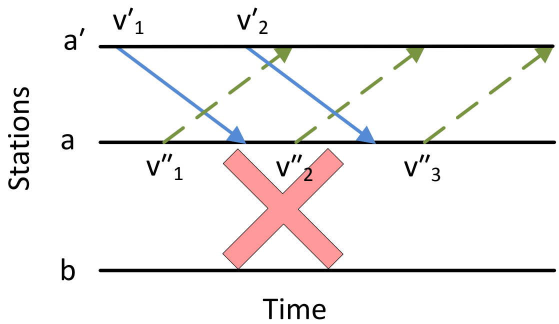


Figure 3.2: Short-turn

Before exploring the possibility of short-turning in an earlier station, it is required to define the services precisely as it is used in the model. Each service is defined as $v^i_{l,n}$ where i indicates the sequence of the service within the line l, and n refers to the train number which is used to distinguish between the same trip at different time. This is shown in Figure 3.3.

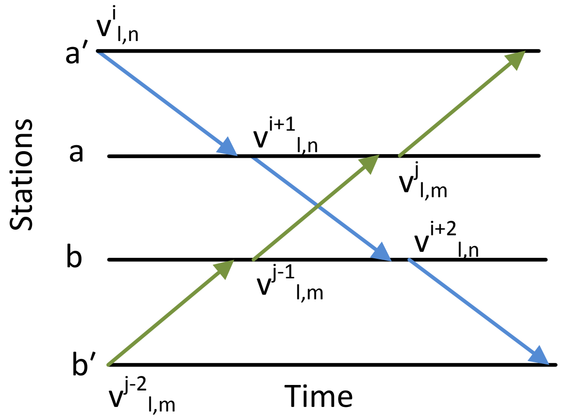


Figure 3.3: Service definition in details

Besides the short-turning problem in one station, the model is extended to multiple short-turning stations. The short-turning possibilities for the service $v^i_{l,n}$ are shown by red arcs in Figure 3.4. In this case either $v^i_{l,n}$ or $v^{i+1}_{l,n}$ short-turn. If $v^i_{l,n}$ short-turns on either three red arcs shown in station a', the service $v^{i+1}_{l,n}$ is cancelled. Consequently all the short-turnings related to the arrival of $v^{i+1}_{l,n}$ are impossible.

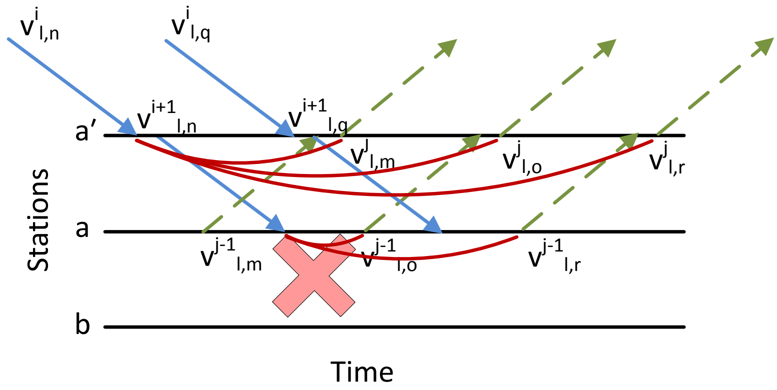


Figure 3.4: Two short-turning stations

Each red arc is called a short-turning pattern which indicates the arriving train, departing services and implicitly the relevant short-turning station. The output of the model would be these short-turning patterns and platforms for all the approaching trains.

3.3 Mixed-integer linear programming formulation

In this section, the MILP formulation is introduced. The model scope and assumptions are discussed in Section 3.3.1. The input parameters are introduced in Section 3.3.2. Then based on the input, the relevant sets are constructed in Section 3.3.3. The defined decision variables are introduced in Section 3.3.4 and finally the objective function and constraints are explained in Section 3.3.5.

3.3.1 Model scope and assumptions

The proposed macroscopic rescheduling model computes the disruption timetable which corresponds to second phase of disruption in the bathtub model. The transition phases are not addressed in this model. The formulation for platform occupation in the current model is limited to those platforms that might be used by the trains that need to be short-turned. Those platforms that are used by other lines that are not disrupted are excluded from the formulation. As mentioned earlier, the proposed MILP is a macroscopic model and does not provide microscopic formulation of the track occupation. A minimum headway is assured between departures and arrivals at the platform track, yet the model is not able to identify the conflict in the in bound or out bound route in the station area. Thus, the result should be checked with a microscopic model. The possibility of reordering the short-turning trains is not included in the model. The current model considers two short-turning stations on each side of the disruption. This assumption can be easily extended to more short-turning stations. It is assumed that the disruption length is known in advance.

3.3.2 Input parameters

The input parameters are of macroscopic details. To compute the disruption timetable, it is required to have infrastructural data, operational data and the disruption scenario.

The infrastructural data consists of a set of stations in the disruption area and the possible platform tracks for each service in the arrival stations. There is a distinction between the stations that are closest to the disruption location and those that are surrounding the closest stations to the disruption area. The surrounding stations are used for early short-turning possibility.

The operational data refers to the relevant lines that operate on the defined set of stations and the services in each line. Moreover, the timetable for each service and the process times (running, dwell, headway and minimum short-turning time) and penalties (for service cancellation and delay) are required.

The disruption scenario indicates the disruption location which is bounded by the closest stations from both sides and the start and end time of the disruption. These input parameters are listed in Table 3.1.

3.3.3 Preprocessed sets based on the disruption scenario

The following sets are constructed based on the disruption scenario, and they will be used in the model.
$L_{Dist} \subset L$: The set of lines l that are planned to operate on the disrupted location during the disruption time.
$L_{Dist} = \{l \in L | S_{v^i_{l,n}} \subseteq S_{Dist}\}$.

Table 3.1: The input parameter used in the macroscopic model

S	The set of all stations s.
L	The set of all lines l.
V	The set of all scheduled services.
$V_{l,n} \subset V$	The n^{th} set of ordered services in line l.
$v^i_{l,n} \subset V_{l,n}$	The i^{th} service in set $V_{l,n}$.
$P_{s,v^i_{l,n}}$	The set of platforms $p^{s,y}_{v^i_{l,n}}$ for service $v^i_{l,n}$ in station s.
$S_{v^i_{l,n}} \subset S$	The departure, arrival stations $\{s^d_{v^i_{l,n}}, s^a_{v^i_{l,n}}\}$ of $v^i_{l,n}$.
$S_{Dist} \subset S$	The closest stations$\{s_a, s_b\}$ around the disrupted area.
$S_{Sur} \subset S$	The stations $\{s_{a'}, s_{b'}\}$ surrounding the stations in S_{Dist}.
$\tau^d_{v^i_{l,n}}$	The scheduled departure time of service $v^i_{l,n}$.
$\tau^a_{v^i_{l,n}}$	The scheduled arrival time of service $v^i_{l,n}$.
$\theta^{min}_{v^i_{l,n}}$	The minimum short-turning time needed for service $v^i_{l,n}$.
$\tau^{run}_{v^i_{l,n}}$	The running time of service $v^i_{l,n}$ between two stations.
$\tau^{dwell}_{v^i_{l,n},v^{i+1}_{l,n}}$	The dwell time between service $v^i_{l,n}$ and service $v^{i+1}_{l,n}$ in the station.
$\tau^{hd}_{v^i_{l,n},v^j_{k,m}}$	The minimum departure headway time between services $v^i_{l,n}$ and $v^j_{k,m}$.
$\omega^c_{v^i_{l,n}}$	The penalty for cancelling service $v^i_{l,n}$.
$\omega^{d^a}_{v^i_{l,n}}$	The penalty for delaying arrival of service $v^i_{l,n}$.
τ^s	The start time of disruption.
τ^e	The end time of disruption.
M	A large constant.

For notation simplification, the services that approach the disrupted area are shown as v' and those that are scheduled to distance the disrupted area are shown as v'' regardless of their line specifications. This simplification is also used later while defining the variables for short-turning patterns in Section 3.3.4.

$V'_s \subset V$: The set of all services $v^i_{l,n}$ scheduled to arrive at the station $s \in S_{Dist} \cup S_{Sur}$ towards the disrupted area.

$$V'_s = \{v^i_{l,n} \in V | s^a_{v^i_{l,n}} = s, s \in S_{Dist} \cup S_{Sur}, s^d_{v^i_{l,n}} \notin S_{Dist}, l \in L_{Dist}\}.$$

$V''_s \subset V$: The set of all services $v^i_{l,n}$ scheduled to depart from station $s \in S$ against the disrupted area.

$$V''_s = \{v^i_{l,n} \in V | s^d_{v^i_{l,n}} = s, s \in S_{Dist} \cup S_{Sur}, s^a_{v^i_{l,n}} \notin S_{Dist}, l \in L_{Dist}\}.$$

In order to find the optimal short-turn pattern, for each approaching train, all the possible departing services (against the disruption area) in each station should be identified first. As shown in Figure 3.4 service $v^i_{l,n}$ can short-turn as one of the three distancing services in station a. The set of the possible short-turnings for the arriving service $v^i_{l,n}$ is defined as $Pair_{v^i_{l,n},*}$.

$$Pair_{v^i_{l,n},*} = \{(v^i_{l,n}, v^j_{l,m}) | v^j_{l,m} \in V''_s, s \in S_{Dist} \cup S_{Sur}, l \in L_{Dist}\},$$
$$\forall v^i_{l,n} \in V'_s, s \in S_{Dist} \cup S_{Sur}, l \in L_{Dist},$$

$$Pair_{*,v^j_{l,m}} = \{(v^i_{l,n}, v^j_{l,m}) | v^i_{l,n} \in V'_s, s \in S_{Dist} \cup S_{Sur}, l \in L_{Dist}\},$$
$$\forall v^j_{l,m} \in V''_s, s \in S_{Dist} \cup S_{Sur}, l \in L_{Dist}.$$

3.3.4 Decision variables

The defined decisions are formulated in either continuous or binary variables. The continuous decision variables represent time and are non-negative:

$t^a_{v^i_{l,n}}$: The arrival time of service $v^i_{l,n}$.
$t^d_{v^i_{l,n}}$: The departure time of service $v^i_{l,n}$.
$d^a_{v^i_{l,n}}$: The arrival delay of service $v^i_{l,n}$.

The decisions regarding occupying a platform track, cancelling a service or choice of short-turning are represented by binary decision variables:

$$c_{v^i_{l,n}} = \begin{cases} 1 & \text{if } v^i_{l,n} \text{ is cancelled,} \\ 0 & \text{otherwise;} \end{cases} \tag{3.1}$$

$$\lambda_{v',v''} = \begin{cases} 1 & \text{if } v' \text{ short-turns as } v'', \\ 0 & \text{otherwise;} \end{cases} \tag{3.2}$$

$$p^{s,y}_{v^i_{l,n}} = \begin{cases} 1 & \text{if } v^i_{l,n} \text{ arrives at platform track } p_{s,y}, \\ 0 & \text{otherwise.} \end{cases} \tag{3.3}$$

3.3.5 Objective function and constraints

The objective function includes two terms. For each service, there is a cancellation and an arrival delay penalties. Thus the objective is to minimize the number of cancelled services and the delays of the operating services.

$$\min \sum_{v^i_{l,n} \in V} (\omega^c_{v^i_{l,n}} \cdot c_{v^i_{l,n}} + \omega^{d^a}_{v^i_{l,n}} \cdot d^a_{v^i_{l,n}}). \tag{3.4}$$

Running, dwell and departure time constraints

Constraints (3.5), (3.6) makes sure that minimum running and dwell times are respected. Constraint (3.7) ensures that the computed departure time is after the original departure time. Constraints (3.8) virtually set the departure times of cancelled services to the original times, so that there is no penalty for their arrival delays.

$$t^a_{v^i_{l,n}} - t^d_{v^i_{l,n}} \geq \tau^{run}_{v^i_{l,n}} \qquad \forall v^i_{l,n} \in V, \tag{3.5}$$
$$t^d_{v^{i+1}_{l,n}} - t^a_{v^i_{l,n}} \geq \tau^{dwell}_{v^i_{l,n}, v^{i+1}_{l,n}} \qquad \forall (v^i_{l,n}, v^{i+1}_{l,n}) \in V, \tag{3.6}$$
$$t^d_{v^i_{l,n}} - \tau^d_{v^i_{l,n}} \geq 0 \qquad \forall v^i_{l,n} \in V, \tag{3.7}$$
$$t^d_{v^i_{l,n}} - \tau^d_{v^i_{l,n}} \leq (1 - c_{v^i_{l,n}}) \cdot M \qquad \forall v^i_{l,n} \in V. \tag{3.8}$$

Short-turnings

Any arriving service $v^i_{l,n} \in V'_s$ possibly short-turns at a planned departure $v^j_{l,m} \in V''_s$ respecting the minimum short-turning time. If service $v^i_{l,n}$ is not short-turned in station $s_{a'}$, then the service $v^{i+1}_{l,n}$ is short-turned in the following station s_a which is the last station before disruption. In order to find the planned departure and related station, the defined binary decision variable $\lambda_{v',v''}$ is used. Constraint (3.9) makes sure that only one planned departure is selected for the arriving train $v^i_{l,n}$ at station $s_{a'}$ or the arriving train $v^{i+1}_{l,n}$ at station s_a. This is illustrated in Figure 3.5.

$$\sum_{(v',v'') \in Pair_{v^i_{l,n},*} \cup Pair_{v^{i+1}_{l,n},*}} \lambda_{v',v''} = 1 \qquad \forall v^i_{l,n} \in V'_s, s \in S_{Sur}. \tag{3.9}$$

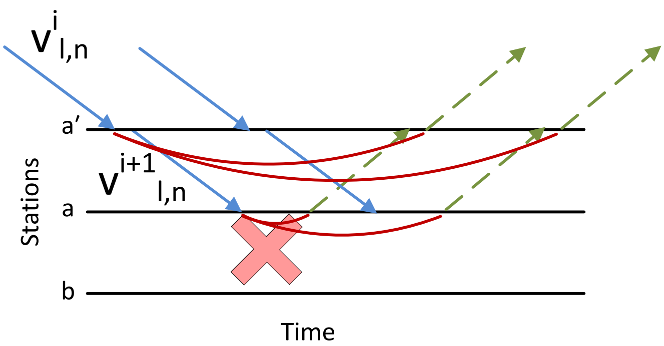


Figure 3.5: The short-turning options for services $v^i_{l,n}$ and $v^{i+1}_{l,n}$.

In case the departing service $v^j_{l,m}$ is not cancelled, at most one train can be assigned to this service. As it is shown in Figure 3.6 this assignment can also occur for the $v^{j-1}_{l,m}$ in the previous station. To make sure that no more than one train is assigned to a planned departure, constraint (3.10) is considered.

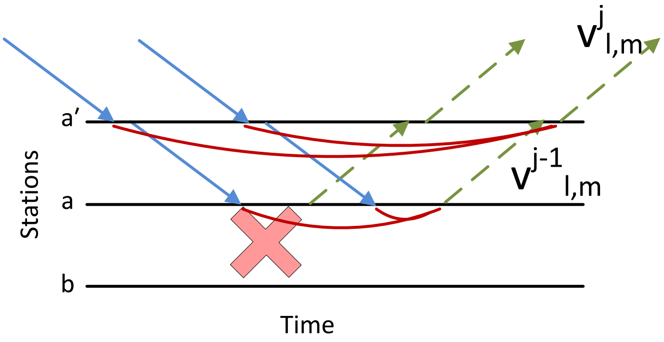


Figure 3.6: The short-turning options for services $v_{l,m}^{j-1}$ and $v_{l,m}^{j}$.

$$\sum_{(v',v'')\in Pair_{*,v_{l,m}^{j}} \cup Pair_{*,v_{l,m}^{j-1}}} \lambda_{v',v''} + c_{v_{l,m}^{j}} = 1 \qquad \forall v_{l,m}^{j} \in V_s'', s \in S_{Sur}. \tag{3.10}$$

If service $v_{l,n}^{i}$ is short-turned in station $s_{a'}$ then the planned departure for service $v_{l,n}^{i+1}$ should be cancelled. This is shown by constraint (3.11).

$$\sum_{(v',v'')\in Pair_{v_{l,n}^{i},*}} \lambda_{v',v''} = c_{v_{l,n}^{i+1}} \qquad \forall v_{l,n}^{i} \in V_s'', s \in S_{Sur}. \tag{3.11}$$

In case there is an arriving service matched for the short-turning $v_{l,m}^{j}$ in station $s_{a'}$ then the service $v_{l,m}^{j-1}$ needs to be cancelled.

$$\sum_{(v',v'')\in Pair_{*,v_{l,m}^{j}}} \lambda_{v',v''} + c_{v_{l,m}^{j}} = c_{v_{l,m}^{j-1}} \qquad \forall v_{l,m}^{j} \in V_s'', s \in S_{Sur}. \tag{3.12}$$

If the service $v_{l,n}^{i+1}$ is cancelled, due to a short-turning in station $s_{a'}$, the relevant pairs should not be selected in the last station s_a. Constraint (3.13) is considered.

$$\sum_{(v',v'')\in Pair_{v_{l,n}^{i+1},*}} \lambda_{v',v''} + c_{v_{l,n}^{i+1}} = 1 \qquad \forall v_{l,n}^{i} \in V_s', s \in S_{Sur}. \tag{3.13}$$

The departure time of the short-turned service should be at least minimum short-turning time after the arrival time of the arriving service. Constraint (3.14) shows this restriction.

$$(1-\lambda_{v',v''})\cdot M + t_{v''}^{d} \geq t_{v'}^{a} + \theta_{v'}^{min}\cdot\lambda_{v',v''} \qquad \forall (v',v'') \in Pair_{v',*}, s \in S_{Sur}\cup S_{Dist}. \tag{3.14}$$

If a departing service $v_{l,m}^{j}$ is cancelled due to the lack of trains, the following services on that line and in the same direction (against the disrupted area) need to be cancelled. Constraint (3.15) guarantees these cancellations. Note that, there might be services from station s_a to station $s_{a'}$. If such a service is cancelled, it doesn't necessarily mean that the following service from $s_{a'}$ against the disrupted area should also be cancelled, since this departure might be matched by an arrival in the station $s_{a'}$. Thus, constraint (3.15) is defined for all the stations on the line, starting from station $s_{a'}$.

$$c_{v_{l,m}^j} \leq c_{v_{l,m}^{k+1}} \qquad \forall v_{l,m}^j \in V_s'', s \in S_{Sur}, k \in [j, |S|-1]. \tag{3.15}$$

For each arriving service $v_{l,n}^i \in V_s', s \in S_{Sur}$ one and only one platform track is needed. Note that this service cannot be cancelled. The platform ocupation for these services are formulated in (3.16). Constraint (3.17) are defined for the services $v_{l,n}^i \in V_s' \cup V_s'', s \in S_{Dist}$ which might get cancelled. If the service $v_{l,n}^i$ is cancelled, there is no need for platform assignment.

$$\sum_{p_{v_{l,n}^i}^{s,y} \in P_{s,v_{l,n}^i}} p_{v_{l,n}^i}^{s,y} = 1 \qquad \forall v_{l,n}^i \in V_s', s \in S_{Sur}, \tag{3.16}$$

$$\sum_{p_{v_{l,n}^i}^{s,y} \in P_{s,v_{l,n}^i}} p_{v_{l,n}^i}^{s,y} + c_{v_{l,n}^i} = 1 \qquad \forall v_{l,n}^i \in V_s' \cup V_s'', s \in S_{Dist}. \tag{3.17}$$

In order to avoid simultaneous platform track occupations by two different trains, constraint (3.18) is considered. This constraint is active in case there is a short-turning taking place. But in order to model the platform occupation in the earlier station $s_{a'}$ where there might be short-turning in one direction and pass through in both directions, the constraint (3.19) is considered to avoid simultaneous platform occupation in case the service is continuing the original route towards the last station s_a with a planned dwell.

$$\begin{aligned}
&(3 - (p_{v'}^{s,y} + p_{v_{w,z}^u}^{s,y}) - \lambda_{v',v''}) \cdot M + t_{v_{w,z}^u}^a \geq t_{v''}^d \\
&\qquad \forall (v', v'') \in Pair_{v',*}, v' \in V_s', s \in S_{Dist} \cup S_{Sur}, \\
&\qquad \forall v_{w,z}^u \in V : s_{v_{w,z}^u}^a = s, \tau_{v_{w,z}^u}^a \geq \tau_{v'}^a,
\end{aligned} \tag{3.18}$$

$$\begin{aligned}
&(c_{v_{l,n}^{i+1}} + 2 - (p_{v_{l,n}^i}^{s,y} + p_{v_{w,z}^u}^{s,y})) \cdot M + t_{v_{w,z}^u}^a \geq t_{v_{l,n}^{i+1}}^d \\
&\qquad \forall v_{l,n}^i \in V_s', s \in S_{Sur}, \\
&\qquad \forall v_{w,z}^u \in V : s_{v_{w,z}^u}^a = s, \tau_{v_{w,z}^u}^a \geq \tau_{v_{l,n}^i}^a.
\end{aligned} \tag{3.19}$$

Constraint (3.20) measures the arrival delays.

$$d_{v_{l,n}^i}^a \geq t_{v_{l,n}^i}^a - \tau_{v_{l,n}^i}^a \qquad \forall v_{l,n}^i \in V. \tag{3.20}$$

3.4 Case study

The model is implemented in Matlab 2014a and Gurobi is used as the solver. For the case study a part of Dutch railway network is selected. Figure 3.7 schematically shows the stations and the line series operating in the disruption area.

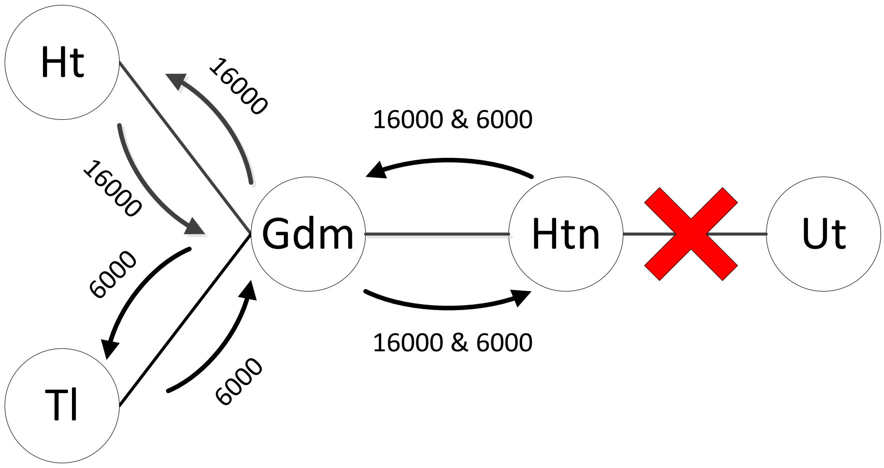


Figure 3.7: The disruption case

The disruption area includes the stations Utrecht (Ut), Houten (Htn), Geldermalsen (Gdm), Tiel (Tl), and 's–Hertogenbosch (Ht). In this case study the disruption timetable is computed for one side of the disruption area (stations Htn, Gdm, Ht and Tl). The disruption timetable for the other side of the disruption (from Ut further) can be computed with the same model. Line 16000 operates between Ut, Ht and line 6000 operates between Ut, Tl. Due to the disruption between Htn and Ut, all trains running towards Ut should either short-turn at Gdm or Htn at the latest. These lines represent the local trains and have scheduled stops in the above mentioned stations. There are also intercity trains that operate in this area, but since they do not stop in Htn and Gdm, they are either short-turned in Ut or Ht and for this reason they are excluded from the case study.

3.4.1 Parameters settings

To implement the model on the case study, the disruption scenario, the infrastructure data and the operational data are required. The disruption scenario is a complete blockage between Ut and Htn that starts around 12:00 and lasts more than three hours till 15:20.

The infrastructure data refers to the disruption stations and relevant platform tracks. The disruption stations which are the closest stations to disruption are Htn and Ut. The surrounding station is Gdm that is the second alternative for short-turning. There are two platform tracks in both short-turning stations.

For the most part, the operational data refers to the timetable. The timetable for the lines 16000 and 6000 over the defined stations is shown in Tables 3.2 and 3.3. Table 3.2 shows the timetable of the trains operating in direction a which is from Ut towards Ht or Tl. Table 3.3 shows the timetable on the opposite direction. Since the scheduled dwell time in Htn is less than a minute, the arrival and departure are the same. The dwell time for line 16000 in Gdm is four minutes in direction a and five minutes in direction b and for line 6000 is two minutes in direction a and seven minutes in direction b.

Table 3.2: The timetable for lines 16000 & 6000 in direction a from Ut to Ht or Tl

Stations (a)	16000	6000	16000	6000
Ut (dep)	:12	:27	:42	:57
Htn (arr & dep)	:21	:36	:51	:06
Gdm (arr)	:36	:51	:06	:21
Gdm (dep)	:40	:53	:10	:23
Tl (arr)	—	:05	—	:35
Ht (arr)	:55	—	:25	—

Table 3.3: The timetable for lines 16000 & 6000 in direction b from Ht or Tl to Ut

Stations (b)	16000	6000	16000	6000
Ht (dep)	:02	—	:32	—
Tl (dep)	—	:18	—	:48
Gdm (arr)	:18	:30	:48	:00
Gdm (dep)	:23	:37	:53	:07
Htn (arr & dep)	:38	:52	:08	:22
Ut (arr)	:48	:02	:18	:32

The timetable provides part of the required operational data (the arrival, departure, dwell times, running times). For headway, 3 minutes as the norm and for the short-turning time, 7 minutes is used following the study made by Chu and Oetting (2013). Some constraints are formulated using the big M method. In this case study 80000 is set as the small but sufficiently large constant for the value of M. These parameters are listed in Table 3.4.

Table 3.4: Model parameters

Headway	Short-turning time	M
180 (sec)	420 (sec)	80000

The penalties for cancellation and delay may vary for different services depending on the tendering contract and operator's policy. Thus in the following section, the implications of using different penalties are analysed.

3.4.2 The experimental setup

To evaluate the impact of costs associated with cancellation and delay on the optimal short-turning patterns, three experiments are performed. In these experiments, the trains are able to short-turn in both stations Htn and Gdm.

The service frequency in Htn and Gdm is around 16 minutes (960 seconds). This means that with each cancelled service, the travellers need to wait at least 16 minutes for the next service. Thus, each cancellation might be translated to 1000 seconds of delay. This value is assumed to be the cancellation penalty. To analyse the result with extreme values, 1 and 10000 are considered as lowest and highest cancellation penalties. In all experiments the delay penalty is fixed to 1 and the cancellation penalty is 1 for the first experiment, 1000 for the second, and 10000 for the third experiment. Obviously, cancellation penalty of 1 is too low which indicates that each cancelled service can be translated into one second of delay. And 10000 is considered for the high cost of cancellation.

To analyse the impact of two short-turning station possibilities, the results are compared to a scenario where all trains have to short-turn in the last station (Htn). In order to compare the results, three more experiments with the same parameters and cancellation penalties (1,1000,10000) are defined. Thus, in the first scenario all the trains are short-turned in the last station (Htn). In the second scenario, the trains can short-turn either in the last station (Htn) or earlier station (Gdm).

3.4.3 Results

The results of three experiments in case of two short-turning stations are illustrated in Figure 3.8 to 3.10. The thick red lines represent the train series 6000 and thin pink lines represent the train series 16000. The trains services of line 16000 operate from Tl to Gdm and for this reason, they are not shown in these plots. The original schedule is shown by dash-dotted blue lines. In case a service operates on time, the realized original schedule is colored either in red or pink depending on the line series. There is no operation between stations Ut and Htn due to disruption. Black lines represent the cancelled services in this area. The short-turning couples are highlighted by green horizontal lines. The vertical distance between these lines indicate the different choice of platforms.

In the first experiment (Figure 3.8), where the cancellation penalty is very low (1), there are many cancelled services between Gdm and Htn. All trains of line 6000 are short-turned in Gdm. Some of the trains of line 16000 are short-turned in Gdm and the rest in Htn. The result shows that with low cancellation penalty, earlier short-turnings (Gdm) are preferred to delayed short-turning at the final station (Htn). The short-turning of those trains belonging to line 16000 in Gdm are shown by the horizontal green lines which are located slightly lower than the other short-turnings. Since the trains arrive from Tl and depart to Tl, the arrivals and departures are not shown in this plot. Clearly the model suggests different short-turning platforms for different train lines.

In the second experiment (Figure 3.9), the cancellation penalty is increased to 1000. Consequently, it is observed that more trains of both lines operate till the last station (Htn) to avoid service cancellation. Half of the services of line 6000 are short-turned in Gdm and as it is shown in Figure 3.9, they depart with some delay.

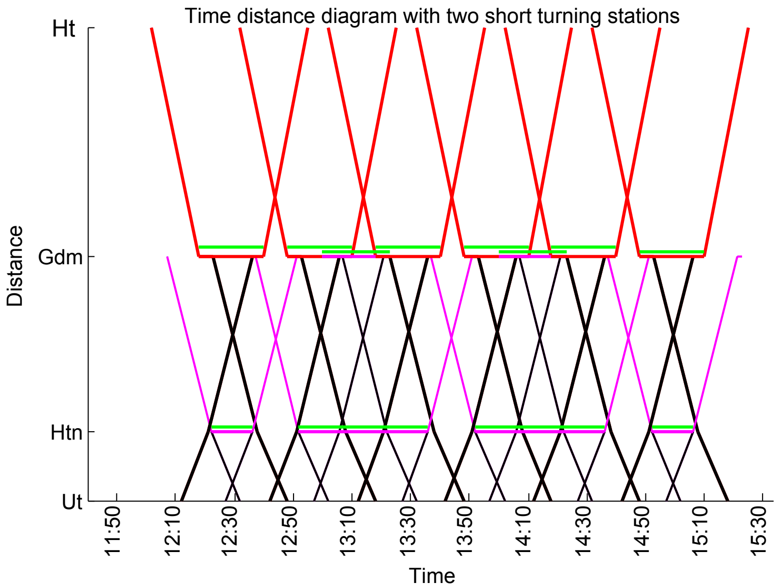


Figure 3.8: First experiment with cancellation penalty of 1

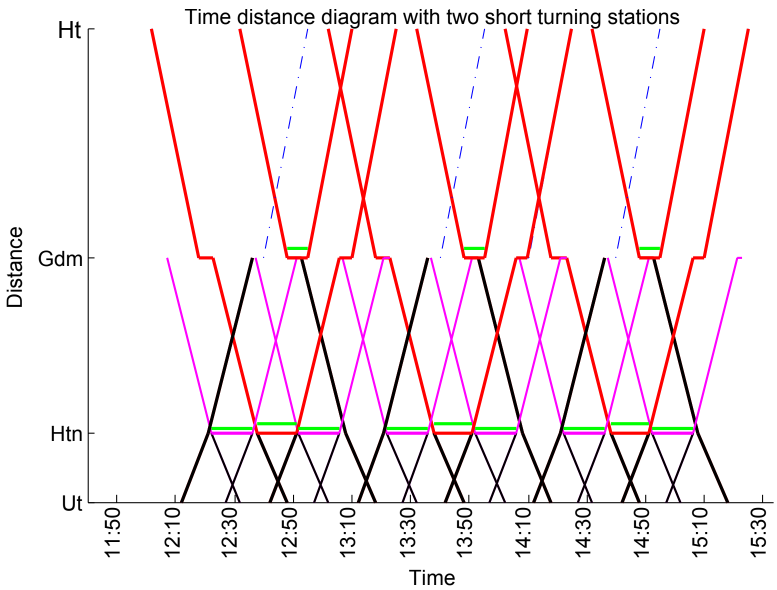


Figure 3.9: Second experiment with cancellation penalty of 1000

In the third experiment (Figure 3.10) where the cancellation penalty is increased to 10000, there are no cancelled services. Clearly this is the result of a large cancellation penalty. Thus, in this scenario, all trains are short-turned at the final station (Htn) but with large delays.

The computation time for all three experiments is less than one second. The results of the three experiments are shown in Table 3.5. The reported number of cancelled services excludes the cancelled services between Ut and Htn. In the first experiment, there are 16 cancelled services with no delays. In the second experiment there are 6 cancelled services and 2700 seconds (45 minutes) of delay and in the third experiment at the expense of 17280 seconds (around 5 hours) of delay no service is cancelled.

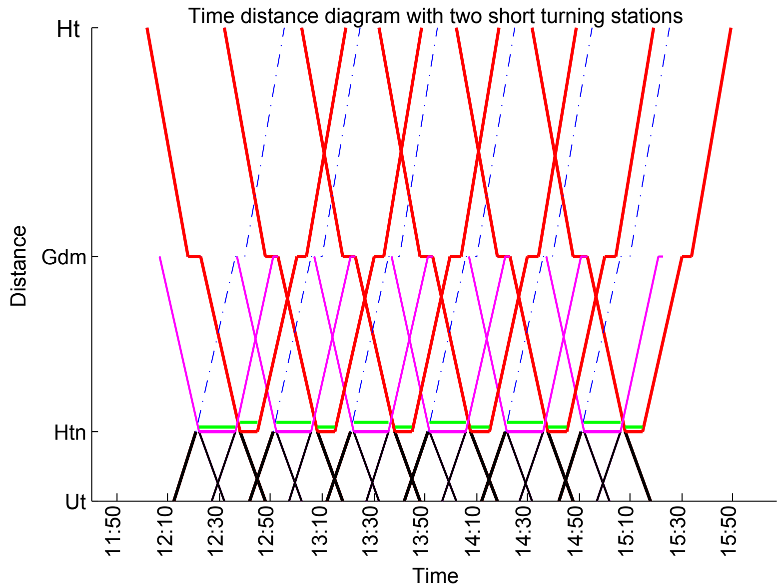


Figure 3.10: Third experiment with cancellation penalty of 10000

Table 3.5: Results of the three experiments

Experiment	Cancel penalty	# Cancelled	Delay (s)	Comp. (s)
1 (Fig.3.8)	1	16	0	0.53
2 (Fig.3.9)	1000	6	2700	0.37
3 (Fig. 3.10)	10000	0	17280	0.15

To understand the impact of including two short-turning stations, the results are compared with a scenario where all trains have to short-turn at the final station (Htn). Obviously the solutions for all the three experiments in scenario 1 where all trains short-turn at Htn corresponds to Figure 3.10. The computed objective values for the three experiments within the two scenarios are shown in Table 3.6. In scenario 1, there is no possibility for early short-turning. Thus, no service is cancelled due to early short-turning in the three experiments. The reason for the difference in the objective function for the three experiments of the first scenario is due to the cancelled services between Ut and Htn. It is possible to conclude that with small cancellation penalty, including the second short-turning stations reduces the objective value considerably.

Table 3.6: The comparison of objective value in two scenarios

Experiment	Cancel penalty	O.F. Scenario (1)	O.F. Scenario (2)
1	1	17304	40
2	1000	41280	32700
3	10000	257280	257280

The canceled services for short distances are easier replaced by bus services. In case the final services (those services operating between the closest stations in one side of the disruption) have short distance operation and the train has to provide many services after it has short-turned, the delay might propagate less by performing an early short-turning. In other words, in some cases it might be favorable to cancel final services to achieve a disruption timetable that differs less from the original timetable.

3.5 Conclusion

In this paper a Mixed Integer Linear Program is developed to compute the disruption timetable. In case of complete blockages, the trains are not able to proceed with their original plan. A common practice is that they short-turn and replace the services on the opposite direction. The focus of the proposed model is to compute the optimal short-turning pattern which includes the arriving train, the departing service and the short-turning platform. The main contribution of the model is the inclusion of the possibility to short-turn in an earlier station upstream of the disruption area. Due to early short-turning, some services need to be cancelled. Thus, the trade off between cancelling some services and delaying other services should be assessed by the traffic controllers depending on the prevailing traffic conditions and the incentives specified in service procurement. A part of the Dutch railway network is selected for the case study. The computation time seems to be promising for a real-time application. The results show that by introducing an earlier station for short-turning, the optimal objective value can decrease.

This model computes macroscopic solution of the optimal short-turning patterns which can provide support for the traffic controllers. However the feasibility of the result should be checked with a more detailed model where the capacity is microscopically formulated. The model can also be extended for the possibility of reordering the short-turned services. The computed disruption timetable can be developed further to include the transition phases.

Chapter 4

Macroscopic multiple-station short-turning model in case of complete railway blockages

Ghaemi, N., Goverde, R.M.P., Cats, O., 2018. Macroscopic multiple-station short-turning model in case of complete railway blockages. *Transportation Research Part C: Emerging Technologies*, 89:113 –132.

4.1 Introduction

In railway operation unplanned events such as infrastructure failures, rolling stock breakdown, and incidents are recurrent and unavoidable. As a result, a part of a railway track might be unavailable for several hours. In such cases, the traffic controllers have to deal with the disrupted traffic. Short-turning is a common practice to isolate the disrupted area. This measure suggests that those train services that are heading towards the disrupted area, short-turn in an earlier station and provide service in the opposite direction. In this way, some services can still be offered in the opposite direction and the trains do not queue up in the stations close to the disrupted area. Consequently, the disrupted area can be isolated from the rest of the network.

To improve the performance during the disruption, traffic controllers commonly use pre-defined solutions called contingency plans. Each contingency plan is manually designed for a specific disrupted area given a specific timetable. These plans resemble if-then scenarios: if a certain part of the infrastructure is out of service, then specific disruption measures should be pursued. The main input for designing contingency plans are the original timetable (basic hourly pattern) and the infrastructure layout around the disrupted location. The contingency plan then provides the disruption timetable structure that includes the cancelled services, operating services, and short-turned services. For each short-turned service, the arrival, departure, platform track and the train line numbers are indicated. The advantage of these contingency plans is that they provide some guidelines and consensus when there is a need for a fast action to deal with the disruption (Ghaemi et al., 2017b).

During disruptions the level of service decreases and remains so until the cause of disruption is solved and the original operation can be resumed. From this perspective the traffic level during a disruption resembles a bathtub as shown in Figure 6.2. Corresponding to the bathtub, the disruption period is divided into three phases. The first and third phases are called transition phases as they represent the transition of operation from the original timetable to the disruption timetable in the second phase and vice versa. The first phase starts as soon as the blockage starts. Usually there are some irregularities (e.g. different short-turnings) before a stable and reduced timetable (disruption timetable) can be observed.

There are several processes during the first phase including receiving the disruption notification, announcing the disruption in the online system, identifying the exact disrupted location, selecting the relevant contingency plan and finally executing the plan. A study by van Zon and Wink (2014) on 452 disruption cases of the Dutch railway network reports that the first phase can take on average around 40 minutes. In this study it is also shown that the longest process relates to selecting the relevant contingency plan and adjusting it which can take on average around 16 minutes. The third phase starts when it is known that the blockage is going to be resolved shortly and the train services can resume operating in the previously disrupted area. However it might take some time to recover from the disruption timetable to the original timetable as is shown in Figure 6.2. For detailed processes during each phase see Ghaemi et al. (2017b).

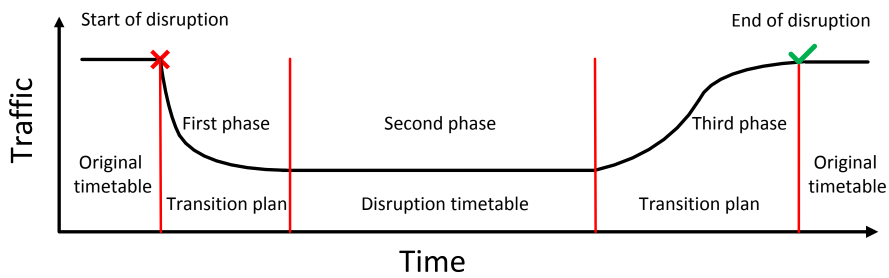


Figure 4.1: The service level during disruptions (Ghaemi et al., 2017b).

Besides being static and inflexible, the main drawback of the contingency plans is that they do not provide any support for handling the transition phases. Having fast and smooth transition plans is essential for quickly resuming the disruption timetable in the second phase and recovering the original timetable in the third phase. The existing contingency plans are not able to provide any support for the execution of the transition phases, since they do not take into account the disruption period. After all, different causes of disruption can lead to different disruption lengths (Zilko et al., 2016). This leaves the traffic controllers without any support for making decisions in the transition phases. Besides the fact that the existing contingency plans do not suggest the optimal solution, with each update in the infrastructure or operation, the contingency plans need to be manually updated. Moreover, certain disruption may not have a corresponding contingency plan. A slight difference between the timetable in operation and the one used for designing the contingency plan may make the latter invalid.

The rescheduling domain in case of disruptions specially at the microscopic level is relatively unexplored, as Cacchiani et al. (2014) and Ghaemi et al. (2017b) conclude. Since disruptions of complete blockages can have a huge impact on the network it is necessary to consider bigger areas as opposed to the disturbances that perturb a timetable locally. The microscopic approaches, such as Pellegrini et al. (2014) or Caimi et al. (2012), can only include relatively small areas due to the magnitude of the modelled details. Despite techniques such as the one developed by Samà et al. (2017) to reduce the number of route choices, considering several stations at the microscopic level can lead to long computation times. Thus the focus of this literature is on the macroscopic rescheduling models that can handle disruptions. Zhan et al. (2016) apply a rolling horizon approach to take into account the uncertainty of disruption length for rescheduling in case of the partial blockage. Xu et al. (2017) developed a rescheduling model for disruptions caused by temporary speed restrictions. Since there is no blockages short-turning is not considered as a rescheduling measure. Coor (1997) investigates the impact of the short-turning strategy on the passenger waiting time on a high-frequency single transit line and concludes that in case of severe delays it is more beneficial than in case of small delays. In another study by Shen and Wilson (2001) different strategies such as short-turning, holding and stop skipping are examined. It is concluded that the combination of short-turning and holding strategies can reduce the mean passenger waiting time considerably. Ghaemi et al. (2016) model short-turning exclusively as a main measure to handle disruptions during the second phase. Only one side of the disruption is considered and the impact of the transitions are discarded. Its focus is on the trade-off between cancellation and delays by selecting different cancellation and delay penalties. Ghaemi et al. (2017a) extend the microscopic rescheduling model developed by Pellegrini et al. (2014) with the short-turning model presented in Ghaemi et al. (2016). Louwerse and Huisman (2014) develop a MILP model to compute the disruption timetable by maximizing the service level. Similarly Binder et al. (2017) develop an ILP model to compute a disruption timetable with three objectives of passenger satisfaction, operational costs and deviation from the original timetable. Veelenturf et al. (2017) developed a heuristic to adapt the timetable during disruption. To find the best adaptation, a list of alternative timetables are evaluated in terms of rolling stock and passenger flow and the one with the least consequences is selected. These references focus on the second phase of the disruption and neglect the transition phases. There are a few models that address the recovery from a disruption such as Jespersen-groth et al. (2009), Meng and Zhou (2011), Narayanaswami and Rangaraj (2013), and Zhan et al. (2015). However, they do not provide any support for the second phase of the disruption. There are a few references such as Nakamura et al.

(2011) and Veelenturf et al. (2016) that provide a disruption timetable and implicitly take into account the recovery phase. The model developed by Nakamura et al. (2011) does not optimize the timetable but instead the solution is provided by performing specific steps. These steps identifying the cancelled and short-turned services, assigning rolling stock to each scheduled departure and finally resolving the mismatch for scheduled departures that need rolling stock to operate. Veelenturf et al. (2016) extends the model by Louwerse and Huisman (2014) which maximizes the service level taking into account three resources; open track, station track and rolling stock. However this model only allows short-turning in the final station before the disruption and the possibility of short-turning in the preceding station due to the limited capacity is not included. In their approach services from the affected lines are divided into three parts from which the second part are those that are scheduled to operate in the disrupted area. In case these services are cancelled, then the first part or third part might also be cancelled. Moreover it is assumed that the third phase takes a specific amount of time. The research on the first phase is indeed limited. Chu and Oetting (2013) provide insight into the processes during the first phase and recommend to take into account the extra time while designing the contingency plans. Hirai et al. (2006) also focus on the first phase by proposing an algorithm to compute the stopping stations for the disturbed train lines.

In case of disruptions the rolling stock circulation is rescheduled based on the rescheduled timetable, as Jespersen-groth et al. (2009) highlight. Thus many rolling stock rescheduling models such as those proposed by Nielsen et al. (2012), Cacchiani et al. (2012) and Wagenaar et al. (2017) assume a predefined timetable.

To the best of our knowledge, the existing literature on optimal rescheduling and short-turning does not concretely address the three phases of disruption and specially the traffic interaction from both sides of the blockage upon the disruption resolution while accounting for rolling stock. For a review of the related literature see Ghaemi et al. (2017b).

This paper presents a macroscopic rescheduling model which is an extension of the model introduced by Ghaemi et al. (2016). The macroscopic rescheduling model computes a three-phase disruption timetable, including the recovery plan for the case of a complete blockage given a certain disruption length. The main contributions of the paper are as follows:

- A macroscopic MILP model is developed to compute the disruption timetable and the transition plans given a certain disruption period.
- Allowing for short-turning at multiple stations while taking the platform track occupation into consideration.
- Accounting for the traffic on both sides of the disrupted location during the three phases.

- Demonstrating how the disruption length affects the optimal periodic short-turning solution of the second phase.

The structure of the paper is as follows. The three-phase rescheduling problem is elaborated in Section 4.2. Section 4.3 presents the mathematical formulation of the MILP model. In Section 4.4 the results of the application of the model on a Dutch railway corridor are discussed. Finally, the conclusions are given in Section 4.5.

4.2 Problem Description

In case of large disruptions, the rescheduling decisions are usually made by the traffic controllers located in the centralized traffic control center who monitor and control the entire network. If there is no relevant contingency plan, the traffic controllers have to quickly respond and devise a feasible plan for short-turning train services that are heading towards the disrupted location. The train services that are running towards the disrupted location are referred to as approaching train services throughout this study. The traffic controllers have to decide how to assign the approaching train services to the scheduled departures in the opposite direction. Having multiple train services that need to be short-turned on both sides of the disrupted location and communicating the plan with other traffic controllers to reach a consensus would take a long time and might postpone the recovery. Hence an algorithm that can quickly compute the optimal short-turning solution on both sides of the blockage as well as the transition to the original timetable can speed up the process. Before defining the problem, it is necessary to explain how a service is defined in this study. Figure 4.2 illustrates the

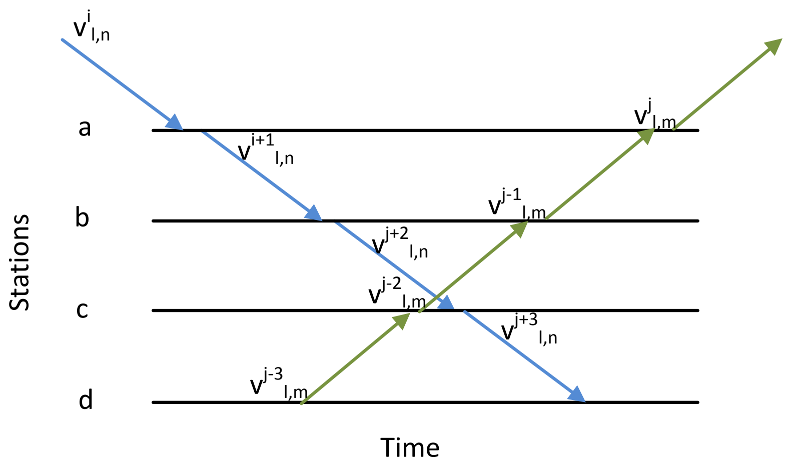


Figure 4.2: Service definition.

time-distance diagram for two opposite trains from station a to station d (downwards) and from station d to station a (upwards). Each service $v^{i}_{l,n}$ is characterized with three indicators: l identifies the line number that determines the stopping stations, n represents the operation time of the service and i indicates the sequence of the service within

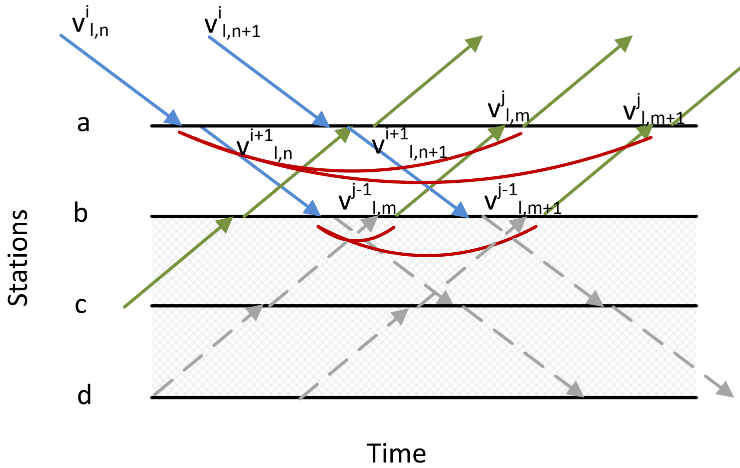


Figure 4.3: Different short-turning possibilities.

line l. In this way each service is recognized as a trip between two consecutive stations. Hence the following service from station a to b that is performed by the rolling stock of service $v^{i}_{l,n}$ from the same line is denoted by $v^{i+1}_{l,n}$. As shown in figure 4.3 the next service of the same line from station a to b is denoted by $v^{i+1}_{l,n+1}$ where $n+1$ indicates that this service operates in the following cycle.

In case there is a disruption in station c, the approaching trains cannot proceed further and they have to short-turn before the disrupted area. In Figure 4.3 an approaching train $v^{i}_{l,n}$ has to short-turn the latest at station b. The blockage results in cancellation of the services from station d to c and from c to b. Thus the services from b to a and from a upwards have to be performed by the short-turning trains. As is illustrated with the red short-turning arcs, there are two scheduled departures possible from station b to a; $v^{j-1}_{l,m}$ and $v^{j-1}_{l,m+1}$. If the capacity is not sufficient for short-turning all approaching trains, then the trains can also short-turn a station earlier to scheduled departures $v^{j}_{l,m}$ or $v^{j}_{l,m+1}$. Thus each approaching train has multiple short-turning possibilities in different stations. The optimal choice of short-turning is the main problem in the second phase of the disruption. The traffic scheduling decisions during the first and third phases directly depend on the start and end times of the disruption period. Note that the optimal short-turning choice in the second phase is dependent of the disruption period. The first phase deals with the services that depart towards the disrupted location before the start of the disruption. Logically these services need to short-turn in the next stations even if the initial schedule did not include this stop. The third phase starts when train services can start again using the previously blocked section and lasts until the original timetable can be resumed. In order to plan for the third phase, it is assumed that the end of the disruption is known in advance.

Figures 4.4 and 4.5 show two time-distance diagrams for a disruption with same start time and two different disruption lengths. In this example, station c is disrupted. The train services need to short-turn either at stations b and d or those preceding them, namely stations a and e.

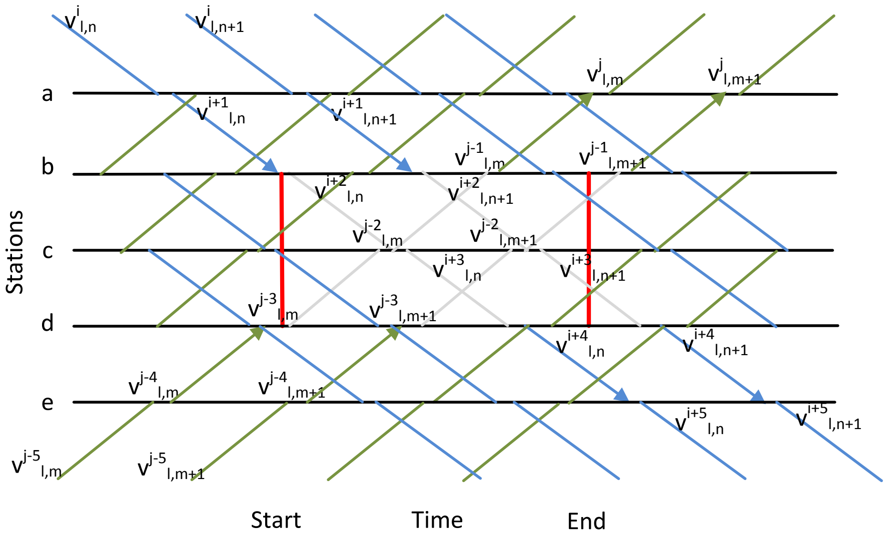


Figure 4.4: Disruption scenario with symmetrical condition.

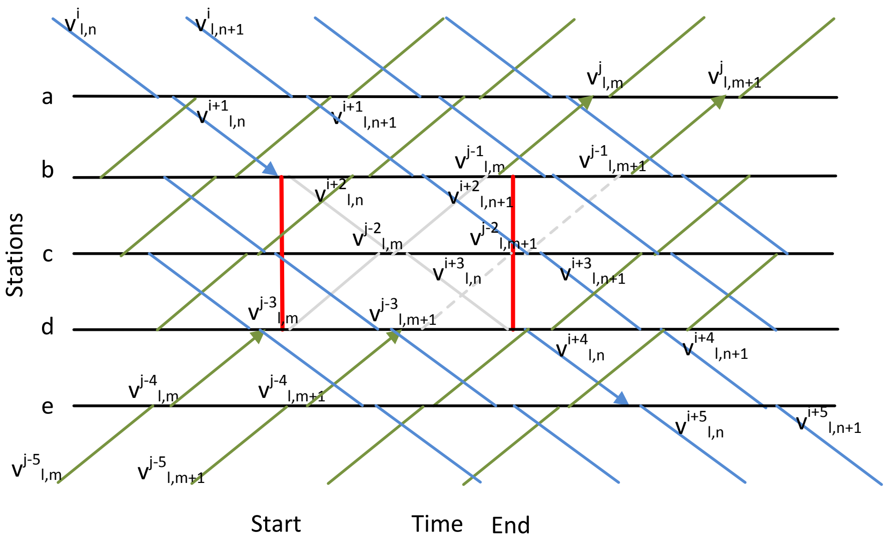


Figure 4.5: Disruption scenario with asymmetrical condition.

The two vertical lines represent the start and end times of the disruption. Note that each short-turning is the assignment of an arriving train to a scheduled departure in the opposite direction. Consequently, the short-turning trains on one side of the disrupted location correspond to the scheduled departures of the short-turnings on the other side of the disrupted location.

For example, if the train service $v^{i}_{l,n}$ (or $v^{i+1}_{l,n}$) short-turns in station a (or b), then $v^{i+4}_{l,n}$ (or $v^{i+5}_{l,n}$) needs to be performed by a short-turning in station d (or e).

The train services that are affected by the blockage are those that run towards disruption with the scheduled arrival at station c and those that are scheduled to depart from station c within the disruption period.

In Figures 4.4 and 4.5, the approaching train services are shown by arrows. Moreover, the scheduled departures on the other side of the disruption corresponding to the approaching train services are also depicted by arrows.

The number of approaching train services for short-turnings on each side of the disruption may either be equal or unequal. Thus, depending on the disruption period there can be either symmetrical (equal) or asymmetrical (unequal) condition. Figure 4.4 and Figure 4.5 show disruption scenarios with symmetrical and asymmetrical conditions, respectively.

In a symmetrical condition, an equal number of approaching train services on both sides of the disrupted location also implies equal approaching train services and scheduled departures on each side. As is shown in Figure 4.4 there are two approaching train services on each side. In this case, the train services $v_{l,n}^{i+1}$ and $v_{l,n+1}^{i+1}$ from one side and train services $v_{l,m}^{j-4}$ and $v_{l,m+1}^{j-4}$ from the other side are approaching stations b and d. These train services need to short-turn at or prior to stations b and d. Note that the model can also suggest early short-turnings of the corresponding services ($v_{l,n}^{i}$, $v_{l,n+1}^{i}$ and $v_{l,m}^{j-5}$, $v_{l,m+1}^{j-5}$) in stations a and e. By short-turning the train services $v_{l,n}^{i+1}$ and $v_{l,m}^{j-4}$, the services $v_{l,n}^{i+2}$ and $v_{l,m}^{j-3}$ need to be cancelled. These cancelled services are represented using solid grey lines. Similarly, the train services $v_{l,n+1}^{i+1}$ and $v_{l,m+1}^{j-4}$ short-turn.

In an asymmetrical condition, an unequal number of approaching train services implies that on one side of the disruption, there are more approaching train services than scheduled departures in the opposite direction and vice versa on the other side. Figure 4.5 is an example where there are two approaching train services $v_{l,m}^{j-4}$ and $v_{l,m+1}^{j-4}$ in station d (or $v_{l,m}^{j-5}$ and $v_{l,m+1}^{j-5}$ in station e) and one approaching train service $v_{l,n}^{i+1}$ in station b (or $v_{l,n}^{i}$ a). Since there are two approaching train services in station d and only one possible scheduled departure in the opposite direction, only one short-turning can take place and the second approaching train has to wait until the disruption is over and it can continue towards station a. In case of an asymmetrical condition, the recovery service is the successive service corresponding to the final approaching train service on the side with more approaching train services. In this case the recovery services $v_{l,m+1}^{j-3}$ can only depart with some delay.

In the third phase, there might be congestion resulting from the train services that are waiting for the end of the disruption period until they can start running towards the other side of the previously blocked section.

4.3 Mixed-Integer Linear Programming Formulation

Before defining the variables and constraints of the Mixed Integer Linear Programming model, it is necessary to introduce the assumptions and construct the relevant sets. Section 4.3.1 lists the underlying assumptions. The sets are defined in Section 4.3.2 followed by the MILP model in Sections 4.3.3 and 4.3.4. Finally Section 4.3.5 describes how different phases of disruption are measured.

4.3.1 Model assumptions

The model in its current formulation addresses the disruption cases where a station is completely blocked for a certain disruption period. However with some minor adjustments, the model can be applied for complete blockages of open track sections. The main assumptions of this model are that the disruption length is known upon occurrence and the original timetable is cyclic. Literature proposes several models to predict the disruption length from which we refer to the model by Zilko et al. (2016) that is based on Copula Bayesian Network.

It is also assumed that each service can only short-turn to replace a service from the same line. Thus the possibility of short-turning an intercity train and replacing a service from the local line is excluded to avoid complications in rolling stock circulation. The proposed MILP problem is a macroscopic model and does not provide microscopic solution that determines the utilization of every track detection section. Instead a minimum headway is considered to avoid any conflict between the operating services. In addition, the running, dwell and short-turning times are assumed as input.

4.3.2 Preprocessed sets based on the disruption period

The notation is listed in Table 4.1. For notation simplification, the approaching train services are shown as v' and those services that are scheduled to approach the disrupted station are denoted by v''. Finally, those services that are scheduled to move away from the disrupted area are denoted as v''' regardless of their line specifications. Before formally defining these sets, an example is used to make a better distinction between them.

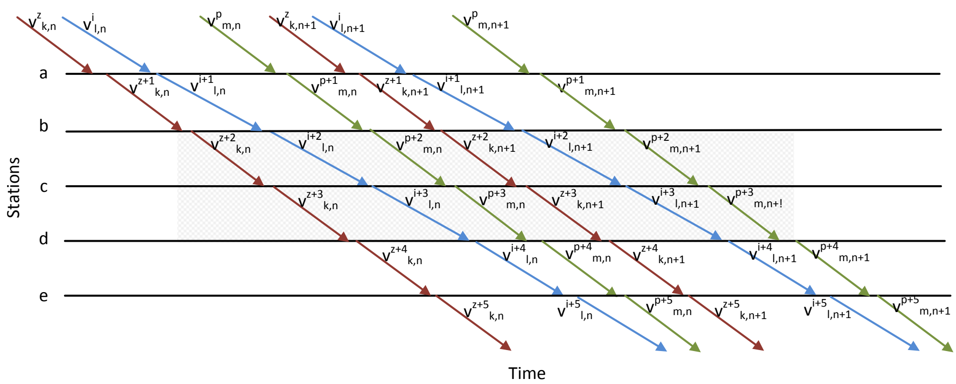


Figure 4.6: Different lines operating in one direction.

This example shows three operating lines (k,l,m) in one direction. Thus the approaching services to station a, b, and c each consist of three sets that are shown distinctively in each column,

$V'_{a,k} = \{v^{z}_{k,n}, v^{z}_{k,n+1}\}$, $\quad V'_{b,k} = \{v^{z+1}_{k,n}, v^{z+1}_{k,n+1}\}$, $\quad V''_{c,k} = \{v^{z+2}_{k,n}, v^{z+2}_{k,n+1}\}$,

$V'_{a,l} = \{v^{i}_{l,n}, v^{i}_{l,n+1}\}$, $\quad V'_{b,l} = \{v^{i+1}_{l,n}, v^{i+1}_{l,n+1}\}$, $\quad V''_{c,l} = \{v^{i+2}_{l,n}, v^{i+2}_{l,n+1}\}$,

Table 4.1: The notation of the input used in the macroscopic model

S	The set of all stations s.
L	The set of all lines l.
V	The set of all scheduled services.
$V_{l,n} \subset V$	The n^{th} set of ordered services in line l.
$v^i_{l,n} \subset V_{l,n}$	The i^{th} service in set $V_{l,n}$.
$P_{s,v^i_{l,n}}$	The set of platform tracks for service $v^i_{l,n}$ in station s.
$S_{v^i_{l,n}} \subset S$	The departure and arrival stations $(s^d_{v^i_{l,n}}, s^a_{v^i_{l,n}})$ of $v^i_{l,n}$.
$S_0 \subset S$	The disrupted station (x).
$S_1 \subset S$	The first surrounding stations (b and d) around the disrupted station x.
$S_2 \subset S$	The secondary surrounding stations (a and e) around stations in S_1.
$S^l \subset S$	The set of possible short-turning stations for line l.
$d^i_{l,n}$	The scheduled departure time of service $v^i_{l,n}$.
$a^i_{l,n}$	The scheduled arrival time of service $v^i_{l,n}$.
$\theta^{min}_{v^i_{l,n}}$	The minimum short-turning time needed for service $v^i_{l,n}$.
$\tau^{run}_{v^i_{l,n}}$	The running time of service $v^i_{l,n}$ between two stations.
$\tau^{dwell}_{v^i_{l,n},v^{i+1}_{l,n}}$	The dwell time between service $v^i_{l,n}$ and service $v^{i+1}_{l,n}$ in the station.
$\tau^h_{v^i_{l,n},v^u_{w,z}}$	The minimum headway time between two train services $v^i_{l,n}$ and $v^u_{w,z}$.
$\omega^c_{v^i_{l,n}}$	The penalty for cancelling service $v^i_{l,n}$.
$\omega^z_{v^i_{l,n}}$	The penalty for delaying the arrival of service $v^i_{l,n}$.
t^s	The start time of disruption.
t^e	The end time of disruption.
M	A large constant.

$$V'_{a,m} = \{v^p_{m,n}, v^p_{m,n+1}\}. \qquad V'_{b,m} = \{v^{p+1}_{m,n}, v^{p+1}_{m,n+1}\}. \qquad V''_{c,m} = \{v^{p+2}_{m,n}, v^{p+2}_{m,n+1}\}.$$

Similarly the services that move away from the disruption and depart from station d and e each consist of three sets that are shown distinctively in each column,

$$V'''_{d,k} = \{v^{z+4}_{k,n}, v^{z+4}_{k,n+1}\}, \qquad V'''_{e,k} = \{v^{z+5}_{k,n}, v^{z+5}_{k,n+1}\},$$
$$V'''_{d,l} = \{v^{i+4}_{l,n}, v^{i+4}_{l,n+1}\}, \qquad V'''_{e,l} = \{v^{i+5}_{l,n}, v^{i+5}_{l,n+1}\},$$
$$V'''_{d,m} = \{v^{p+4}_{m,n}, v^{p+4}_{m,n+1}\}. \qquad V'''_{e,m} = \{v^{p+5}_{m,n}, v^{p+5}_{m,n+1}\}.$$

In the preprocessing step, the following sets are defined.

- The set of lines l that are planned to operate in the disrupted area during the disruption,

$$L_{Dist} = \{l \in L | \exists i, n, S_{v^i_{l,n}} \subseteq \{S_1, S_0\},\ t^s \leq a^i_{l,n} \leq t^e\}.$$

- The set of all approaching services $v^i_{l,n}$ to station $s \in S_1 \cup S_2$ from line l for which the service $v^{i+1}_{l,n}$ (or $v^{i+2}_{l,n}$) is scheduled to arrive at S_0 within the disruption period,

$$V'_{s,l} = \{v^i_{l,n} \in V | s = s^a_{v^i_{l,n}}, s^d_{v^i_{l,n}} \notin \{S_1, x\}, \exists z \in \{i+1, i+2\}, t^s < a^z_{l,n} < t^e, \},$$
$$\forall s \in S_1 \cup S_2, l \in L_{Dist}.$$

- The set of all services $v^i_{l,n}$ from line l that are scheduled to depart from station $s \in S_1$ and arrive at station x within the disruption period,

$$V''_{s,l} = \{v^i_{l,n} \in V | s = s^d_{v^i_{l,n}}, s^a_{v^i_{l,n}} = x, v^{i-1}_{l,n} \in V'_{s,l}\},\ \forall s \in S_1, l \in L_{Dist}.$$

- The set of services that are scheduled to depart from station $s \in S_1 \cup S_2$ from line $l \in L_{Dist}$ and run away from station x,

$$V'''_{s,l} = \{v^j_{l,m} \in V | s^d_{v^j_{l,m}} = s, v^{j-2}_{l,m}, v^{j-3}_{l,m} \in V''_{\bar{s},l}, \bar{s} \in S_1, l \in L_{Dist}\},\ \forall s \in S_1 \cup S_2.$$

- To compute the optimal short-turnings, all the possible pairs of approaching train services and scheduled departures in the opposite direction in the relevant stations are defined by the following sets,

$$Out_{v^i_{l,n}} = \{(v^i_{l,n}, v^j_{l,m}) | v^j_{l,m} \in V'''_{s,l}\},\quad \forall v^i_{l,n} \in V'_{s,l}, s \in S_1 \cup S_2, l \in L_{Dist},$$
$$In_{v^j_{l,m}} = \{(v^i_{l,n}, v^j_{l,m}) | v^i_{l,n} \in V'_{s,l}\},\quad \forall v^j_{l,m} \in V'''_{s,l}, s \in S_1 \cup S_2, l \in L_{Dist}.$$

- Since the disruption period is assumed to be known in advance, in the preprocessing step the services in the first phase can be predetermined. Considering the first phase starting with a reduction in the traffic level, the approaching services in the first phase are denoted as $V'_{s,l,red}$. This set consists of the approaching services to station s from line l that depart before the start of the disruption and arrive within the disruption period. They are a subset of the approaching services $V'_{s,l}$ that already departed from their possible short-turning station and they have to short-turn in the final station before the disruption. They are defined by the following set,

$$V'_{s,l,red} = \{v^i_{l,n} \in V'_{s,l} \mid d^i_{l,n} \leq t^s, s \notin S^l\},\quad \forall l \in L_{Dist}.$$

- Similarly the scheduled departures in the opposite direction in the first phase are denoted as $V'''_{s,l,red}$. This set consists of the first scheduled departures from station s and line l in the opposite direction for which there is no rolling stock available and thus can be performed by short-turning the approaching train in the first phase. The scheduled departures in the opposite direction in the first phase are defined by the following set,

$$V'''_{s,l,red} = \{v^j_{l,m} \in V'''_{s,l} \mid d^j_{l,m} < d^j_{l,w}, s \notin S^l\},\quad \forall v^j_{l,w} \in V'''_{s,l}, l \in L_{Dist}.$$

- Based on the defined sets in the first phase, the short-turning couples of the first phase are denoted as sht_{red} and defined by the following set,

$$sht_{red} = \{(v^i_{l,n}, v^j_{l,m}) \mid v^i_{l,n} \in V'_{s,l,red}, v^j_{l,m} \in V'''_{s,l,red}\}, \quad \forall l \in L_{Dist}.$$

- Likewise, the services of the third phase can be predetermined. The services that may use the blocked section after the disruption is over, are called recovery services and are denoted as $V''_{s,l,rec}$. The recovery service is defined as the last service on those lines which have a greater number of approaching services than scheduled departures in the opposite direction:

$$V''_{s,l,rec} = \begin{cases} \{v^i_{l,n} \in V''_{s,l} \mid a^i_{l,w} < a^i_{l,n}\}, \quad \forall v^i_{l,w} \in V''_{s,l}, s \in S_1, l \in L_{Dist} & \text{if } |V'_{s,l}| > |V'''_{s,l}| \\ \emptyset, & \text{otherwise.} \end{cases}$$

4.3.3 Decision variables

The decision variables are formulated as either continuous or binary variables. The continuous decision variables represent time and are non-negative:

$t^a_{v^i_{l,n}}$: The arrival time of service $v^i_{l,n}$.
$t^d_{v^i_{l,n}}$: The departure time of service $v^i_{l,n}$.
$z_{v^i_{l,n}}$: The arrival delay of service $v^i_{l,n}$.

The decisions regarding occupying a platform track, cancelling a service, and the choice of short-turning are represented by binary decision variables:

$$p_{v^i_{l,n},q} = \begin{cases} 1 & \text{if } v^i_{l,n} \text{ arrives at platform track } q, \\ 0 & \text{otherwise;} \end{cases}$$

$$c^i_{l,n} = \begin{cases} 1 & \text{if } v^i_{l,n} \text{ is cancelled,} \\ 0 & \text{otherwise;} \end{cases}$$

$$\lambda_{v',v'''} = \begin{cases} 1 & \text{if } v' \text{ short-turns to } v''', \\ 0 & \text{otherwise.} \end{cases}$$

4.3.4 Objective function and constraints

The objective function includes two terms, penalized cancellations and delay,

$$\min \sum_{v^i_{l,n} \in V} (\omega^c_{v^i_{l,n}} \cdot c^i_{l,n} + \omega^z_{v^i_{l,n}} \cdot z_{v^i_{l,n}}), \tag{4.1}$$

where $\omega^c_{v^i_{l,n}}$ and $\omega^z_{v^i_{l,n}}$ are penalties for cancellation and arrival delay of service $v^i_{l,n}$.

Running, dwell, delay and departure time constraints

$$t^a_{v^i_{l,n}} - t^d_{v^i_{l,n}} = \tau^{run}_{v^i_{l,n}}, \qquad \forall v^i_{l,n} \in V, \tag{4.2}$$

$$t^d_{v^{i+1}_{l,n}} - t^a_{v^i_{l,n}} + M \cdot (c^i_{l,n} + c^{i+1}_{l,n}) \geq \tau^{dwell}_{v^i_{l,n}, v^{i+1}_{l,n}}, \qquad \forall v^i_{l,n}, v^{i+1}_{l,n} \in V, \tag{4.3}$$

$$t^d_{v^i_{l,n}} - d^i_{l,n} \geq 0, \qquad \forall v^i_{l,n} \in V, \tag{4.4}$$

$$t^d_{v^i_{l,n}} - d^i_{l,n} \leq (1 - c^i_{l,n}) \cdot M, \qquad \forall v^i_{l,n} \in V, \tag{4.5}$$

$$z_{v^i_{l,n}} = t^a_{v^i_{l,n}} - a^i_{l,n} \qquad \forall v^i_{l,n} \in V, \tag{4.6}$$

$$t^d_{v^i_{l,n}} \geq t^e \qquad \forall v^i_{l,n} \in V''_{s,l,rec}, s \in S_1, l \in L_{Dist} \tag{4.7}$$

Minimum running and dwell times are considered by constraints (4.2) and (4.3). The departures should respect the schedule. Constraints (4.4) enforce this restriction. To avoid double penalties for cancelled services, their operations are modelled on time. Constraints (4.5) make sure that the departures of cancelled services are the same as the schedule. Constraints (4.6) measure the arrival delays. The recovery services can only operate after the end of the disruption. Constraints (4.7) ensure this restriction.

Short-turning constraints

$$\sum_{(v',v''') \in Out_{v^i_{l,n}} \cup Out_{v^{i+1}_{l,n}}} \lambda_{v',v'''} = c^{i+2}_{l,n}, \qquad \forall v^i_{l,n} \in V'_{s,l}, s \in S_2, l \in L_{Dist}, \tag{4.8}$$

$$\sum_{(v',v''') \in In_{v^j_{l,m}} \cup In_{v^{j-1}_{l,m}}} \lambda_{v',v'''} + c^j_{l,m} = c^{j-2}_{l,m}, \qquad \forall v^j_{l,m} \in V'''_{s,l}, s \in S_2, l \in L_{Dist}, \tag{4.9}$$

$$\sum_{(v',v''') \in Out_{v^i_{l,n}}} \lambda_{v',v'''} = c^{i+1}_{l,n}, \qquad \forall v^i_{l,n} \in V'_{s,l}, s \in S_2, l \in L_{Dist}, \tag{4.10}$$

$$\sum_{(v',v''') \in In_{v^j_{l,m}}} \lambda_{v',v'''} + c^j_{l,m} = c^{j-1}_{l,m}, \qquad \forall v^j_{l,m} \in V'''_{s,l}, s \in S_2, l \in L_{Dist}, \tag{4.11}$$

$$\sum_{(v',v''') \in Out_{v^{i+1}_{l,n}}} \lambda_{v',v'''} + c^{i+1}_{l,n} \leq 1, \qquad \forall v^i_{l,n} \in V'_{s,l}, s \in S_2, l \in L_{Dist}, \tag{4.12}$$

$$(1 - \lambda_{v',v'''}) \cdot M + t^d_{v'''} \geq t^a_{v'} + \theta^{min}_{v'}, \qquad \forall (v', v''') \in Out_{v'}, \tag{4.13}$$

$$c^j_{l,m} \leq c^{k+1}_{l,m}, \qquad \forall v^j_{l,m} \in V'''_{s,l}, s \in S_2, l \in L_{Dist}, k \in [j, |S| - 1], \tag{4.14}$$

$$\lambda_{v',v'''} = 1, \qquad \forall (v', v''') \in sht_{red}. \tag{4.15}$$

The short-turning constraints are better explained by the time distance diagram shown in Figure 4.3. Every approaching service to the disrupted area has to short-turn in a station preceding the blockage. Assuming the arrival station of $v^i_{l,n}$ to be station $a \in S_2$, then it implies that service $v^{i+2}_{l,n}$ has to be cancelled due to the blockage unless $v^{i+2}_{l,n}$ can wait in the final station and then arrives at station c which was disrupted. In case service $v^{i+2}_{l,n} \in V''_{s,l}$ is cancelled then $v^i_{l,n}$ or $v^{i+1}_{l,n}$ has to short-turn. Otherwise the approaching train can continue as the recovery service. Constraints (4.8) enforce this relation. There should be a train assigned to each scheduled departure in the opposite direction. Thus, there are three options for each scheduled departure in the opposite direction. If there is no available train that can operate this service, it needs to be cancelled. Otherwise either an approaching train service or the recovery train service from the other side of disruption is assigned. This possibility is present through Constraints (4.9). Each early short-turning leads to two cancelled services. To give an example, if service $v^i_{l,n}$ is short-turned as service $v^j_{l,m}$ in a station upstream of the closest station to the blockage, then the following service $v^{i+1}_{l,n}$ will be cancelled. Likewise the preceding service of $v^j_{l,m}$, $v^{j-1}_{l,m}$, will be cancelled. These cancellations are considered in constraints (4.10) and (4.11). Constraints (4.12) make sure that if service $v^{i+1}_{l,n}$ is cancelled due to a short-turning in an earlier station a (or e), the relevant pairs should not be selected in the last station b (or d). For each short-turning there should be a minimum short-turning time between the arrival of the approaching train service and the scheduled departure in the opposite direction. Constraints (4.13) ensure the minimum short-turning time. If a departing service from stations a (or e) that runs away from the disruption is cancelled, then the following services need to be cancelled. Constraints (4.14) guarantee these cancellations for the remaining services of the line. The short-turning couples of the first phase that are defined in the preprocessing step are realized by imposing their short-turning variables through Constraints (4.15).

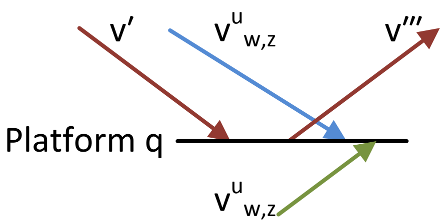


Figure 4.7: The platform occupation constraint for short-turning services.

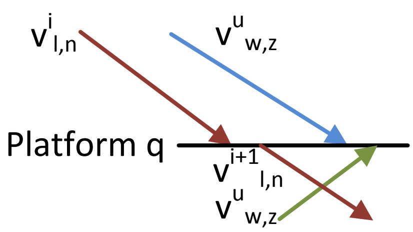


Figure 4.8: The platform occupation constraint for the non short-turning services.

Platform constraints

$$\sum_{q\in P_{s,v^i_{l,n}}} p_{v^i_{l,n},q} + c^i_{l,n} = 1 \qquad \forall v^i_{l,n} \in V'_{s,l} \cup V'''_{s,l}, s \in S_1 \cup S_2, l \in L_{Dist}, \tag{4.16}$$

$$(3-(p_{v',q}+p_{v^u_{w,z},q})-\lambda_{v',v'''})\cdot M + t^a_{v^u_{w,z}} \geq t^d_{v'''} + \tau^h_{v^i_{l,n},v^u_{w,z}}, \ \forall (v',v''') \in Out_{v'}, v' \in V'_{s,l},$$
$$s \in S_1 \cup S_2, l \in L_{Dist}, \ \forall v^u_{w,z} \in V : s^a_{v^u_{w,z}} = s, a^u_{w,z} \geq a^{v'}, \forall q \in P_{s,v'} \cap P_{s,v^u_{w,z}}, \tag{4.17}$$

$$(c^{i+1}_{l,n} + 2 - (p_{v^i_{l,n},q} + p_{v^u_{w,z},q}))\cdot M + t^a_{v^u_{w,z}} \geq t^d_{v^{i+1}_{l,n}} + \tau^h_{v^i_{l,n},v^u_{w,z}}, \ \forall v^i_{l,n} \in V'_{s,l}, s \in S_2, l \in L_{Dist},$$
$$\forall v^u_{w,z} \in V : s^a_{v^u_{w,z}} = s, a^u_{w,z} \geq a^i_{l,n} \ \forall q \in P_{s,v^i_{l,n}} \cap P_{s,v^u_{w,z}}. \tag{4.18}$$

Constraints (4.16) guarantee a platform assignment for each arriving service. Figures (4.7) and (4.8) visualize the constraints (4.17) and (4.18). Constraints (4.17) make sure that in case train service v' is being short-turned as service v''' using platform track q then any next arriving service $v^u_{w,z}$ should wait until the minimum headway time after the departure of v''' if it uses the same platform track q. Similarly, constraints (4.18) ensure the platform occupation is unique to only one train service at a time for those services that do not short-turn.

4.3.5 Postprocessed measures of disruption phases

To measure the lengths of each phase of disruption, there should be a distinction between phases. The phases are measured within the short-turning stations. In this approach the first phase starts as soon as the disruption starts. It is acknowledged that in practice the first phase may take longer due to the time needed for communication and reaching an agreement on how to proceed with the decisions made by the traffic controllers. The end of the first phase, which is also the start of the second phase, is defined as the time that (fewer) trains operate regularly again and no more irregularities caused by the first phase are observed. The regular operation includes short-turnings that repeat every cycle. If the services of the first phase can short-turn on time, then the first phase ends as soon as the latest service of the first phase departs after short-turning. In case the short-turnings of the first phase cause delay, then the end of the first phase is measured at the latest arrival at the short-turning stations. The second phase lasts until the earliest departure of the recovery services from the short-turning stations. This time point is the beginning of the third phase which lasts until the latest arrival of the recovery services at the short-turning stations.

4.4 Case Study

The model is applied to a mainly double-track railway corridor from Utrecht (Ut) to 's-Hertogenbosch (Ht) in the middle of the Netherlands. The model is implemented in MATLAB R2016b and solved by Gurobi. The toolbox YALMIP (Löfberg, 2004) is used to construct the MILP model. The optimal solutions are achieved with zero gaps. The corridor is illustrated in Figure 4.9 and includes 13 stations and 7 lines with each a frequency of two services per hour in each direction. So 14 trains per hour per direction operate in this corridor. The case study considers a disruption that takes place at station Geldermalsen (Gdm). There are different intercity and local train lines operating in this corridor. These lines are colored differently in Figure 4.9. The original timetable for this corridor is illustrated in Figure 4.10. Two intercity lines IC800 (in light green) and IC3500 (in dark green) and two local lines (called sprinters (SPR) in Dutch) SPR16000 (in orange) and SPR6000 (in blue) run through Geldermalsen. The local line SPR36700 (in purple) provide services to Geldermalsen. The intercity lines have scheduled stops only at stations Utrecht (Ut) and 's-Hertogenbosch (Ht). Thus, in case of a disruption in Geldermalsen, the IC train services need to short-turn in these stations. The SPR train services SPR16000 and SPR6000 have scheduled stops at Utrecht Lunetten (Utl), Houten (Htn), Houten Castellum (Htnc), Culemborg (Cl), and Geldermalsen. From Geldermalsen, SPR6000 runs towards the east to station Tiel Passewaaij (Tlpsw) and SPR16000 operates towards the south to Zaltbommel (Zbm) and 's-Hertogenbosch. The short-turning stations to the south of Geldermalsen for the SPR services are Zbm or Ht, and for IC services only Ht. The short-turning stations to the north of Geldermalsen are Cl or Htnc for SPR services. The two lines IC3600 (in light blue) and SPR4400 (in pink) are not affected by the disruption in Gdm. However since they stop in Ht, they are included in the model. The IC services short-turn in Ut which due to its complexity is not included in this case study. The stations Beesd and Tiel Passewaaij are not frequently served. So the short-turnings in these stations can be performed on schedule without introducing any delay, thus their short-turnings are excluded in the case study. Table 4.2 lists the stops for each line.

Table 4.2: Lines

Line	Stops								
IC800	Ut	Ht							
IC3500	Ut	Ht							
IC3600	Hto	Ht	Tb						
SPR36700	Bsd	Gdm							
SPR4400	Hto	Ht	Vg						
SPR6000	Ut	Utl	Htn	Htnc	Cl	Gdm	Tlpsw		
SPR16000	Ut	Utl	Htn	Htnc	Cl	Gdm	Zbm	Ht	Tb

4.4.1 Parameters and experiment settings

To test and demonstrate the impact of the disruption on the optimal short-turning solution, four experiments are performed with different disruption periods. In the first experiment, it is shown that with the same disruption length, there could be different

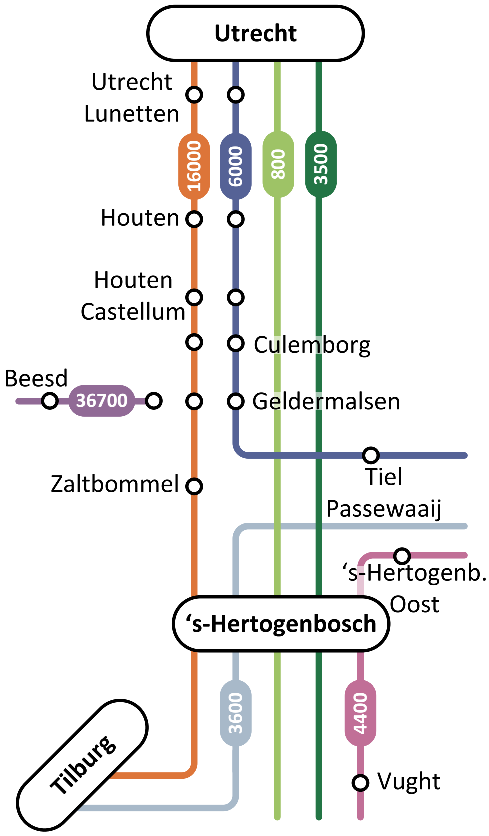


Figure 4.9: The disrupted corridor.

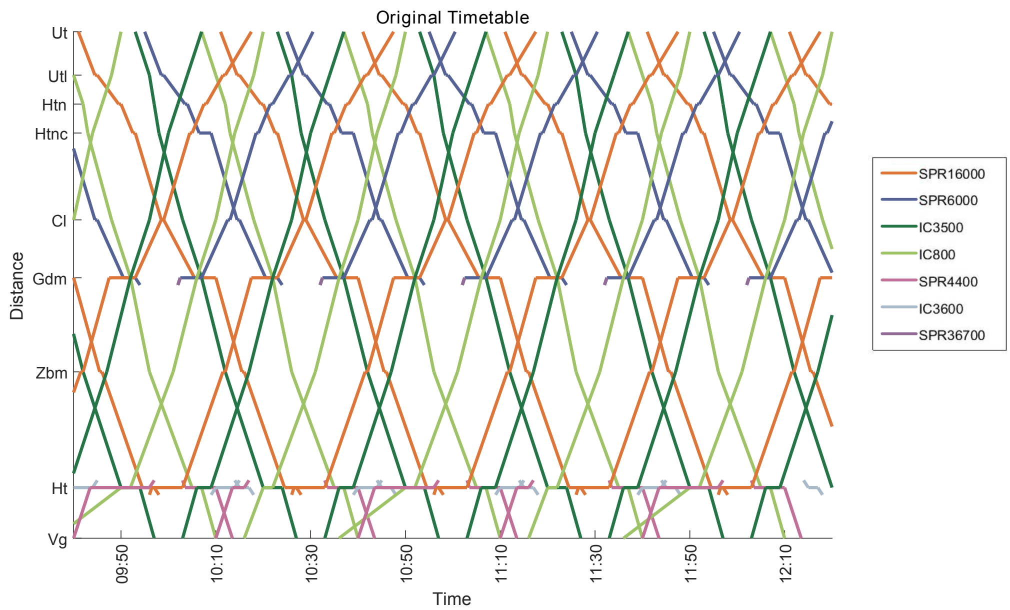


Figure 4.10: The time-distance diagram of the original timetable.

optimal solutions depending on the start time of the disruption. This is the result of the different first phase. In the second experiment, it is shown that with the same disruption start time, the third phase could differ due to different disruption lengths. In the third experiment, the three phases of disruption for two scenarios are measured. In the fourth experiment, the optimal solution and the performance of the model with in particular the relation between the cancellation and delay are investigated under various disruption periods. In the experiments the duration of each phase is measured. The delay and cancellation for intercity services are penalized more than the delay and cancellation of local train services. The exact parameters' values and the number of platform tracks in the short-turning stations are detailed in Tables 4.3 and 4.4.

Table 4.3: Parameters

Parameter	Notation	Value
Short-turning time	$\theta^{min}_{v^i_{l,n}}$	5 (min)
Headway time	$\tau^h_{v^i_{l,n},v^u_{w,z}}$	3 (min)
Big M	M	50000
IC cancellation penalty	$\omega^c_{v^i_{l,n}}, \forall v^i_{l,n} \in V, l \in$ {IC800, IC3500, IC3600}	10000
SPR cancellation penalty	$\omega^c_{v^i_{l,n}}, \forall v^i_{l,n} \in V, l \in$ { SPR36700, SPR4400, SPR6000, SPR16000}	1000
IC delay penalty	$\omega^{d^a}_{v^i_{l,n}}, \forall v^i_{l,n} \in V, l \in$ {IC800, IC3500, IC3600}	10
SPR delay penalty	$\omega^{d^a}_{v^i_{l,n}}, \forall v^i_{l,n} \in V, l \in$ {SPR36700, SPR4400, SPR6000, SPR16000}	1

Table 4.4: platforms

Station	Htnc	Cl	Gdm	Zbm	Ht
Number of platform tracks	2	2	4	2	5

4.4.2 Experiment one: Different start time of disruption and fixed disruption length

In this experiment, station Gdm is disrupted for 30 minutes. Two scenarios with respect to different disruption start time are considered. In the first scenario (Figure 4.11), the disruption starts at 09:45 and in the second scenario (Figure 4.12) it starts at 10:00. In these figures, different train lines are identified by different colors which correspond to those used in Figure 4.9. The cancelled services are colored in grey. In this experiment there is an equal number of approaching train services from line SPR16000 (in orange) and SPR6000 (in blue) on both sides of the disruption (one approaching train service and one scheduled departure in the opposite direction). The intercity train services from lines IC3500 (in dark green) and IC800 (in light green) have to short-turn in Ht. However, in Figure 4.11 it is shown that the service from IC3500 (in dark green) departs from Ht before the start of disruption. Thus, this service is part of the services within the first phase of the disruption and has to short-turn in the following station which is Zbm although this line does not have any stops until Ut. Similarly on the other side of the disruption, the service from IC800 should have short-turned in Ut. However the disruption starts after the departure of this train from Ut. So this service is short-turned in station Cl. The short-turnings that are part of the first phase are shown by the horizontal green line. The other horizontal lines that connect an arriving train service to a scheduled departure in the opposite direction, are the optimal short-turning solutions within the second phase. Station Cl has two platform tracks that are occupied by the services from line SPR6000 (in blue) and IC800 (in light green). Hence, there is no platform track available for the short-turning of service from SPR16000 (in orange) in Cl. So the optimal solution suggests an early short-turning for this line in station Htnc. On the other side of the disruption, the short-turning of the service from line 16000 (in orange) in Zbm, corresponds exactly to those in station Cl. It is also observed that the same occurs to the short-turning of IC800 (in light green) in both stations Cl and Ht. Zbm has two platform tracks, which are occupied by services from line IC3500 (in dark green) and SPR16000 (in orange). So the next service from line SPR16000 (in orange) can arrive with some delay which is the result of the minimum headway. This delay is the difference between the dashed line which is the scheduled train path and the solid line which is the computed path. Obviously, in this scenario, the third phase includes some delays.

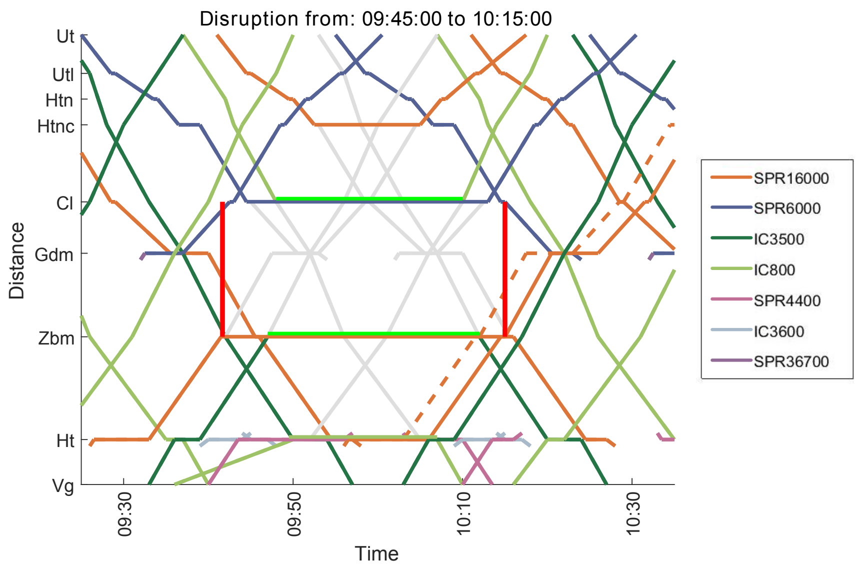


Figure 4.11: Optimal short-turning solution for disruption from 9:45 to 10:15.

Figure 4.12 shows the result for the disruption that starts at 10:00, and reveals different optimal short-turning solutions on both sides of the disruption. In this scenario the train service from line SPR6000 (in blue) short-turns in Htnc, due to the fact that both platforms of station Cl are occupied by short-turning services from line SPR16000 (in orange) and IC3500 (in dark green). On the other side of the disruption, a departure delay of one minute is observed after the short-turning of train service SPR16000 (in orange) at station Zbm caused by the minimum short-turning time of 5 minutes. In this scenario, the third phase is executed smoothly without any delay.

Table 4.5 shows the results of the first experiment. The second column reports the

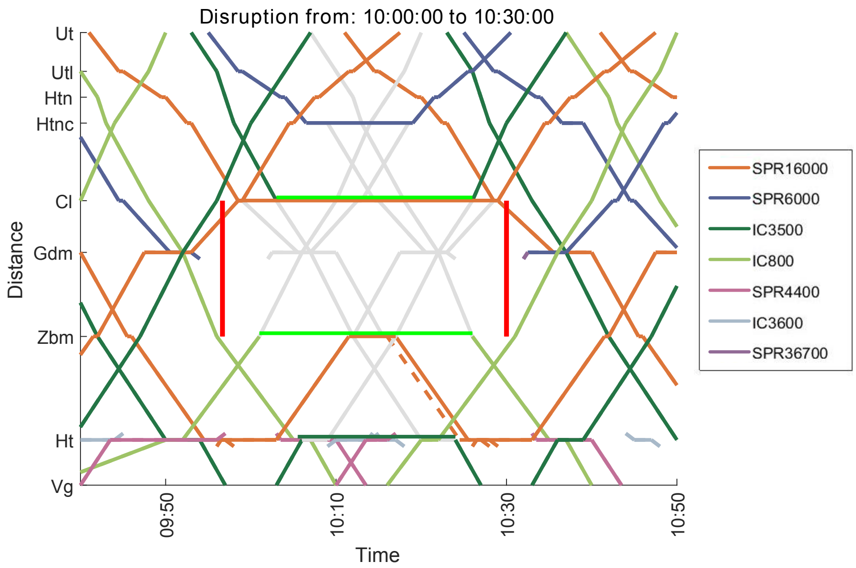


Figure 4.12: Optimal short-turning solution for disruption from 10:00 to 10:30.

affected train services (including the cancelled and delayed services) over the total services. In both scenarios, there are 29 cancelled services. Note that each service is defined as a trip between two consecutive stations. There are two cancelled services resulting from early short-turning due to the IC services of the first phase in both scenarios. The remaining 27 cancelled services include the services in the disrupted area (between Cl and Zbm) and those related to the short-turning of the IC services in the first phase. The delay is measured for each arrival while the reported delay is computed by adding all the arrival delays. In the first scenario, there are 7 delayed services of line SPR16000 from Ht to Ut. The large delay for SPR16000 is caused by the limited platform track capacity due to short-turnings. Thus in total there are 36 affected train services in the disruption between 9:45 and 10:15. In the second scenario, there are two delayed services of line SPR16000 which are caused by respecting the minimum short-turning time. So there are 31 affected services in the second scenario. Due to a smaller delay in the second scenario, a lower objective function value is attained. The computation time of both scenarios are less than a second.

Since the disruption lengths of these scenarios are short, only a few short-turnings of the first phase are taking place. This conclusion is made by observing the irregularities of IC short-turnings in station Cl and Zbm. Thus, the first phase is defined from the beginning of the disruption until the latest departures of the IC services (IC800 from Cl and IC3500 from Zbm). On both sides of the disruption these IC services wait for a long time to short-turn to the next scheduled departure. These long short-turnings of the first phase, postpone the second phase. Due to the short disruption period, the third phase starts before a reduced and regular timetable for the second phase can be operated. In the first scenario, the third phase starts with the departure of the recovery service from Ht and lasts until the arrival at station Htnc. In the second scenario, there is no recovery service, so the third phase has a length of zero. This experiment demonstrates that the optimal solutions proposed by the model may differ for the scenarios with the same disruption length but different start times of the disruption. In other words, the impact of disruptions of the same lengths in terms of the delay can differ if they have different start times.

Table 4.5: The results of experiment one.

Disruption period	Affected /total services	# Cancelled services	Delays (s)	Obj. function	Comp. time (s)
9:45 to 10:15	36/210	29	1260	192260	0.12
10:00 to 10:30	31/210	29	120	191120	0.08

4.4.3 Experiment Two: Fixed start time of disruption and different disruption lengths

In this experiment the start time of the disruption is kept fixed whereas different disruption lengths are considered. This experiment is hence devised to explore the role of the disruption length on the optimal solution, specially during the third phase. Figure 4.13 shows the optimal short-turning solution for the scenario with a disruption between 10:00 and 10:40. The approaching train service from line SPR6000 (in blue) has to wait for 17 minutes in station Htnc, until it can proceed and use a platform track in station Cl. The reason that the optimal solution does not suggest the early short-turning for this line is that it would have resulted in more cancelled services. As illustrated, more delay is observed in the third phase in comparison with experiment one. The main reason is that in this scenario, there is an unequal number of approaching train services from line SPR16000 (in orange) and scheduled departures in the opposite direction in station Cl. To be specific, there are two approaching train services and one scheduled departure in the opposite direction. Thus, the second approaching service is recognized as the recovery service and has to wait in Cl until the disruption is over by the time it arrives at Gdm and then it can resume the original train path with some delay. Similarly on the other side of disruption, there are two approaching train services from line IC800 (in light green) and one scheduled departure in the opposite direction in station Zbm. Thus, the second approaching train service has to depart from Zbm with some delay to arrive at Gdm after the disruption is over.

In order to improve the third phase, it might be beneficial to resume the original timetable later so that the symmetrical condition is achieved. Figure 4.14 shows the optimal short-turning solution for the scenario where resuming the original timetable occurs 13 minutes after the end of disruption. In this scenario, due to the equality between the number of approaching train services and the number of scheduled departure in the opposite direction, the third phase is rather smooth.

The results of experiment two are listed in Table 4.6. From the results, it is concluded that by resuming the original timetable later, the number of cancelled services is increased by 57% and the delay is reduced by 52%. Note that the cancelled services are limited to those computed by the model between Cl and Zbm, nonetheless the delay can propagate to stations located outside of the control area. Specially if there are alternative modes of transport in the disrupted area, cancelling a few more services might be more preferred by the train operator than introducing a delay to the network due to the asymmetrical condition. At the same time, different penalties could be considered to provide train operators with alternative solutions. Similar to the previous experiment the model computes the optimal solution quickly.

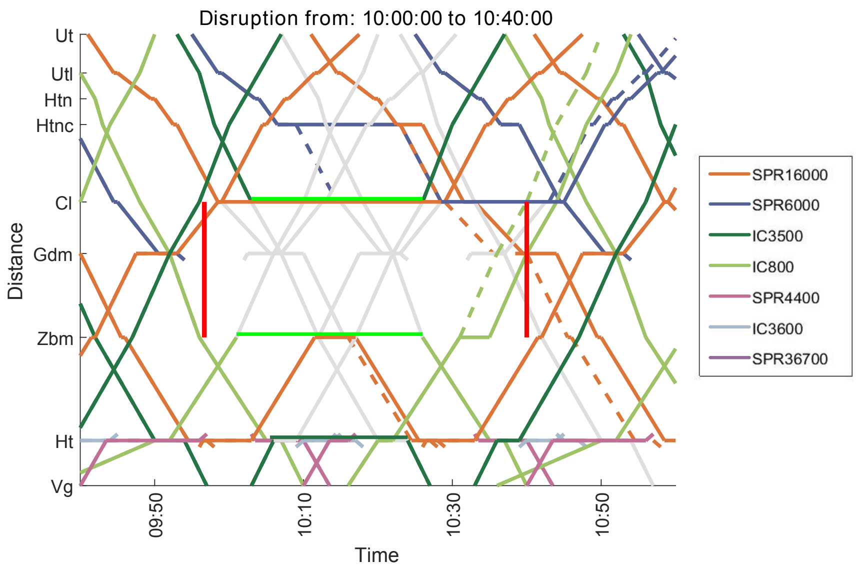


Figure 4.13: Optimal short-turning solution for disruption from 10:00 to 10:40.

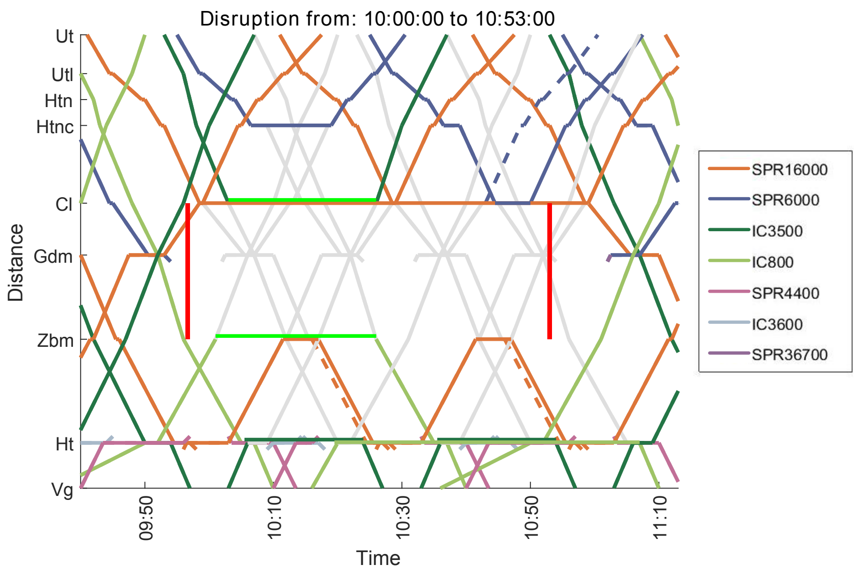


Figure 4.14: Optimal short-turning solution for disruption from 10:00 to 10:53.

From this experiment it is concluded that in the proposed model which encompasses the transition phase back to normal operations, the disruption length plays an important

Table 4.6: The results of experiment two.

Disruption period	Affected /total services	# Cancelled services	Delays (s)	Obj. function	Comp. time (s)
10:00 to 10:40	59/245	42	4020	292980	0.19
10:00 to 10:53	74/281	66	1920	481920	0.31

role in determining the delay introduced in the final transition phase. The disruption period can determine whether there is a symmetrical or asymmetrical condition. It is observed that by resuming the original timetable later, it is possible to reach the symmetrical condition and hence the delay can be decreased at the cost of increasing the number of cancellations.

4.4.4 Experiment three: Measuring the three phases

The three phases of disruption can better be distinguished with longer disruption periods. In this experiment two scenarios (90 minutes and 100 minutes) are defined to show how different phases are measured.

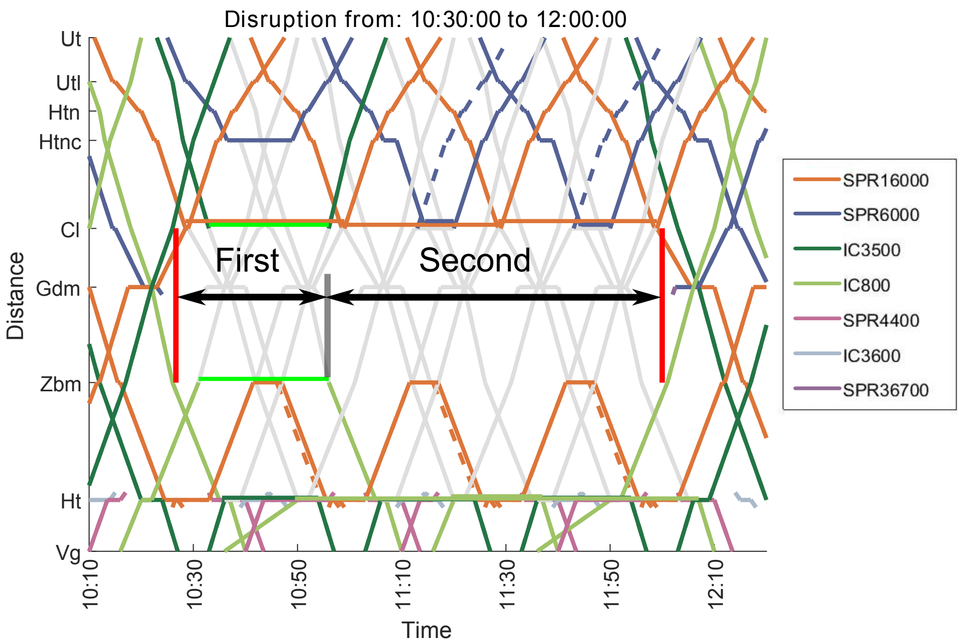


Figure 4.15: Optimal short-turning solution for disruption from 10:30 to 12:00.

The optimal short-turning solutions for the three phases are illustrated in Figures 4.15 and 4.16. In both scenarios, the first phase lasts until the latest departure of the first phase short-turnings. Thus, first phase ends with the departure of a service from line IC800 (in light green) from Zbm to Ht. The second phase starts at the same time point. During the second phase the services from lines SPR16000 (in orange), SPR6000 (in blue), IC3500 (in dark green), and IC800 (in light green) short-turn regularly. The

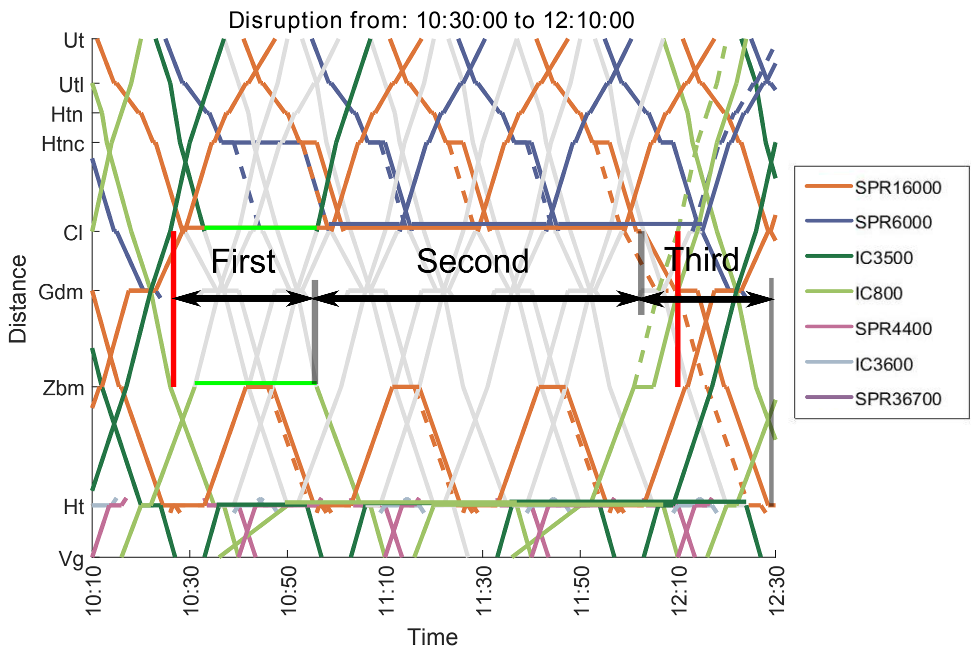


Figure 4.16: Optimal short-turning solution for disruption from 10:30 to 12:10.

second phase ends with the start of the third phase. Due to the symmetrical condition in the first scenario, there are no recovery services and thus the second phase ends at the end of the disruption. In this scenario the recovery is immediate.

In the second scenario, due to the asymmetrical condition, there are recovery services from both sides of the disruption. The second phase ends at the earliest departure of the recovery services which in this scenario is the departure of the recovery service from line SPR16000 (in orange). As defined in section 4.3.5, the third phase lasts until the latest arrival of the recovery services at the short-turning stations. These measurements are listed in Table 4.7.

Table 4.7: Lengths of the three phases

Scenario	First phase (s)	Second phase (s)	Third phase (s)
10:30 to 12:00	1560	3840	0
10:30 to 12:10	1560	4020	1560

4.4.5 Experiment four: Increasing disruption lengths

In this experiment, the disruption start time is fixed and the disruption length is increased from one to five hours with intervals of 10 minutes. Figures 4.17 and 4.18 show the optimal short-turning solution for two selected disruption lengths of 180 and 190 minutes, respectively. It is observed that in the second phase the short-turning of the intercity train services IC800 (in light green) and IC3500 (in dark green) at Ht and the local train service SPR16000 (in orange) in Zbm and Cl remain the same even though the disruption length is increasing. However, the optimal short-turning of the local train services from lines SPR6000 (in blue) changes. The reason this change for line SPR6000 occurs is that the disruption is located at the end of the line and the departures are scheduled slightly earlier than the arrivals. Since there is no train service arriving from the other side after the disruption then some services should be cancelled due to the lack of rolling stock in case there are more scheduled departures than approaching services.

In the symmetrical disruption scenarios, the departures would take place with some delay as the arrivals are after the scheduled departures. In the asymmetrical disruption scenarios, where a scheduled departure should be cancelled, the optimal solution would be to cancel the first scheduled departure so that the rest of departures can take place more on time. This results in alternation of the short-turning choice as the disruption length increases.

With increased disruption length, the short-turnings of line SPR16000 in Cl as shown in Figure 4.17 repeats every 30 minutes (i.e. disruption end times at minutes 0, and 30). In between each half an hour (with disruptions ending at minutes 10, 20, 40, and 50), the short-turning choice shown in Figure 4.18 occurs. The optimal solution for the third phase also repeats every half an hour. In other words, the recovery plans for disruptions ending at minutes 10 and 40 are the same. This similarity is also valid for disruption periods ending at minutes 20 and 50 as well as minutes 0 and 30.

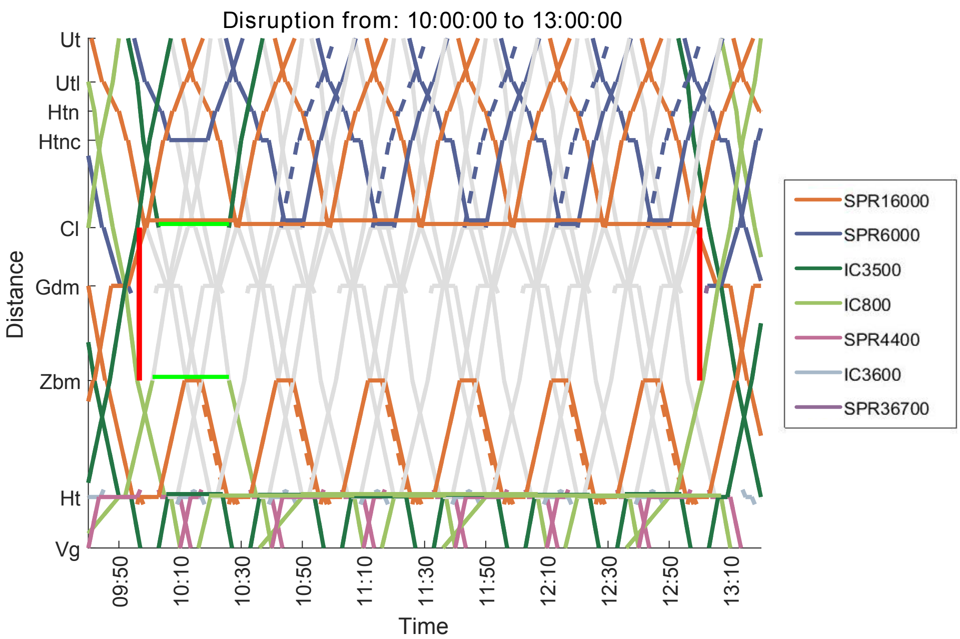


Figure 4.17: Optimal short-turning solution for disruption from 10:00 to 13:00.

The relation between the disruption length, delay and number of cancelled services is illustrated in Figure 4.19. As expected, the number of cancelled services (represented by red circles) steadily increases for increasingly longer disruptions. The delay, which is plotted by the blue line, is also increasing with some oscillation. Interestingly, the

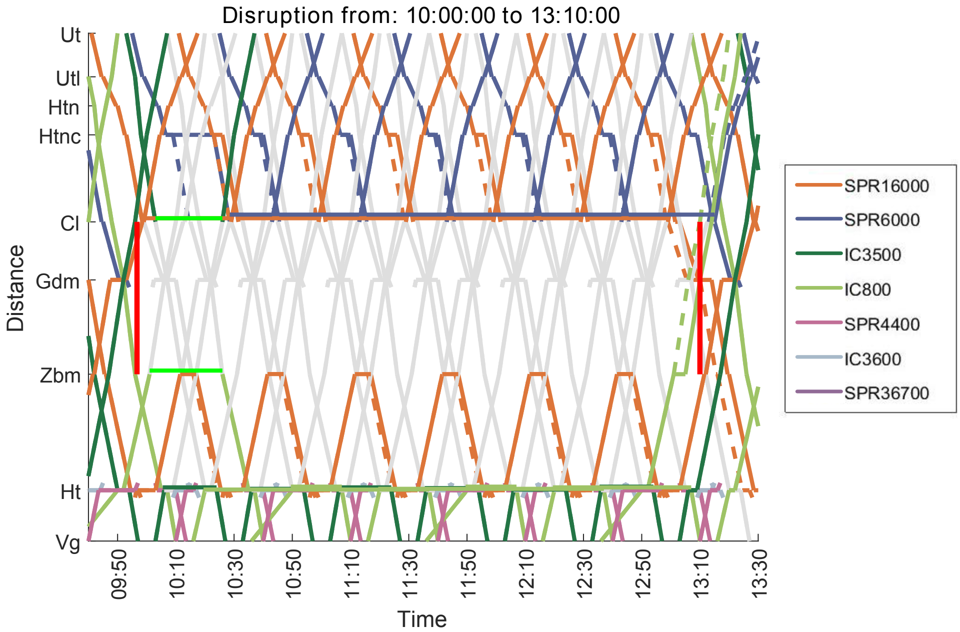


Figure 4.18: Optimal short-turning solution for disruption from 10:00 to 13:10.

extent of oscillation grows with disruption length. The peaks in the delay line are the results of waiting for the end of the disruption that occurs in the third phase. It is therefore concluded that in case of long disruptions corresponding to the peaks, by minor extension of the disruption length, the delay can be reduced considerably at the cost of an increase in the number of cancellations.

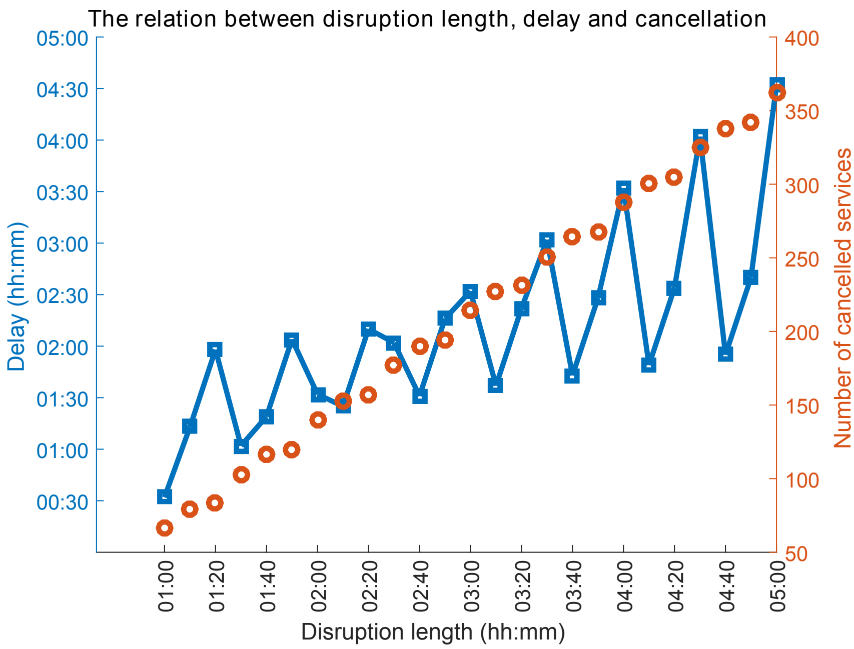


Figure 4.19: The relation between the disruption length, delay and number of cancelled services.

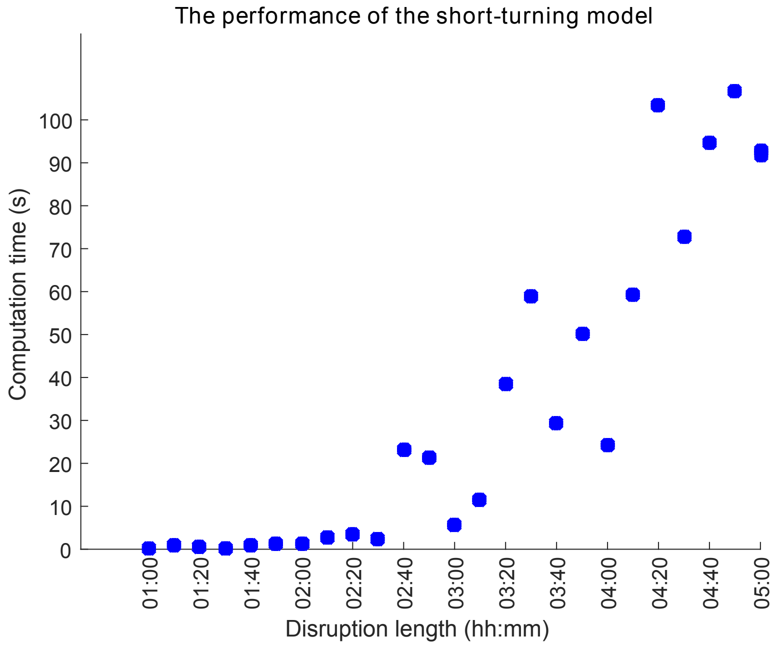


Figure 4.20: The computation time of the short-turning model.

The real-time applicability of the model depends on the computation time. Figure 4.20 shows the computation time of the short-turning model for given different disruption lengths. It is observed that computing the disruption timetable and the transition plans for a period of three hours for such a busy corridor takes less than 10 seconds. The computation time of a new timetable for a disruption period up to five hours takes less than two minutes.

4.5 Conclusion

In this paper, a MILP model is proposed to compute the disruption timetable and the transition plans for complete blockages based on the disruption period. In this formulation, the rescheduling measures of short-turning, partial cancellation, and re-timing are applied on the traffic on both sides of the disrupted location. Depending on the available rolling stock and infrastructure capacity, the short-turnings can take place in multiple stations. Given the disruption period, different services might need to be short-turned on each side of the blockage. The number of short-turning train services on both sides can be either equal (symmetrical) or unequal (asymmetrical) depending on the disruption period. In the asymmetrical scenarios, the extra train services need to wait until the end of the disruption and then proceed and operate on the recently resolved track section. This waiting will postpone the recovery back to the original timetable.

The model is applied to a dense Dutch railway corridor. Several experiments revealed the importance of the disruption period (the start time and the disruption length) in the optimal short-turning solution. The computation time is promising for real-time application. It is concluded that different disruption periods can result in different optimal short-turning choices. Depending on the disruption start time, different services might be affected during the first phase, which would result in different transition plans. Given a certain disruption start time, different disruption lengths can also result in different transition plans for the third phase. The optimal short-turning choice during the second phase can alternate depending on the disruption length. This alternation is due to the symmetrical and asymmetrical conditions for the lines without traffic interaction from both sides of the blockage and those whose scheduled departures are earlier than the arrivals at the short-turning stations. In addition, these choices repeat as the disruption length increases. Since the original timetable is periodic, for a long enough disruption length a periodic pattern will emerge that fits in the periodic timetable of the (undisrupted) rest of the network. The transitions between the three steady-states of the normal (1st and 3rd phase) and disrupted (2nd phase) period timetable will largely determine the periodic pattern during the 2nd phase, which in turn depends on the start and end times of the disruption as shown in the fourth experiment. In asymmetrical scenarios, the delay can be decreased by resuming the original timetable later than the end of disruption to reach the symmetrical condition. However, resuming the original timetable later will lead to more cancelled services. Therefore a rule is necessary to make a trade-off between the number of cancelled services and the delay.

Currently, the model cannot suggest the shortest time required after the end of disruption to reach the symmetrical condition. Finding this time point given the disruption start time would be a next research direction. Another direction is to investigate the optimal short-turning solutions with uncertain disruption lengths. With minor adjustments, the model can be applied on disruption cases of open track blockages. It is also interesting to use a microscopic short-turning model to improve the accuracy of the capacity allocation in the short-turning stations.

Chapter 5

A microscopic model for optimal train short-turnings during complete blockages

Apart from minor updates, this chapter has been published as:

Ghaemi, N., Cats, O., Goverde, R.M.P., 2017. A microscopic model for optimal train short-turnings during complete blockages. *Transportation Research Part B: Methodological*, 105:423 –437.

5.1 Introduction

Railway operations are prone to unplanned events such as infrastructure failure or incidents. A timetable is designed to recover from small delays. However, in case of events that can lead to the blockage of a track section for several hours, the resources need to be rescheduled. Trains approaching the blockage cannot proceed with their original plans and have to short-turn at a station close to the disruption. Simultaneously, trains from the opposite direction are not able to pass the blockage and provide services further.

A common practice in case of complete blockages in railway operation is to short-turn trains. Short-turning is a measure that uses the arriving trains at a station before a disruption area to perform services in the opposite direction for which the trains could not reach the station from the other side of the disruption. The short-turning measure prevents the congestion of trains in the stations close to the disrupted area by maintaining the rolling stock circulation in the network. Providing services in the opposite direction can isolate the disrupted area by reducing delay propagation to the neighbouring stations.

To provide support for the traffic controllers, predefined solutions are generally used. These solutions which are called contingency plans are common practice in many countries such as the Netherlands, Germany, Switzerland, Denmark and Japan as pointed out by Chu and Oetting (2013). The solution provided by a contingency plan consists of cancelled, rerouted or short-turned services including the arrival and departure times and platform tracks. Obviously each contingency plan is designed for a specific location and a specific timetable.

The contingency plans are designed manually, therefore the suggested solution might not be optimal. For example the suggested solution does not always consider the operational constraints such as minimum short-turning time which eventually would result in an infeasible solution. Moreover they are not sufficiently detailed on the infrastructure allocation and they cannot cover all possible disruption scenarios throughout the entire network. Changes in the timetable or the infrastructure require an updated contingency plan. In case there is no relevant contingency plan, the traffic controllers have to deal with the disruption without any support. Therefore there is a need to develop an algorithm that is able to compute an optimal rescheduling solution in real-time.

There are several macroscopic rescheduling approaches proposed by Louwerse and Huisman (2014), Zhan et al. (2015) and Veelenturf et al. (2016). However providing a feasible solution requires a microscopic representation of the infrastructure and operation. Ghaemi et al. (2017b) show the importance of employing microscopic models for rescheduling in case of disruptions. As Cacchiani et al. (2014) and Ghaemi et al. (2017b) conclude, there are very few references that model disruptions at the microscopic level. The existing microscopic models can also be classified based on the covered level of detail. By doing so it is observed that none of the existing models such as Hirai et al. (2009) and Corman et al. (2011a) provide a comprehensive solution with a sufficient level of detail for the entire disruption period. Pellegrini et al. (2014) developed a microscopic optimization model that provides rescheduling and rerouting solutions for railway disturbance management. The model computes the optimal route choice for each service by calculating the track section occupation based on the blocking time model (Hansen and Pachl, 2014). The advantage of this model is that the simultaneous occupation of each track section is avoided by defining an order variable. Unlike other microscopic rescheduling models such as Caimi et al. (2011) and Lusby et al. (2011) there is no need for pre-processing the track occupation for detecting any conflict.

To deal with disruptions of a complete blockage Ghaemi et al. (2016) propose a short-turning optimization model in which the arriving trains at the final station (before disruption) are assigned to the scheduled departures in the opposite direction. The final station before disruption is referred to as the primary short-turning station. The model allows the possibility for short-turning not only at the primary short-turning station, but also at a preceding station which represents the secondary short-turning station. Two main limitations of this model are that it excludes the possibility of reordering services and the infrastructure and operation are not considered at the microscopic level of detail. Fixed order can impose unnecessary restriction on the solution. For example by fixing the operation order of two train services from local and intercity lines might result in a situation where the intercity train is delayed because the preceding local train is delayed. While this can be avoided by considering a flexible order.

The model proposed by Ghaemi et al. (2016) does not include the infrastructure and operation details and only computes the arrivals and departures. Thus based on these arrivals and departures the position of the trains along the routes can be roughly estimated. However in order to detect possible conflicts, it is necessary to know the precise running of the trains on track section level. Formulating the infrastructure and operation with a fine level of detail is essential to understand the real capacity.

To give an example, in case of short-turnings, knowing the number of platform tracks in the station is not sufficient to compute a feasible solution. Although each platform track can be assigned to one short-turning at a time, but there might be conflicts with other trains in the inbound and outbound routes to and from the station. A conflict can be resolved by either rerouting or rescheduling the operation. Thus it is important to carefully take into account the movements of the trains specially in the short-turning stations.

The contribution of this study is a rescheduling model that selects the optimal short-turning stations, in/out bound routes and platform sections for all the services including the short-turning trains. In this paper we adopt the microscopic rescheduling model by Pellegrini et al. (2014) and extend it with the short-turning possibility introduced by Ghaemi et al. (2016) for the case of a complete blockage. In this way the limitations of the model by Ghaemi et al. (2016) are removed as the microscopic model takes into account the reordering possibility and represents the infrastructure and operation with fine level of detail. The extended MILP model computes optimal rerouting and rescheduling solutions for cases of complete blockages where all the approaching trains towards the blockage need to short-turn. Moreover some services might need to be cancelled. A key assumption of this extension is that a reliable disruption length estimate is available. There are different approaches to estimate the disruption length such as the one developed by Zilko et al. (2016) using Copula Bayesian Network. Within the disruption period, the arriving trains should be short-turned and assigned to the departing schedules in the opposite direction. The extended part includes the choice of short-turning taking into account the operational constraints such as minimum short-turning time. In other words, the model determines which scheduled departing service in the opposite direction is being performed by each approaching train. Since all the approaching trains to the disrupted area need to short-turn, there might not be enough capacity in the primary short-turning station. For this reason the possibility of short-turning at a secondary station is included. Although an early short-turning implies more service cancellations, it can result in less total delay.

The remaining of the paper is structured as follow: in Section 5.2, first the macro short-turning model and the micro rescheduling model are described briefly and then the formulation of the integrated model is presented. Section 5.3 shows the application of the model on two Dutch railway corridors and finally Section 5.4 discusses the conclusions.

5.2 Microscopic short-turning formulation

In this section, the mathematical formulation of the microscopic short-turning model is presented. As addressed previously, the microscopic short-turning model is partly based on the short-turning model introduced by Ghaemi et al. (2016) and partly based on the microscopic rescheduling model developed by Pellegrini et al. (2014). Before describing each model it is necessary to define the notation used in this model. The notation is listed in Table 5.1.

5.2.1 Short-turning decisions

The main task of the short-turning model is to assign the arriving trains to the scheduled departures in the opposite direction. It is common to short-turn the arriving services as the scheduled departure services from the same line. So there should be a distinction between services from different lines. In addition to the line indicator it is also required to know the time of the operation and the order of the service within the line. Thus within the short-turning model each service v is defined with three indicators $v^i_{l,n}$ where l represents the line number, n represents the operation time and i indicates the sequence of the service within the line l. To give an example, Figure 5.1 shows a time-distance diagram for a disruption scenario between stations a and b. The services running downwards to the disrupted area cannot operate further than station a. Thus, they can either short-turn at the primary short-turning station a or at the secondary short-turning station a'. As shown with red arcs, the short-turning possibilities for the approaching service $v^i_{l,n}$ in station a' are the three scheduled departures $v^j_{l,m}$,$v^j_{l,o}$ or $v^j_{l,r}$ in the opposite direction. In case service $v^i_{l,n}$ short-turns in station a', it is called an early short-turning. Each early short-turning leads to cancellation of two services. In this example if service $v^i_{l,n}$ short-turns as $v^j_{l,m}$, then services $v^{i+1}_{l,n}$ and $v^{j-1}_{l,m}$ need to be cancelled. Alternatively service $v^i_{l,n}$ can continue as service $v^{i+1}_{l,n}$ and short-turn as either services $v^{j-1}_{l,m}$, $v^{j-1}_{l,o}$ or $v^{j-1}_{l,r}$. Obviously in this example one of the scheduled departures needs to be cancelled as there are two arriving trains and three scheduled departures. In case service $v^{i+1}_{l,n}$ short-turns as service $v^{j-1}_{l,m}$, the departure of this service will be delayed as the arrival of service $v^{i+1}_{l,n}$ is taking place after the scheduled departure of service $v^{j-1}_{l,m}$.

The short-turning model requires a preprocessing phase to make a distinction between the arriving services and scheduled departures in the opposite direction. In this phase the approaching services towards the disruption area that are arriving at station h within the disruption period are identified as V'_h. Note that station h is either the primary

Table 5.1: The notation used in the microscopic model

H	The set of stations h.
S	The set of track sections s.
P	The set of platform tracks p.
B	The set of block sections b.
R	The set of routes r.
L	The set of lines l.
V	The set of scheduled services.
SI	The set of track sections in the interlocking area.
SO	The set of track sections in the open track.
S_v	The set of all track sections that can be used by service v.
R_v	The set of all routes that can be used by service v.
$R_{v,s}$	The set of all routes that can be used by v and contain section s.
H_v	The set of departure and arrival stations of service v.
τ_v^d	The scheduled departure time of service v.
τ_v^a	The scheduled arrival time of service v.
h_v^a	The arrival station of service v.
h_v^d	The departure station of service v.
s_O	The virtual track section that represents the start of each route.
s_D	The virtual track section that represents the end of each route.
$p_{r,s}$	The previous track section of s along the route r.
$f_{r,s}$	The following track section of s along the route r.
$u_{r,s}$	The last track section of the block including track section s along route r
$t_{v,r,s}^{run}$	The running time of train v on the track section s along the route r.
S^r	The ordered set of all track sections of route r.
B_r	The ordered set of all block sections composing route r.
$S_{r,b}$	The ordered set of all track sections composing block section b along route r.
$\theta_{v',v''}^{min}$	The minimum short-turning time needed for service v'.
$\delta_{v,\hat{v}}$	The dwell time between the arrival of v and departure of $\hat{v}$.
$q_{r,s}$	The first track section of the previous block of section s along the route r.
t^r	The time needed for signal sight and reaction.
t^s	The switching time needed for release and setup the track section.
t^c	The clearing time.
ω_v^c	The penalty for cancelling service v.
ω_v^d	The penalty for delaying the arrival of service v.
$f(v,\hat{v})$	Indicator: 1 if $\hat{v}$ uses the same rolling stock as v after v in the same direction.
M	A sufficiently large constant.
$V_l \subset V$	The set of services in line l in both directions.
$V_{l,n} \subset V$	The n^{th} set of ordered services in line l.
$v_{l,n}^i$	The i^{th} service in set $V_{l,n}$.
h_a	The primary short-turning station.
$h_{a'}$	The secondary short-turning station.
H_{sht}	The short-turning stations (h_a and $h_{a'}$).
L_{Dist}	The lines that are affected by the disruption.
V_h'	The services approaching the disruption with arrival station at h.
V_h''	The services moving away from the disruption with departure at h.
$Pair_{v_{l,n}^i,*}$	The set of all possible scheduled departures that can be performed by $v_{l,n}^i$.
$Pair_{*,v_{l,m}^j}$	The set of all possible arriving services that can be short-turned to $v_{l,m}^j$.
$Pair_{l,h}$	The short-turning pairs for line l in station h.
$Pair_h$	All the short-turning pairs in station h.

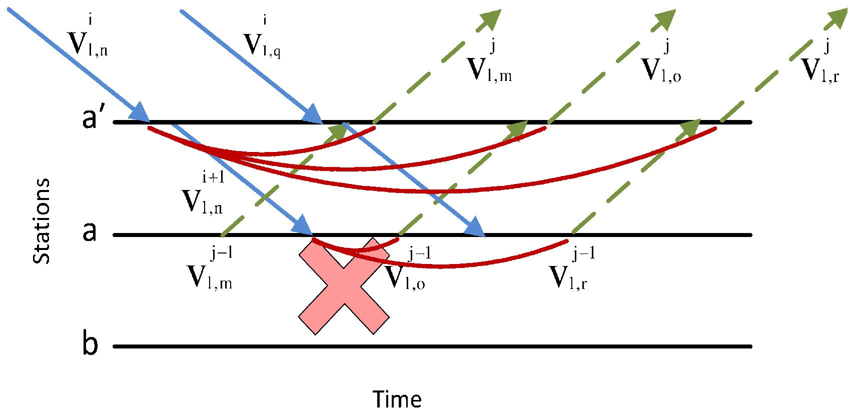


Figure 5.1: The possible short-turnings either at the primary or at the secondary short-turning station.

short-turning station which is noted as h_a or it can be the secondary short-turning station noted as $h_{a'}$. These two stations are called short-turning stations and are referred as H_{sht}. The scheduled departures in the opposite direction that depart from station h within the disruption period are identified as V''_h. Similarly station h can either represent the primary or the secondary short-turning station. The short-turning possibilities for each approaching service $v^i_{l,n}$ are identified as $Pair_{v^i_{l,n},*}$ where $*$ represents several possibilities for scheduled departures. And $Pair_{*,v^j_{l,m}}$ represents all the arriving services possibilities for the scheduled departure $v^j_{l,m}$.

5.2.2 Microscopic rescheduling model

Here a brief review of the microscopic rescheduling model is given as it has been extensively described by Pellegrini et al. (2014). In this model, each service has a set of alternative routes between its departure and arrival stations to select from. Each route might consist of several block sections and each block section might consist of several track sections. The input of the model contains the running time of each service on each track section and the original timetable. The objective of the model is to minimize the deviation of the computed timetable from the original timetable. The blocking time model mentioned by Hansen and Pachl (2014) is used to formulate the capacity consumption. In this approach the conflicts are avoided by computing an order variable that prevents simultaneous track utilization.

5.2.3 Mathematical formulation of the microscopic short-turning model

In this section, the mathematical formulation of the extended model is presented. The aim of the extended model is to compute a disruption timetable that is feasible at the microscopic level of detail. The disruption timetable is developed based on short-turning decisions. Thus, the short-turning of services is microscopically formulated. In addition to minimizing delay, the second objective is to minimize the number of cancelled services. The output of the model provides the optimal inbound and outbound routes for each short-turning in either of the short-turning stations. The decision variables are introduced in Table 5.2. The extended parts that are mostly described in Section 5.2.3 can be distinguished by the short-turning ($\lambda_{v',v''}$) and cancellation (c_v) decisions.

Table 5.2: The decision variables

$x_{r,v}$	If route r is selected for service v then $x_{r,v}=1$, otherwise $x_{r,v}=0$
$y_{v,\bar{v},s}$	If service v uses section s before service $\bar{v}$, then $y_{v,\bar{v},s}=1$, otherwise $y_{v,\bar{v},s}=0$.
$e_{v,r,s}$	The time when service v enters track section s along the route r.
$b^s_{v,s}$	The start of the blocking time of track section s for service v.
$b^e_{v,s}$	The end of the blocking time of track section s for service v.
d_v	The arrival delay of service v.
c_v	If service v is cancelled, then $c_v=1$, otherwise $c_v=0$
$\lambda_{v',v''}$	If service v' short-turns as v'' then $\lambda_{v',v''}=1$, otherwise $\lambda_{v',v''}=0$.

The objective is to minimize the weighted sum of delays and cancelled services:

$$\min \sum_{v\in V} \omega^c_v \cdot c_v + \sum_{v\in V} \omega^d_v \cdot d_v. \tag{5.1}$$

Short-turning constraints

The short-turning constraints are given as follows.

$$\sum_{(v',v'')\in Pair^h_{v^i_{l,n},*} \cup Pair^h_{v^{i+1}_{l,n},*}} \lambda_{v',v''} = 1, \qquad \forall v^i_{l,n} \in V'_{h_{a'}}, \tag{5.2}$$

$$\sum_{(v',v'')\in Pair_{*,v^j_{l,m}} \cup Pair_{*,v^{j-1}_{l,m}}} \lambda_{v',v''} + c_{v^j_{l,m}} = 1, \qquad \forall v^j_{l,m} \in V''_{h_{a'}}, \tag{5.3}$$

$$c_{v^j_{l,m}} \le c_{v^{k+1}_{l,m}}, \qquad \forall v^j_{l,m} \in V''_{h_{a'}}, k \in [j, |l|-1], \tag{5.4}$$

$$\sum_{(v',v'')\in Pair_{v^i_{l,n},*}} \lambda_{v',v''} = c_{v^{i+1}_{l,n}}, \qquad \forall v^i_{l,n} \in V'_{h_{a'}}, \tag{5.5}$$

$$\sum_{(v',v'')\in Pair^h_{*,v^j_{l,m}}} \lambda_{v',v''} + c_{v^j_{l,m}} = c_{v^{j-1}_{l,m}}, \qquad \forall v^j_{l,m} \in V''_{h_{a'}}, \tag{5.6}$$

$$(1-\lambda_{v',v''})\cdot M + \sum_{r\in R_{v''}} e_{v'',r,s_0} \ge \sum_{r\in R_{v'}} e_{v',r,s_D} + \theta^{min}_{v,v'} \cdot x_{r,v'}, \quad \forall (v',v'') \in Pair_h, h \in H_{sht}, \tag{5.7}$$

$$\sum_{r\in R_{v',s}} x_{r,v'} \le \sum_{r\in R_{v'',s}} x_{r,v''} + (1-\lambda_{v',v''})\cdot M, \qquad \forall (v',v'') \in Pair_h, h \in H_{sht}, s \in P, \tag{5.8}$$

$$\sum_{r\in R_{v'',s}} x_{r,v''} \leq \sum_{r\in R_{v',s}} x_{r,v'} + (1-\lambda_{v',v''})\cdot M, \qquad \forall (v',v'')\in Pair_h, h\in H_{sht}, s\in P, \tag{5.9}$$

$$\sum_{r\in R_{v'',s}:p_{r,s}=s_O} b^s_{v'',s} < \sum_{r\in R_{v',s}:f_{r,s}=s_D} b^e_{v',s} + (1-\lambda_{v',v''})\cdot M, \quad \forall (v',v'')\in Pair_h, h\in H_{sht}. \tag{5.10}$$

Constraints (5.2) ensure that all the services that approach the disruption area, should short-turn in either short-turning stations. Each scheduled departure $v^j_{l,m}$ in the opposite direction can take place if there is an arriving service assigned to it in either station of H_{sht}. Otherwise, as shown in constraints (5.3) the scheduled service $v^j_{l,m}$ needs to be cancelled. If a scheduled departure $v^j_{l,m}$ is cancelled, all the following services $v^{j+1}_{l,m}$, $v^{j+2}_{l,m}$,...etc. need to be cancelled. This is ensured by constraints (5.4). In case service $v^i_{l,n}$ is short-turned in the secondary short-turning station, the following service $v^{i+1}_{l,n}$ that was planned to continue in the same direction, has to be cancelled, $c_{v^{i+1}_{l,n}} = 1$. Short-turning in the secondary short-turning station also means that there should be another cancelled service. If service $v^j_{l,m}$ is the result of short-turning service $v^i_{l,n}$, then service $v^{j-1}_{l,m}$ should be cancelled. Constraints (5.5) and (5.6) formulate these cancellations. The departure times of the short-turned trains should respect the minimum short-turning time. Constraints (5.7) ensure the minimum short-turning time. Here the big M method is used to model the different possibilities of short-turning. Constraints (5.8) and (5.9) guarantee that the short-turned trains are departing from the same platform that is used for the arrival. To model the capacity, the blocking time for each track section is considered. The start and end time of each blocking time are represented by $b^s_{v,s}$ and $b^e_{v,s}$. In case of a short-turning the relevant track section of the platform track should be kept occupied. Hence, the start of the blocking time of the block section for the departing train should take place before the end of the blocking time for the arriving train. This is formulated by constraints (5.10).

Extended microscopic rescheduling constraints

The rest of the constraints are extended to incorporate the trains short-turnings.

$$\sum_{r\in R_v} x_{r,v} + c_v = 1, \qquad \forall v\in V, \tag{5.11}$$

$$e_{v,r,s} \leq M\cdot x_{r,v}, \qquad \forall v\in V, r\in R_v, s\in S_r, \tag{5.12}$$

$$e_{v,r,s} \geq \tau^d_v \cdot x_{r,v}, \qquad \forall v\in V, r\in R_v, s\in S_r, \tag{5.13}$$

$$e_{v,r,s} = e_{v,r,p_{r,s}} + t^{run}_{v,r,p_{r,s}} \cdot x_{r,v}, \qquad \forall v\in V, r\in R_v, s\in S_r, \tag{5.14}$$

$$d_v = \sum_{r \in R_v} e_{v,r,s_D} - \tau_v^a \cdot (1 - c_v), \qquad \forall v \in V, \tag{5.15}$$

$$c_{\hat{v}} \cdot M + \sum_{r \in R_{\hat{v}}} e_{\hat{v},r,s_O} \geq \sum_{r \in R_v} e_{v,r,s_D} + \delta_{v,\hat{v}} \cdot x_{r,v}, \qquad \forall v, \hat{v} \in V : f(v,\hat{v}) = 1, \tag{5.16}$$

$$\sum_{r \in R_{\hat{v},s} : p_{r,s} = s_O} b^s_{\hat{v},s} - c_{\hat{v}} \cdot M \leq \sum_{r \in R_{v,s} : f_{r,s} = s_D} b^e_{v,s} + c_v \cdot M, \quad \forall v, \hat{v} \in V : f(v,\hat{v}) = 1, \tag{5.17}$$

$$\sum_{r \in R_{v,s}} x_{r,v} - c_v \cdot M \leq \sum_{r \in R_{\hat{v},s}} x_{r,\hat{v}} + c_{\hat{v}} \cdot M, \qquad \forall v, \hat{v} \in V : f(v,\hat{v}) = 1, s \in P, \tag{5.18}$$

$$\sum_{r \in R_{\hat{v},s}} x_{r,\hat{v}} - c_{\hat{v}} \cdot M \leq \sum_{r \in R_{v,s}} x_{r,v} + c_v \cdot M, \qquad \forall v, \hat{v} \in V : f(v,\hat{v}) = 1, s \in P. \tag{5.19}$$

For each running service, exactly one route should be assigned as formulated by constraints (5.11). Constraints (5.12) make sure that the entrance time for all the track sections related to the unselected routes are zero. The entrance time of train v on track section s along the selected route r should at least be equal to the scheduled departure time τ_v^d. This is taken into account by constraints (5.13). The entrance time for each track section along the route can be computed by the sum of the entrance time of the previous track section and the running time on the previous track section. For this reason the constraints (5.14) are considered. The arrival delay of each service is formulated by constraints (5.15) which measure the difference between the actual arrival time $e_{v,r,s_{D,r}}$ and the scheduled arrival time τ_v^a.

If service $\hat{v}$ uses the same rolling stock as service v after service v has been completed in the same direction, then the dwell time, platform occupation and the platform choice consistency should be taken into account for the pair $(v,\hat{v})$. Constraints (5.16) make sure that the entrance time of the departing service $\hat{v}$ in the first track section of its selected route should respect the dwell time after the arrival of service v. During the dwell time, the selected platform track should be occupied. Thus, constraints (5.17) extend the start time of the selected platform track blocking time of the departing service $\hat{v}$, in order to block this platform track section during the dwell time. Each platform track can be the first track section of several outbound routes and the final track section of several inbound routes. The selected outbound route for the departing service $\hat{v}$ should correspond to the selected inbound route for the arriving service v. This platform choice consistency is modelled through constraints (5.18) and (5.19).

$$b^s_{v,s} = \sum_{r \in R_{v,s}} (e_{v,r,q_{r,s}} - t^r x_{r,v}),$$
$$\forall v \in V,\ s \in S_v : (v \notin V_h'', h \in H_{sht}), (\nexists \hat{v} \in V : f(v,\hat{v}) = 1) \vee (\forall r \in R_v : q_{r,s} \neq f_{r,s_O}), \tag{5.20}$$

$$b^s_{v,s} \leq \sum_{r \in R_{v,s}} (e_{v,r,q_{r,s}} - t^r x_{r,v}),$$
$$\forall v \in V, s \in S_v, : (v \in V''_h, h \in H_{sht}), (\exists \hat{v} \in V : f(v,\hat{v}) = 1), (\forall r \in R_v : q_{r,s} = f_{r,s_O}), \tag{5.21}$$

$$b^e_{v,s} = \sum_{r \in R_{v,s}} (e_{v,r,s} + (t^{run}_{v,r,s} + t^c + t^s) x_{r,v}), \qquad \forall v \in V, s \in SI, \tag{5.22}$$

$$b^e_{v,s} \geq \sum_{r \in R_{v,s}} (e_{v,r,f_{r,u_{r,s}}} + (t^c + t^s) x_{r,v}), \qquad \forall v \in V, s \in SO, \tag{5.23}$$

$$y_{v,\bar{v},s} + y_{\bar{v},v,s} = 1, \qquad \forall (v,\bar{v}) \in V, s \in S_v \cap S_{\bar{v}}, \tag{5.24}$$

$$b^e_{\bar{v},s} \leq b^s_{v,s} + M \cdot y_{v,\bar{v},s}, \qquad \forall (v,\bar{v}) \in V : s \in S_v \cap S_{\bar{v}}. \tag{5.25}$$

Each blocking time starts t^r before the train enters the reservation track section $q_{r,s}$ of track section s. Constraints (5.20) represent the start of a blocking time for all the trains and track sections, except when they start after short-turning or dwelling. The start of the block for those services that depart after a dwell or short-turn are formulated by constraints (5.21). In an interlocking area each blocking time ends after the train has passed all track sections from the reservation track section $q_{r,s}$ to the end of the considered track section s plus the time needed for clearance and release. On an open track the blocking times end when the train exits the last track section of the block. The reason for this difference is that in the interlocking area, there are switches that can belong to multiple block sections. Keeping the switches occupied until the train leaves the block section would consume unnecessary capacity. Thus, in interlocking areas the sectional-release route-locking principle is modelled where the subsequent track sections on the route are released one by one or in groups after specific release points, whereas for open track blocks all track sections in the block are released simultaneously. The end of the blocking time for the interlocking sections are represented by constraints (5.22) and for the open track sections are shown by constraints (5.23). To exclude the possibility of blocking a track section by more than one train, an order is defined for each track section that may be used by each pair of trains. This relation is shown by constraints (5.24). To avoid conflict, constraints (5.25) ensure that the start blocking time of the second train occurs after the end blocking time of the first train.

5.3 Case study

The model is applied on two corridors of the Dutch railway network. In both cases there are two short-turning stations. In the first case two small stations are selected so that the functionality of the microscopic short-turning model and the impacts of its parameters can be shown in more details. In the second case the performance of the model on larger stations is investigated where there are multiple platforms and several switches offering more routes within the short-turning stations. The model is implemented in MATLAB R2016b and solved by Gurobi. The toolbox YALMIP by Löfberg (2012) is used to construct the MILP model.

5.3.1 First case: Parameter analysis

The model is applied on a railway corridor in the middle of The Netherlands. Figure 5.2 shows the corridor from station Nijmegen through Nijmegen Dukenburg (Nmd), Wijchen (Wc), Ravenstein (Rvs), Oss (O) and further towards Den Bosch Oost (Hto). This corridor for the most part has double tracks, except between stations Wijchen and Ravenstein there is a single track serving trains in both directions. The disruption occurs between station Oss and Den Bosch Oost, thus all the arriving trains from Nijmegen have to short-turn latest at station Oss back to Nijmegen.

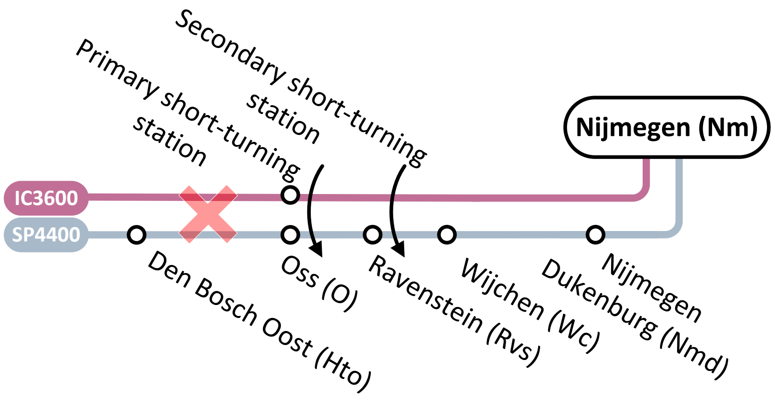


Figure 5.2: The affected lines in the first case study.

The timetable and disruption location are the same as presented in Ghaemi et al. (2017b). The required running times are computed by the microscopic model developed by Bešinović et al. (2017). In the original timetable, two train lines operate between stations Nijmegen and Den Bosch: an intercity (IC) and local train line (called sprinters (SP) in Dutch). To make a distinction between opposite services of the same line odd and even numbers are used depending on the travel direction. For example the services of the lines IC3600 and SP4400 run from station Den Bosch to Nijmegen, and services of the lines IC3601 and SP4401 run in the opposite direction. The last two digits of the train line numbers indicate the operation time of that line during the day. For instance IC3617 departs at 06:18:00 from Nijmegen. The next IC train in the same direction departs half an hour later at 06:48:00 as IC3619. Both lines IC3600 and SP4400 operate with a frequency of two services per hour in each direction. The IC services can only short-turn in station O as they have a planned stop at this station. However the SP services have planned stops at all the stations. Thus, early short-turnings are considered for SP services at station Rvs.

Figure 5.3 shows the track layout for the short-turning stations O and Rvs. The SP services can short-turn on the upper or lower track of either stations and IC services can only short-turn on the upper or lower track of station O. The routes r_1 and r_2 are the routes for short-turning for both IC and SP services in station O. Later, the results are visualized based on these routes.

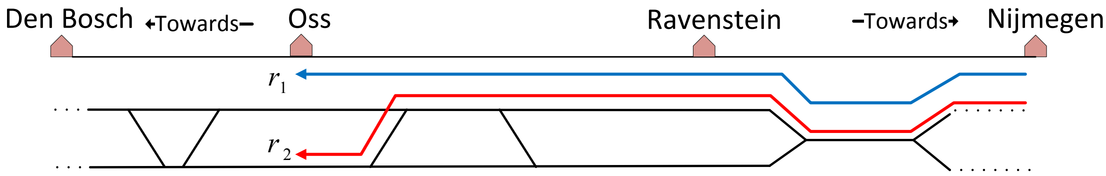


Figure 5.3: The track layout of short-turning stations O and Rvs.

Table 5.3 shows the hourly pattern of the original timetable for the two lines SP4400 and IC3600. The actual service numbers are represented by ** as they vary for each hour. The departures and arrivals are indicated by the minutes in the hour. For instance the first row can represent the service IC3617 that departs from Nm at 06:18 and arrives at O at 06:32. The parameters used in the model are listed in Table 5.4.

Table 5.3: Original timetable

Train lines	Dep from Nm	Arr to O
IC36**	18	32
SP44**	23	43
IC36**	48	02
SP44**	53	13
Train lines	**Dep from O**	**Arr to Nm**
SP44**	14	35
IC36**	26	44
SP44**	44	05
IC36**	56	14

Table 5.4: Parameters

Parameters	Value (s)
Min short-turning time ($\theta^{min}_{v',v''}$)	360
Signal reaction time (t^r)	10
Release and setup time (t^s)	2
Clearing time (t^c)	3

The disruption starts around 6:00 and it is assumed that it lasts until 8:00. Within this period three IC services IC3617, IC3619, IC3621 arrive at station O and cannot operate further due to the disruption and have to short-turn in station O. There are four IC services IC3618, IC3620, IC3622, IC3624 scheduled from station O to Nm within the disruption period. Thus, three of these services can be operated by the three arriving services resulting in an IC service cancellation from O to Nm. The model decides which IC service is better to be cancelled. The service IC3623 is the first service that arrives at O slightly after the end of disruption and can operate on the planned route further than station O. Within the disruption period, there are four SP services SP4417, SP4419, SP4421, SP4423, that arrive at station O and they have to short-turn as four SP services SP4418, SP4420, SP4422, SP4424 scheduled in the opposite direction. As mentioned, the short-turning of the SP services can either be at the final station (O) or at the preceding station (Rvs). Since each early short-turning results in two service cancellations, the optimal solution highly depends on the considered cancellation penalty. Besides penalized cancellations, the objective function includes penalized arrival delay. The choice of penalties can be decided based on the priority of the services. To show the impact of the cancellation and arrival penalties on the optimal short-turning solution, four experiments are performed. In the first and second experiments the impacts of small and large cancellation penalties on the optimal solution are shown. In the third and forth experiments the arrival delay of IC services are penalized to illustrate the impacts of the different delay penalties on the optimal solution. To make the disruption timetable stable against delays, one minute buffer time is considered between trains at the single track.

In experiment 1 small cancellation penalties ($\omega_v^c = 100$) and arrival delay penalty ($\omega_v^d = 1$) are considered for all services. As concluded by the macroscopic short-turning model (Ghaemi et al., 2016), the result with small cancellation penalty might suggest early short-turnings. The same result can be observed from the microscopic short-turning model with small cancellation penalty. This result for route r_2 is visualized in the blocking time diagram shown in Figure 5.4. The red dashed lines represent the original timetable and the solid blue lines represent the computed timetable. As shown in this diagram, SP4417 short-turns as SP4418, SP4419 as SP4420, SP4421 as SP4422, and SP4423 as SP4424 in station Rvs. The microscopic short-turning model also computes the optimal inbound and outbound routes (platform track) for short-turnings. The SP short-turnings in Rvs are shown by the long blocks. The IC services can only short-turn at station O where IC3617 short-turns as IC3620, IC3619 as IC3622, IC3621 as IC3624, and the cancelled IC service is IC3618. The solution suggests that the optimal platform track for IC short-turnings is the lower track in station O.

In experiment 2 the cancellation penalty is increased ($\omega_v^c = 1000$) while the arrival delay ($\omega_v^d = 1$) is the same. It is observed that the choice of short-turning station changes around $\omega_v^c = 365$. In case the cancellation penalty is large, the optimal solution suggests to short-turn all the services at the final station O. Figure 5.5 shows the blocking time diagram of the optimal solution with large cancellation penalty for route r_2. The reason that the SP short-turnings are not visualized in this figure is that they short-turn on the upper track of station O which belongs to route r_1. For each short-turn a minimum short-turning time should be respected. From the original timetable, it

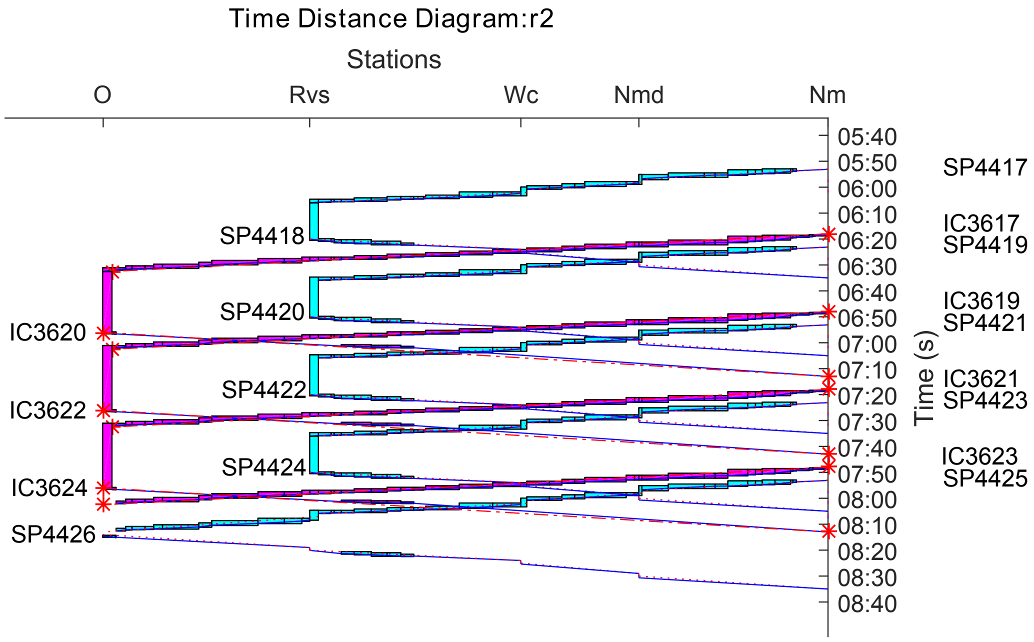


Figure 5.4: The blocking time result of the microscopic short-turning model with small cancellation penalty from experiment 1.

is observed that in station O there is just one minute between the arrival of SP services and the departures in the opposite direction. Thus, there is not enough short-turning time inbetween arrival and departure of SP services. This would result in a delayed departure of SP services from O to Nm. This delay will cause a conflict on the single track between Rvs and Wc, with the IC services from station Nm towards O. To avoid the conflict, the microscopic short-turning model suggests a departure delay of around ninety three seconds for IC services from Nm. This of course is the result of considering the same punctuality preference for both IC and SP services. In case the IC services have a higher punctuality priority, this can be considered by setting a large IC arrival delay penalty.

In experiment 3, besides the large cancellation penalty for all services ($\omega_v^c = 1000$), delayed arrivals of IC services are largely penalized ($\omega_v^d = 1000$) whereas in experiments 1 and 2, this penalty was 1. Figure 5.6 shows the optimal result. Since the IC arrival delays are penalized, it is observed that SP4418 is delayed more so that IC3617 uses the single track first to avoid arrival delay for IC3617. This solution suggests that short-turning the arriving SP services (SP4419, SP4421, and SP4423) at the secondary short-turning station Rvs is better than short-turning them at station O, although the cancellation penalty is large. The reason is that if the SP services were short-turned in O, then there would be a conflict on the single track with the IC services from Nm as explained in Experiment 2. In this case, changing the order still causes conflicts on the single track with IC services from O. Thus, in case the SP services were short-turned at station O, their departures would largely be delayed. However, since IC3618 is cancelled, SP4418 is not delayed further and with an order change, the IC3617 arrival

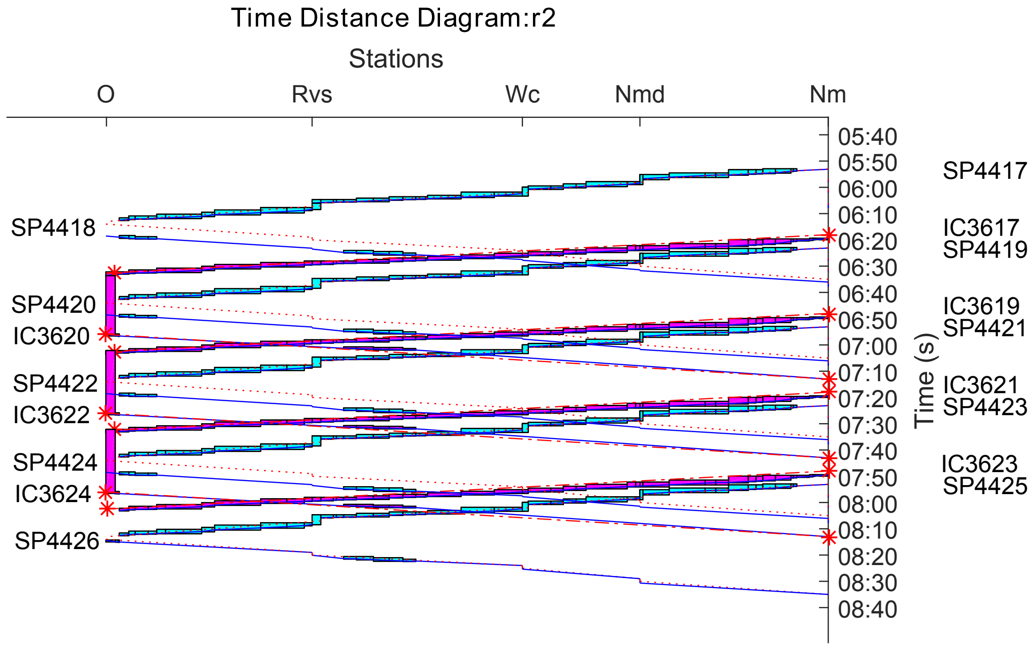


Figure 5.5: The blocking time result of the microscopic short-turning model with large cancellation penalty from experiment 2.

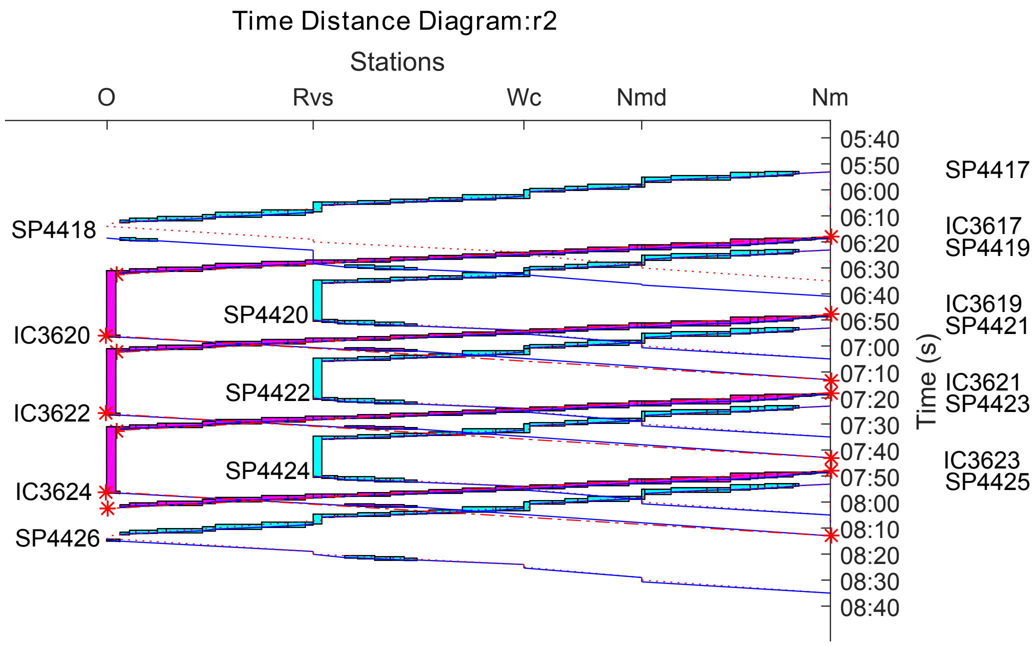


Figure 5.6: The blocking time result of the microscopic short-turning model with large penalty for cancellation and IC arrival delay from experiment 3.

delay is avoided.

In Experiment 4, both cancellation of all services and delayed arrivals of IC services are extremely penalized ($\omega_v^c = 10000$, $\omega_v^d = 10000$). Figure 5.7 shows the result where all services are short-turned at the final station. As shown in this figure, the order of SP and IC operation on the single track is changed. For example, service SP4418 runs on the single track after IC3617. SP4420 is delayed as it waits for IC3620 to depart first and then SP4420 departs the station. This delay causes a conflict with SP4421 on the single track. For this reason, the departure of SP4421 from Wc is delayed around three minutes. Since IC3618 is cancelled, SP4418 is able to depart the station with smaller delay than SP4420, SP4422 and SP4424. Service IC3623 is the first service that can again proceed after O. Thus the arrival of this service is planned on the original route. The final SP short-turning takes place very close to the end of the disruption, thus another solution might be to cancel the service SP4424 and wait until the disruption is over and then continue towards Ht. This solution should be assessed considering the traffic from the other side of the disruption.

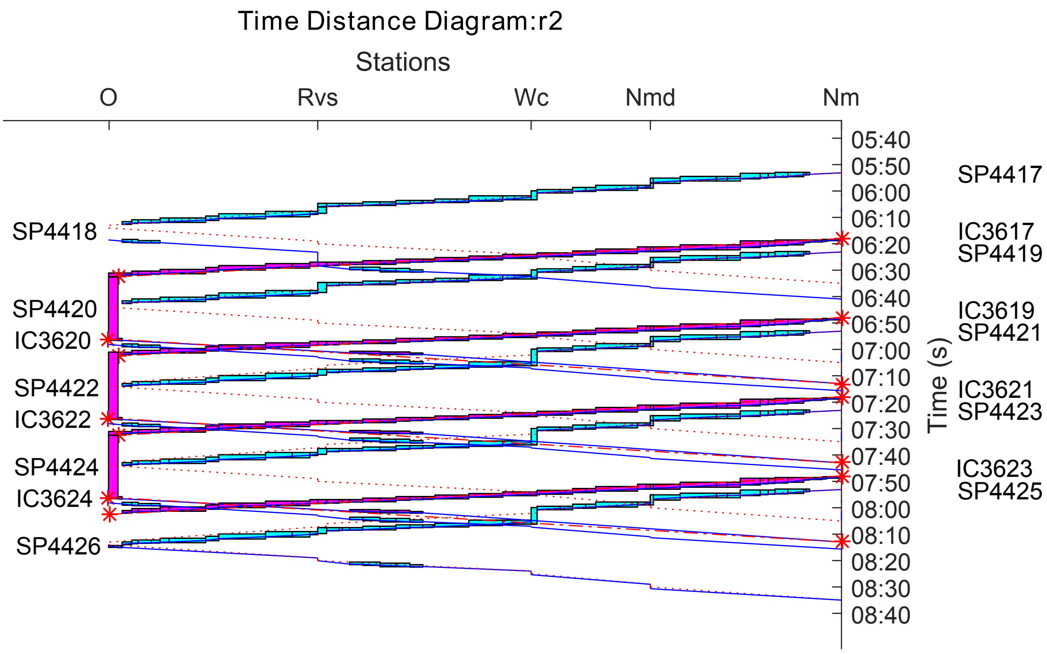


Figure 5.7: The blocking time result of the microscopic short-turning model with extremely large penalties for cancellation and IC arrival delay from experiment 4.

Table 5.5 shows the number of cancelled services, the total arrival delays and average arrival delay for both IC and SP services in the four experiments. In experiment 1, 8 SP services are cancelled so that the remaining services can operate on time. In experiment 2, the SP cancellation is avoided by increasing the penalties and it is observed that more services are operating with delay. In experiment 3, 6 SP services are cancelled which are the result of early short-turnings. Due to the large penalty for IC arrival delay, it is observed that none of the IC services are delayed. In experiment 4, the extremely large penalty for cancellation and IC arrival delay results in considerable delay for SP services.

The different solutions can be shown to professional experts along with their performance indicators. A first check with experts from the infrastructure manager was in favour of the solution in experiment 1 since no delay at Nijmegen would isolate the problem to the corridor between Nijmegen and Oss and thus prevent impact to the rest of the network. However, this argument does not incorporate the inconvenience to passengers of the cancelled services and the costs and effort of running alternative bus services to bring the passengers to Oss. For the railway undertaking these indicators might play a much larger role. Hence, varying the penalties can be used to generate essentially different solutions with their performance indicators that could be evaluated by experts from different perspectives to find an overall best strategy.

Table 5.5: The results of the microscopic short-turning model for the four experiments

Experiment	# Cancelled SP	SP arr. delay (s)	SP av. delay (s)	# Cancelled IC	IC arr. delay (s)	IC av. delay (s)
1	8	0	0	1	0	0
2	0	2658	66.45	1	261	37.2
3	6	1539	45.26	1	0	0
4	0	11198	279.95	1	0	0

5.3.2 Second case: Performance analysis

In this case, the model is applied on another Dutch railway corridor, which is shown in Figure 5.8. The disruption occurs in station Geldermalsen (Gdm) and thus the affected train services have to short-turn in one of the preceding stations: Zaltbommel (Zbm) or Den Bosch (Ht). In this case a disruption of half an hour is assumed between 10:00 and 10:30. The three intercity and two local lines serving station Ht (with a frequency of two per hour per direction) make station Ht an important interchange station in the middle of The Netherlands. Lines IC3500 and IC800 provide services between Vught (Vg) and Zbm and further. Lines SP4400 and IC3600 (which are already introduced in the previous case) operate between Tilburg (Tb) and Hto and beyond towards Nijmegen. Line SP16000 provides services between stations Tb and Zbm and beyond. Since the intercity services from lines IC3500 and IC800 do not have a planned stop at station Zbm, they have to short-turn at station Ht while those from SP16000 can short-turn at both stations Zbm and Ht. The services of lines SP4400 and IC3600 pass through Ht and do not short-turn as they do not traverse the disrupted station Gdm.

Station Ht has eight tracks five of which have platforms (see Figure 5.9). The platform tracks are numbered from top to bottom. Tracks that do not have platforms are used by train services (such as freight services) which do not have any stop at Ht. There

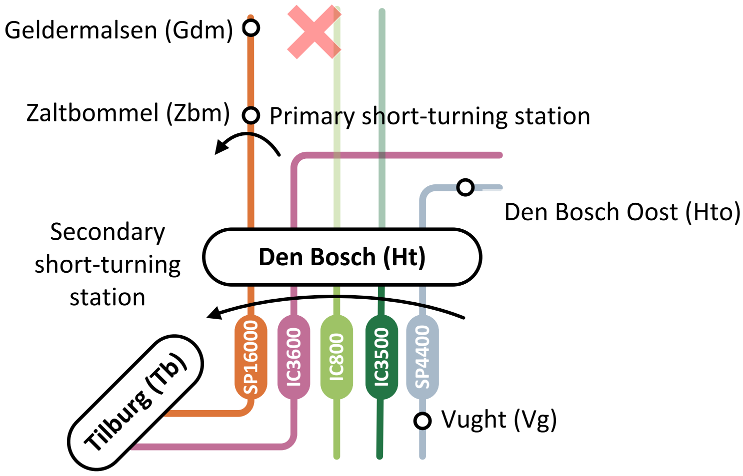


Figure 5.8: The affected lines in the second case study.

are several switches in the station that allow the train services to use different platform tracks. Consequently there are many route choices for each train arriving at Ht or departing from each platform. These routes are listed in Table 6.

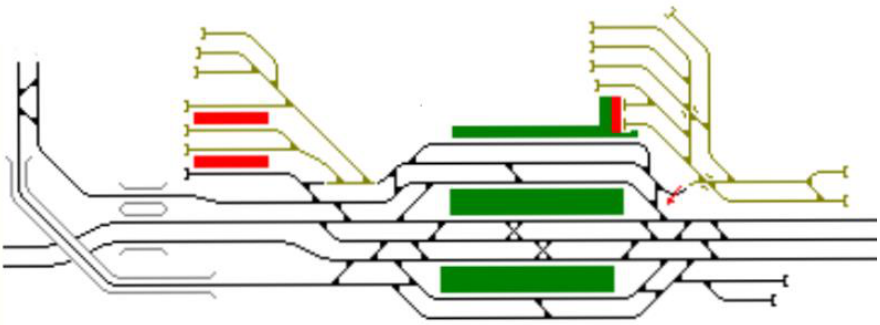


Figure 5.9: The layout of station Ht. Source: www.sporenplan.nl by Zeegers (2017).

The result for the optimal platform track occupation of the original timetable is shown in Figure 5.10. Note that this platform track allocation is different from the actual one but used here as a reference to the computations of the disrupted cases. The arrows illustrate the direction of the services that can be either from Tb\Vg towards Hto\Zbm or vice versa. It is observed that the IC services of line IC3600 from Tb towards Hto dwell on platform track 3 while the opposite services from the same line dwell on platform track 7. The IC services of lines IC800 and IC3500 from Vg towards Zbm dwell on platform track 6 while their opposite services dwell on platform track 4. The local services of line SP4400 use platform track 4 in the direction from Vg to Hto and platform track 7 in the opposite direction. Finally, the local services of line SP16000 from Tb to Zbm dwell on platform track 6 and their opposite services dwell on platform track 7.

The result for the optimal platform track occupation of the disruption is shown in Figure 5.11. In this case the services IC836, IC3538, and SP16038 need to short-turn. Since cancellation is largely penalized ($\omega_v^c = 1000$) the SP16038 is short-turned

Table 5.6: The number of routes and track sections between each OD station pairs.

OD stations	# Routes	# Track sections
Tb-Ht	5	101
Ht-Zbm	7	73
Vg-Ht	5	34
Ht-Hto	12	70
Zbm-Ht	7	66
Ht-Tb	6	120
Hto-Ht	10	50
Ht-Vg	9	42

at the primary short-turning station Zbm as service SP16039. The optimal solution suggests that IC836 short-turns on platform track 6 and continues as IC839. Note that the train that has to operate as IC839 cannot reach Ht due to the blockage. Meanwhile, IC837 arrives at Ht from Zbm. This is the last service from Zbm before the start of the disruption. The long platform track occupation by the short-turning of service IC836 causes conflicts for those services that are scheduled to dwell on this platform during this short-turning. Consequently they have to be rerouted to other platform tracks. From Figure 5.10 it is concluded that the services that are scheduled to arrive at platform track 6 between the arrival of IC836 and departure of IC839 should be rerouted to other platform tracks. Thus, services SP16038, IC3538, IC838, SP16040, and IC3540 need to be rerouted. Figure 5.11 shows that SP16038 and SP16040 are rerouted to platform track 3 and the rest (IC3538, IC838, IC3540) are rerouted to platform track 4.

IC3538 short-turns on platform track 4 and operates as IC3539. Due to this short-turning SP4438 cannot dwell on platform track 4 and thus is rerouted to platform track 3. To avoid a conflict with IC3638, the latter is rerouted to platform track 1. However it is observed that the rescheduled arrival of IC3538 is around 4 minutes later than the scheduled arrival. Moreover, the arrival of IC838 is delayed around 7 minutes. To understand the reason for these delays, the blocking time diagram for a route from Vg to the platform track 4 of Ht is plotted in Figure 5.12. Similar to the blocking time diagrams of the previous case, the reason that some train paths are partly shown is that those train services run only on parts of the plotted route. The blocks in Ht correspond to the platform track occupation of services IC835, SP4436, IC3537, IC837, IC3538 (short-turning), IC838, IC3540, SP4440, and IC3541. By observing this plot, it is concluded that the order of services between 9:30 and 10:00 resembles the order of services between 10:30 and 11:00. However a different order is observed for the services between 10:00 to 10:30. As mentioned earlier, the difference relates to IC3538 and IC838 which are reordered and thus, delayed. Since the original dwell platform track of IC3538 (platform track 6) is occupied for the short-turning of IC836, this service has to short-turn on platform track 4. This was not the case for the service IC3536

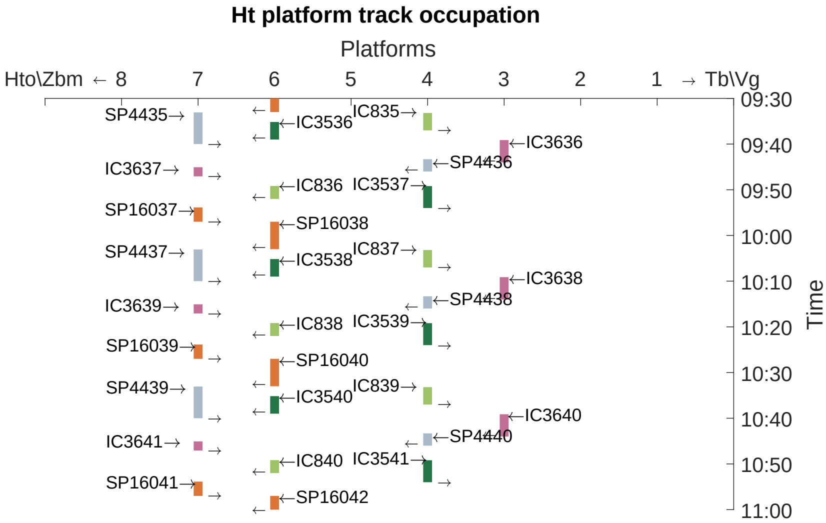


Figure 5.10: The result for the platform track occupation of the original timetable in the secondary short-turning station, Ht.

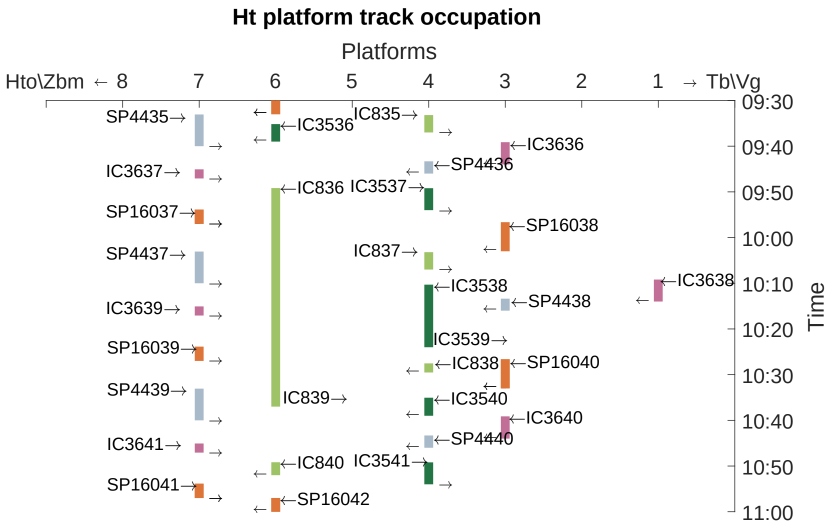


Figure 5.11: The rescheduled platform track occupation in the secondary short-turning station, Ht.

of the previous cycle which was not affected by the disruption and could continue according to the original timetable. From Figure 5.12 it is observed that platform track 4 is occupied by service IC837 and thus IC3538 cannot arrive at this platform on time. At the same time, the delayed IC3538 causes conflict with IC3638. Since delaying IC3638 from Tb to Ht will cause another delay for the next service from Ht to Hto, the solution suggests a reordering between IC3538 and IC3638 so that this delay cannot propagate and only affect one service (IC3538). Due to this short-turning IC838 is delayed and to avoid any conflict with SP16040, the order is changed. Services IC840 and SP16042 are not affected by the disruption anymore and use their original dwelling platform track (6). The services that dwell on platform track 7 remain unchanged.

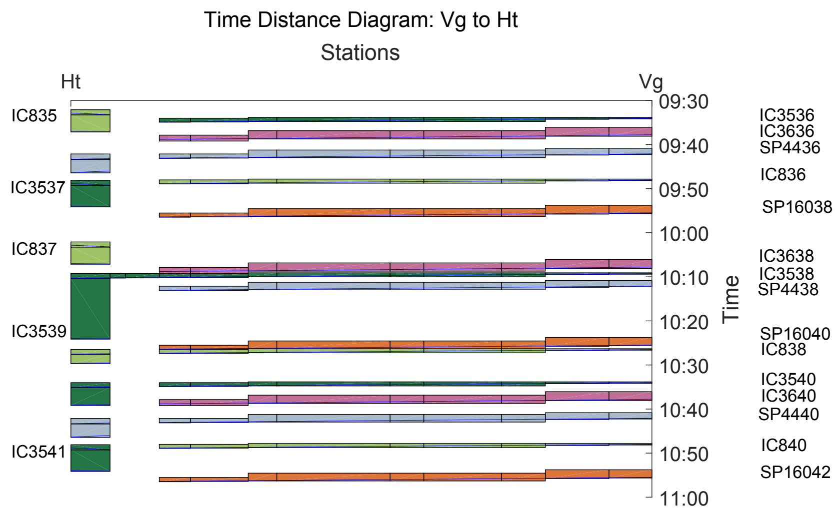


Figure 5.12: The blocking time result of the microscopic short-turning model for a route between Vg and the platform track 4 in Ht.

Figure 5.13 shows the corresponding blocking time for a route between platform track 7 in Ht and Tb.

In order to investigate the performance of the model, the disruption length is increased from 30 to 60 minutes with even intervals of 10 minutes. Table 5.7 reports the problem size of each disruption in terms of the binary variables, continuous variables, constraints and the computation time. The total number of services, number of cancelled services and total delay for each disruption are listed in the sixth, seventh and eight columns. As expected, with an increase in the disruption length the number of variables and constraints grows. An increased growth is observed in the computation time of longer disruption lengths. The number of cancelled services and total delay increase by longer disruptions. Note that the numbers in the seventh column presents the cancelled services in the network shown in Figure 5.8 and does not take into account the services beyond Gdm that are also affected by this disruption. From Table 7, it is concluded that the optimal solution for a disruption up to one hour can be computed in 1 minute and 20 seconds. Moreover it is observed that with increased disruption length

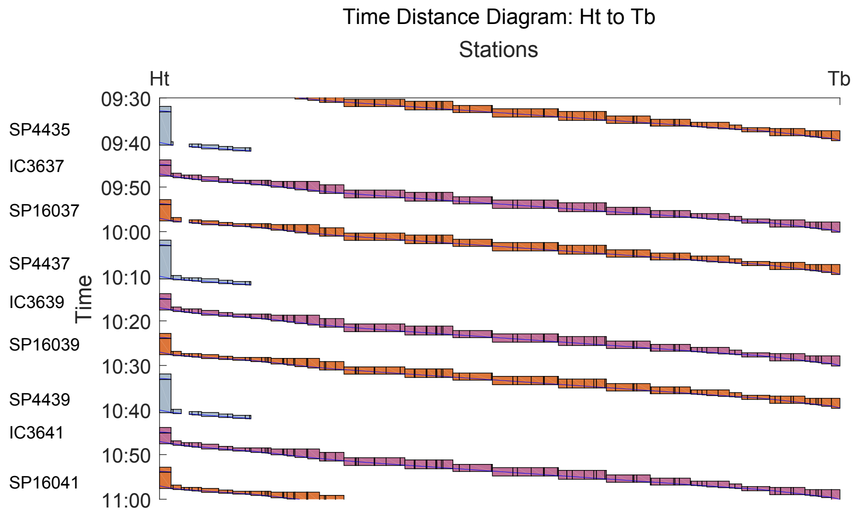


Figure 5.13: The blocking time result of the microscopic short-turning model for a route between platform track 7 in Ht and Tb.

the short-turning choices and platform tracks repeat. This repetition is due to the cyclic nature of the timetable. Thus the solution for a disruption length of 30 minutes can be similarly applied to a disruption length of 60 minutes by using the same short-turning choices and platform tracks for services during the second period of 30 minutes.

Table 5.7: The performance of the microscopic short-turning model for different disruption lengths.

Disruption length (min)	# Binary variables	# Continuous variables	# Const -raints	Computation time (s)	# Service	# Cancelled IC	Delay (min)
30	10452	15251	78490	11.18	32	10	19
40	14129	17763	94342	20.82	36	15	12
50	18814	19633	108750	36.06	42	17	12
60	24814	23002	132109	80.11	48	20	30

5.4 Conclusions

In this paper a microscopic short-turning model was presented for disruption management that includes short-turning variables and constraints. The microscopic short-turning model allocates the arriving services to the scheduled departures in the opposite direction taking into account the operational constraints such as running time, minimum short-turning time and dwell time, while computing the optimal conflict-free routes for all services including the short-turning ones. Moreover the model offers the possibility of short-turning in a secondary short-turning station.

The model is applied on two Dutch railway corridors. From the first case study, it is concluded that the optimal short-turning station depends on the penalties considered for cancellation and arrival delays. It was observed that with a small cancellation penalty, the solution proposes short-turnings at the secondary short-turning station. The result of this solution shows the least propagated delays which support the advantage of including a second short-turning station. As the cancellation penalty increases, the model finds optimal short-turnings at the final station to avoid service cancellations. It was also shown that the model proposes to change the order of services in case there is a distinction between the importance of punctuality for different services. As shown in the case study the microscopic visualisation of the optimal solution can provide support to the traffic controllers.

In the second case the performance of the microscopic short-turning model on a big station with multiple routes and platform tracks is investigated. It was shown that there might be platform changes for the lines that are not directly impacted by the disruption and only dwell in the short-turning station. For a disruption length of 1 hour the model is able to compute the optimal solution quickly for a big station such as Ht. The computation time of the optimal solution can grow rapidly with increased disruption length. However it was observed that the short-turning and platform track choices repeat due to the cyclic nature of the timetable. This allows the traffic controllers to apply the optimal solution for the following cycles.

One of the future research directions is exploring different values for delay and cancellation penalties. It is also interesting to model partial blockages where some services are prioritized over the others. In addition, the model can be extended by formulating the interaction of the traffic between both sides of the blockage before and after the disruption. Moreover, the rescheduling model can be extended to include the passenger demand and the impacts of the disruption timetable on the passengers travel times.

Chapter 6

Impact of Railway Disruption Predictions and Rescheduling on Passenger Delays

Ghaemi, N., Zilko, A. A., Yan, F., Kurowicka, D., Cats, O., Goverde, R.M.P., 2018. Impact of Railway Disruption Predictions and Rescheduling on Passenger Delays. Accepted in: *Journal of Rail Transport Planning & Management.*

6.1 Introduction

Railway operations are repeatedly disrupted by events such as technical and mechanical failures of infrastructure and rolling stock, traffic accidents and malicious attacks. Railway timetables are usually designed to compensate for some delays by including time allowances. However in case of long disruptions and infrastructure unavailability, these time allowances are ineffective and a new timetable should be designed with adjusted train services. Before making any decision regarding the traffic, the relevant information about the disruption should be collected. Upon occurrence of a disruption, there is usually a high level of uncertainty regarding the situation. It takes some time before the exact location and the nature of the disruption is known to the traffic controllers. Once the cause of disruption and the location is known, the traffic controllers are able to proceed with handling the disrupted traffic. An essential piece of information that has a crucial role in their decisions regarding the traffic is the predicted disruption length. Since any change in the timetable is costly, if the predicted length is shorter than a specific threshold then they might decide not to implement major changes to the timetable. In case the length is larger than the threshold, the prediction is used for rescheduling the timetable. Moreover the disruption length and the changes of the timetable should be communicated to the passengers so they can make informed decisions about their trips when they are disturbed. Thus a reliable disruption length prediction is key information in designing a new timetable that can limit the negative impact on the passengers.

The length of a disruption depends on many factors like the type of failure, the component that failed, the repair needed, and the spare parts that a repair crew has with them. However, data on most of these factors are not available, which leaves much uncertainty in any prediction of the disruption length. Zilko et al. (2016) developed a probabilistic Bayesian Network model to predict the disruption length using conditioning on information that becomes available about a disruption. However, most factors included are indirect, like accessibility of the disruption location. Hence, the obtained distributions of disruption lengths still exhibit a wide range. Then the next question is how to get a point estimate from this distribution that can be used by traffic controllers as a prediction of the disruption length and take actions accordingly. Simply taking the mean (expected value) may not be effective. On one hand, a point estimate could be optimistic and underestimate the disruption by which traffic controllers have to rethink their decisions and passengers may have taken the wrong decisions about their travel compared with the optimal choice if they would have known the exact disruption duration. On the other hand, a point estimate could also be pessimistic and overestimate the disruption which might lead to unnecessary train cancellations and long travel times for passengers.

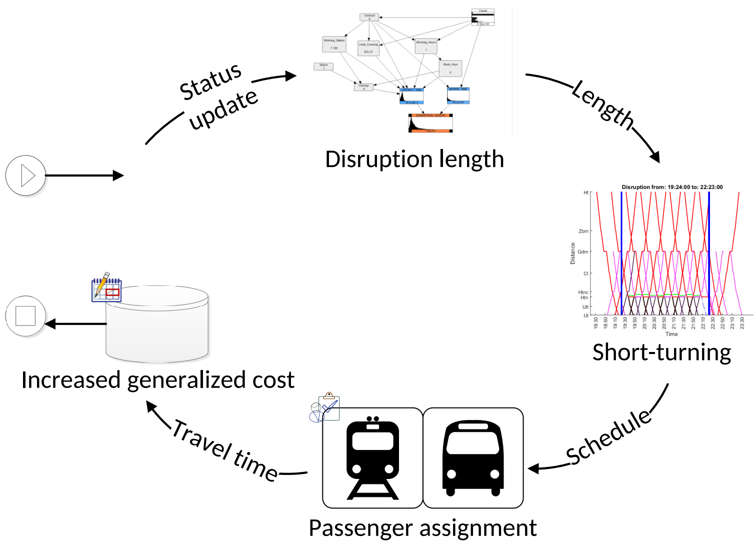


Figure 6.1: The interaction between the models

In this paper a framework is proposed to investigate the effects of different choices of predictions on the rescheduling solution and consequently the passenger delay. The contribution of the framework is the unique integration of three components (see Figure 6.1):

- Estimating the disruption length as a point estimate from a conditional distribution based on available data.
- Rescheduling the timetable given the estimated disruption length.
- Measuring the passenger delays based on the computed adjusted schedule.

The framework provides the possibility of reproducing different disruption scenarios, where the information about the disruption is gradually updated and accordingly the timetable is rescheduled and finally the impact on the passengers is measured. This allows testing the consequences of different disruption lengths and their over- or underestimation with the corresponding mitigation measures on passenger flows and travel time losses.

In the remaining of the paper, the process of handling disruption and the relevant literature is presented in Section 6.2. The three components are described in more details in Section 6.3. The modeling framework is then demonstrated using an application to part of the Dutch railway network in Section 6.4. In this Section the impacts of the optimistic and pessimistic estimates are modeled and assessed. Section 6.5 concludes with practical implications and directions for future studies.

6.2 Disruption management

The decisions regarding the rescheduling of resources need to be carefully communicated between the railway infrastructure manager, the train operators and other involved actors to ensure the feasibility of the plan. To facilitate the challenging task of the traffic controllers in such cases, many countries use contingency plans designed specifically for disruption scenarios (Chu and Oetting, 2013). In The Netherlands these plans are manually designed by expert traffic controllers and are specific for each location and disruption case regardless of disruption length.

The proposed solution in the contingency plans is based on the timetable (basic hourly pattern) and the remaining capacity of the disrupted location. The solution instructs the traffic controllers how to deal with the disrupted traffic by determining cancelled services, short-turned or rerouted services and services that are allowed to operate as in the original timetable. Short-turnings are particularly beneficial for isolating the disrupted area, while maintaining services on both sides of the disruption. This implies short-turning the arriving trains at a station before the disruption (on both sides) and continue service in the opposite direction. In case of short-turning, the stations where the short-turning should occur as well as the platforms and departure times also need to be determined. By means of simulating the short-turning Coor (1997) concluded that this measure is most efficient in case of large disruptions.

The traffic level during a disruption can be conceptualized as a process that resembles a bathtub (Ghaemi et al., 2017b). As shown in Figure 6.2 some services need to be cancelled due to the disruption. This reduction in train traffic starts immediately after the disruption occurs. Three phases can be identified within the disruption period. In the first phase the traffic controllers are facing lots of uncertainty regarding the disruption location, cause and most importantly the estimation of disruption length. In Dutch railway practice, rough estimates exist for the length of different kinds of disruptions. These estimates are used to inform the passengers about the expected disruption length. Once the location is known, the traffic controllers retrieve the relevant contingency plan designed for that specific location. In case there is a need for repairing the disrupted infra, the repairmen are sent to the field to deal with the cause of disruption. The repairmen estimate the required time for resolving the problem and report it to the traffic controllers. If the cause of disruption is resolved earlier than the informed disruption length, the operation is not resumed before the communicated time. In case the disruption takes longer than the initially estimated length, the passengers are updated with a new disruption length. Throughout this paper the estimates that are longer than the actual disruption length are referred to as pessimistic and those that are shorter than the real length are referred to as optimistic estimates.

Once the communicated length has passed and the cause of the disruption has been removed, the traffic can resume and recover back to the original level. The first and third phases are called transition phases where the operation has a transition from the original timetable to the disruption timetable and vice versa. The contingency plan corresponds to the second phase of the bathtub model where there is a steady though decreased level of traffic. Since there is no reliable disruption length estimation, the contingency plans do not provide any insight regarding the third phase of the transition from the disruption timetable to the original timetable. In practice, the effects of different disruption length estimations on the rescheduled timetable during the three phases of disruption, and consequently the affected passengers, are unknown.

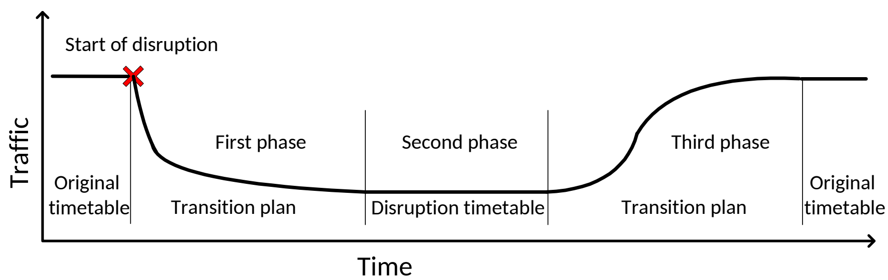


Figure 6.2: The service level during disruptions

While the bathtub model is widely known and used to conceptualize traffic states during disruptions, only limited research efforts have been devoted to analyzing and modeling railway disruption management. Ghaemi et al. (2017b) provide a review of rescheduling models for disruptions and conclude that only a few studies considered all three phases. Examples of such models were developed by Veelenturf et al. (2016) and Nakamura et al. (2011). However, the disruption length is assumed to be known in advance and passenger delays are not taken into consideration. Meng and Zhou (2011), Yang et al. (2013) and Yang et al. (2014) model the third phase by taking into account the uncertainty of the disruption length. Besides the lack of a timetable for the first and second phase, their approaches do not explicitly model the influencing factors on the disruption length. In particular, Yang et al. (2013) and Yang et al. (2014) model the disruption length as a fuzzy variable that reflects the estimation by expert judgment. Hirai et al. (2009) and Zhan et al. (2015) focus on the first phase where trains need to stop before the disruption area. However both approaches disregard the uncertainty regarding the disruption length and the consequences for passenger delay. De-Los-Santos et al. (2012) and Cats (2016) introduce indexes for measuring network robustness by measuring the effects of disruptions in terms of changes in passengers travel times. Yet the defined indexes are not suitable for real-time application where the disruption length is not yet known and might get updated frequently. Canca et al. (2016) propose a short-turning model to accommodate extra demand induced by a disruption at the tactical level, but the disruption length is not taken into account. Zhan et al. (2016) and Nielsen et al. (2012) incorporate the uncertainty of disruption length for rescheduling through a rolling horizon framework. Their approaches do not include the impact factors on the disruption length. Moreover, the impact of the rescheduled timetable on the passengers is disregarded. Kumazawa et al. (2008) develop a rescheduling model considering passenger inconvenience. They do not provide any information regarding the length of the disruption. Cats and Jenelius (2014) analyze the impacts of disruptions on passenger welfare using a non-equilibrium passenger loading model. They quantify the value of real-time information provision in case of disruption.

As mentioned above, the contingency plans do not provide any instructions regarding the transition phases and the proposed solution is given independently of the disruption length estimation. The changes of the disruption lengths are discussed by Takeuchi and Tomii (2005). In reality, the disruption length is very uncertain. Having a reliable disruption length prediction is instrumental in devising the rescheduling measures and thus for achieving a smooth and fast transition to the original timetable in the third phase of the bathtub model. To tackle this problem, Zilko et al. (2016) represent the disruption length as a probabilistic model. Several determinants of disruption length are considered from which the joint distribution between disruption length and these factors is constructed with a Copula Bayesian Network. Having the joint distribution enables the traffic controller to obtain a conditional distribution of disruption length when a disruption occurs, by conditioning the model on the observed values of the influencing factors.

A disruption length prediction is derived from this conditional distribution. Having a probability distribution enables the traffic controller to choose different values of prediction corresponding to different quantiles of the distribution. If the controller is optimistic about the disruption length, a lower quantile of the distribution can be chosen. Alternatively, a higher quantile of the distribution can be chosen. Without a reliable length estimation, there is no support for the traffic controllers for the third transition phase.

6.3 Framework

The framework in a nutshell consists of three models; disruption length model, short-turning model and dynamic passenger assignment model (see Figure 6.1). The interaction between these models is designed in such a way that the real-time uncertainty of the disruption is captured. During disruption the information about the problem becomes available to the traffic controllers gradually. To model this gradual information update, an iterative approach is designed. With each information update, a disruption length is predicted and then used for rescheduling. The new schedule is then used for evaluating the impact of the disruption on the passengers. Different causes of disruption would lead to different disruption length distributions. The short-turning model does not consider severe weather conditions that would have altered the entire timetable. Each iteration starts with an information update. The iterative process terminates once the disruption is over. Different performance indicators are defined to evaluate the impact of different disruption length predictions on passenger-related metrics. The three components are explained in detail in sub-sections 6.3.1 to 6.3.3 and the interaction between these components and the passenger-related key performance indicators are described in sub-section 6.3.4.

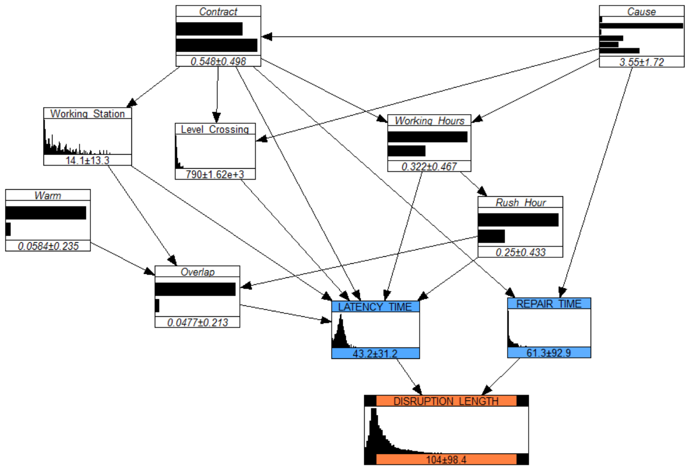
6.3.1 Disruption Length Model

We use the probabilistic distribution length model of Zilko et al. (2016) to compute conditional probability distribution of the disruption length. The disruption length is divided into two sequential stages: the *latency time* and the *repair time*. The latency time is the length of time the mechanics need to get to the disrupted site while the repair time is the length of time they need to repair the problem.

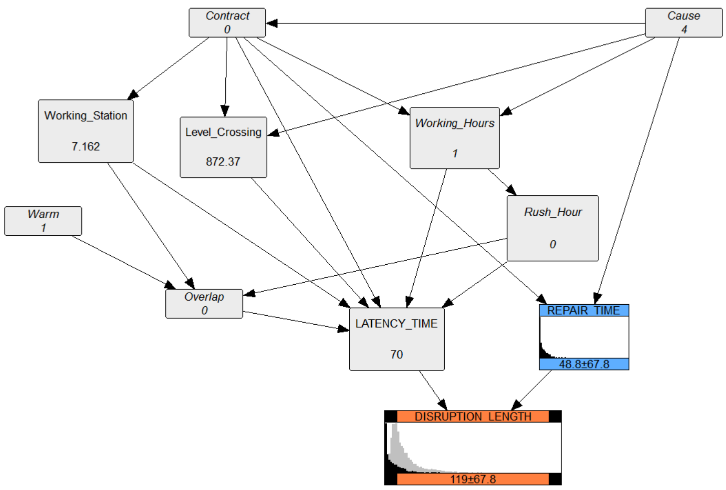
The joint distribution between the latency time and repair time with the influencing factors is constructed using a Copula Bayesian Network. As a prototype, a Copula Bayesian Network model has been constructed for disruptions caused by track circuit failures in the Netherlands. These disruptions are affected by eight influencing factors: (1) contract type, (2) distance to the nearest mechanics' workshop, (3) distance to the nearest level crossing, (4) whether or not the disruption is during the mechanics' contractual working time, (5) whether or not the temperature is above 25^oC, (6) whether or not the disruption occurs during rush hour, (7) whether or not there is another disruption going on at the same time, and (8) the cause of disruption (Zilko et al., 2016). To give an example, factor (5) is considered because the track circuits as part of the rail infrastructure are prone to failure for high temperatures.

The Copula Bayesian Network uses a Bayesian network to represent the dependence between the variables. A Bayesian network is a directed acyclic graph consisting of nodes and arcs, representing the variables and flow of influence between the variables, respectively. Figure 6.3(a) presents the track circuit disruption length model. The eleven nodes in the structure correspond to the ten variables in the model and the variable

"Disruption Length" which is the sum of the latency and repair times. The distribution of each variable is shown in the box of each node. From these histograms it can be seen whether the variable is continuous or discrete. In the header of each box, the variable name is shown. The footers show the mean value and (after $\pm$) the standard deviation of each distribution. The blue boxes represent the latency and repair time which are influenced by the other variables. Influences are represented by arcs. Eventually, the variable disruption length shown in the orange box is the sum of the latency and repair times. The arcs represent the flow of influence between the variables. The absence of an arc between two nodes indicates (conditional) independence between the variables the two nodes represent.



(a) The unconditional track circuit Bayesian network



(b) A conditional track circuit Bayesian network

Figure 6.3: The track circuit Bayesian network.

The joint distribution of the ten variables is constructed using *copula*. A copula is an n-dimensional joint distribution in the unit hypercube of n uniform random variables. It is a popular tool to model the dependence between variables (see, e.g. (Nelsen, 2006;

Joe, 2014)). The theorem of Sklar states that any cumulative distribution function $(X_1,\ldots,X_n)$, denoted as $F_{1,\ldots,n}$, can be rewritten in terms of the corresponding copula C as

$$F_{1,\ldots,n}(x_1,\ldots,x_n) = C(F_1(x_1),\ldots,F_n(x_n)) \tag{6.1}$$

where $F_i(X_i)$ denotes the marginal distribution of the i-th variable. There are many different copula families. This approach used the multivariate Normal, or Gaussian, copula C_Σ to construct the TC disruption length model. This copula is defined as

$$C_\Sigma(u_1,\ldots,u_n) = \Phi_\Sigma(\Phi^{-1}(u_1),\ldots,\Phi^{-1}(u_n)) \tag{6.2}$$

where Φ^{-1} denotes the inverse cumulative distribution of a univariate standard normal distribution and Φ_Σ denotes the cumulative joint distribution of a multivariate normal distribution with a mean value of zero and correlation matrix Σ. The parameter Σ of the track circuit disruption length model corresponds to the arcs in the Bayesian network structure in Figure 6.3. This copula is of interest because it allows conditionalization to be computed rapidly, a very useful feature in the real-time decision making environment of the traffic control centers.

The copula parameter Σ is computed using the maximum likelihood approach to disruption data from the database provided by the rail infrastructure manager. The constructed model, as presented in Figure 6.3, was validated using empirical data with the model being able to obtain a good conditional distribution of disruption length (Zilko et al., 2016). Figure 6.3(a) presents the unconditional Bayesian network, i.e., the track circuit Bayesian network model when no information is available. Figure 6.3(b) presents a conditional Bayesian network when information about the influencing factors is available. Notice that the distribution of disruption length changes. The distribution now has a different shape with updated mean and standard deviation values presented in the footer of the box.

However, conditionalization on the variable Cause can only be performed after the mechanics diagnose the problem and find the cause. This time is called the "diagnosis time". Unfortunately, the diagnosis time is not available in the data and is actually included in the definition of repair time. The data does not provide any information to allow decoupling the diagnosis time from the actual repair time. In practice, usually the mechanics are given 15 minutes to diagnose the problem after they arrive at the site. Therefore, in this model we assumed that diagnosis time always takes 15 minutes and the cause is always found in this time.

This modeling component is adopted in this paper and integrated into the real-time prediction and mitigation framework. Its outcome is the conditional distribution of disruption length, i.e., the distribution of disruption length given actual information of the influencing factors. Moreover, the computation of the conditional distribution is done very fast, and the model has been validated to the Dutch railway disruption data.

The next section describes the short-turning model. The disruption period is used to compute the new schedule. Thus a quantile needs to be selected from the conditional distribution of disruption length that will be used as a point estimate for the disruption length to the short-turning model.

6.3.2 Short-Turning Model

The short-turning model is designed to cope with the disruption cases of complete blockages where no train can use the infrastructure during the disruption period. In such cases, all the trains running towards the disruption location should short-turn before the blockage or be cancelled. The short-turning model is the Mixed Integer Linear Program introduced in Ghaemi et al. (2016) that computes the optimal short-turning time and station for each approaching train service. The rescheduling measures include short-turning, partial cancellation, and platform track assignment while the original train orders are maintained. The notation is introduced in Table 6.1.

We briefly discuss the optimal short-turning problem while focusing on the recovery plan. In this formulation a service is a trip between a departure and arrival (either with or without dwell time). Thus, a train line that may have multiple stops, consists of an ordered set of services performed by a train. Each service is denoted as $v^i_{l,n}$ where i indicates the sequence order of the service within the operational line, l is the line number that determines the stops and n determines the time of operation.

The short-turning model is an assignment model that allocates the arriving trains to scheduled departures in the opposite direction. In the example illustrated in Figures 6.4 to 6.6 there is a disruption between stations a and b. In this example service $v^i_{l,n}$, can either short-turn in station a' to serve $v^j_{l,m}$,$v^j_{l,o}$, or $v^j_{l,r}$ or it can continue as service $v^{i+1}_{l,n}$ and short-turn to serve $v^{j-1}_{l,m}$,$v^{j-1}_{l,o}$ or $v^{j-1}_{l,r}$ in station a. Obviously in case $v^{i+1}_{l,n}$ short-turns to serve $v^{j-1}_{l,m}$, this departure would be delayed. The reason is that the arrival time of train $v^{i+1}_{l,n}$ is scheduled after the departure of service $v^{j-1}_{l,m}$ which is shown in grey. The short-turning possibilities are shown by the red arcs for the arriving service $v^i_{l,n}$. The output of the model is the short-turning pattern which refers to the selected arc that determines the departure time correlated to an arriving train.

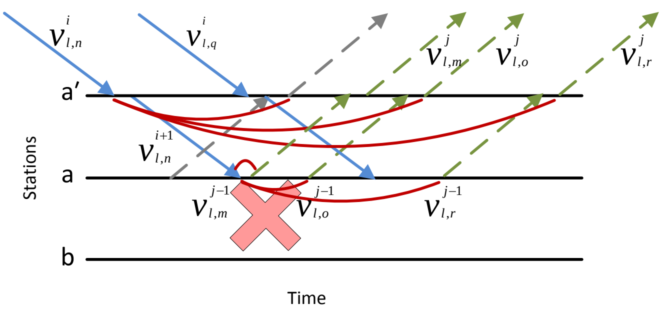


Figure 6.4: The possible short-turning patterns

If the short-turning of service $v^i_{l,n}$ occurs in an earlier station a' to serve $v^j_{l,m}$ as shown in Figure 6.5 then the service $v^{i+1}_{l,n}$, all of the associated short-turning patterns in station

Table 6.1: The notation of the input used in the short-turning model

S	The set of all stations s.
L	The set of all lines l.
V	The set of all scheduled services.
$V_{l,n} \subset V$	The n^{th} set of ordered services in line l.
$v^i_{l,n} \subset V_{l,n}$	The i^{th} service in set $V_{l,n}$.
$P_{s,v^i_{l,n}}$	The set of platform tracks for service $v^i_{l,n}$ in station s.
$S_{v^i_{l,n}} \subset S$	The departure and arrival stations $(s^d_{v^i_{l,n}}, s^a_{v^i_{l,n}})$ of $v^i_{l,n}$.
$S_1 \subset S$	The first surrounding station (a) around the disrupted area x.
$S_2 \subset S$	The secondary surrounding station (a') around stations in S_1.
$S^l \subset S$	The set of possible short-turning stations for line l.
$d^i_{l,n}$	The scheduled departure time of service $v^i_{l,n}$.
$a^i_{l,n}$	The scheduled arrival time of service $v^i_{l,n}$.
$\theta^{min}_{v^i_{l,n}}$	The minimum short-turning time needed for service $v^i_{l,n}$.
$\tau^{run}_{v^i_{l,n}}$	The running time of service $v^i_{l,n}$ between two stations.
$\tau^{dwell}_{v^i_{l,n},v^{i+1}_{l,n}}$	The dwell time between service $v^i_{l,n}$ and service $v^{i+1}_{l,n}$ in the station.
$\tau^h_{v^i_{l,n},v^u_{w,z}}$	The minimum headway time between two train services $v^i_{l,n}$ and $v^u_{w,z}$.
$\omega^c_{v^i_{l,n}}$	The penalty for cancelling service $v^i_{l,n}$.
$\omega^z_{v^i_{l,n}}$	The penalty for delaying the arrival of service $v^i_{l,n}$.
$Out_{v^i_{l,n}}$	The possible scheduled departures for the arriving service $v^i_{l,n}$.
$In_{v^j_{l,m}}$	The possible arriving services for the scheduled departure $v^j_{l,m}$.
$L_{Dist} \subset L$	The set of lines that are affected by the disruption.
$V'_{s,l} \subset V$	The arriving services from line l at station s.
$V'''_{s,l} \subset V$	The scheduled departures in the opposite direction from line l at station s.
M	A large constant.

a, and $v^{j-1}_{l,m}$ should be cancelled. The passengers travelling between these stations will be affected by these cancellations. Notwithstanding, early short-turning can reduce the delay propagation to the opposite stations (Ghaemi et al., 2016).

In the preprocessing phase, we define the services that operate in the disruption area

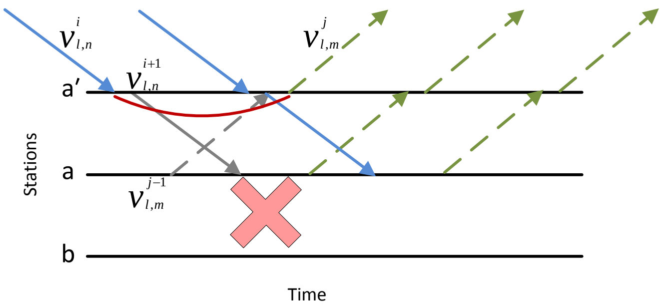
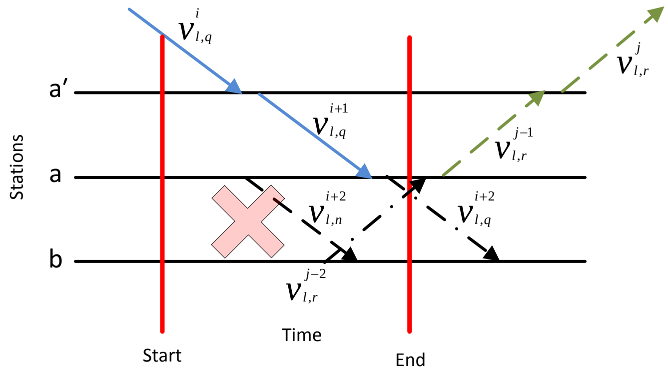


Figure 6.5: The cancellation resulting from short-turning in station a'

during the disruption period. Those services with both planned departure and arrival within the disruption area and period are cancelled. If there is a service towards the disrupted location that departed before the start of the disruption, then it is assumed that this train service could continue its journey. In case the departure of the approaching services towards the disrupted area is within the disruption period and the arrival is close to the end of disruption, then it might be better to wait until the disruption is over and then depart on the original route. The main decision for the final service is whether to continue short-turning or wait until the disruption is over and continue on the original route. This decision concerns those trains that arrive close to the end of the disruption period. If there are more arriving services than the number of scheduled departures in the opposite direction within the disruption period, then the extra train service (due to the periodicity of the timetable, there is usually one extra train service) should wait until the disruption is over before using the recently resolved blockage. If there are more scheduled departures in the opposite direction, then the final arriving train can either short-turn or wait until the disruption is over and continue in the same direction. Based on this decision, there would be a cancellation either for the scheduled departure in the opposite direction, or the scheduled departure in the same direction. The short-turning model computes the disruption timetable for the second phase of disruption and the transitions. With a disruption length prediction we are able to plan the recovery phase where trains are able to continue their original routes and start using the track after the blockage ends.

A set of candidate transition services that might be cancelled needs to be defined. As shown in Figure 6.6, service $v^{i+2}_{l,n}$ is cancelled since its departure and arrival is within the disruption period. The transition services ($v^{i+2}_{l,q}$ and $v^{j-2}_{l,r}$ shown by dash-dotted arrows) are planned to depart before the end of disruption and arrive after the disruption. These services are either cancelled or wait until the disruption is over and continue on their original route. In other words, for transition services the possibility for operating on the original route with a possible delay is considered. In this example, in case service $v^{j-2}_{l,r}$ is cancelled, the following service $v^{j-1}_{l,r}$ is either performed by a short-turning in station a or should also be cancelled. But if the service $v^{j-2}_{l,r}$ is not cancelled, it should depart after the end of disruption and this would introduce a delay to all of the following services performed by this train. For notation simplification,



pl

Figure 6.6: The transition services shown by dash-dotted arrows ($v^{i+2}_{l,q}$ in one direction and $v^{j-2}_{l,r}$ in the other direction)

the approaching train services are shown as v' and those services that are scheduled to depart in the opposite direction are denoted by v'''.The model includes four continuous variables; $t^{a}_{v^{i}_{l,n}}$ (arrival time of $v^{i}_{l,n}$), $t^{d}_{v^{i}_{l,n}}$ (departure time of $v^{i}_{l,n}$), $d^{a}_{v^{i}_{l,n}}$ (arrival delay of $v^{i}_{l,n}$), and $d^{d}_{v^{i}_{l,n}}$ (departure delay of $v^{i}_{l,n}$). In addition, there are three binary variables; $c^{i}_{l,n}$ (cancellation of service $v^{i}_{l,n}$), $\lambda_{v',v'''}$ (the short-turning pair (v',v''')), and $p_{v^{i}_{l,n},q}$ (the assignment of platform track q to $v^{i}_{l,n}$).

The main objective of the short-turning model (6.3) is to minimize the departure and arrival delay ($d^{d}_{v^{i}_{l,n}}$, $d^{a}_{v^{i}_{l,n}}$) and the number of cancelled services. The penalties assigned to departure or arrival delay and a cancelled service $v^{i}_{l,n}$ are denoted by $\omega^{dd}_{v^{i}_{l,n}}$,$\omega^{da}_{v^{i}_{l,n}}$ and $\omega^{c}_{v^{i}_{l,n}}$, respectively. The objective function is formulated as

$$\min \sum_{v^{i}_{l,n}\in V} (\omega^{dd}_{v^{i}_{l,n}} \cdot d^{d}_{v^{i}_{l,n}} + \omega^{da}_{v^{i}_{l,n}} \cdot d^{a}_{v^{i}_{l,n}} + \omega^{c}_{v^{i}_{l,n}} \cdot c_{v^{i}_{l,n}}). \tag{6.3}$$

In addition to the operational constraints that guarantee the feasibility of the operation such as running times, departures, etc. short-turning constraints are also considered. For the complete MILP model we refer to Ghaemi et al. (2018). Ghaemi et al. (2017a) extend the developed short-turning MILP with a microscopic rescheduling model. To describe the essence of the rescheduling model, the short-turning constraints are explained here. The short-turning constraints ensure a feasible short-turning plan.

$$\sum_{(v',v''')\in Out_{v^{i}_{l,n}} \cup Out_{v^{i+1}_{l,n}}} \lambda_{v',v'''} = c^{i+2}_{l,n}, \qquad \forall v^{i}_{l,n} \in V'_{s,l}, s \in S_2, l \in L_{Dist}, \tag{6.4}$$

$$\sum_{(v',v''')\in In_{v^{j}_{l,m}} \cup In_{v^{j-1}_{l,m}}} \lambda_{v',v'''} + c^{j}_{l,m} = c^{j-2}_{l,m}, \qquad \forall v^{j}_{l,m} \in V'''_{s,l}, s \in S_2, l \in L_{Dist}, \tag{6.5}$$

$$\sum_{(v',v''')\in Out_{v^i_{l,n}}} \lambda_{v',v'''} = c^{i+1}_{l,n}, \qquad \forall v^i_{l,n} \in V'_{s,l}, s \in S_2, l \in L_{Dist}, \tag{6.6}$$

$$\sum_{(v',v''')\in In_{v^j_{l,m}}} \lambda_{v',v'''} + c^j_{l,m} = c^{j-1}_{l,m}, \qquad \forall v^j_{l,m} \in V'''_{s,l}, s \in S_2, l \in L_{Dist}, \tag{6.7}$$

$$\sum_{(v',v''')\in Out_{v^{i+1}_{l,n}}} \lambda_{v',v'''} + c^{i+1}_{l,n} \leq 1, \qquad \forall v^i_{l,n} \in V'_{s,l}, s \in S_2, l \in L_{Dist}, \tag{6.8}$$

$$(1-\lambda_{v',v'''})\cdot M + t^d_{v'''} \geq t^a_{v'} + \theta^{min}_{v'}, \qquad \forall (v',v''') \in Out_{v'}, \tag{6.9}$$

$$\sum_{q\in P_{s,v^i_{l,n}}} p_{v^i_{l,n},q} + c^i_{l,n} = 1 \qquad \forall v^i_{l,n} \in V'_{s,l} \cup V'''_{s,l}, s \in S_1 \cup S_2, l \in L_{Dist}, \tag{6.10}$$

Constraints (6.4) make sure that every approaching service should either short-turn at a station prior to the disruption area, which leads to cancellation of one service (in the disrupted area) or continue, that only happens after the end of disruption. For every scheduled departure in the opposite direction there should be only one matching approaching service in case of short-turning. This relation is ensured by constraints (6.5). In case of early short-turning, there will be two cancelled services that are guaranteed by constraints (6.6) and (6.7). If service $v^{i+1}_{l,n}$ is cancelled due to an early short-turning, no short-turning couple can be selected for service $v^{i+1}_{l,n}$. This relation is represented by constraints (6.8). To ensure the minimum short-turning, constraints (6.9) are considered. If the service $v^i_{l,n}$ is not cancelled, a platform should be assigned to it. Constraints (6.10) represent this assignment.

6.3.3 Dynamic Passenger Assignment Model under Disruptions

A dynamic passenger assignment model is developed to represent how passengers are distributed over the network in the event of a disruption. The dynamic passenger assignment model allows assessing the impact of alternative scenarios on passengers by calculating passengers' total travel delay, transfer times and the number of transfers compared to the scheduled timetable. Based on the given rescheduled timetable, the dynamic passenger assignment model generates alternative travel routes for each pair of origin and destination (OD) and assigns passengers to selected routes from the corresponding alternative routes. Data concerning the number of daily passengers between all pairs of OD stations based on smart card transactions was obtained from the Netherlands Railways (*Nederlandse Spoorwegen*/NS). The daily distribution of passenger demand was specified based on data made available by NS which manifests the conventional morning and afternoon peaks. Passengers face different route choice conditions during the course of the disruption. In particular, three phases, as illustrated in Figure 6.7. Under normal operations route choice is based on the planned timetable. When a disruption occurs, a rescheduled timetable is generated based on the predicted disruption length and passengers are informed of the new departure times after which they will choose their route based on the prevailing conditions. Hence, passengers choose from a new set of alternative routes based on the rescheduled timetable. Furthermore, passengers who have already boarded a train might need to reroute as a consequence of the disruption and the rescheduling. Additional updates to the disruption length predictions may result in additional rescheduling of train services and consequently the rerouting of passengers. Finally, when the disruption has ended, delays might still occur as the service recovers back to the original timetable. For this reason, the simulation time that is denoted by t_{sim} ends after a certain simulation period denoted by t_{ult}. Here the simulation refers to the probabilistic and dynamic passenger route choice model based on the new schedule. Note that the simulation period is longer than the disruption period.

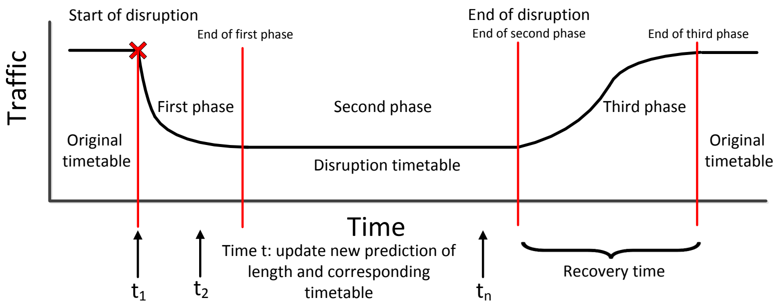


Figure 6.7: Transition points in the process of dynamic passenger loading

The dynamic passenger assignment model consists of three main steps. In the first step, alternative routes for each origin-destination (OD) pair are generated, followed by a probabilistic route choice model based on the framework of discrete random utility models. The latter determines the share of passengers that are assigned to each route. In the final step, the passenger travel time is measured. The overall workflow is depicted in Figure 6.8.

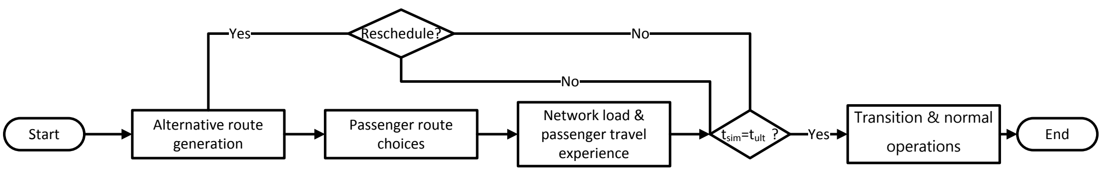


Figure 6.8: Passenger loading model under disruption

The dynamic passenger assignment model under a disruption is conducted as shown in Figure 6.8 by performing the following sequence of steps:

- **Step 1:** Alternative route generation: Given a passenger OD demand matrix and scheduled timetable, find alternative routes for each pair of stations and calculate passenger's total in-vehicle time and transfer time for each route. This is an initialization phase.

- **Step 2:** Passenger route choice: Simulate passenger generation and train movements. Progress simulation clock from the beginning of the disruption. Use a logit model to obtain the passenger proportion of each route.

- **Step 3:** Network load and passenger travel experience: Obtain the passenger load on each train route segment and calculate the generalised cost for each passenger route departing on each minute.

- **Step 4:** Update: In case the simulation period is not over and the schedule is updated, then repeat from step 2.

- **Step 5:** Transition and normal operations: Repeat step 4 until the last prediction is made, then simulate the model until t_{ult} in order to have a fair comparison among prediction scenarios. Passenger loading results are assessed by calculating the following outputs: passenger total generalised travel time, total passenger nominal travel time, the number of passengers, average passenger transfer time, the number of average transfer, average in-vehicle time, average waiting time, average train load and link load.

The core three steps are described in the following subsections.

Alternative route generation

Given a timetable, either the original or the outcome of the rescheduling model, the alternative route generation module computes a set of alternatives from which individuals travelling between a given pair of OD will choose from. Note that for the ODs that contain the blocked section, bus services are considered during the disruption. However the bus services are not considered during the non-disrupted situation, as they are considerably slower than the train services. The choice-set is generated by iteratively searching for routes with an increasing number of transfers. A forward search algorithm is applied where transfer alternatives further downstream are examined by considering all scheduled train trips and their corresponding stopping pattern and scheduled arrival and departure times. For indirect alternatives, the transfer time must be within a user-defined acceptable range, $[\gamma^{min}_{trans}, \gamma^{max}_{trans}]$, satisfying the minimum transfer time to ensure a sufficient time between train arrival and the next train departure, and a maximum transfer time to avoid excessively long transfer times. In addition, indirect alternatives that induce a detour that exceeds a user-defined ratio of γ^{max}_{detour} are removed from the choice-set as well as alternatives that are dominated by other alternatives when considering the number of transfers, in-vehicle time, transfer time and service level (i.e. intercity vs. regional). For each of the alternatives obtained in this process, the following attributes are stored along with the route itinerary: total travel time, number of transfers, total in-vehicle time and transfer time. These attributes are then used in the following choice step.

Passenger route choices

A multinomial logit (MNL) choice model is applied for route choice, to calculate the share of passengers travelling along each route alternative, shown as

$$P_{ijk} = \frac{exp(-\theta \widetilde{t}_{ijk})}{\sum_{k \in R_{ij}} exp(-\theta \widetilde{t}_{ijk})} \tag{6.11}$$

P_{ijk} is the share of passengers that choose route k when travelling between i to j and R_{ij} is the set of alternative routes from i to j. Route k consists of an ordered set of legs denoted by a sequence of stations, $k = (s_{k,1}, s_{k,2}, ..., s_{k,|k|})$ and $s_{k,m} \in S$ where S is the set of stations in the network, $\widetilde{t}_{ijk}$ is the total generalized cost of route k for a given OD pair (ij), and θ is the logit scale factor for route choice.

Network load and passenger travel experience

The passenger travel experience is measured by the generalized travel time that consists of waiting time, in-vehicle time, transfer time and other fixed penalties as

$$\widetilde{t}_{ijk} = \beta^{w} \cdot t^{w}_{s_{k,1}} + \sum_{v=1}^{|k|-1} \beta^{in} \cdot t^{in}_{s_{k,v}, s_{k,v+1}} + \sum_{q=2}^{|k|-1} \beta^{tr-time} \cdot t^{tr}_{k,q} + \beta^{tr} \cdot N^{tr} + \beta^{re} \cdot N^{re} \tag{6.12}$$

t^{w}_{s}, $t^{in}_{s_1,s_2}$ and t^{tr}_{s} are the initial waiting time, in-vehicle time and transfer time, respectively, and β^{w}, β^{in} and $\beta^{tr-time}$ are the corresponding weights. $N^{tr} = |k| - 1$ and N^{re} stand for the number of transfer and rerouting decisions, and β^{tr} and β^{re} are penalty terms for each transfer and rerouting respectively, represented in time equivalent units. The well-known "independence from irrelevant alternatives" (IIA) property of the MNL model is partially counteracted by the filtering rules which result in a choice-set comprising of distinct alternatives, where the most correlated paths are either eliminated due to dominance rules or merged into hyper-paths as described in Cats et al. (2016). By calculating the choice model probabilities, the dynamic passenger assignment on each diachronic time-dependent network link can be calculated by

$$f_{ijk} = d_{ij} \cdot P_{ijk} \tag{6.13}$$

where d_{ij} is the number of passengers from i to j. The actual nominal travel time can be obtained as

$$t_{ijk} = t^{w}_{s_{k,1}} + \sum_{v=1}^{|k|-1} t^{in}_{s_{k,v}, s_{k,v+1}} + \sum_{q=2}^{|k|-1} t^{tr}_{k,q} \tag{6.14}$$

Analysing the impacts in terms of changes in total generalized travel time allow the summation of several passenger-related costs (e.g. transfer penalties, delays) using a compensatory function that is equivalent to total passenger welfare loss (Cats and Jenelius, 2014). Furthermore, using passenger value of time, impacts can be monetarized to assess the value of total time losses.

6.3.4 Interaction Between the Models

The three models interact in a dynamic fashion, i.e., interaction occurs every time new information becomes available. New information can be input concerning the observed influencing factors in the disruption length model or when we learn that the previous disruption length prediction was too short. Figure 6.9 shows an example of a disruption.

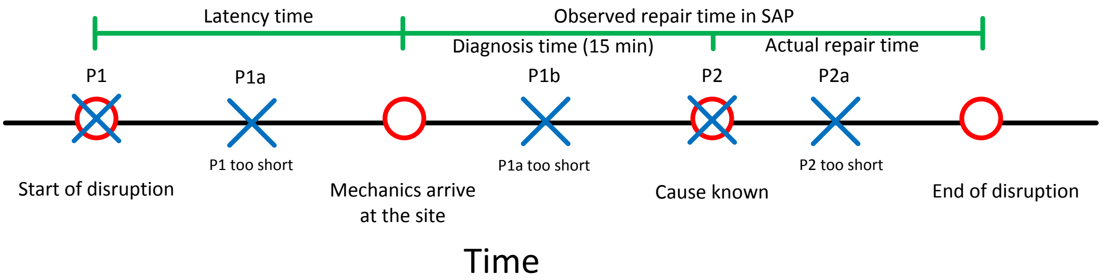


Figure 6.9: The time diagram of a railway disruption

The crosses in this time diagram illustrate when during the disruption period the interaction might take place. When a disruption occurs, only the influencing factors of the latency time are typically known. The unconditional Bayesian network is conditionalized based on this information. Predictions made from this conditional Bayesian network model are called the P1 predictions where, mainly, the latency time is predicted using the additional sources of information, potentially yielding more accurate predictions. P1 suggests that the disruption ends within a certain time period marked by P1a. The start and end time of the disruption period that are predicted by P1 are communicated to the short-turning model. Based on the disruption location, the relevant timetable and the disruption period, a disruption timetable is computed and passed on to the dynamic passenger assignment model.

When the predicted length P1 has elapsed, it might be realized that the disruption is not over yet. If the prediction is too short, the disruption is still unresolved even after the predicted disruption ends. This situation occurs when the prediction is too "optimistic", i.e. the chosen quantile of the conditional distribution of disruption length is too low for the case. If this happens, the prediction is updated by approximating a new conditional distribution of disruption length on the information that the disruption length is longer than the last prediction. This is done via sampling the original conditional distribution on the quantiles higher than the prediction. In this paper, these "revised" predictions are denoted alphabetically in orderly fashion. For instance, a P1 prediction is updated to P1a, P1b, and so on. With each prediction update the cycle shown in Figure 6.1 repeats and the mentioned statistics are computed and stored.

Fifteen minutes after the arrival of the mechanics to the disruption site, they report the diagnosis about the cause of disruption. Knowing the cause of disruption, the Bayesian network is further conditionalized. The new conditional Bayesian network is used to produce the P2 predictions. Similarly with each prediction update, the short-turning model computes the disruption timetable and the passenger assignment model computes and stores the total number of affected passengers, generalized travel time, and total number of reroutings and transfers.

To measure and compare the impact of alternative disruption management scenarios the following key performance indicators (KPIs) are computed and stored:

1. The total number of passengers being affected during the disruption period.
2. The total experienced generalized travel time corresponding to equation (6.12) of all passengers considered in the experiment.
3. The total number of passenger reroutings and transfers.

6.4 Experiments

The framework that is applied on a part of the Dutch railway network is depicted in Figure 6.10. The disruption length model is constructed using the computationally-efficient software called UNINET, which was developed at Delft University of Technology and is available at www.lighttwist.net/wp/uninet. The short-turning model is implemented in MATLAB, YALMIP (Löfberg, 2012) is used to construct the MILP, and Gurobi is used as the solver. The dynamic passenger assignment model is constructed in MATLAB. In the experiment, we consider a complete blockage in the railway segment between stations Utrecht and Houten. The blockage is caused by a track circuit failure.

Two local train lines are considered by the short-turning model: line 16000 between Utrecht (Ut) and 's Hertogenbosch (Ht) and line 6000 between Ut and Tiel (Tl). Due to the disruption, these trains have the possibility to short-turn either at station Geldermalsen (Gdm) or the latest at station Houten (Htn).

To study the effect of different choices of quantiles of the conditional distribution of predicted disruption length, different disruption length predictions are examined. For each prediction, when a successive prediction is made, the new prediction is chosen to be the value of the new conditional distribution corresponding to the same quantile as in the previous prediction. For instance, when a prediction using the quantile 50% (median) is updated, the new prediction is also taken to be the median of the updated conditional distribution. In principle, this does not necessarily have to be the case. This choice is made to narrow down the space of possible "combinations" of prediction scenarios.

Note that the P1 predictions are only valid until new information regarding the cause is available from which the updated P2 predictions can be made. This means that the

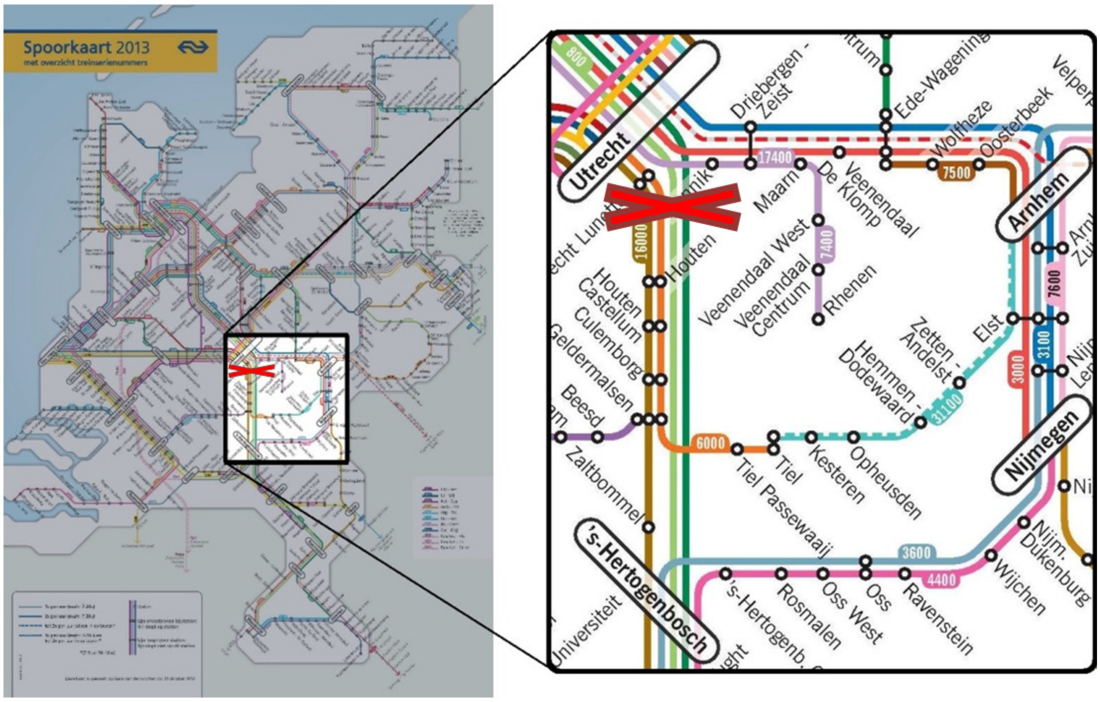


Figure 6.10: The area the dynamic passenger assignment model considers in the experiment. The illustration is adapted from NS' main train service map. Source: The Dutch railways (NS).

P1 predictions and the entailed disruption timetables are only used until at most 15 minutes after the mechanics arrive at the disrupted site.

The P2 predictions are updated until the actual disruption ends. When this happens, no new timetable is computed and the last P2 timetable is run until the P2 predicted end of disruption. This choice is made to penalize a prediction that is too "pessimistic", i.e., a prediction that surpasses the realized disruption length. In contrast, choosing a low quantile is undesirable because it is likely to be too optimistic and thus results in many "revised" predictions. This is not attractive from the passengers' point of view, who will presumably perceive the communicated information as unreliable. Additionally, having many "revised" predictions is not practical from a logistical point of view. In practice, every time a new prediction is made, aside from the train traffic, the traffic controllers must also revise the rolling stock and crew assignments. Therefore, train operators are not inclined to choose the lower quantile predictions. Therefore, in this experiment, we only consider the 25% quantile as the representative of these scenarios for comparison. The remaining quantiles that are considered in the experiments are 50%, 75%, 85%, 90%, as well as the mean.

The short-turning model computes the disruption timetable for lines 16000 and 6000 through stations Ut, Htn, Houten Castellum (Htnc), Culemborg (Cl), Gdm, Tiel Passewaaij (Tpsw), Tl, Zaltbommel (Zbm) and Ht. It is assumed that the new schedule is immediately available and communicated to the passengers (e.g. journey planner information is populated with the new timetable). For the rescheduling, the timetable of

2016 is considered. In the short-turning model, the main parameters are the penalties for arrival, departure delays and cancelled services. Since the interval of the services in Houten is either 16 or 14 minutes in both directions, and with each cancelled service the travellers need to wait around a quarter of an hour for the next train, the cancellation penalty ($\omega^{c}_{v^{i}_{l,n}}$) is set to 1000 seconds. Arrival and departure delays ($\omega^{d^a}_{v^{i}_{l,n}}$ and $\omega^{d^d}_{v^{i}_{l,n}}$) are equally penalized by 1. Moreover the minimum short-turning time is assumed to be 7 minutes (420 seconds). For the choice of minimum short-turning time we refer to the study by Chu and Oetting (2013). A norm of 3 minutes is considered for the minimum headway.

Given a disruption timetable, the dynamic passenger assignment model computes the passenger traffic. Due to data availability limitations, the dynamic passenger assignment model considers in this case study only the passenger trips for which both origin and destination are within the case study area, i.e. the loop shown in Figure 6.10. The route choice model parameters are specified as follows: $\beta^{w} = 2$, $\beta^{in} = 1$, $\beta^{tr-time} = 2$, $\beta^{tr} = 5$, $\beta^{re} = 10$. For more details on the specification of the travel cost weights, see Cats et al. (2016).

The total demand in the case study network is considered inelastic, assuming that temporary service reductions do not have implications on other trip decisions such as mode and destination choices, which may or may not be feasible responses in a real situation. Empirical evidence from unplanned network disruptions shows that people are relatively reluctant to change travel mode (see Zhu et al. (2010) and references therein).

Passengers travelling between Utrecht Centraal and Houten stations have two alternatives: to detour via Arnhem and Nijmegen or to take the public bus service between the two stations. The travel time by bus between Utrecht Centraal station and Houten is about 35 minutes while a regular train service would have taken only 9 minutes. On the other hand, the detour via Arnhem and Nijmegen is also not very attractive due to the tremendous detour it induces. For passengers travelling to Houten from Utrecht, this detour takes almost 2 hours. To fairly compare the different choices of predictions, we monitor the train traffic and passengers flow for a fixed period of six hours in all scenarios. Two actual disruption cases are chosen and examined. As already mentioned, different variables can impact the disruption length. Here we are particularly interested in examining the impact of time. Thus the consequence of the same disruption occurring on a different day or time-of-day is investigated. Since considering different parameters would have hamper the comparison and the ability to perform a comparison and draw conclusions, the same parameters were used in all cases. Due to the long computation time needed for the dynamic passenger assignment distribution model we examine only four case studies; weekday afternoon, weekday evening, Saturday evening and Saturday afternoon which are explained in detail in the following sections.

6.4.1 Case Study 1: Weekday afternoon

The first case study is based on an incident which occurred on Thursday, 10 July 2014. The incident started at 14:22 and had the information listed in Tables 6.2. Moreover, the real observed latency and repair time are 70 and 73 minutes, respectively. This means the total disruption length is $70 + 73 = 143$ minutes.

Table 6.2: The initial information of the disruption case 1

Contract type	OPC
Working station distance	7.1620
Level Crossing distance	872.372
Working Time	yes
Warm	yes
Rush Hour	no
Overlapping disruption	no
Cause	a setting problem caused by heat

Table 6.3 presents the P1 predictions which are presented in terms of the length (in minutes) and the predicted end of disruption in time. Notice that in the scenario corresponding to the 25% quantile, in total there are 8 predictions that are generated throughout the disruption. The predictions in Table 6.3 are used by the short-turning model to produce the disruption timetable whose cyclic characteristics are shown in Table 6.4. This Table contains the number of cancelled services ($\#C$), the number of delayed services ($\#D$), the number of short-turned services ($\#ST$), and the total train delay in minute (Del).

Table 6.3: The P1 predictions for Case Study 1.

Qtl	P1		P1a		P1b	
(%)	Length	Time	Length	Time	Length	Time
25	49	15:11	72	15:34	97	15:59
50	81	15:43	144	16:46		
75	143	16:45				
85	205	17:47				
90	254	18:36				
Mean	118	16:20				

At 15:32, the mechanics arrive at the site. After 15 minutes of diagnosis time, the cause of a track circuit failure is identified and at 15:47 the P1 predictions are updated to the P2 predictions. These P2 predictions are presented in Table 6.5. The results of the short-turning model are shown in Tables 6.6 and 6.7.

Each timetable is used when the prediction is still "valid", i.e., it has not changed. For instance, the disruption timetable generated with the P1a prediction of the 50% quantile is used only for four minutes between 15:43 and 15:47 (15 minutes after their

Table 6.4: The results of the short-turning model for P1 in Case Study 1.

Qtl	P1				P1a				P1b			
(%)	#C	#D	#ST	Del.	#C	#D	#ST	Del.	#C	#D	#ST	Del.
25	12	2	3	6	20	0	5	0	28	0	7	0
50	20	9	5	24	40	0	10	0				
75	40	0	10	0								
85	56	0	14	0								
90	68	0	17	0								
Mean	32	0	8	0								

Table 6.5: The P2 predictions for Case Study 1.

Qtl	P2		P2a		P2b		P2c		P2d	
(%)	Length	Time	Length	Time	Length	Time	Length	Time	Length	Time
25	85	15:47	102	16:04	118	16:20	135	16:37	150	16:52
50	95	15:57	134	16:36	179	17:21				
75	133	16:35	240	18:22						
85	160	17:02								
90	194	17:36								
Mean	119	16:21	188	17:30						

Table 6.6: The results of the short-turning model for P2 in Case Study 1.

Qtl	P2				P2a				P2b			
(%)	#C	#D	#ST	Del.	#C	#D	#ST	Del.	#C	#D	#ST	Del.
25	24	0	6	0	28	0	7	0	32	0	8	0
50	24	9	6	24	36	0	9	0	48	0	12	0
75	36	0	9	0	64	0	16	0				
85	44	0	11	0								
90	52	0	13	0								
Mean	32	0	8	0	52	0	13	0				

Table 6.7: The remaining results of the short-turning model for P2 for Case Study 1.

Qtl	P2c				P2d			
(%)	#C	#D	#ST	Del.	#C	#D	#ST	Del.
25	36	0	9	0	40	0	10	0

arrival at the disrupted location). At 15:47, the prediction is updated to P2 and a new disruption timetable is constructed.

These disruption timetables are used by the dynamic passenger assignment model to compute passenger route choice and the resulting passenger distribution over train services for six hours between 14:22 and 20:22. In this period, there are 22163 passengers who are traveling in the case study area. We measure the impact on the passengers for each choice of quantile. The results are presented in Table 6.8.

The last row of Table 6.8 shows the benchmark case with the true disruption length. In this case, the true end time of disruption is already known when the disruption starts at

Table 6.8: The impact of different predictions to the passengers in Case Study 1.

Qtl (%)	Excess (minute)	# Affected Passengers	Inc. Orig (%)	Inc. Bench (%)	# Rerouting 1	# Rerouting 2	# Transfers
25	7	8948	17.71	0.26	595	4	3597
50	36	11469	20.53	2.67	466	1	4015
75	97	16560	24.33	5.90	247	0	4671
85	17	9791	17.56	0.13	5	0	3775
90	51	12854	20.16	2.35	0	0	4126
Mean	45	12299	20.33	2.49	282	0	4136
Real	0	8374	17.4026	0	0	0	3773

14:22[1]. Each scenario is compared to this case to measure the increase in the impact of the prediction on the passengers with respect to the ideal situation.

The second column of Table 6.8 shows the difference (in minute) between the true end of disruption and the last P2 prediction when the blocked railway section between Utrecht and Houten is opened for train operation. The third column presents the total number of passengers travelling during the blockage of the section. The fourth and fifth column provide the increase (in %) in the total generalized travel time with respect to the normal situation without disruption and the benchmark, respectively. In the sixth and seventh column, the total number of passengers who have to reroute once or twice in each scenario is provided. The number of transfers performed by the passengers can be found in the last column.

The benchmark case represents the best possible situation. In this case, fewer passengers are affected and no passengers have to be rerouted since the initially provisioned information is accurate. Unsurprisingly, the increase in the generalized travel time with respect to the no disruption situation is also the lowest.

In general, the longer the difference between the true end of disruption and the last P2 prediction is, the more passengers are affected. However, this does not necessarily translate to a higher total generalized travel time. Notice that the increase in the generalized travel time is higher in the 25%-quantile scenario than in the 85%-quantile scenario even though the difference between the prediction and the realized value is only 7 minutes in the former and 17 minutes in the latter. The eight predictions in the 25%-quantile scenario cause many passengers to reroute due to the frequent updates of the disruption timetable. Consequently, the total generalized travel time is penalized severely. In the 85%-quantile scenario, much fewer passengers need to reroute due to the pessimistic prediction.

Notice that the P2 predicted end time of the disruption of the 75%-quantile scenario (at 16:35, see Table 6.5) is 10 minutes shorter than the actual end time. Because of this slightly too optimistic prediction, the predicted end time is updated to P2a which is at 18:22. This new prediction is dramatically too long and consequently disrupts the late

[1]This is the best possible situation but, of course, is not realistic.

afternoon peak demand period. As a result, this scenario is the worst as indicated by the number of affected passengers and the increase of the total generalized travel time.

6.4.2 Case Study 1A: Weekday evening

In order to investigate the effect of the disruption's time of occurrence on the choice of predictions, an artificial disruption is considered in this case study. The exact same disruption as in Case Study 1 is assumed to occur later on the same day, at 19:24. The realizations of the latency and repair time of this artificial disruption are taken from the values of the computed conditional distribution of latency and repair time which correspond to the same quantiles as the realizations of Case Study 1. In this case, the latency and repair time are 89 and 73 minutes, respectively. The total length is 162 minutes and the disruption ends at 22:06.

The P1 predictions and the short-turning results are presented in Table 6.9 and 6.10.

Table 6.9: The P1 predictions for Case Study 1A.

Qtl	P1		P1a		P1b		P1c	
(%)	Length	Time	Length	Time	Length	Time	Length	Time
25	54	20:18	77	20:41	102	21:06	127	21:31
50	86	20:50	149	21:53				
75	149	21:53						
85	209	22:53						
90	258	23:42						
Mean	122	21:26						

Table 6.10: The results of the short-turning model for P1 in Case Study 1A.

Qtl	P1				P1a				P1b				P1c			
(%)	#C	#D	#ST	Del.	#C	#D	#ST	Del.	#C	#D	#ST	Del.	#C	#D	#ST	Del.
25	19	0	3	0	23	2	4	6	31	0	6	0	39	0	8	0
50	27	0	5	0	43	2	9	2								
75	43	2	9	2												
85	55	5	12	39												
90	73	2	15	8												
Mean	35	9	7	15												

The P2 predictions are made at 21:08, 15 minutes after the mechanics' actual arrival time at 20:53. These predictions are presented in Table 6.11. The corresponding results of the short-turning model are represented in Table 6.12 and 6.13.

As before, the predictions are used by the short-turning model to produce the disruption timetables which are used by the dynamic passenger assignment model to attain the distribution of passengers traffic. Between 19:24 and 01:24, 7102 passengers are traveling in the case study area. Notice that there are fewer passengers in this set-up

Table 6.11: The P2 predictions for Case Study 1A.

Qtl	P2		P2a		P2b		P2c		P2d	
(%)	Length	Time	Length	Time	Length	Time	Length	Time	Length	Time
25	104	21:08	121	21:25	137	21:41	154	21:58	169	22:13
50	114	21:18	153	21:57	198	22:42				
75	152	21:56	259	23:43						
85	179	22:23								
90	213	22:57								
Mean	138	21:42	207	22:51						

Table 6.12: The results of the short-turning model for P2 in Case Study 1A.

Qtl	P2				P2a				P2b			
(%)	#C	#D	#ST	Del.	#C	#D	#ST	Del.	#C	#D	#ST	Del.
25	31	0	6	0	35	2	7	6	39	2	8	6
50	35	0	7	0	43	9	9	24	55	2	12	8
75	43	9	9	15	73	2	15	10				
85	47	4	10	38								
90	55	12	12	69								
Mean	39	9	8	15	55	5	12	31				
Real	47	0	10	0								

than the previous one due to the different time of the day under consideration. Table 6.14 summarizes the impact on passengers for each quantile.

In comparison to Case Study 1, the increase in the total generalized travel time with respect to the normal situation is higher. This is because the disruption is longer than in the previous case study due to the longer latency time.

The benchmark case still represents the best situation with fewer passengers being affected. The total generalized travel time is the lowest in this scenario and no passengers are rerouted.

The longer the last P2 prediction is, the more passengers are affected by the disruption. For this reason, the 75%-quantile scenario yields the highest total generalized travel time. Notice that as in Case Study 1, the P2 prediction of this scenario is 10 minutes shorter than the actual end time of the disruption. Consequently, the prediction is updated to P2a, which is then too long.

The nine predictions in the 25% quantile scenario cause many passengers to reroute. In this scenario, the simulation shows that there are a total of 1487 rerouting activities, out of which 438 had to reroute once and 195 had to reroute twice in addition to a considerable number of passengers who needed to reroute more than twice. As a result, the total generalized travel time of this scenario is the second largest due to the heavy penalty associated with rerouting.

Table 6.13: The remaining results of the short-turning model for P2 in Case Study 1A.

Qtl	P2c				P2d			
(%)	#C	#D	#ST	Del.	#C	#D	#ST	Del.
25	43	9	9	33	47	2	10	10

Table 6.14: The impact of different predictions to the passengers in Case Study 1A.

Qtl	Excess	# Affected	Inc. Orig	Inc. Bench	# Rerouting		# Transfers
(%)	(minute)	Passengers	(%)	(%)	1	2	
25	7	4966	32.68	7.47	438	195	1353
50	36	5563	31.09	6.18	479	8	1430
75	97	6563	35.12	9.45	83	0	1512
85	17	5180	29.46	4.86	52	0	1379
90	51	5843	32.15	7.05	0	0	1461
Mean	45	5733	27.16	3.00	91	0	1306
Real	0	4812	23.4516	0	0	0	1291

6.4.3 Case Study 2: Saturday evening

In this case study, we consider another real track circuit disruption at the same location which occured on Saturday, 18 October 2014 and started at 19:24. The incident had the information shown in Table 6.15. The observed latency and repair time are 47 and 88 minutes, respectively, with a total length of 135 minutes.

Table 6.15: The initial information of the disruption case 2

Contract type	OPC
Working station distance	7.1620
Level Crossing distance	872.372
Working Time	no
Warm	no
Rush Hour	no
Overlapping disruption	no
Cause	a cable problem

The P1 predictions and the short-turning results for this case study are presented in Tables 6.16 and 6.17. Fifteen minutes after the mechanics' actual arrival time at 20:11, the P2 predictions are made. Tables 6.18 and 6.19 presents these predictions and the short-turning model. Table 6.20 summarizes the impact on passengers for each choice of quantile.

The benchmark case represents the best possible situation. With the least number of affected passengers with no need for rerouting, the total generalized travel time is the lowest of all scenarios.

Notice that the final predicted end time of disruption of the 50%-quantile and 75%-quantile scenario are the same. Consequently, the same number of passengers are

Table 6.16: The P1 predictions for Case Study 2.

Qtl	P1		P1a	
(%)	Length	Time	Length	Time
25	54	20:18	77	20:41
50	86	20:50		
75	149	21:53		
85	209	22:53		
90	258	23:42		
Mean	122	21:26		

Table 6.17: The results of short-turning model for P1 for Case Study 2.

Qtl	P1				P1a			
(%)	#C	#D	#ST	Del.	#C	#D	#ST	Del.
25	19	0	3	0	23	2	4	6
50	27	0	5	0				
75	43	2	9	2				
85	55	5	12	39				
90	73	2	15	8				
Mean	35	9	7	15				

Table 6.18: The P2 predictions for Case Study 2.

Qtl	P2		P2a		P2b		P2c	
(%)	Length	Time	Length	Time	Length	Time	Length	Time
25	67	20:31	94	20:58	120	21:24	151	21:55
50	104	21:08	173	22:17				
75	173	22:17						
85	237	23:21						
90	280	00:04						
Mean	142	21:46						

Table 6.19: The results of short-turning model for P2 for Case Study 2.

Qtl	P2				P2a				P2b				P2c			
(%)	#C	#D	#ST	Del.	#C	#D	#ST	Del.	#C	#D	#ST	Del.	#C	#D	#ST	Del.
25	23	0	4	0	27	9	5	33	35	2	7	4	43	2	9	6
50	31	0	6	0	47	2	10	18								
75	47	2	10	18												
85	65	7	13	102												
90	77	8	16	79												
Mean	43	0	9	0												
Real	39	2	8	2												

affected in both cases. However, the 50%-quantile scenario has three predictions while the 75%-quantile scenario has only two. Consequently, many passengers need to be rerouted and more transfers need to be performed in the former. This results with higher total generalized travel time in the case of the 50%-quantile scenario. The

Table 6.20: The impact of different predictions to the passengers in Case Study 2.

Qtl (%)	Excess (minute)	# Affected Passengers	Inc. Orig (%)	Inc. Bench (%)	# Rerouting 1	# Rerouting 2	# Transfer
25	16	4562	14.43	0.64	426	32	1219
50	38	5052	17.11	2.99	252	32	1506
75	38	5052	16.11	2.11	0	0	1437
85	102	6246	19.30	4.92	0	0	1558
90	145	6792	21.43	6.79	0	0	1693
Mean	7	4351	14.89	1.04	2	0	1385
Real	0	4182	13.7099	0	0	0	1309

pessimistic 90%-quantile scenario disturbs the greatest number of passengers because of a P2 prediction that is too long. Consequently, the total generalized travel time is the largest, making this scenario the worst performing one in this case study.

6.4.4 Case Study 2A: Saturday afternoon

Similarly to Case Study 1A, the incident in Case Study 2 is also considered to occur at a different time of the day. In this case study, we assume this hypothetical incident to occur on the same day at 14:22. In this case, because the incident occurs during the weekend, the prediction lengths do not change from Case Study 2; only the time-dependent passenger demand generation process is adjusted. Tables 6.21 and 6.22 present the P1 predictions and the corresponding short-turning results. The P2 predictions and the short-turning results are presented in Tables 6.23 and 6.24.

Table 6.21: The P1 predictions for Case Study 2A.

Qtl (%)	P1 Length	P1 Time	P1a Length	P1a Time
25	54	15:16	77	15:39
50	86	15:48		
75	149	16:51		
85	209	17:51		
90	258	18:40		
Mean	122	16:24		

The impact of different scenarios on the passengers is presented in Table 6.25. Notice that more passengers are affected by the disruption in comparison to Case Study 2. This is due to the disruption occurring during the day time when more passengers are travelling.

Like the previous three case studies, the scenario with the true disruption length is the best performing one in terms of the total generalized travel time. The least number of passengers are affected and none of them have to change their travel plans.

Table 6.22: The results of the short-turning model for P1 in Case Study 2A.

Qtl	P1				P1a			
(%)	#C	#D	#ST	Del.	#C	#D	#ST	Del.
25	16	0	4	0	20	2	5	2
50	24	0	6	0				
75	40	0	10	0				
85	56	0	14	0				
90	68	2	17	4				
Mean	32	2	8	4				

Table 6.23: The P2 predictions for Case Study 2A.

Qtl	P2		P2a		P2b		P2c	
(%)	Length	Time	Length	Time	Length	Time	Length	Time
25	67	15:29	94	15:56	120	16:22	151	16:53
50	104	16:06	173	17:15				
75	173	17:15						
85	237	18:19						
90	280	19:02						
Mean	142	16:44						

Table 6.24: The results of short-turning model for P2 for Case Study 2A.

Qtl	P2				P2a				P2b				P2c			
(%)	#C	#D	#ST	Del.	#C	#D	#ST	Del.	#C	#D	#ST	Del.	#C	#D	#ST	Del.
25	20	0	5	0	24	9	6	15	32	0	8	0	40	2	10	2
50	28	0	7	0	48	0	12	0								
75	48	0	12	0												
85	64	0	16	0												
90	76	0	19	0												
Mean	36	9	9	33												
Real	36	0	9	0												

Table 6.25: The impact of different predictions to the passengers in Case Study 2A.

Qtl	Excess	# Affected	Inc. Orig	Inc. Bench	# Rerouting		# Transfers
(%)	(minute)	Passengers	(%)	(%)	1	2	
25	16	9031	12.31	1.22	723	120	3249
50	38	10928	15.87	4.43	491	46	3725
75	38	10928	14.60	3.28	0	0	3703
85	102	16359	19.95	8.11	0	0	4549
90	145	19044	23.25	11.08	0	0	5069
Mean	7	8294	11.10	0.13	4	0	3128
Real	0	7736	10.9567	0	0	0	3128

As in Case Study 2, the difference between the predicted end of disruption and the truth is 38 minutes in both the 50%-quantile and the 75%-quantile scenario. However, the increase in the generalized travel time is higher in the former case. This is due to the more frequent prediction updates so many passengers have to reroute and slightly more transfers are needed. Consequently, the total generalized travel time of this scenario is penalized more.

The very pessimistic 90% quantile scenario performs the worst in terms of the total generalized travel time. The dramatic difference between the predicted end of disruption and the truth means a lot of passengers are affected by the disruption. As a result, the total generalized travel time becomes very high.

6.5 Conclusions and Future Work

In railway operation, different disruption length predictions can lead to different consequences for the passengers. In this paper a framework is developed to investigate the impacts of disruption length prediction on the total passengers generalized travel time.

This framework integrates three models; a disruption length model using a Baysian network approach, a short-turning model formulated as a MILP, and a dynamic passenger assignment model using a multi-stage passenger load approach. The integration of these models has a unique iterative approach starting with a disruption length prediction, then rescheduling trains by short-turning them based on the predicted length, and finally measuring the passengers generalized travel time. The new iteration takes place upon receiving an update that leads to a new disruption prediction length, which results in an updated schedule and finally the new passenger generalized travel time is computed. These iterations continue until the disruption ends. In the dynamic passenger assignment model, the generalized travel time consists of the weighted total travel time of all passengers which takes into the account the waiting time, the in-vehicle time, the transfer time, the number of transfers, and the number of reroutings.

In a series of case studies, we have shown how different choices of predictions of disruption length will affect the passengers in terms of the generalized travel time. Our finding is that on one hand, when the prediction is too optimistic, many passengers have to be rerouted which increases the inconvenience and, hence, the total generalized travel cost. On the other hand, when the prediction is too pessimistic, more passengers are affected which results in a higher total generalized travel cost. The result from the case study corresponds to the current prediction practice which is using a pessimistic prediction that reduces the chance of further changes in the plan. When the prediction is just slightly shorter than the realized value, more passengers are affected. This is evident especially with pessimistic predictions which lead to keeping the track blocked much longer than necessary, significantly beyond the end of the disruption. The experiments provide thus insights on the impact of the predictions on passengers delays.

A hypothesis that can be investigated further is that "starting with pessimistic predictions and thereafter gradually switching to the optimistic predictions might result in a better overall prediction". We cannot conclude based on a few case studies which value of the conditional distribution of disruption length is the best for a prediction. To draw such a conclusion, many more case studies need to be performed. However, we show that different quantiles led to the smallest generalized travel time of passengers under different scenarios. The close-to-optimal solution can be found by testing a large number of points from the solution space, i.e., by generating many different realizations of disruption length from the conditional distribution. For each realization, the short-turning model and the dynamic passenger assignment model should then be run to compute the effect of different choices of disruption length predictions.

Moreover when a prediction had to be updated we took the same quantile of the conditional distributions. For future research direction the choice of quantile in the P2 prediction should be investigated to see whether there is a dependency on the quantile that realizes the latency time in the P1 prediction. The realization of the latency time might indicate how fast/slow the mechanics work on the specified incident which might be a useful information to produce a more accurate P2 prediction. Other possibilities could be considered as well.

The function of the total generalized travel time specified in this study can be extended in future studies. During peak demand periods and disruptions it is especially relevant to consider vehicle capacity constraints and the vehicle type. The bus service between Utrecht and Houten provides significantly less seat capacity than the train service. Moreover, different vehicle types provide different levels of comfort to the passengers. An Intercity train is generally more comfortable than a Sprinter train or a bus service. This can be accommodated in equation (6.12) by adding a weight corresponding to the vehicle type to the second term.

Choosing generalized travel time as the primary evaluation/selection criterion means the impact of the uncertainty in disruption length is only measured from the passengers' point of view. With this cost function, an optimistic prediction is not attractive only because it causes inconvenience to the passengers who would have to reroute. Note that we have not captured all costs associated with an optimistic prediction that the traffic control faces. However, from an operational point of view, having a lot of timetable updates is not practical due to the logistical issues that need to be carried out. For instance, the rolling stock and crew assignments need to be reorganized accordingly with every update. Future studies may incorporate additional aspects into the cost function in order to better reflect the aspects influencing real-time decision making in the context of disruption management.

Note that the effect of different predictions depends considerably on the location and the time of the incident. This is evident in the results of the case studies investigated in this paper. This is presumably even more pronounced in denser areas where there is a greater hierarchy among different locations, such as the Amsterdam area. Aside from the greater number of alternative rail services, passengers may switch to other modes of public transport, consisting of metro, tram and bus, which contribute to network redundancy.

Chapter 7

Conclusions

The work presented in this thesis is dedicated to developing a decision support system for improving the current railway disruption management. The models developed in this research are relevant for railway networks with cyclic timetables (e.g. half an hour period) and disruptions of complete blockages where no train service can use part of the track for several hours. The focus of the rescheduling models is on the application of short-turning for handling the train services that are heading towards the blockage.

In this chapter first the main findings are presented in section 7.1. Then a number of recommendations are given to practitioners in section 7.2 and, finally possible future research directions are discussed in section 7.3.

7.1 Main findings

To answer the main research question "*How to optimize short-turnings of train services in case of complete blockages?* " several sub questions were defined. Here the answers to these questions are summarized.

- What measures can be considered for railway disruption management in practice and literature? (Chapter 2)

  The main measure used to deal with disruptions in case of cyclic timetables is to short-turn services. Short-turning embeds station rerouting, replatforming, retiming and reordering depending on the specific characteristics of the station layouts, corridor layout, signalling, rolling stock, original timetable and routes, disruption location, time of disruption start, and disruption length. In Chapter 5, a short-turning model incorporating all these characteristic has been developed as a mixed-integer linear programming model implementing flexible blocking time stairways consisting of the capacity occupation of all trains over their routes with the optimal short-turning station for each train, which are computed over the entire disruption length and the transition phase beyond such that the resulting train paths are conflict-free, and a trade-off is minimized between train service cancellations and delays with respect to the original timetable.

Most of the short-turnings occur in the second phase of disruption. In Chapter 2 the processes during the disruption and particularly during each phase of the disruption period are analyzed. Then the existing models were classified based on their applications in each phase. The literature review revealed that most of the algorithms are developed at the macroscopic level where only arrival and departure events at stations or main junctions are of interest. Few models are developed at the microscopic level where the train movement along the track block sections is considered. The microscopic models can give a better insight about the capacity consumption during disruptions. However none of them focused particularly on the short-turning measure. Moreover, the transition phases are rarely addressed specially at the microscopic level. To show the possible support for the traffic controllers during disruptions, a microscopic rescheduling model is implemented and adjusted with predefined short-turning decisions to show the potential differences of the three phases of disruption at the microscopic level.

- How to apply the short-turning measure to minimize the negative impact to the rest of the network? (Chapter 3)

  By including multiple short-turning stations, the short-turning measure can better prevent the delay propagation. In Chapter 3 a macroscopic short-turning model is formulated as a Mixed Integer Linear Program and implemented in MATLAB using the YALMIP optimization toolbox and Gurobi as the solver. The short-turning decisions that used to be predefined in the previous chapter, are modelled as decision variables in this chapter. The short-turning choices are not limited to the final station before the disruption, but also include the possibility of short-turning in the preceding station. Through the case study, it was shown that the negative impact in terms of delay to the rest of the network can be reduced at the cost of canceling more services in the control area. The magnitude of the cancellation penalty compared to the delay penalty is key to determine when cancelling services by short-turning in the preceding station is the best option. It was concluded that considering a flexible short-turning station is beneficial.

- How can the optimal short-turning solution depend on the disruption period? (Chapter 4)

  The disruption period determines the affected services. Depending on the disruption period the number of approaching train services towards the disrupted area could be equal or unequal to the number of scheduled departures in the opposite direction. In the equal condition the third phase is smoother than the one resulting from the unequal condition.

  The number of approaching services on one side during a disruption corresponds to the number of scheduled departures on the other side of disruption. In case of inequality, there are more scheduled departures than approaching services on one side of the disruption. The extra scheduled departures then are operated with some delay by the extra approaching services from the other side after the disruption.

In Chapter 4 the macroscopic short-turning model that is introduced in the previous chapter is extended and applied to both sides of the disrupted area. The computation time is promising for real-time application of the model on similar networks. Since the interaction of the traffic from both sides are taken into account in this extended version, the transition phases could be defined and their length could be measured. The short-turning decisions in each station depends on the disruption period. A dense corridor of the Dutch railway corridor with multiple lines was selected for the case study. It was concluded that by ensuring the equality between the approaching services and scheduled departures in the opposite direction, a faster third phase is achieved. The first phase is taken into account by considering the operating IC services that should short-turn before the second phase can start. Moreover the periodicity of the disruption timetable as the result of a cyclic original timetable was shown.

- How can the short-turning measure be modelled to address platform allocation and conflict-free routes at the microscopic level? (Chapter 5)

  In Chapter 5 the short-turning measure is modelled at the microscopic level. In this chapter a microscopic rescheduling model that was developed to deal with disturbances is extended to include short-turning as a measure to deal with disruptions. Besides selecting the optimal short-turning station, the model computes the conflict-free routes for all services including the short-turning ones. The model provides a detailed optimal solution that includes the blocking times of all operational services along the selected routes at the level of track circuit sections. Two case studies have been performed to show the usability and performance of the model. The first case study showed that depending on the priorities selected by the traffic controllers about the cancellation or delay penalties different optimal solutions can be achieved. The second case study was performed on a bigger station with five operating lines. The purpose of this study was to show the performance of the model on a bigger disrupted area. Similar to the macroscopic short-turning model, the microscopic model is implemented in MATLAB using the YALMIP toolbox and is solved by Gurobi. The result showed that the model was able to compute the optimal microscopic solution for a medium size station (with eight platform track sections) in less than two minutes.

- How can different disruption length predictions impact the short-turning solution and consequently the passengers? (Chapter 6)

  In Chapter 6 a framework was developed to analyze the impact of the predicted disruption length on the short-turning solution and consequently on the passenger generalized travel time. Given the existing data, the computed disruption length distribution still has a large variance. In order to compute the short-turning solution, it is necessary to select a specific disruption length from the computed distribution. If the selected length is shorter than the real disruption length, then it is called an optimistic prediction. On the contrary, when the prediction is longer than the real disruption length it is referred to as a pessimistic prediction. From the case studies, it is observed that, when the prediction is too optimistic, many passengers have to reroute which causes an increase in the total generalized travel cost. If the prediction is too pessimistic the track will be blocked longer than necessary, and thus, more passengers are affected which results in a higher total generalized travel cost. Similarly when the prediction is just slightly shorter than the truth, more passengers are also affected. This is evident specially with pessimistic predictions which lead to keeping the track blocked much longer than necessary, significantly beyond the end of disruption.

7.2 Recommendation for practice

A contingency plan is a predefined solution that is designed specifically for a disrupted infrastructure given a specific timetable. Obviously these plans can only provide a solution given certain timetable and infrastructure. The performed research concludes that the contingency plans can be replaced by a fast and efficient algorithm that can compute optimal solutions. It is well acknowledged that the literature still needs to be enriched with more high performance rescheduling models. However the trust and demand from the railway sector can boost the advancements of such developments that eventually benefit the traffic controllers.

Applying a microscopic rescheduling model at the network level is computationally expensive. Thus, at the network level, a macroscopic rescheduling model can provide support to the central traffic controllers whom should make decision at a higher level. At the local level, given the macroscopic solution, the microscopic rescheduling model can provide details about the rerouted services within the stations to the signallers.

Alternatively the microscopic model can be applied locally to the disrupted area and in case the optimal solution indicates some delays, as long as the computational power allows the affected areas can be added to the model.

It might be a long way until such rescheduling models can be used real-time. But currently they can be used offline for training and planning purposes. For example the developed microscopic short-turning model in this research can already be used to examine the feasibility of the existing contingency plans at the microscopic detail. In addition they can be used to compute new contingency plans for different disruption scenarios. Applying the developed model has the advantage of considering multiple short-turning stations. Different disruption scenarios could be defined and arranged in a serious gaming setting where traffic controllers have to make decisions regarding the short-turning choices including routes within the stations. The decision making times and the decisions themselves can be compared with the situation where such decision support tools are provided.

During the SmartOCCR research it was observed that accessing historical data about different disruptions and their causes took some time and when it was processed, the quality of the data did not meet the expectation. This data was needed to set up the disruption length prediction model in the other SmartOCCR project. More detailed information about the disruptions was expected to be accessed from the contractors who are responsible to deal with the cause of disruptions. Since it can reveal the performance of the contractor, this data is not transparent to the infrastructure manager. Due to the conflict of interest, not all the contractors were willing to share their data. Accessing quality data improves the disruption length prediction model. Thus it is of great importance that the train undertakings and the infrastructure managers improve the processes of collecting and maintaining data so that it can provide better insights.

7.3 Future research directions

The focus of the developed models in this research was on the disruptions of complete blockages. It is also interesting to model partial blockages where parts of tracks are blocked while others are operational. In addition, the considered operation in this research is based on cyclic timetables where there is a high frequency of operating lines in two opposite directions. In no (or long) cyclic operations, the short-turning measure might not be the most common rescheduling measure. This is also the case when freight trains are affected by the disruption and thus short-turning is not an option. In such cases, the transition phases might be more complicated. This is due to the fact that some trains might need to be shunted into the yards in the first transition phase and then again in the third phase they should be shunted back into the operation. If a train is taken out from the rolling stock circulation, then many services need to be cancelled. Moreover in both transition phases there might be a need to add new train paths to those services that cannot short-turn on an existing path.

Due to the time limit, investigating the transition phases were not performed thoroughly in this research. However it is of great importance to model the transition phases at the microscopic level. Specially in the third phase, where some delays might be introduced due to the unequal short-turning situation, the nature of the problem changes to disturbance management and can be investigated by the existing microscopic models.

In the recent years the literature is shifting towards passenger oriented rescheduling. Specially due to the smart cards, nowadays there are more data available about the passengers and their travel times. Penalizing cancellations and delays can be improved by knowing the passenger demand.

As shown in this research the choice of penalties plays an important role in the optimal solution. It is necessary to define a framework that can provide some guidelines regarding the choice of penalties given some characteristics such as the preferences of the infrastructure manager.

The model could be applied to multiple disruptions in a network disregarding the computational capability as long as there are no common lines between the disrupted locations. Otherwise, the model should be extended to cover the effects of short-turning the trains of the common lines in one disrupted location on the traffic of the other locations.

The rescheduling models developed in this research can be extended to include the rolling stock circulation. Although the short-turning measure can maintain the main structure of the timetable during the disruption, it changes the rolling stock circulation from its original plan. The train compositions that are scheduled to meet the demand during peak and off peak hours can change due to the short-turnings and thus it can create a capacity drop. Moreover the problem can propagate to the next day if there are different train units staying in the depots at the end of the day. To resume the original rolling stock schedule extra measures could be considered to shorten the recovery phase.

No train can be operated without qualified crew. It is interesting to investigate changes in the crew schedules due to the short-turnings and whether an integrated model that takes into account the crew scheduling constraints can result in a better solution.

The above mentioned topics are all in the direction of finding an optimized solution. Obviously the successful implementation of such algorithms can only be realized with an improved communication and information flow both between the traffic controllers and also with the passengers. The amount of information and its format, the time of communication, and the involved operators are all existing research questions.

Bibliography

Acuna-Agost, R., Michelon, P., Feillet, D., and Gueye, S. (2011a). A MIP-based local search method for the railway rescheduling problem. *Networks*, 57(1):69–86.

Acuna-Agost, R., Michelon, P., Feillet, D., and Gueye, S. (2011b). SAPI: Statistical analysis of propagation of incidents. a new approach for rescheduling trains after disruptions. *European Journal of Operational Research*, 215(1):227 – 243.

Bešinović, N., Goverde, R. M. P., and Quaglietta, E. (2017). Microscopic models and network transformations for automated railway traffic planning. *Computer-Aided Civil and Infrastructure Engineering*, 32(2):89–106.

Binder, S., Maknoon, Y., and Bierlaire, M. (2017). The multi-objective railway timetable rescheduling problem. *Transportation Research Part C: Emerging Technologies*, 78:78–94.

Cacchiani, V., Caprara, A., Galli, L., Kroon, L., Marti, G., and Toth, P. (2012). Railway rolling stock planning: Robustness against large disruptions. *Transportation Science*, 46(2):217–232.

Cacchiani, V., Huisman, D., Kidd, M., Kroon, L., Toth, P., Veelenturf, L., and Wagenaar, J. (2014). An overview of recovery models and algorithms for real-time railway rescheduling. *Transportation Research Part B: Methodological*, 63:15–37.

Caimi, G., Chudak, F., Fuchsberger, M., Laumanns, M., and Zenklusen, R. (2011). A new resource-constrained multicommodity flow model for conflict-free train routing and scheduling. *Transportation Science*, 45(2):212–227.

Caimi, G., Fuchsberger, M., Laumanns, M., and Luthi, M. (2012). A model predictive control approach for discrete-time rescheduling in complex central railway station areas. *Computers & Operations Research*, 39(11):2578–2593.

Canca, D., Barrena, E., Laporte, G., and Ortega, F. A. (2016). A short-turning policy for the management of demand disruptions in rapid transit systems. *Annals of Operations Research*, 246(1):145–166.

Cats, O. (2016). The robustness value of public transport development plans. *Journal of Transport Geography*, 51:236 – 246.

Cats, O. and Jenelius, E. (2014). Dynamic vulnerability analysis of public transport networks: Mitigation effects of real-time information. *Networks and Spatial Economics*, 14(3):435–463.

Cats, O., West, J., and Eliasson, J. (2016). A dynamic stochastic model for evaluating congestion and crowding effects in transit systems. *Transportation Research Part B: Methodological*, 89:43 – 57.

Chu, F. and Oetting, A. (2013). Modeling capacity consumption considering disruption program characteristics and the transition phase to steady operations during disruptions. *Journal of Rail Transport Planning & Management*, 3:54–67.

Coor, G. T. (1997). Analysis of the short-turning strategy on high-frequency transit lines by. Technical report, Massachusetts Institute of Technology.

Corman, F., D'ariano, A., Hansen, Ingo, A., Pacciarelli, D., and Pranzo, M. (2011a). Dispatching trains during seriously disrupted traffic situations. In *International Conference on Networking, Sensing and Control*, pages 323–328. Elsevier, Amsterdam.

Corman, F., D'Ariano, A., Hansen, I. A., Pacciarelli, D., and Pranzo, M. (2011b). Dispatching trains during seriously disrupted traffic situations. In *2011 International Conference on Networking, Sensing and Control*, pages 323–328.

Corman, F., DAriano, A., Pacciarelli, D., and Pranzo, M. (2009). Evaluation of green wave policy in real-time railway traffic management. *Transportation Research Part C: Emerging Technologies*, 17(6):607–616.

D'Ariano, A., Corman, F., and Pacciarelli, D.and Pranzo, M. (2008). Reordering and local rerouting strategies to manage train traffic in real time. *Transportation Science*, 42(4):405–419.

De-Los-Santos, A., Laporte, G., Mesa, J. A., and Perea, F. (2012). Evaluating passenger robustness in a rail transit network. *Transportation Research Part C: Emerging Technologies*, 20(1):34 – 46.

Dollevoet, T., Huisman, D., Schmidt, M., and Schbel, A. (2012). Delay management with rerouting of passengers. *Transportation Science*, 46(1):74–89.

European Commission (2001). *Directive 2001/14/EC of the European Parliament and of the Council of 26 February 2001 on the allocation of railway infrastructure capacity and the levying of charges for the use of railway infrastructure and safety certification*. Official Journal of the european Communities, L 75, 29-46.

European Commission (2009). *amending Directive 2009/149/EC of the European Parliament and of the Council as regards Common Safety Indicators and common methods to calculate accident costs*. Official Journal of the European Union, L 313, 65-74.

Ghaemi, N., Cats, O., and Goverde, R. M. P. (2017a). A microscopic model for optimal train short-turnings during complete blockages. *Transportation Research Part B: Methodological*, 105:423 – 437.

Ghaemi, N., Cats, O., and Goverde, R. M. P. (2017b). Railway disruption management challenges and possible solution directions. *Public Transport*, 9(1):343–364.

Ghaemi, N., Cats, O., and Goverde, R. M. P. (2018). Macroscopic multiple-station short-turning model in case of complete railway blockages. *Transportation Research Part C: Emerging Technologies*, 89:113 – 132.

Ghaemi, N., Goverde, R. M. P., and Cats, O. (2016). Railway disruption timetable: Short-turnings in case of complete blockage. In *2016 IEEE International Conference on Intelligent Rail Transportation (ICIRT)*, pages 210–218.

Groth, J. J., Clausen, J., and Larsen, J. (2006). Optimal reinsertion of cancelled train line. Technical report.

Hansen, I. A. and Pachl, J. (2014). *Railway timetabling and operations*. Eurailpress.

Hirai, C., Kunimatsu, T., Tomii, N., Kondu, S., and Takaba, M. (2009). A train stop deployment planning algorithm using a petri-net-based modelling approach. *Quarterly Report of RTRI*, 50(1):8–13.

Hirai, C., Tomii, N., Tashiro, Y., Kondou, S., and Fujimori, A. (2006). An algorithm for train rescheduling using rescheduling pattern description language R. *Computers in Railways X*, 1:551–561.

Jespersen-groth, J., Potthoff, D., Clausen, J., Huisman, D., and Kroon, L. (2009). Disruption management in passenger railway transportation. *Robust and Online Large-Scale Optimization. Lecture Notes in Computer Science*, 5868:399–421.

Joe, H. (2014). *Dependence Modelling with Copulas*. CRC Press.

Kecman, P., Corman, F., D'Ariano, A., and Goverde, R. M. P. (2013). Rescheduling models for railway traffic management in large-scale networks. *Public Transport*, 5(1):95–123.

Kumazawa, K., Hara, K., and Koseki, T. (2008). A novel train rescheduling algorithm for correcting disrupted train operations in a dense urban environment. *Computers in Railways XI, WIT Press*, 103:565–574.

Löfberg, J. (2004). Yalmip : A toolbox for modeling and optimization in matlab. In *In Proceedings of the CACSD Conference*. Taipei, Taiwan.

Löfberg, J. (2012). Automatic robust convex programming. *Optimization methods and software*, 27(1):115–129.

Louwerse, I. and Huisman, D. (2014). Adjusting a railway timetable in case of partial or complete blockades. *European Journal of Operational Research*, 235(3):583–593.

Lusby, R., Larsen, J., Ryan, D., and Ehrgott, M. (2011). Routing Trains Through Railway Junctions: A New Set-Packing Approach. *Transportation Science*, 45(2):228–245.

Meng, L. and Zhou, X. (2011). Robust single-track train dispatching model under a dynamic and stochastic environment: A scenario-based rolling horizon solution approach. *Transportation Research Part B: Methodological*, 45(7):1080–1102.

Nakamura, T., Hirai, C., and Nishioka, Y. (2011). A practical train rescheduling algorithm using three predetermined factors. Technical report.

Narayanaswami, S. and Rangaraj, N. (2013). Modelling disruptions and resolving conflicts optimally in a railway schedule. *Computers & Industrial Engineering*, 64(1):469–481.

Nederlandse Spoorwegen (2016). NS annual report 2016.

Nelsen, R. B. (2006). *An Introduction to Copula*. Springer, New York.

Nielsen, L. K., Kroon, L., and Marti, G. (2012). A rolling horizon approach for disruption management of railway rolling stock. *European Journal of Operational Research*, 220(2):496 – 509.

Pellegrini, P., Marlière, G., and Rodriguez, J. (2014). Optimal train routing and scheduling for managing traffic perturbations in complex junctions. *Transportation Research Part B: Methodological*, 59:58–80.

Rodriguez, J. (2007). A constraint programming model for real-time train scheduling at junctions. *Transportation Research Part B: Methodological*, 41(2):231–245.

Samà, M., Pellegrini, P., DAriano, A., Rodriguez, J., and Pacciarelli, D. (2017). On the tactical and operational train routing selection problem. *Transportation Research Part C: Emerging Technologies*, 76:1 – 15.

Schöbel, A. (2009). Capacity constraints in delay management. *Public Transport*, 1(2):135–154.

Shen, S. and Wilson, N. H. (2001). An optimal integrated real-time disruption control model for rail transit systems. In *Computer-aided scheduling of public transport*, pages 335–363. Springer, Berlin.

Takeuchi, Y. and Tomii, N. (2005). Robustness indices for train rescheduling. In *Proceedings of the 1st international seminar on railway operations modeling and analysis (RailDelft 2005), June*, pages 08–10.

Törnquist, J. and Persson, J. A. (2007). N-tracked railway traffic re-scheduling during disturbances. *Transportation Research Part B: Methodological*, 41(3):342–362.

van Zon, F. and Wink, M. (2014). Lean transformation: Communication during disruptions. Technical report, ProRail.

Veelenturf, L. P., Kidd, M. P., Cacchiani, V., Kroon, L. G., and Toth, P. (2016). A railway timetable rescheduling approach for handling large-scale disruptions. *Transportation Science*, 50(3):841–862.

Veelenturf, L. P., Kroon, L. G., and Marti, G. (2017). Passenger oriented railway disruption management by adapting timetables and rolling stock schedules. *Transportation Research Part C: Emerging Technologies*, 80:133 – 147.

Wagenaar, J., Kroon, L., and Fragkos, I. (2017). Rolling stock rescheduling in passenger railway transportation using dead-heading trips and adjusted passenger demand. *Transportation Research Part B: Methodological*, 101:140 – 161.

Xu, P., Corman, F., Peng, Q., and Luan, X. (2017). A train rescheduling model integrating speed management during disruptions of high-speed traffic under a quasi-moving block system. *Transportation Research Part B: Methodological*, 104:638 – 666.

Yang, L., Zhou, X., and Gao, Z. (2013). Rescheduling trains with scenario-based fuzzy recovery time representation on two-way double-track railways. *Soft Computing*, 17(4):605–616.

Yang, L., Zhou, X., and Gao, Z. (2014). Credibility-based rescheduling model in a double-track railway network: a fuzzy reliable optimization approach. *Omega*, 48:75 – 93.

Zeegers, S. (2017). www.sporenplan.nl, 2017. accessed: 28-08-2017.

Zhan, S., Kroon, L. G., Veelenturf, L. P., and Wagenaar, J. C. (2015). Real-time high-speed train rescheduling in case of a complete blockage. *Transportation Research Part B: Methodological*, 78:182 – 201.

Zhan, S., Kroon, L. G., Zhao, J., and Peng, Q. (2016). A rolling horizon approach to the high speed train rescheduling problem in case of a partial segment blockage. *Transportation Research Part E: Logistics and Transportation Review*, 95:32 – 61.

Zhu, S., Levinson, D., Liu, H. X., and Harder, K. (2010). The traffic and behavioral effects of the i-35w mississippi river bridge collapse. *Transportation Research Part A: Policy and Practice*, 44(10):771–784.

Zilko, A. A., Kurowicka, D., and Goverde, R. M. P. (2016). Modeling railway disruption lengths with copula bayesian networks. *Transportation Research Part C: Emerging Technologies*, 68:350 – 368.

Zwaneveld, P. J., Kroon, L. G., Van Hoesel, S. P. M., and Ambergen, H. W. (1996). Routing Trains through railway stations: model formulation and algorithms. *Transportation Science*, 128:14–33.

Summary

Railway operations such as any other public transport modes, follows a timetable. However, unplanned events can disrupt the operation. In such occasions the traffic controllers have to deal with the disrupted traffic. Due to the complexity of coordinating the timetable, rolling stock, and crew, the traffic controllers face difficulties handling the traffic. With the advancement of digitalization and computational power, rescheduling algorithms can provide support to the traffic controllers.

This thesis aims at providing support to the traffic controllers through rescheduling algorithms in case of complete blockages. A common practice in railway operations in case of complete blockage is to short-turn train services that are heading towards a blockage. This measure assigns the services that are approaching a station before the blockage to the scheduled services in the opposite direction. In this way, the disrupted area can be better isolated from the rest of the network. The main objective of this thesis is to optimize the short-turnings of the train services.

To have a better perspective on the existing algorithms and the procedures in practice, a review was performed that included both literature on timetable rescheduling models for railway disruption management and the current practice in the Dutch railway operations. The traffic level during disruption is divided into three phases representing the decrease of the traffic due to the capacity drop, the stable traffic level that is achieved after a while and finally the increase of the traffic level to the original timetable after the cause of blockage has been removed. First and third phases are called transition phases as they represent transition from the original timetable to the disruption timetable and vice versa. The challenges that traffic controllers are facing in each phase of disruption are determined. The existing approaches are classified based on their applicability within the three disruption phases. From the review, it was concluded that most of the existing algorithms are developed at the macroscopic level where only the arrival and departures at the stations or main junctions are of interest. Among the few existing microscopic rescheduling models none of them take the short-turning measure into account. In addition, it was observed that the transition phases are not explored in the literature. To emphasis the support that can be provided to the traffic controller which can differ in the three phases, a microscopic rescheduling model was implemented which adjusted the timetable with predefined short-turning decisions.

The following step was to relax the predefined short-turning decisions and let the model select the optimal short-turning choice for each approaching train service. A macro-

scopic short-turning model was formulated as a Mixed Integer Linear Program that assigns the approaching train services to scheduled departures in the opposite direction. The model was implemented in MATLAB using the YALMIP optimization toolbox and Gurobi as the solver. In addition, the possibility of short-turning in the preceding station is taken into account. The case study that took into account one side of the blockage showed that including multiple stations for short-turning can be beneficial for reducing delay propagation. However this advantage is at the cost of more service cancellations in the control area. Thus, the optimal solution regarding the short-turning station depends largely on the considered penalties for cancellation and delay.

The next step was to include both sides of the blockage. Note that short-turning assigns the approaching train services to the scheduled departures in the opposite direction. The approaching services on one side of the blockage correspond to the scheduled departures in the opposite direction of the other side of blockage and vice versa. Having this in mind, the MILP model was extended to include both sides of the blockage. Depending on the disruption length, different services can be affected. Given the disruption length, if the number of approaching services is equal to the scheduled departures in the opposite direction, then there are an equal number of short-turnings on both sides. Otherwise, the extra approaching service has to wait until the disruption is over and the blockage is resolve so that the extra approaching train can proceed to the other side. Since the traffic of both sides and the disruption length are taken into account, it was possible to define and measure the transition phases. The model was applied to a corridor of the Dutch railway network where multiple train lines operate. It was shown that the optimal solution was computed fast for such a control area. The case study emphasizes the importance of the disruption period in the optimal short-turning choice. By ensuring an equal situation, an immediate recovery from the disruption timetable to the original timetable can be achieved. Moreover, the computed disruption timetable showed a cyclic pattern that can be described by the periodicity of the original timetable.

In the following step, to ensure the feasibility of the short-turnings at the microscopic level, the short-turning decision variables and constraints were integrated into a microscopic rescheduling model. The extended microscopic short-turning model is able to compute the optimal short-turning solution that includes conflict-free routes at the track circuit section level. The model computes the blocking stairways for each service and allows the possibility of short-turning in multiple stations. To show the applicability and performance of the model, two case studies were performed. In the first case with two possible short-turning routes for each of the two stations, it was shown that the optimal solution can differ depending on the cancellation and delay penalties. The second case showed that the model is able to compute the optimal solution for a bigger station with five operating lines within two minutes.

In the final step, to analyze the impact of the disruption length on the short-turning solution and consequently on the passengers an evaluation framework was developed. The framework consists of three models; a disruption length model using a Baysian network approach, the short-turning model, and a dynamic passenger assignment model using a multi-stage passenger loading approach. The interaction between the models has a unique iterative approach that starts with the disruption length prediction, followed by computing the optimal short-turning solution given the predicted length, and finally measuring the passengers generalized travel time. The generalized travel time consists of a weighted sum of in-vehicle time, transfer time, number of transfers, and the number of reroutings. With each information update, a new prediction is made and a new short-turning solution is computed and finally the passenger generalized travel time is measured again. These iterations continues until the end of the disruption. The output of the disruption length model is a distribution of the predicted length. In order to compute the short-turning solution, it is required to select a specific disruption length from the computed distribution. If the selected length is shorter or longer than the real length, then the prediction is referred to as optimistic or pessimistic prediction respectively. The performed case studies reveal that with the optimistic prediction, there will be many updates in the timetable that results in passengers having to reroute several times. With the pessimistic prediction, the track will be blocked longer than necessary and consequently more passengers are affected.

In summary, this thesis demonstrated that including multiple short-turning stations can result in a better isolation of the blockage from the neighboring stations that costs more cancellations in the disrupted area but less propagated delay to the rest of the network. Moreover the application of the developed models showed that the disruption period has an essential role on the optimal solution.

Samenvatting

Railvervoer, zoals de meeste vormen van openbaar vervoer, verloopt volgens een dienstregeling. Ongeplande gebeurtenissen kunnen het railverkeer echter verstoren. In dergelijke gevallen heeft de verkeersleiding de taak om het verstoorde verkeer te beheersen. Vanwege de complexiteit van het cordineren van de dienstregeling, het materieel en personeelsplannen, ondervindt de verkeersleiding problemen bij het verwerken van het verkeer. Met de vooruitgang van digitalisering en rekenkracht kunnen algoritmen voor herplanning ondersteuning bieden aan de verkeersleiding.

Dit proefschrift beoogt ondersteuning te leveren aan de verkeersleiding door middel van algoritmes voor de herplanning van het treinverkeer in geval van volledige versperringen. Een gangbare praktijk bij railvervoer in geval van een volledige versperring is het kortkeren van treinen die op een versperring afstevenen. Deze maatregel zorgt ervoor dat treinen die een station naderen vr de blokkade omkeren, zodat deze treinen voor geplande ritten in de tegenovergestelde richting ingezet worden. Op deze manier kan het verstoorde gebied beter worden gesoleerd van de rest van het netwerk. Het hoofddoel van dit proefschrift is het optimaliseren van het kortkeren van de treindiensten.

Om een beter inzicht te krijgen in de bestaande algoritmes en de procedures in de praktijk, is een review uitgevoerd met zowel literatuur over dienstregeling herplanningsmodellen voor bijsturing en de huidige praktijk in het Nederlandse railvervoer. Het verkeersniveau tijdens een verstoring is verdeeld in drie fasen namelijk de afname van het verkeer als gevolg van de capaciteitsvermindering, het stabiele verkeersniveau dat na een tijdje wordt bereikt, en tot slot de toename van het verkeersniveau naar de oorspronkelijke dienstregeling nadat de oorzaak van de versperring is opgelost. De eerste en derde fasen worden overgangsfasen genoemd omdat ze de overgang van de oorspronkelijke dienstregeling naar de verstoringsdienstregeling weergeven en vice versa. De uitdagingen waarmee de verkeersleiding in elke fase van een verstoring worden geconfronteerd zijn in kaart gebracht. De bestaande aanpakken zijn geclassificeerd op basis van hun toepasbaarheid binnen de drie verstoringsfasen. Uit de evaluatie is geconcludeerd dat de meeste van de bestaande algoritmes zijn ontwikkeld op macroscopische niveau, waarbij alleen de aankomst op en het vertrek van de stations of hoofdknooppunten van belang zijn. Geen van de weinige bestaande microscopische modellen houdt rekening met de kortkeermaatregel. Bovendien is opgemerkt dat de overgangsfasen niet in de literatuur zijn onderzocht. Om de ondersteuning te benadrukken die kan worden geboden aan de verkeersleiding is een microscopisch herplanningsmodel gemplementeerd dat de dienstregeling aanpast met vooraf gedefinieerde kortkeerbeslissingen.

De volgende stap was om de vooraf gedefinieerde kortkeerbeslissingen te versoepelen en het model de optimale kortkeerkeuzes te laten maken voor elke trein. Een macroscopisch kortkeermodel werd geformuleerd als een Mixed Integer Linear Program dat de naderende treindiensten toewijst aan geplande vertrekken in de tegenovergestelde richting. Het model werd gemplementeerd in MATLAB met behulp van de YALMIP optimalisatie toolbox en Gurobi als de oplosser. Bovendien wordt rekening gehouden met de mogelijkheid om in het voorliggende station kort te keren. De casestudie die rekening hield met n kant van de blokkade liet zien dat het meenemen van meerdere stations voor kortkeren gunstig kan zijn voor het verminderen van vertragingsvoortplanting. Dit voordeel gaat echter ten koste van meer diensten-annuleringen in het regelgebied. De optimale oplossing met betrekking tot het kortkeerstation hangt dus grotendeels af van de overwogen weegfactoren voor annulering en vertraging.

De volgende stap was om beide zijden van de blokkade mee te nemen. Merk op dat kortkeren de naderende treinen toewijst aan de geplande vertrekken in de tegenovergestelde richting. De naderende treinen aan de ene kant van de blokkade corresponderen met de geplande vertrekken in de tegenovergestelde richting van de andere kant van de blokkade en vice versa. Met dit in gedachten werd het MILP-model uitgebreid met beide zijden van de blokkade. Afhankelijk van de lengte van de storing kunnen verschillende diensten worden benvloed. Afhankelijk van de lengte van de verstoring, als het aantal naderende diensten gelijk is aan de geplande vertrekken in de tegenovergestelde richting, zijn er aan beide zijden evenveel kortkerende treinen. Anders moet de extra naderende trein wachten tot de storing voorbij is en de versperring opgelost is, zodat de extra naderende trein door kan rijden. Omdat het verkeer van beide kanten alsmede de lengte van de verstoring mee worden genomen, was het mogelijk om de overgangsfasen te definiren en te meten. Het model was toegepast op een corridor van het Nederlandse spoorwegnet waar meerdere treinseries rijden. Er werd aangetoond dat de optimale oplossing snel werd berekend voor een dergelijk regelgebied. De casestudie benadrukt het belang van de verstoringsperiode in de optimale kortkerenkeuze. Door te zorgen voor een gelijke situatie kan een onmiddellijke teruggang van de gestoorde dienstregeling naar de oorspronkelijke dienstregeling worden bereikt. Bovendien vertoonde de berekende gestoorde dienstregeling een cyclisch patroon dat kan worden beschreven aan de hand van de periodiciteit van de oorspronkelijke dienstregeling.

Om de haalbaarheid van het kortkeren op microscopisch niveau te garanderen, werden in de volgende stap de kortkeerbeslisvariabelen en -beperkingen gentegreerd in een microscopisch herplanningsmodel. Het uitgebreide microscopische kortkeermodel is in staat om de optimale kortkeeroplossing te berekenen die conflictvrije routes omvat op het niveau van de spoorsecties. Het model berekent de bloktijdtrappen voor elke treindienst en biedt de mogelijkheid om in meerdere stations kort te keren. Om de toepasbaarheid en prestaties van het model te tonen, werden twee casestudies uitgevoerd. In het eerste geval, met twee mogelijke kortkeerroutes voor elk van de twee stations, werd aangetoond dat de optimale oplossing kan verschillen afhankelijk van de opheffing- en vertragingsweegfactoren. Het tweede geval toonde aan dat het model binnen twee minuten de optimale oplossing voor een groter station met vijf treinseries kan berekenen.

In de laatste stap werd een evaluatiekader ontwikkeld om de impact van de storingslengte op de kortkeeroplossing en vervolgens op de passagiers te analyseren,. Het raamwerk bestaat uit drie modellen; een storingsduurmodel met behulp van een Bayesiaans netwerk, het kortkeermodel, en een dynamisch reizigerstoewijzingsmodel met behulp van een meerstapsbenadering voor het laden van reizigers. De interactie tussen de modellen heeft een unieke iteratieve benadering die begint met de voorspelling van de duur van de storing, gevolgd door het berekenen van de optimale kortkeeroplossing gezien de voorspelde lengte, en ten slotte het meten van de gegeneerde reistijd van de passagiers. De gegeneraliseerde reistijd bestaat uit een gewogen som van de tijd in het voertuig, de overstaptijd, het aantal overstappen en het aantal omwegen. Bij elke informatie-update wordt een nieuwe voorspelling gedaan en een nieuwe kortkeeroplossing berekend en ten slotte wordt de algemene reistijd van de passagier opnieuw gemeten. Deze iteraties gaan door tot het einde van de versperring. De uitkomst van het storingsduurmodel is een verdeling van de voorspelde lengte. Om de kortkeeroplossing te berekenen, is het nodig om een specifieke storingslengte uit de berekende verdeling te selecteren. Als de geselecteerde lengte korter of langer is dan de werkelijke lengte wordt de voorspelling aangeduid als respectievelijk een optimistische of pessimistische voorspelling. Uit de uitgevoerde casestudies blijkt dat met de optimistische voorspelling er veel updates in de dienstregeling zullen zijn die ertoe leiden dat passagiers verschillende keren moeten omrijden. Met de pessimistische voorspelling wordt het traject langer geblokkeerd dan noodzakelijk en worden er dus meer passagiers getroffen.

Samengevat demonstreert dit proefschrift dat het meenemen van meerdere kortkeerstations kan resulteren in een betere isolatie van de versperring van de naburige stations met meer opheffingen in het verstoorde gebied, maar minder gepropageerde vertraging naar de rest van het netwerk. Bovendien toonde de toepassing van de ontwikkelde modellen aan dat de versperringsduur een essentile rol speelt bij de optimale oplossing.

About the author

Nadjla Ghaemi was born in Tehran, Iran, in 1985. In 2008, she obtained a bachelor's degree in Industrial Engineering from Tehran Polytechnic University. In the same year, she started her master of Engineering, and Policy Analysis at Delft University of Technology in the faculty of Technology, Policy and Management. After working as a researcher for half a year at the same department, she started her Ph.D. on railway disruption management at the Department of Transport & Planning at Delft University of Technology. The research was funded by the partnership programme ExploRail of technology foundation STW and the Dutch railway infrastructure manager ProRail, project no. 12257: "Smart Information and Decision Support for Railway Operation Control Centres (SmartOCCR)". The research was performed under the supervision of Prof. dr. R.M.P. Goverde and Dr. Oded Cats and in collaboration with the Department of Applied Mathematics.

Her research interests include optimization models and data analysis techniques for improving the performance of complex operations.

Publications

Journal articles

- Ghaemi, N., Cats, O., Goverde, R.M.P., 2017. Railway disruption management challenges and possible solution directions. *Public Transport* 9 (1): 343 –364.
- Ghaemi, N., Goverde, R.M.P., Cats, O., 2018. Macroscopic multiple-station short-turning model in case of complete railway blockages. *Transportation Research Part C: Emerging Technologies*, 89:113 –132.
- Ghaemi, N., Cats, O., Goverde, R.M.P., 2017. A microscopic model for optimal train short-turnings during complete blockages. *Transportation Research Part B: Methodological*, 105:423 –437.
- Ghaemi, N., Zilko, A. A., Yan, F., Kurowicka, D., Cats, O., Goverde, R.M.P., 2018. Impact of Railway Disruption Predictions and Rescheduling on Passenger Delays. Accepted in: *Journal of Rail Transport Planning & Management.*

Peer-reviewed conference contributions

- Ghaemi, N., Goverde, R.M.P., (2014). Review of models for railway disruption management. In *Proc. 6th International Conference on Railway Operations Modelling and Analysis*, Tokyo, March 2015.
- Ghaemi, N., Goverde, R.M.P, Cats, O., (2015). *Optimal rerouting of short-turning trains during track obstructions. In Conference on Advanced Systems in Public Transport (CASPT 2015)*, Rotterdam, July 2015.
- Ghaemi, N., Goverde, R.M.P., Cats, O., (2016). Railway disruption timetable: Short-turnings in case of complete blockage. 2016 *IEEE International Conference on Intelligent Rail Transportation (ICIRT)*, 210 –218.
- Ghaemi, N., Cats, O., Goverde, R.M.P., (2017). Microscopic algorithm for optimally short-turning trains in case of complete blockage. In *Proc. 7th International Conference on Railway Operations Modelling and Analysis*, Lille, April 2017.

TRAIL Thesis Series

The following list contains the most recent dissertations in the TRAIL Thesis Series. For a complete overview of more than 150 titles see the TRAIL website: www.rsTRAIL.nl.

The TRAIL Thesis Series is a series of the Netherlands TRAIL Research School on transport, infrastructure and logistics.

Ghaemi, N., *Short-turning Trains during Full Blockages in Railway Disruption Management*, T2018/4, July 2018, TRAIL Thesis Series, the Netherlands

Gun, van der J.P.T., *Multimodal Transportation Simulation for Emergencies using the Link Transmission Model*, T2018/3, May 2018, TRAIL Thesis Series, the Netherlands

Van Riessen, B., *Optimal Transportation Plans and Portfolios for Synchromodal Container Networks*, T2018/2, March 2018, TRAIL Thesis Series, the Netherlands

Saeedi, H., *Network-Level Analysis of the Market and Performance of Intermodal Freight Transport*, T2018/1, March 2018, TRAIL Thesis Series, the Netherlands

Ypsilantis, P., *The Design, Planning and Execution of Sustainable Intermodal Port-hinterland Transport Networks*, T2017/14, December 2017, TRAIL Thesis Series, the Netherlands

Han, Y, *Fast Model Predictive Control Approaches for Road Traffic Control*, T2017/13, December 2017, TRAIL Thesis Series, the Netherlands

Wang, P., *Train Trajectory Optimization Methods for Energy-Efficient Railway Operations*, T2017/12, December 2017, TRAIL Thesis Series, the Netherlands

Weg, G.S. van de, *Efficient Algorithms for Network-wide Road Traffic Control*, T2017/11, October 2017, TRAIL Thesis Series, the Netherlands

He, D., *Energy Saving for Belt Conveyors by Speed Control*, T2017/10, July 2017, TRAIL Thesis Series, the Netherlands

Bešinović, N., *Integrated Capacity Assessment and Timetabling Models for Dense Railway Networks*, T2017/9, July 2017, TRAIL Thesis Series, the Netherlands

Chen, G., *Surface Wear Reduction of Bulk Solids Handling Equipment Using Bionic Design*, T2017/8, June 2017, TRAIL Thesis Series, the Netherlands

Kurapati, S., *Situation Awareness for Socio Technical Systems: A simulation gaming study in intermodal transport operations*, T2017/7, June 2017, TRAIL Thesis Series, the Netherlands

Jamshidnejad, A., *Efficient Predictive Model-Based and Fuzzy Control for Green Urban Mobility*, T2017/6, June 2017, TRAIL Thesis Series, the Netherlands

Araghi, Y., *Consumer Heterogeneity, Transport and the Environment*, T2017/5, May 2017, TRAIL Thesis Series, the Netherlands

Kasraian Moghaddam, D., *Transport Networks, Land Use and Travel Behaviour: A long term investigation*, T2017/4, May 2017, TRAIL Thesis Series, the Netherlands

Smits, E.-S., *Strategic Network Modelling for Passenger Transport Pricing*, T2017/3, May 2017, TRAIL Thesis Series, the Netherlands

Tasseron, G., *Bottom-Up Information Provision in Urban Parking: An in-depth analysis of impacts on parking dynamics*, T2017/2, March 2017, TRAIL Thesis Series, the Netherlands

Halim, R.A., *Strategic Modeling of Global Container Transport Networks: Exploring the future of port-hinterland and maritime container transport networks*, T2017/1, March 2017, TRAIL Thesis Series, the Netherlands

Olde Keizer, M.C.A., *Condition-Based Maintenance for Complex Systems: Coordinating maintenance and logistics planning for the process industries*, T2016/26, December 2016, TRAIL Thesis Series, the Netherlands

Zheng, H., *Coordination of Waterborn AGVs*, T2016/25, December 2016, TRAIL Thesis Series, the Netherlands

Yuan, K., *Capacity Drop on Freeways: Traffic dynamics, theory and Modeling*, T2016/24, December 2016, TRAIL Thesis Series, the Netherlands

Li, S., *Coordinated Planning of Inland Vessels for Large Seaports*, T2016/23, December 2016, TRAIL Thesis Series, the Netherlands

Berg, M. van den, *The Influence of Herding on Departure Choice in Case of Evacuation: Design and analysis of a serious gaming experimental set-up*, T2016/22, December 2016, TRAIL Thesis Series, the Netherlands

Luo, R., *Multi-Agent Control of urban Transportation Networks and of Hybrid Systems with Limited Information Sharing*, T2016/21, November 2016, TRAIL Thesis Series, the Netherlands

Campanella, M., *Microscopic Modelling of Walking Behavior*, T2016/20, November 2016, TRAIL Thesis Series, the Netherlands

Horst, M. van der, *Coordination in Hinterland Chains: An institutional analysis of port-related transport*, T2016/19, November 2016, TRAIL Thesis Series, the Netherlands

Beukenkamp, W., *Securing Safety: Resilience time as a hidden critical factor*, T2016/18, October 2016, TRAIL Thesis Series, the Netherlands

Mingardo, G., *Articles on Parking Polic*y, T2016/17, October 2016, TRAIL Thesis Series, the Netherlands

Duives, D.C., *Analysis and Modelling of Pedestrian Movement Dynamics at Large-scale Events*, T2016/16, October 2016, TRAIL Thesis Series, the Netherlands

Wan Ahmad, W.N.K., *Contextual Factors of Sustainable Supply Chain Management Practices in the Oil and Gas Industry*, T2016/15, September 2016, TRAIL Thesis Series, the Netherlands