MASTER THESIS

AN OPTIMIZATION MODEL FOR RAIL LINE CROSSOVER LOCATIONS CONSIDERING THE COST OF DELAY

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PREFACE

This document is the final work of my thesis to obtain a Civil Engineering and Management master degree at the University of Twente in Enschede. I am happy to present this document, which is the result of my graduation research which I worked on during the last six months of my student days.

I would like to thank the colleagues of Sweco for their enthusiasm and helpful input for my research. During the first months of my graduation period, it was nice to work with you at the offices in De Bilt and Zwolle, and it was fun to take a walk during the lunch breaks. Unfortunately, during the last months of my graduation period, the offices were closed due to the outbreak of the COVID-19 virus. This made it more difficult to work on my thesis in full concentration, but I want to thank my parents for the opportunity to live there during this difficult time, so that I still had a nice working environment to finish my thesis.

I want to thank Jaap for his time and input to my research. You always came up with ideas to move forward during our meetings, with critical questions and comments and by providing contacts for data sources. I also want to thank Kostas for the comments that scientifically improved the work. Lastly, I would like to thank Eric as well, for his feedback and overseeing role during the feedback moments at the university.

I hope that this research contributes to the use of scientific research at engineering firms. I think this research is a good example of how exact methods from scientific research can be combined with cool rail projects from engineering firms to improve the argumentation of design choices of construction projects.

Willem Trommelen
June 7th, 2020

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SUMMARY

Double track rail lines are often provided with crossovers. A crossover is a pair of two switches, making it possible to ride from the inbound track to the outbound track and vice versa. One of the functions of crossovers is the possibility for alternative schedules during disturbances on the rail line. Rail lines without rerouting options are often split up in two circuits during disruptions. This makes it possible to still use the non-disrupted track part during disruptions. To operate a shortened part of the line, a crossover is needed to turn back to the track in the right direction when turning to the other direction. Turning can be done beyond the last-to-reach station, without passengers. Another option is to turn at the station and change the switch while passengers get off and on. In that case, the tram is guided to the correct track after or before turning. Tram lines often do not have a crossover before and after every station. This means that a large part of the line is often unavailable during disruptions. Sometimes operators do this on purpose, they use buses to connect the stations in case of disruptions. However, this is not a realistic measure in all cases. Sometimes the bus routes are much longer than the rail line. Adding crossovers is a trade-off. Crossovers have high purchase and maintenance cost. Moreover, crossovers break down often, because they are vulnerable railway parts. Therefore, the delay benefits of crossovers are sometimes lower than the delay cost. In recent years, rail managers try to use as little as possible crossovers in their networks. They try to use the crossovers as effective as possible.

Past works studied the trade-off topic of rail infra cost versus passenger impact as well. However, those works were only able to compare a few alternatives, because the degraded schedules had to be assigned manually. They concluded that passenger delay is a fair indicator for rail line performance, for passengers, operators and governments. There are no past works that developed an optimization problem for crossovers. In this thesis, this is done by minimizing passenger delay. The optimization model is set up for the location of crossovers for double track light rail lines. The model is specific for lines without rerouting options via another rail line in the network. The model minimizes the total monetized passenger delay cost, by modelling all possible disruption scenarios on each track segment. A track segment is a track part between two stations, between two crossovers or between a crossover and a stop. For the complete segment yields that the same degraded schedule is the best option. An algorithm is defined to determine the degraded operation schedule for these disruption scenarios. For each origin-destination pair (station to station on the case study line), the travel time during disruptions is calculated. The model also considers walking or another public transport line if that is quicker during the disruption. A set of potential crossover locations is defined, and the delay cost are calculated for all of these potential location combinations. To do this, all disruption scenarios with their probability and average duration are used. Analysis to the maximum potential crossover location set size is done, considering the computer computation time. A case study is used to determine the usability of the model outcome. The case study is a new tram line in Bergen (Norway). This line connects the city centre, a university, a hospital and some suburbs. Using busses in case of disruptions is not a realistic option here, because the tram line traverses two mountains without roads.

The optimal design according to the model is compared to the actual design. This actual design is currently being constructed in Bergen. For each origin-destination pairs (station to station), there is analysed if the effect is positive or negative. The model is also compared to a crossover performance optimization model. This model counts the crossover usage, without taking passenger numbers and delay minutes into account. Key performance indicators from past works are used to compare the designs: crossover performance, delay minutes, connectivity during disruptions and the number of passengers delayed more than 5 minutes. Validation tests are done using random numbers for the disruption probability, average duration and number of passengers between all stations. The best design according to the delay minimization model seems robust according to these tests. In this design, travellers have 10% less delay on average during non-recurrent disruptions than with the real design. However, the assumptions and simplifications of the model could have influence on the delay minutes. They might be slightly higher in practice, because the transition phases and capacity of vehicles are neglected in this study.

SAMENVATTING

Op dubbelspoorse spoorlijnen liggen overloopwissels die onder andere gebruikt worden voor alternatieve dienstregelingen tijdens storingen. Een overloopwissel is een tweetal wissels die het mogelijk maakt om naar het spoor in tegengestelde richting te rijden, of van het spoor in tegengestelde richting naar het reguliere spoor. Voor spoorlijnen waar geen omrijdroutes beschikbaar zijn, wordt in de verstoringsdienstregeling vaak één lijn opgeknipt in twee lijnen. Het niet verstoorde deel van de lijn kan dan toch nog gebruikt worden. Om een ingekort deel van de spoorlijn te gebruiken is een overloopwissel nodig om bij het keren weer op het spoor van de juiste rijrichting uit te komen. Er kan na het station gekeerd worden, zonder passagiers, of op het station. In dat geval wordt het wissel bij het binnenrijden van het station omgezet, zodat bij het wegrijden het andere spoor opgereden wordt. Vooral bij tramlijnen liggen deze overloopwissels niet bij alle haltes, dus is soms een groot deel van de lijn niet beschikbaar tijdens een verstoring. Soms kiest een vervoerder hier bewust voor en worden er bussen ingezet om de stations te verbinden. Dit is alleen niet op elke lijn een realistische oplossing, bijvoorbeeld als er dan erg ver omgereden moet worden. Het plaatsen van een overloopwissel is een compromis vanwege hoge aanschaf- en onderhoudskosten. Bovendien gaat een wissel vaak kapot, dus weegt de extra vertraging door wisselstoringen soms niet op tegen de extra flexibiliteit die het wissel brengt. De laatste jaren worden er daarom zo min mogelijk wissels aangelegd op nieuwe spoorlijnen en de wissels die wel aangelegd worden zo effectief mogelijk gebruikt.

Voorgaande wetenschappelijke werken hebben de afweging van rail-infrakosten versus passagiersimpact ook al bestudeerd. Deze werken konden alleen de passagierskosten van een paar varianten berekenen, omdat de storingsdienstregelingen handmatig gedefinieerd moesten worden voor elke variant. Zij concludeerden dat vertragingsminuten een eerlijke prestatiemeter voor spoorlijnen is, voor passagiers, vervoerders en overheden. Er zijn nog geen wetenschappelijke werken die een optimalisatiemodel voor overloopwissels hebben ontwikkeld. In deze thesis is dit gedaan met een minimalisatiefunctie van vertragingsminuten. Dit optimalisatiemodel is opgesteld voor de locatie van overloopwissels voor dubbelspoorse light raillijnen waarbij niet omgereden kan worden via een andere spoorlijn in het netwerk. In het model worden de totale kosten van vertraging van alle passagiers geminimaliseerd, door de storingen op elk segment te modelleren. Een segment is een stuk rails tussen twee stations, tussen twee wissels of tussen een station en een wissel. Voor het hele segment geldt dat eenzelfde bijstuurscenario het beste is. Er is een algoritme ontworpen die de alternatieve dienstregeling bepaalt. Er wordt voor elk herkomst-bestemmingspaar (station naar station op de casus lijn) berekend wat de reistijd is tijdens de verstoring en of een andere openbaar vervoerslijn of lopen op dat moment sneller is. Voor een set met potentiele overloopwissellocaties worden voor alle overloopwisselcombinaties de totale vertragingskosten berekend. Hierbij worden alle verstoringsscenario's gemodelleerd, met bijbehorende geschatte kans en gemiddelde verstoringsduur. Er is onderzocht tot welk aantal potentiele wissellocaties de computerrekentijd toereikend is. Een casus spoorlijn is gebruikt om de bruikbaarheid van de resultaten van het model te testen. Een nieuwe tramlijn in Bergen (Noorwegen) is hiervoor gebruikt. Hier wordt een nieuwe tramlijn aangelegd van het centrum via een universiteit en een ziekenhuis naar buitengelegen wijken. Storingen opvangen met bussen is hier geen realistische optie, omdat de spoorlijn twee bergen doorkruist waar geen wegen liggen.

Het ontwerp dat volgens het optimalisatiemodel het beste is, wordt vergeleken met het ontwerp waarvan de constructie momenteel gaande is in Bergen. Daarnaast is onderzocht voor welke herkomst-bestemmingsparen het ontwerp niet gunstig is en voor welke wel. Ook wordt het model vergeleken met een optimalisatiefunctie die alleen naar de prestatie van de wissels kijkt en niet naar vertraging en passagiersaantallen. Meerdere indicatoren uit werken uit het verleden zijn gebruikt om de ontwerpen te vergelijken: de wisselprestatie (aantal keren dat de wissels gebruikt worden), vertragingsminuten, connectiviteit van de stations tijdens verstoringen en aantal passagiers met een vertraging groter dan 5 minuten. Validatietests met willekeurige getallen voor de storings-kansen, storingsduur en aantal passagiers tussen elk station zijn gedaan om de robuustheid van de ontwerpen te bekijken. Uit deze tests blijkt dat met het vertragingsminimalisatiemodel een robuuster ontwerp verkregen kan worden dan het werkelijke ontwerp. In dit ontwerp hebben reizigers gemiddeld 10% minder vertraging tijdens grote storingen. Daarbij dient de opmerking gemaakt te worden dat de aannames ervoor zorgen dat de vertraging in werkelijkheid groter is, omdat voertuigcapaciteiten en transitiefases verwaarloost zijn in het model.

An optimization model for rail line crossover locations considering the cost of delay

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Abstract

In this paper, we introduce a method to optimize crossover locations of an independent rail line by minimizing the cost of passenger delay. Recent past works showed that including passenger delay in the decision of rail design choices could be beneficial from an economical and societal perspective. However, those works were only able to evaluate a few alternatives, because the degraded schedules had to be determined manually. In this thesis, a minimization problem is defined to determine the optimal crossover location strategy for independent rail lines. An algorithm is developed to determine alternative operation schedules in case of disruptions. To evaluate a set of crossovers, this algorithm is used to determine the cost of delays for all segments on a rail line with their failure probability and average duration. Mode changes to walking and other Public Transport lines are considered in the model as well. An integer non-linear black box minimization problem is set up to find the best design. The monetized cost of delay is used to analyse the trade-off of flexibility of an extra crossover versus the purchase and scheduled maintenance cost of this crossover. We also show to what extent of set sizes the problem is solvable, and what measures can reduce the number of runs. In this work, the model is specifically tested for light rail lines. a case study light rail line in Bergen (Norway) is used to compare the model result to the actual design. Passenger delay during large disturbances is 10% lower on average in the optimized design compared to the actual design. We compare the designs using Key Performance Indicators: passenger delay, crossover performance, connectivity and passengers delayed more than 5 minutes. Validation scenarios are gained using random input values for the demand, disruption probability and disruption duration, to show that a robust design can be generated with the passenger delay optimization model.

Keywords: crossover location design, minimizing delays, rail line reliability, robust rail network design

1. Introduction

Rail transport is becoming increasingly important in many countries. People use the train more often as an alternative to the car, because the road network faces well known problems like congestion, environmental impact and use of public space (CBS, 2016). Due to this increase in train travelers, more and more trains operate in the same infrastructure. This results in a smaller headway among successive trains and thus unexpected events, such as a switch failure, might impact significantly the rail operations. An unexpected event may affect a lot of passengers. Because of this pressure, rail infrastructure managers strive to minimize the total impact of disruptions. One way to do this is to build the infrastructure as reliable as possible, by placing as low as possible number of risky rail parts like level crossings and switches, and by placing those elements at optimal locations, to ensure enough detour possibilities (ProRail, 2019). Because of the operational pressures, infrastructure design alternatives with an optimal number of crossovers, tracks and level crossings at the optimal location are preferred. There is a trade-off of the costs of an extra crossover and the costs of unreliability. Placing an extra crossover increases the price of a rail line, because of purchase and scheduled maintenance costs. On the other hand, an extra crossover could reduce the unreliability cost of a rail line, because there are more turning nodes or possibilities to move to the track meant for train traffic in the opposite direction. The reliability effects of the extra crossover might also be negative, because the crossover itself might fail as well. Therefore, an extra crossover might have more negative disruption than positive effects. Because of the complexity of the unreliability costs and because these cost are not direct cost for operators or governments, it is not common to calculate the effects of an extra crossover in the design phase of rail projects.

This thesis focuses on the optimization of crossovers on a double-track independent rail line. These simple rail lines do not have possibilities to reroute vehicles via another part of the network. There is only one possibility to operate the line in case of disruptions: splitting the line in two circuits. The best method to split the line depends on the location of crossovers and the location of the disrupted track part. An example of a degraded mode on an independent double track rail line is shown in Figure 1. In this paper, an algorithm is defined to determine these disruption schedules automatically.

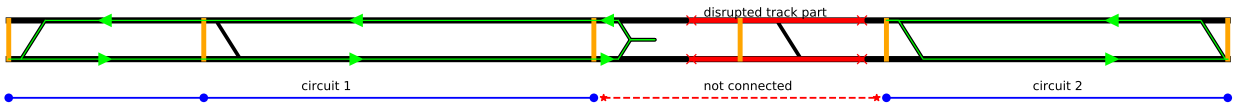


Figure 1: Example of an alternative operation schedule

Depending on the availability of crossovers, a disruption schedule can be defined. The phases of a disruption consists of a transition plan (moving vehicles away from the disrupted track parts), disruption timetable (operating the line as much as possible without the disrupted track part) and another transition phase to move back to the original timetable. This thesis focuses on rail lines that operate under high frequency. The transition phases are small for these lines, because there are a lot of vehicles on all segments of the line. Therefore, it takes not much time to move to the disruption schedule. If the headway on a rail line is for example 30 minutes, a long transition phase is needed to move to the disruption schedule, because the rolling stock is probably not available at the required locations.

Past works have studied the mentioned trade-off of adding network links by modelling the reliability due to disruptions of Public Transport networks. Tahmasseby (2009) considered impacts of stochastic events on Public Transport networks and evaluated the mentioned trade-off by calculating the effect of infrastructure measures such as bypasses to improve public transport network reliability. They provided conclusions about network changes that would be worth the investment and maintenance cost money because of the decrease in reliability cost. They showed that including unreliability costs (monetized passenger delay) might lead to different design strategies. It is not only beneficial from a passenger point of view, but also from an operator point of view. More people use a PT line if it is more reliable, so more ticket income can be generated. Moreover, railway project clients (municipalities or governments) prefer reliable designs, because disruptions could cause road traffic jams and they can overload other PT lines. Yap et al. (2015) considered the importance of robust public transport networks from a full passenger perspective. They modelled exposure from non-recurrent disturbances and the impact of these disturbances. They quantified the societal costs of non-robustness of these vulnerable links, so that the positive and negative effects of an extra link in the network can be considered on those locations. They showed that including passenger delay leads to more fair design alternatives. Those works differ from this thesis, because they did not consider a set of potential network links. They investigated a small set of alternative designs and they used manually generated predefined disruption schedules to calculate the impact for passengers.

The aim of this research is to develop a deterministic model to determine the optimal placement strategy of a number of crossovers. The location of crossovers and the number of crossovers will be optimized by minimizing passenger delay. To do this, an algorithm is developed to determine the best degraded schedule for all disruption scenarios. In this work, the reliability cost of a rail line is defined by the total monetized cost of delay: the difference between actual and scheduled travel time from origin stop to destination stop for all passengers. In an optimal design, the purchase and maintenance cost of a crossover should weigh up to the benefits in unreliability cost in case of disruptions. Multiple performance indicators from past works are used to evaluate the output designs and to compare them to the actual design. A case study to a rail line in Bergen (Norway) is used to determine if considering reliability costs in the Life Cycle Costs of a railway line leads to a more robust design. Four performance indicators are used, and two test with fixed and random input parameters are done to analyze if the design output is robust. This case study line is suitable, because there are no rerouting possibilities via other rail lines in the area. This is beneficial for the complexity and the running time of the model. Moreover, the headway of the original timetable is five minutes, so the transition time to the disruption timetable is small. Therefore, it is assumable to neglect the transition phases. An analyses to the maximum set sizes of the model is done, to determine how large the network can be.

Chapter 2 provides the related past works and describes the contribution of this work. In chapter 3, the methods of the thesis are presented. Chapter 4 is about the relation between the set sizes and the computation time. In chapter 5, the case study results of the thesis are described. A validation study is done in chapter 6. After this, the discussion, conclusion and recommendation of this thesis are provided.

2. Literature

In this chapter, a literature review about optimizing rail infrastructure is performed. Firstly, the current state of art in indicators for disturbance impact on rail networks is given. Secondly, the trade-off of infrastructure cost and flexibility is explained. This clarifies the benefits of including passenger delay in design choices of rail projects. This literature chapter ends with the contribution of this work.

2.1. Modelling disturbance impact on Public Transport networks and the role of crossovers

There are two categories of disturbances in Public Transport networks: *recurrent* or *non-recurrent* events. Recurrent events occur due to normal public transport demand variations, different drivers' behavior, traffic signals, and so on. It is not possible to use crossovers to reduce the delay impacts of these variations. Non-recurrent events happen due to failures of an infrastructure component, failures of operator service, irregular demand fluctuations, bad weather, incidents, road works and public events (Korteweg and Rienstra, 2010; Savelberg and Bakker, 2010). Non-recurrent disturbances reduce infrastructure availability and lead to adjustments in the supplied Public Transport (PT) services. Crossovers might help to reduce the disturbance impact of non-recurrent disruptions, because they facilitate flexibility measures on the rail network. To determine the disruption probability of a rail segment for non-recurrent disruptions, it is important to know the *frequency* of break downs of rail infrastructure components and the *duration* of these disruption events. These two combined is called *exposure* (Cats et al., 2016). The frequency and duration of disruptions is a factor that determines the risk of a railway line. In rail networks, signal, switch and power supply failures are the most critical infrastructural disruption components (Veiseth et al., 2007). However, a lot of disruptions are caused by non-infrastructure related disturbances as suicide, vehicle breakdown and blockages. There are past works that use historical data from a set of disruption events and cluster it to predict disruption probability and duration distributions (Veiseth et al., 2007; Yap, 2014). When a link on a rail network is blocked, an alternative schedule can be used that avoids the disrupted link. The possibilities for an alternative schedule depends on the availability of links in the network. The more switches, the more possibilities for alternative schedules. To do this, operators can use crossovers which are originally constructed to reach maintenance buildings or depots. They can also use crossovers which are originally constructed for splitting or merging two rail lines. However, it is also possible to construct crossovers especially for disruption management. When a disruption occurs, there is a transition phase before a disruption timetable can be operational. Vehicles and drivers have to be moved to certain locations, because the state of the network at the moment of the disruption is not necessarily the state of the invented disruption schedule. The same happens when the disruption is over: a transition phase between the disruption schedule and the regular schedule (Ghaemi et al., 2016). This process of disruption schedules and transition phases is called the bathtub model. 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. (2017) provide a review of rescheduling models for disruptions and conclude that only a few studies considered all three phases. The transition phases are often neglected when the network is simple and the headway is small.

van Loon et al. (2011) investigated that on some lines in The Netherlands the number of passengers became 10% higher because of small reliability improvements. PT operators prefer extra travelers, because then they have more ticket income. Local governments prefer reliable rail lines, because disruptions cause traffic jams crowds on other PT lines. One might wonder why railway designs do not have as much as possible links and nodes, because of their reliability benefits. However, switches are vulnerable railway infrastructure parts. Switches break down often, and the purchase and maintenance cost are high. Therefore, asset managers want as little as possible switches in their networks.

2.2. Modelling the trade-off of infrastructure cost and flexibility

To tackle the mentioned trade-off of crossover flexibility versus cost, scientific research is done to the usefulness of switches in networks. With this information, one could consider to remove a switch or one might choose another location. To determine the crossover cost factor of the mentioned trade-off, asset management studies are often used. However, there is a lot of variation in these cost. The cost depend on many factors, like network design, maintenance frequency, operation schedules and rolling stock properties. Therefore, complex models are needed to calculate these costs. The cost and benefits of the flexibility of crossovers are difficult to calculate as well. The costs could be addressed from a *passenger* point of view (demand-side), or from a *railway manager* point of view (supply-side). Mishra et al. (2012) summarized PT network connectivity indicators. They are supply based, because they only consider network characteristics. An example of a connectivity index is developed by Nieminen (1974). They count the number of direct connections to the node. Another supply-based approach to evaluate the benefit of a crossover is to count the number of times that the crossover is used per year in disruption schedules (Hoeffelman, 2012). They did this for a part of the rail network of The Netherlands. However, the usage of a crossover is not a complete indicator for the performance of a crossover. The beneficial minutes on the degraded schedule for the vehicles are important as well. There are past works that determine the impact of disruptions on infrastructure networks by addressing the reliability of a rail network. Zhang et al. (2018) used a similar method to calculate the contribution of the node to the network connectivity, and hence to the network efficiency to calculate the cost of disruptions by using the repair cost, other disruption cost and lost ticket income. The goal of this work is to derive decisions regarding the most resilient recovery strategy after infrastructure-damaging disruptions. More advanced works calculated the impact of all vehicles in the network (Fischetti et al., 2009; Kroon et al., 2008; Rietveld et al., 2001; Zoeteman, 2001, 2003; Lamper, 2019). Another way to express the impact of disruptions is to calculate the percentage of vehicles' schedule deviations within a certain bandwidth. Using this method, only trains delayed more than x minutes are considered as delayed. This could be monetized by giving a penalty for those trains. When assuming the examined period is homogeneous (for instance rush-hour on working days in a month), the passenger pattern on the line is assumed to be fixed and all passengers are able to board to the first arriving vehicle, the waiting times can be defined as $\frac{1}{2} \cdot headway$ (Osuna and Newell, 1972; van Oort, 2014). Assuming this, delays can be calculated for networks with multiple lines, as Landex and Nielsen (2010) did. They modelled train delays with simulations for a network with four rail lines. They excluded the rerouting choices of the passengers, they all wait until the train rides again. However, the impact of a disruption depends on the rescheduling options for passengers. Moreover, the number of affected passengers is important as well. Therefore, supply-based works are not the fairest way to assess rail lines. There are past works that include passenger-based indicators in their methods to cope with the trade-off of placing a switch. However, they did not consider the number of passengers in the vehicles. Another possible way of addressing the trade of is by summing the impact of disruptions of all passengers (Dewilde et al., 2014; Khademi et al., 2018; Tahmasseby et al., 2008; van Oort, 2014; Zhang et al., 2018; Scott et al., 2006). Summing the impact of all passengers requires more data, but it is a fairer way of addressing the reliability impact. Doing it this way, areas with more travelers have more priority for flexibility measures, which means that the total societal and economical benefits are higher.

A recent railway network reliability study is done by Yap (2014). He addressed the trade-off of crossover flexibility versus crossover cost, by calculating the total delay cost for all passengers. To consider the trade off between purchase/scheduled maintenance costs and the unreliability impact, he compared the unreliability costs to the Life Cycle Costs of a railway project by doing a cost-benefit analysis. His model is able to calculate reliability costs on a multi-model network. His research focuses on the trade-off of extra links and its costs, by finding links with the highest risk, to add a link. The vulnerability of the links is modelled using a Monte Carlo simulation. He provided design suggestions to improve the network, considering the trade-off of extra elements and the costs of it. The objective function included investment costs, reduced comfort costs, costs for non-facilitated demand and cancellation costs. To give a more fair view of the trade-off of reliability cost and purchase/maintenance costs, more advanced factors could be added. Tahmasseby et al. (2008) did this by using an objective function with the following cost factors: travel costs including regular travel time variations, service operation costs, infrastructure investment & maintenance costs, extra travel costs in non-recurrent conditions, trip cancellation cost in non-recurrent conditions, extra operation costs in non-recurrent conditions, extra investment costs for building infrastructure shortcut possibilities for detours. Because of the high number of cost components, the research only evaluated a couple of bypass measures. They calculated the robustness of adding a bypass railway in The Hague, to determine which one is the most beneficial. The complexity of this work would make it hard to use as an optimization model for a set of crossovers. The disruption scenarios are defined manually. The model is too complex to do this using an algorithm. The translation from delay minutes to costs of done by using a Value Of Time value, which is a cost factor for time, calculated by for example Bovy and Hoogendoorn-Lanser (2005) and Warffemius (2013). Value Of Time definitions are different for waiting time, delay, in vehicle time and transfer time. Moreover, the Value Of Time might be different for different transport modes and for urban and non-urban areas (Ramherdi et al., 1997).

Although extensive research has been carried out on performance of rail networks and research has been carried out on considering the trade-off of crossover flexibility and cost comparing a couple of rail project alternatives, no single study exists which includes passenger delay in an optimization problem for crossover location design. Past works showed that including passenger delay in design choices can be beneficial for passengers, operators and railway project clients, and they introduced methods to calculate passenger delay.

2.3. Contribution

Recent past works introduced methods to include passenger delay and comfort in design choice analyses of rail networks (Yap et al., 2015; Tahmasseby et al., 2008). In the past, rail networks were mainly built to the wishes of operators and clients, for example by using network connectivity indicators (Nieminen, 1974) or crossover usage (Hoeffelman, 2012). Yap et al. (2015) and Tahmasseby et al. (2008) both concluded that a cost-benefit analysis of a rail project can be more positive from an economical and societal point of view if passenger factors are included in the consideration. This does not mean that passengers are the only stakeholder that benefit from a more reliable line. The more reliable a PT line is, the more people use the PT line (van Loon et al., 2011). Public transport operators want as little delay as possible as well, they earn more if more people use the PT line. Local authorities also have an interest in a reliable railway line. Disruptions on a rail line can cause traffic jams on roads, because people might use the car in this situation, and a disturbance can also cause other PT lines to become overloaded. Following the conclusions of Yap et al. (2015) and Tahmasseby et al. (2008), passenger delay is used in this paper to create an optimization problem for crossovers for an independent double track rail line. There are no past works that created network optimization problems using passenger-based indicators for rail networks. The minimized and monetized delay cost are compared to the investment and planned maintenance cost of a crossover to address the trade off of crossover flexibility versus the cost and extra break downs of the crossover. To do this, a set of disruptive events and a set of potential crossover locations are set up, and the delay for passengers is calculated for all possible crossover combinations. Past works did determine disruption schedules manually. However, this is not possible for an optimization model, because the number of scenarios is huge. An algorithm is defined to determine the degraded schedule automatically. Mode changes are considered, to see if walking or another public transport mode is quicker during the disruption.

The best design is the design with the lowest sum of delay minutes of all passengers for all disruption events. This is called the Unreliability Cost model (UC model). A case study rail line in Bergen is used to evaluate the model output. The actual design of this line is compared to the UC model. Another design is created by maximizing the usage of the crossovers (Crossover Performance model). For these three designs, experiments with predefined and random input values are done to determine if the UC model generates a robust design. To do this, extra Key Performance Indicators from past works (passengers delayed more than 5 minutes, network connectivity) are used. If a high number of potential crossover locations is set up, the number of scenarios might be very large. Therefore, analysis to the relation between computation time versus the number of potential crossover locations and the number of crossovers in the design is done.

This paper contributes:

- Optimization of crossover locations from a passenger point of view by using passenger delay as a minimization problem to find the best design strategy for a crossover location combination
- Addressing the trade off of the benefits in delay for passengers through flexibility provided by crossovers versus the extra costs and breakdowns of crossovers
- An algorithm to determine degraded schedules for any disruption at any location for an independent double-track rail line
- An analysis to the relation between computation time and set sizes to determine for which set sizes the model is practicable, and possible options to reduce the run time
- Evaluating the robustness of the optimized design by comparing the optimized design and the actual design, using several Key Performance Indicators and random input values

3. Methodology

An optimization problem is defined in this paper. Firstly, the assumptions, input parameters and variables of the problem are given. Thereafter, the formulation to find the optimal design is explained.

3.1. Assumptions and nomenclature

The following assumptions have been used in the modeling part of this work:

(A1) Three time periods on a day with homogeneous demand are considered: morning peak, afternoon peak and the rest of the time;

(A2) Multiple disruptions do not occur at the same time;

(A3) The rail operator will always choose a disruption schedule with two circuits if possible, as done by Neves (2018). (See Figure 4);

(A4) Capacity constraints of all public transport vehicles are neglected, as done by Yap et al. (2015);

(A5) Transition phases from regular schedule to degraded schedule and back to regular schedule are neglected, which is only possible for high-frequency rail lines (a vehicle every 5-10 minutes), because more drivers and vehicles are available on all parts of such lines (Ghaemi et al., 2017);

(A6) The origin and destination of all passengers are one of the case study rail line stations, and they do not cancel their trip or use their car.

Assumption A1 makes sure that the model is not too complex. Disruptions that occur in one time period, do not overlap another time period. All failures are handled in one period. Because this is the case for all periods, this averages each other, so that the result is still realistic. For optimal design outcome, this does probably not have effects. It could have influence on the unreliability cost, if there are a lot of variations in demand over the day or over the year. For one rail line, multiple disruptions at the same time (Assumption A2) is unlikely. If the model is extended to a bigger network, changing this assumption should be considered.

Specifically for a case study, one should be sure if Assumption A3 can be assumed. For example, if vehicles with a driver's cabin at only one side, another degraded scheduling method must be used. Moreover, if operators are allowed to cancel a part of the line during a disruption, even if a circuit is possible, this must be added to the model, because it could be that a crossover is not used in practice, while it is an important crossover according to the model. Assumption A4 could have influence on the unreliability cost, because the delay is much larger if passengers have to wait to a next vehicle if the vehicle is full. It probably has minor effects on the design outcome, because the capacity limit is a problem for all PT services. Therefore, the unreliability cost are probably higher in practice, because the model is optimistic about the delay time. Assumption A5 does not have much influence on the design outcome. However, it has influence on the unreliability cost, because it takes a while before the trams drive according to the degraded schedule. In this transition phase, the delay is probably higher than during the degraded schedule. Due to this assumption, the unreliability cost might be higher in practice. This assumption makes the model only useful for lines with a high operation frequency (a vehicle every 5-10 minutes). It depends on the case study if Assumption A6 has much influence on the unreliability cost. In reality, people might have faster detour options, for example if they live closer to another bus stop. Therefore, the unreliability cost might be lower in practice.

We consider an independent rail line with two tracks, where four crossover types could be added. The crossover types are presented in Figure 2. Figure 3 represents a schematic overview of a fictitious rail line with 5 crossovers, and 5 stations (orange). The black crossovers are necessary for the regular timetable, they can not be removed. The pink crossovers are for disruption timetables. The goal of the model is to find the optimal crossovers from the set of pink crossovers. Between every station and every crossover, a disruption might occur. If possible, an alternative operation schedule can be set up, depending on the location. In Figure 4, an example of a disruption with the degraded schedule is drawn. In this situation, there is a disruption between 1400 and 2100 on the inbound track. The crossovers make it possible to connect all stops by using two circuits. A transfer is needed at the second station.

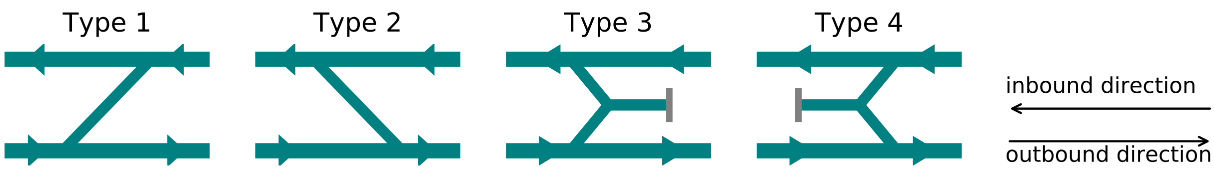


Figure 2: Crossover types (fltr): facing crossover, trailing crossover, tail track (inbound), tail track crossover (outbound)

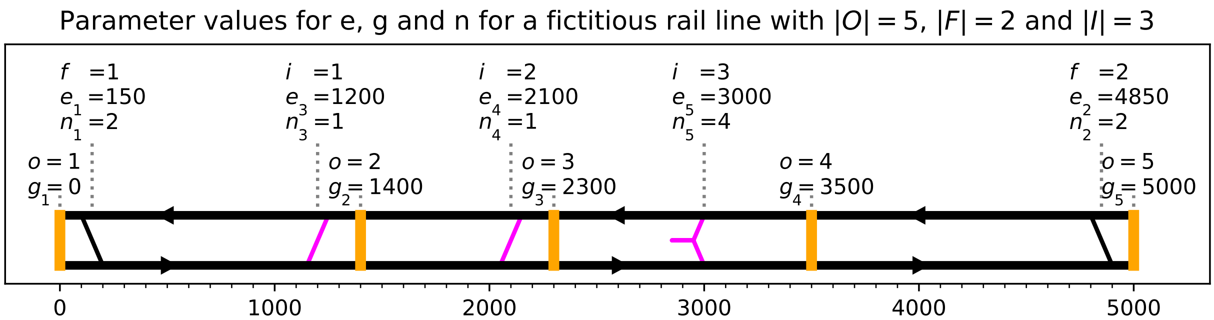


Figure 3: Parameter notation

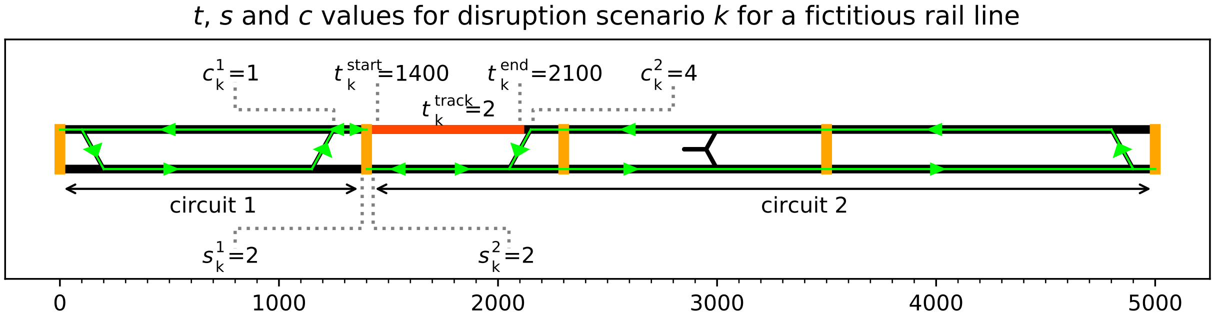


Figure 4: Example of the variables and parameters for the degraded operation mode for disruption scenario k

Before proceeding to the modelling, we introduce the nomenclature.

Nomenclature

Sets

I	set of potential crossovers, $I = \langle 1, ...i, ..., \|I\| \rangle$;
F	set of fixed crossovers, needed to operate the line in normal conditions, $F = \langle 1, ...f, ..., \|F\| \rangle$;
O	set of stations on the rail line, $O = \langle 1, ...o, ..., \|O\| \rangle$;
K	set of disruption scenarios, $K = \langle 1, ...k, ..., \|K\| \rangle$;

Parameters

$\mathbf{t}^{start}$	$\|K\|$-valued array where t_k^{start} is the begin location in meters relative to the begin of the line of disruption scenario k (see Figure 4). t_k^{start} can be a crossover, a station or the boundary of vulnerable infrastructure (e.g. road crossing or tunnel);
$\mathbf{t}^{end}$	$\|K\|$-valued array where t_k^{end} is the end location in meters relative to the begin of the line of disruption scenario k (see Figure 4). t_k^{end} can be a crossover, a station or the boundary of vulnerable infrastructure (e.g. road crossing or tunnel);
$\mathbf{t}^{track}$	$\|K\|$-valued array where t_k^{track} is the disrupted track of disruption scenario k [outbound track=1, inbound track=2, both tracks=3] (see Figure 4);
$\mathbf{Y}^{walk}$	$\|O\| \times \|O\|$ matrix of traveling times where $y_{o,d}^{walk}$ is the travel time by foot from o to d, where $o \in O$ and $d \in O$;
$\mathbf{Y}^{pt,mp}$	$\|O\| \times \|O\|$ matrix of traveling times where $y_{o,d}^{pt,mp}$ is the travel time using public transport other than the case study line during the morning peak from o to d, where $o \in O$ and $d \in O$;
$\mathbf{Y}^{pt,ap}$	$\|O\| \times \|O\|$ matrix of traveling times where $y_{o,d}^{pt,ap}$ is the travel time using public transport other than the case study line during the afternoon peak from o to d, where $o \in O$ and $d \in O$;
$\mathbf{Y}^{pt,re}$	$\|O\| \times \|O\|$ matrix of traveling times where $y_{o,d}^{pt,re}$ is the travel time using public transport other than the case study line outside of peak hours and weekend days from o to d, where $o \in O$ and $d \in O$;
$\mathbf{Y}^{reg}$	$\|O\| \times \|O\|$ matrix of traveling times where $y_{o,d}^{reg}$ is the travel time using the case study line in normal operation from o to d, where $o \in O$ and $d \in O$;
$\mathbf{Y}^{cross}$	$\|O\| \times \|O\| \times (\|F\| + \|I\|)$ matrix where $y_{o,d,i}^{cross}$ is the extra riding time from o to d over the case study rail line when riding over crossover i with a reduced speed, relative to the regular ride time without crossovers;
$\mathbf{B}$	$\|O\| \times (\|F\| + \|I\|)$ matrix where each element $b_{o,i}$ is the ride time from crossover i to station o and back to i. These values are needed to calculate the headway if one track is (partly) used for two directions in the circuit;

r $|K|$-valued vector where each r_k denotes the probability per year of disruption scenario k (minutes);

v $|K|$-valued vector where each v_k of vector **v** denotes the average duration of disruption scenario k (minutes);

J $|O| \times |O|$ matrix of demands per minute on the rail line. Each element $j_{o,d}$ of matrix **J** is the average demand from o to d on the case study rail line, where $o \in O$ and $d \in O$;

n $(|F|+|I|)$-sized vector with crossover type information. Each element n_i denotes the direction and type of the crossover (Figure 2)

$$n_i = \begin{cases} 1, \text{regular crossover; facing position (making it possible to ride to another track)} \\ 2, \text{regular crossover; trailing position (making it possible to merge from two tracks} \\ \quad \text{into one)} \\ 3, \text{tail track crossover; making it possible to move from the outbound to the} \\ \quad \text{inbound direction} \\ 4, \text{tail track crossover; making it possible to move from the inbound to the} \\ \quad \text{outbound direction} \end{cases}$$

e $(|F| + |I|)$-sized vector of crossover locations, where e_i is the distance from the begin of the line to crossover i [meters];

g $|O|$-sized vector of station locations, where g_o is the distance from the begin of the line to station o [meters];

γ number of crossovers that must be applied in the design, $\gamma \in \mathbb{N}$ and $\gamma \leq |I|$;

β value of time associated with passenger delay time [NOK/minute];

h^{base} headway in regular operation schedule [minutes];

μ^{mp} percentage of morning peek hours relative to the total operating hours in a week [%];

μ^{ap} percentage of afternoon peek hours relative to the total operating hours in a week [%];

θ percentage of demand traveling during rush hours relative to the total demand [%];

M large number;

Decision Variables

x $|I|$ vector of the decision variables where each $x_i \in \mathbf{x}$ can take a binary value {0,1} with $x_i = 1$ denoting that the i-th crossover is included in the design;

Variables

$\mathbf{h}^1$ $|K|$-sized array of headway values where h^1_k is the headway in the circuit ahead the disruption during disruption scenario k;

$\mathbf{h}^2$ $|K|$-sized array of headway values where h^2_k is the headway in the circuit beyond the disruption during disruption scenario k;

$\mathbf{c}^1$ $|K|$-sized array where c^1_k is 0 if there is no circuit ahead the disruption possible, or no crossover is needed for disruption schedule scenario k. If a crossover is needed for disruption schedule k ahead the disruption, $c^1_k \in \{F, I\}$ corresponding to the used crossover;

$\mathbf{c}^2$ $|K|$-sized array where c^2_k is 0 if there is no circuit beyond the disruption possible, or no crossover is needed for disruption schedule scenario k. If a crossover is needed for disruption schedule k beyond the disruption, $c^2_k \in \{F, I\}$ corresponding to the used crossover;

$\mathbf{s}^1$ $|K|$-sized array where $s^1_k \in O$ is the last stop that can be reached ahead the disruption, relative to the first stop of the line, in disruption scenario k;

$\mathbf{s}^2$ $|K|$-sized array where $s^2_k \in O$ is the first stop that can be reached beyond the disruption, relative to the last stop of the line, in disruption scenario k;

$\mathbf{a}^1$	$\lvert K\rvert$-sized binary array where $a_k^1 = 1$ if crossover c_k^1 lies beyond s_k^1 in the degraded schedule in disruption scenario k;
$\mathbf{a}^2$	$\lvert K\rvert$-sized binary array where $a_k^2 = 1$ if crossover c_k^2 lies ahead s_k^2 in the degraded schedule in disruption scenario k;
$\mathbf{Y}^{rail}$	$\lvert O\rvert \times \lvert O\rvert \times \lvert K\rvert$ matrix of traveling times where $y_{o,d,k}^{rail}$ is the travel time using the case study rail line from o to d during disruption k, where $o \in O$ and $d \in O$;
$\mathbf{Z}^{mp}$	$\lvert O\rvert \times \lvert O\rvert \times \lvert K\rvert$ matrix of delay minutes where $z_{o,d,k}^{mp}$ is the delay for passengers traveling from o to d during the morning peak in disruption scenario k, by using the quickest transport option: (1) using the (delayed) case study rail line, (2) by foot, or (3) using the quickest alternative public transport mode, or a combination of multiple of the modes, where $o \in O$ and $d \in O$;
$\mathbf{Z}^{ap}$	$\lvert O\rvert \times \lvert O\rvert \times \lvert K\rvert$ matrix of delay minutes where $z_{o,d,k}^{ap}$ is the delay for passengers traveling from o to d during the afternoon peak in disruption scenario k, by using the quickest transport option: (1) using the (delayed) case study rail line, (2) by foot, or (3) using the quickest alternative public transport mode, or a combination of multiple of the modes, where $o \in O$ and $d \in O$;
$\mathbf{Z}^{re}$	$\lvert O\rvert \times \lvert O\rvert \times \lvert K\rvert$ matrix of delay minutes where $z_{o,d,k}^{re}$ is the delay for passengers traveling from o to d outside the peak hours in disruption scenario k, by using the quickest transport option: (1) using the (delayed) case study rail line, (2) by foot, or (3) using the quickest alternative public transport mode, or a combination of multiple of the modes, where $o \in O$ and $d \in O$;

3.2. Parameter values

The degraded schedule for a rail line depends on the location of the disruption. Therefore, the rail line is divided into railway sections. All crossovers and stations are the boundary of a section. The expected disruption frequency ($\mathbf{r}$) and duration ($\mathbf{v}$) are determined using historical data. Past works defined the top disruptive events and probability and duration for non-specific disruptive event types, using Yap et al. (2015); Tahmasseby et al. (2008); Wang et al. (2005). Some disruptive events require case study specific data to determine the probability and duration of the events. In the design phase of rail projects, a RAMS (Reliability - Availability - Maintainability - Safety) study is often made. In a RAMS study, the frequency and duration of disruptive events are usually determined. These numbers are gained from historical data of rail projects in the same area. These reports are made to predict if maintenance, availability and safety requirements from the client will be accomplished. The following disruption events are considered in this thesis:

- Vehicle breakdown
- Power/catenary failures
- Track failure
- Disruptive event on a road crossing
- Switch failure
- Tunnel system failure

The station locations are fixed input parameters, as presented in Figure 3. This fictitious line consists of 5 stops ($|O| = 5$, with station locations g_o). The black crossovers are fixed crossovers, necessary for regular operation ($|F| = 2$). The three pink crossovers might be installed or not ($|I| = 3$), the goal of this paper is to find the optimal combination of these pink crossovers. The location of the crossovers is defined in $\mathbf{e}$. The crossover type (regular crossover in left direction, regular crossover in right direction, tail track in inbound direction, tail track in outbound direction) are defined in $\mathbf{n}$.

The number of travelers per day ($\mathbf{J}$) can be gained from transport models if the rail line is a new to build line. If the line is already existing, historical data can be used. A set of potential crossover locations ($\mathbf{e}$) and $\mathbf{n}$ can be created by placing the different crossover types before and after each stop. For all crossovers, it is necessary to know the headway it would have if single track operation from any stop to this crossover is active. $\mathbf{t}^{start}$, $\mathbf{t}^{end}$ and $\mathbf{t}^{track}$ have to be filled with the begin and end locations for the disruptions k. For disruptions that can occur at any location, the begin and end locations are the begin and end locations of the sections. This is done because within these sections, the same degraded schedule is optimal. The boundaries of these sections are the locations of the stations and the locations of the crossovers. The number of sections on the rail line is therefore $|F|+|O|+\gamma$. On every section, a disruption can happen on the inbound track, outbound track or both tracks. For disruptions for specific locations (e.g. events on a road crossing), the specific location have to be added to t_k^{start} and t_k^{end}. $\mathbf{Y}^{reg}$ can be calculated with the ride time model from (Janssen, 2018), considering a speed limitation of using the crossover to move to the opposite track. This model calculates the travel time for railway lines by simulating the line. The following case study specific input data is required for the ride time model:

1. slope changes along the line [m, slope]
2. location of the stops [m]
3. maximum speed changes along the line [m, speed]
4. location of road crossings [m]
5. location of switches and required crossovers [m]
6. rolling stock information: length [m], maximum power [W], acceleration [N] and deceleration [N]

$\mathbf{y}^{cross}$ is calculated with the ride time model as well, by adding a speed limitation for crossovers. The difference in time between the regular operation and the operation with the crossover speed limitation is the extra time it takes to ride over a crossover. For example, 15 km/h is a regular speed for trams to ride over a 1:6 crossover. This speed limitation is not required if the turnout position of the crossover is in its straight direction, which is the case in normal circumstances. Ride time matrix $\mathbf{B}$ can be filled by calculating the ride time from stop o to crossover i or f and back to o, including the stop time at stations and the terminus time for the driver to move in the other direction. In Figure 5, the ride time calculation example ($b_{3,2}$) is given. In this situation, the headway is limited by the ride time on the single track part from crossover with $i = 2$, to the station with $o = 3$. The tram first leaves the crossover with a limited speed and drives to the station. At the station, passengers are unloaded and loaded again and the driver moves to the driver's cabin at the other side of the tram. Thereafter, the tram rides back at the same track in the opposite direction. The headway that can be scheduled for this degraded mode is limited by time this whole process takes.

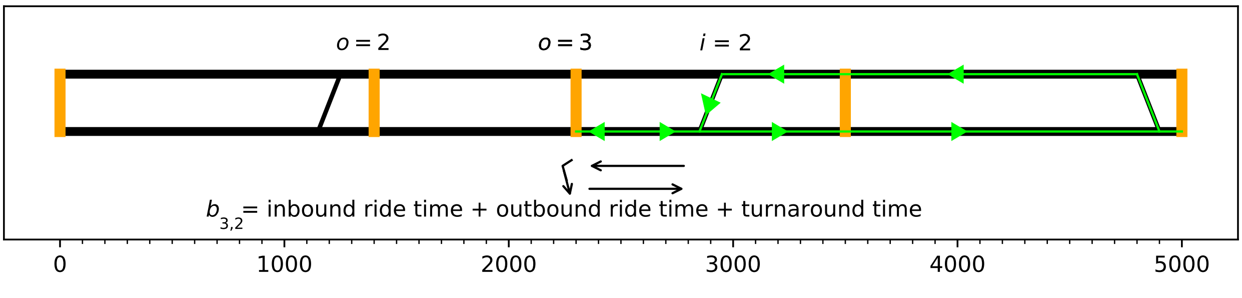


Figure 5: Calculating $b_{3,2}$ for a fiction's rail line. The ride time of the single track part is calculated by the ride time in two directions, plus the turn around time at station $o = 3$ (moving the driver to the other cabin). The values in $\mathbf{b}$ are used to calculate the headway for the disruption schedules.

Sometimes, it is possible to reach more than one station on a single track (Figure 6). In this fictitious situation, the ride time ($b_{2,2}$) can be calculated by adding two times the station stopping time and the regular riding time in two directions to the ride time $b_{3,2}$. The headway that can be scheduled for this degraded mode is limited by time this whole process takes.

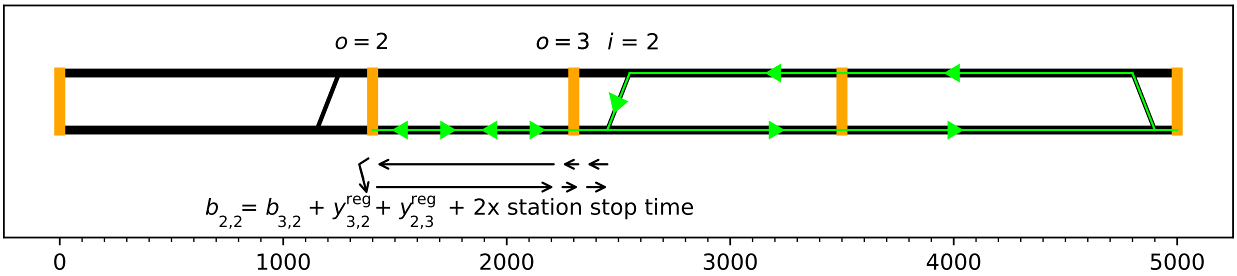


Figure 6: Calculating $b_{2,2}$ for a fiction's rail line. The ride time of the single track part is calculated by the ride time in two directions, the stop time at station $o = 3$ in both directions, plus the turn around time at station $o = 2$ (moving the driver to the other cabin). The values in $\mathbf{b}$ are used to calculate the headway for the disruption schedules.

$\mathbf{Y}^{walk}$, $\mathbf{Y}^{pt,mp}$, $\mathbf{Y}^{pt,ap}$ and $\mathbf{Y}^{pt,re}$ can be gained from transport models in the case study area. In this work, a Google Maps Python plug in is used. This plug in can be used to calculate travel times for public transport and walking for different time periods of the day. The advantage of this plug in is that it can be applied to any rail line in the world. However, the plug in has a disadvantage: it is only possible to calculate the shortest path of Public Transport for the current network. If public transport lines will be cancelled after implementing a new rail line, this has to be changed manually in $\mathbf{Y}^{walk}$, $\mathbf{Y}^{pt,mp}$, $\mathbf{Y}^{pt,ap}$ and $\mathbf{Y}^{pt,re}$. If more advanced network changes must be evaluated, advanced transport models have to be used to get the parameter values $\mathbf{Y}^{walk}$, $\mathbf{Y}^{pt,mp}$, $\mathbf{Y}^{pt,ap}$ and $\mathbf{Y}^{pt,re}$, for example using OmniTRANS. One might choose a fixed value for γ, if the number of crossovers that can be applied in the design is fixed. However, one can use different values for γ if the impact of an extra crossover has to be analyzed. β can be gained from scientific Value Of Time studies, depending on the country of the case study. In this research, three time periods are considered. Morning peaks, afternoon peaks and the rest of the time. The length in hours of the morning (μ^m) and afternoon (μ^a) peak depends on the area. The number of passengers traveling during rush hours is expressed in the percentage of total travelers on the line (θ).

This research focuses on non-recurrent unplanned events. K only consists of unplanned disruption scenarios. Crossovers are also used for track maintenance vehicles and to move rolling stock to garages and yards. However, those crossovers are fixed values in the optimization model, because they must be placed on a certain location. Crossovers might also be used for degraded schedules during planned maintenance works. However, temporary 'California' crossovers can also be used to keep operating the tram or light rail line as much as possible during maintenance works (Figure 7). Two hours are needed to place those switches, so they are not used for unplanned events. Therefore, it is not necessary to optimize the crossover locations for planned maintenance works. California switches are not common for heavy rail.

For each rail line section, both tracks might be blocked during a disturbance, or just one of the two tracks. ($\mathbf{t}^{track}$). A crossover consists of two switches, which both have a failing probability. Therefore, the number of disruption scenarios $|K|$ can be calculated by $3 \cdot (|F| + |O| + \gamma - 1) + 2 \cdot (|F| + \gamma)$ plus the disruptions with a specific location (e.g. tunnels and road crossings), because those disruptions can block more than one section.

3.3. Decision variable values

The decision variables consist of one binary vector $\mathbf{x}$ of length $|I|$. All elements x_i correspond to one potential crossover location in the design. If $x_i = 1$, it means that the i-th crossover is applied in the design, so that the crossover can be used for degraded modes.

Figure 7: California Switch: a temporary crossover for planned maintenance works. (Picture of DigitaleTram.nl (2005))

3.4. Variable values

For each of the disruptions $k \in K$, the degraded schedule has to be determined. A *degraded schedule* is based on operating the line without using the disrupted track section. If the crossover set $\mathbf{x}$ changes, the degraded schedules change as well, because more stops might be reachable. In this research, there is assumed that two disruptions do not occur at the same time, because the probability of this is very small and the number of scenarios would be too much. For a rail line of 9 km with 9 stops, the probability of two disruptions at the same time is very low. The algorithm is based on the degraded schedules defined in Neves (2018). These operation plans are only suitable for rail vehicles with a driver's cabin at both sides, so that turning loops are not necessary to turn in the other direction.

The model is able to determine the degraded schedule for an independent double track line that operates under high frequency. The transition phases are not modelled as they have minor influence for lines with a small headway (Ghaemi et al., 2016). A small headway means that there are a lot of vehicles everywhere on the line. Therefore, the transition times from regular service to degraded schedule and from degraded schedule to regular service can be disregarded (Ghaemi et al., 2017). In this thesis, there is made use of two circuits in the disruption timetables (See Figure 4), unless no circuit is possible on one side of the disruption. In that case, one circuit is used.

In this thesis, four types of crossovers considered, as presented earlier in Figure 2. Type 1 and 2 are regular crossovers, in the two possible directions. These crossovers can only be used to move to the other track (Figure 8). Type one is placed in the *facing* position. At facing points, one line splits into two in the direction of travel. Type 2 is placed in the *trailing* direction. At trailing points, two tracks merge into one in the direction of travel (Liu et al., 2015). Type 3 and 4 are tail track crossovers, which can be used to turn in the other direction or to store a vehicle (Figure 9). Another crossover type is the scissors crossover. This is a double crossover with the functionality of both the trailing as well as the facing crossover. In this research, a scissors crossover is considered as two regular crossovers (one in the trailing position and one in the facing position) at the same location.

In Table 5, the possible turning options for degraded operation schedules are shown. If one of the two track directions is unavailable, the track direction could be alternated to make sure both directions could still be operated. However, because one track has to be used in two directions, the vehicle headway is limited by the ride times. The turning options in Table 5 are the common used for light rail and trams. These turning methods are gained from a Bergen light rail operational concept (Neves, 2018). In theory, there are more advanced degraded schedules possible. For example, using a crossover to move to the track in opposite direction and than use another crossover to go back to the regular track again (Figure 10). However, that method requires a lot of communication between tram drivers and train traffic controllers, because one track is used in two directions, and two switches have to be controlled continuously. Therefore, this option

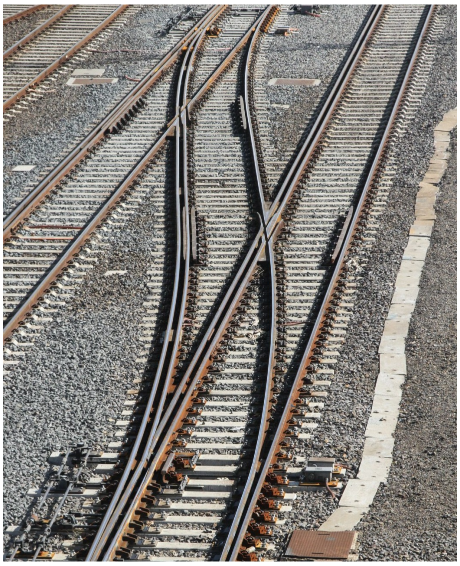


Figure 8: Example of a regular crossover (type 1) - Picture of Wongm's Rail Gallery (WongmsRailGallery, 2014)

Figure 9: Example of a tail track crossover (type 3 or 4) - Picture of Wikimedia (Pi.1415926535, 2018)

is not used in practice, and so not considered in this research. This might be different for metro lines and heavy rail, because they have safety systems to prevent collision between two trains. The minimal headway is larger fur such rail systems. To find the degraded schedule for all disruptions K for a given crossover combination setting $\mathbf{x}$, an algorithm is set up. A flowchart of this algorithm can be find in Appendix A. This flowchart can be followed for light rail lines that do not share lanes with road vehicles. If there are track segments that are integrated in the road network, driving in the opposite direction is not possible on those tracks.

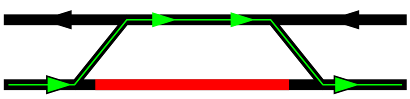
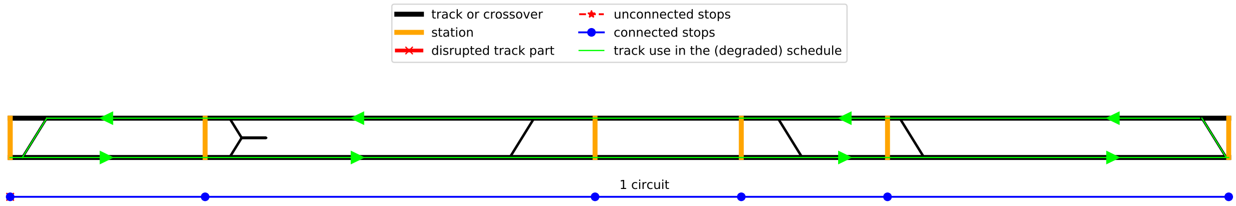


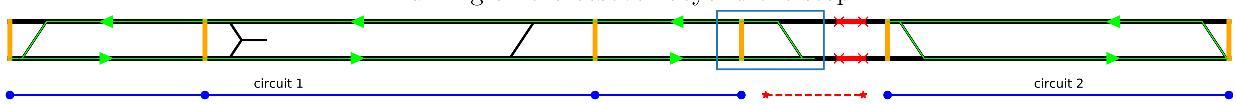
Figure 10: Bypassing a disruption using the wrong-way track

Degraded operation options on an independent rail line

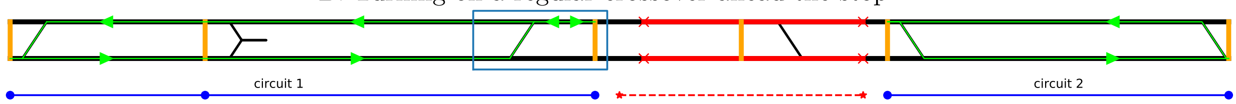
Regular operation and legend



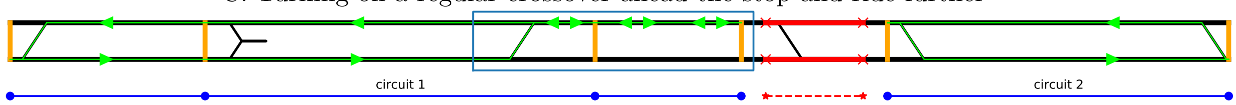
A: Turning on a crossover beyond the stop



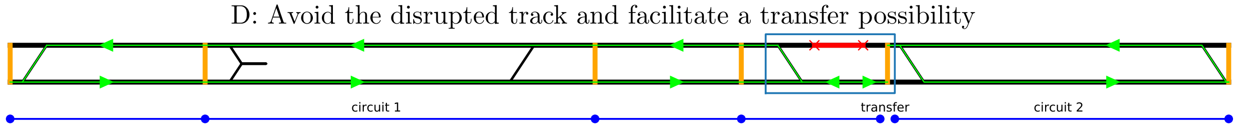
B: Turning on a regular crossover ahead the stop



C: Turning on a regular crossover ahead the stop and ride further



D: Avoid the disrupted track and facilitate a transfer possibility



E: Single track operation between two stations, without using crossovers

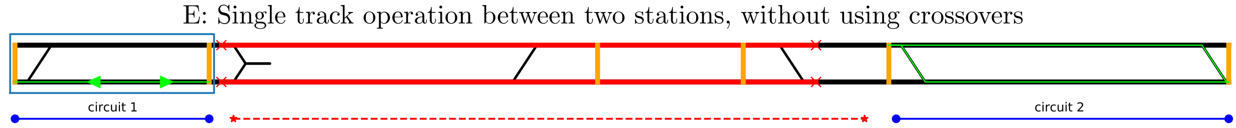


Table 5: Turning options for degraded operation schedules: The different options are visualized for circuit 1. Circuit 2 has the same degraded schedule in all situations.

The algorithm tries to determine the circuit in the sequence of Table 5. Firstly, there is tried to find a route by turning beyond the stop on a tail track or regular crossover (Table 5, situation A). If that is not possible, the algorithm tries to find a crossover ahead the last reachable stop (Table 5, situation B). More than one stops can be reached by riding in two directions on a single track (Table 5, situation C). If only one track is blocked, it is sometimes possible to connect all stops, by facilitating a transfer (Table 5, situation D). If the stops are still not connected, a single track operation service is an option, by using only one of the two tracks (Table 5, situation E). This option has a disadvantage, only one vehicle can be used, because passing is not possible. Therefore, the waiting times for passengers might be high. If the disruption occurs at the beginning or the end of the line, it might happen that only one circuit is used, at one side of the disruption. The output of the algorithm is the information about the two circuits that are the best to use for a disruption: the stations that can be reached (s_k^1 and s_k^2) and the used crossovers (c_k^1 and c_k^2). The vectors for circuit 2 ($\mathbf{s}^2$ and $\mathbf{c}^2$) are calculated the same way as presented in Appendix A, but in the reversed way, because a route as long as possible starting from the end of the line has to be found instead of starting at the begin of the line.

To calculate the waiting time of the passengers during disruption k, the headway for the two circuits are calculated by using Formula 1 and 2.

$$h_k^1 \triangleq \begin{cases} \max(h^{base}, b_{s_k^1,c_k^1}), \text{if } g_{s_k^1} > e_{c_k^1} \\ h^{base}, \text{otherwise} \end{cases} \qquad \forall k \in K \tag{1}$$

$$h_k^2 \triangleq \begin{cases} \max(h^{base}, b_{s_k^2,c_k^2}), \text{if } g_{s_k^2} < e_{c_k^2} \\ h^{base}, \text{otherwise} \end{cases} \qquad \forall k \in K \tag{2}$$

Formula 1 calculates the headway for the first circuit, Formula 2 calculates the headway for the second circuit. If the line is operated using only one circuit, one of the two values is not calculated. In Formulas 1 and 2, the upper condition checks if the degraded schedule uses single track for both directions. This is the case when the crossover is located ahead of the last to reach station (see Figure 4). If so, the headway is limited by the time it takes to ride the single track part in two directions, and time for the driver to move to the other driver's cabin of the tram (see Figure 5 and 6). If the headway is smaller than the regular headway, the value of h_k^1 or h_k^2 is equal to h^{base}, because the regular number of trams per hour will then be used in this degraded schedule. If the degraded schedule does not require single track operation, the second line in Formulas 1 and 2 makes sure that the headway is the regular headway (h^{base}).

The trams have a lower speed limit to ride over a crossover to the other track. In $\mathbf{Y}^{cross}$, the extra ride times from all stops $o \in O$ to any stop $d \in O$ considering the speed limitation over crossover i or f. The speed limitation is only needed for trams in one direction, depending on the crossover type (1 or 2). Same as in the headway calculation, the travel time is not limited if the crossover lies beyond the last-to-reach stop. In that case, the tram is turning in the other direction without passengers. a_k^1 and a_k^2 are binary variables. They are 1 if the crossover is used ahead the last-to-reach stop (with passengers in the tram), and they are 0 if the crossover is used beyond the last-to-reach stop (without passengers in the tram) These conditions are stated in Formula 3 and 4.

$$a_k^1 \triangleq \begin{cases} 1, \text{if } e_{c_k^1} < g_{s_k^1} \\ 0, \text{otherwise} \end{cases} \qquad \forall k \in K \tag{3}$$

$$a_k^2 \triangleq \begin{cases} 1, \text{if } e_{c_k^2} > g_{s_k^2} \\ 0, \text{otherwise} \end{cases} \qquad \forall k \in K \tag{4}$$

The used crossovers (c_k^1 and c_k^2), the stops that are still connected during disruption scenario k (s_k^1 and s_k^2,), the headways on the two circuits (h_k^1 and h_k^2), and the degraded operation binary value ($a_k^1$and a_k^2) are now known. Formula 5 can be used to calculate the travel time using the case study rail line during disruption k.

$$y_{o,d,k}^{rail} \triangleq \begin{cases} M, & \text{if } s_k^1 < s_k^2 \text{ and } (d > s_k^1 \text{ and } o \leq s_k^2) \text{ or } (o > s_k^1 \text{ and } d \leq s_k^2) \\ y_{o,d}^{reg} + a_k^1 \cdot y_{o,d,c_k^1}^{cross} + a_k^2 \cdot y_{o,d,c_k^2}^{cross} + (\frac{1}{2} \cdot h_k^2), & \text{if } s_k^1 = s_k^2 \text{ and } (o < s_k^1 \text{ and } d > s_k^2) \\ y_{o,d}^{reg} + a_k^1 \cdot y_{o,d,c_k^1}^{cross} + a_k^2 \cdot y_{o,d,c_k^2}^{cross} + (\frac{1}{2} \cdot h_k^1), & \text{if } s_k^1 = s_k^2 \text{ and } (o > s_k^2 \text{ and } d < s_k^1) \\ y_{o,d}^{reg} + a_k^1 \cdot y_{o,d,c_k^1}^{cross} + a_k^2 \cdot y_{o,d,c_k^2}^{cross} & \text{, otherwise} \end{cases} \quad \forall o \in O, d \in O, k \in K \tag{5}$$

If two station are disconnected in the degraded schedule for disruption scenario k, the travel time is infinitely high in $y^{rail}_{o,d,k}$ (first line in Equation 5). If a transfer from the first circuit to the second circuit is needed to travel from o to d, (For example as in Figure 4), the condition in the second line in Equation 5 is calculating the travel time: a transfer time of $\frac{1}{2}$ times the headway of the second circuit (h^2_k) is calculated as the average waiting time. If a transfer from the second circuit to the first circuit is needed to travel from o to d, the condition in the third line in Equation 5 is calculating the travel time: a transfer time of $\frac{1}{2}$ times the headway of the first circuit (h^1_k) is calculated as the average waiting time. If a transfer is not needed, and the stops o and d are connected during k, the fourth line in Equation 5 calculates the travel time by using the case study rail line ($y^{rail}_{o,d,k}$). a^1_k or a^2_k determines if the extra time of riding over a crossover is added up to the regular travel time of the tram.

The travel time from o and d by using the case study line might be infinite during k, if stations o and d are unconnected in the degraded schedule. In this case, people might cancel their trip or change their transport mode to car, bike or another public transport mode. Public transport operators have to offer a service, and cannot assume that people have their own car. In this research, there is assumed that people choose to walk, still use the rail line or take another public transport line. There is assumed that all passengers choose the quickest option. For the goals of the model this is acceptable, because the goal of the model is not to calculate travel times as accurate as possible. The goal is to design the infrastructure in a way that the effect for passengers in case of disruptions is as low as possible. For some case study areas, this might not be suitable. If there are no alternative PT routes available, the delay might be very long since the model assumes that all passengers will walk or wait until the disruption is over. For these case studies, bus bridging should be included. Bus bridging is often used during disruptions for rail lines with no alternative PT lines. However, to do this, operators should be asked to know how they use buses in case of disruptions. Algorithm 1 shows the method to calculate the delay for passengers traveling from stop o to stop d during disruption k. There is tried to find shorter route than the travel time in the disrupted schedule, by walking or taking another public transport line. It is also possible to partly use the disrupted line and to do the other part of the route by foot or another public transport line. To do this, the transport time from the origin station o to d is split, by adding a station α between the origin and destination stop. for all possible α (all stations between o and d), there is calculated if making one of the trips by foot or other public transport, and the other trip with the case study rail line is a quicker option then doing the complete trip by foot, public transport or by the disrupted case study line.

Algorithm 1 determine the quickest route from o to d in case of disruption scenario k ($\forall o \in O, d \in O, k \in K$), for crossover set $\mathbf{x}$

input $y^{rail}_{o,d,k}, y^{pt,mp}_{o,d}, y^{pt,ap}_{o,d}, y^{pt,re}_{o,d}, y^{walk}_{o,d}, y^{reg}_{o,d}, v_k, h^1_k, h^2_k$

for all τ **in** (mp, ap, re) **do** ▷ morning peak, afternoon peak, rest
  $z^{\tau}_{o,d,k} \leftarrow \min\Big(y^{rail}_{o,d,k}, y^{pt,\tau}_{o,d}, y^{walk}_{o,d}, y^{reg}_{o,d} + v_k\Big) - y^{reg}_{o,d,k}$
  if $o < d$ **then**
    for all $\alpha \in \langle o+1, o+2, ..., d-1\rangle$ **do**
      if $y^{rail}_{o,\alpha,k} + \min(y^{pt,\tau}_{\alpha,d}, y^{walk}_{\alpha,d}) + \frac{1}{2}h^2_k - y^{reg}_{o,d,k} < z_{o,d,k}$ **then**
        $z^{\tau}_{o,d,k} \leftarrow y^{rail}_{o,\alpha,k} + \min(y^{pt,\tau}_{\alpha,d}, y^{walk}_{\alpha,d}) + \frac{1}{2}h^2_k - y^{reg}_{o,d,k}$
      end if
      if $\min(y^{pt,\tau}_{o,\alpha}, y^{walk}_{o,\alpha}) + y^{rail}_{\alpha,d,k} + \frac{1}{2}h^1_k - y^{reg}_{o,d,k} < z_{o,d,k}$ **then**
        $z^{\tau}_{o,d,k} \leftarrow \min(y^{pt,\tau}_{o,\alpha}, y^{walk}_{o,\alpha}) + y^{rail}_{\alpha,d,k} + \frac{1}{2}h^1_k - y^{reg}_{o,d,k}$
      end if
    end for
  else if $o > d$ **then**
    for all $\alpha \in \langle o-1, o-2, ..., d+1\rangle$ **do**
      if $y^{rail}_{o,\alpha,k} + \min(y^{pt,\tau}_{\alpha,d}, y^{walk}_{\alpha,d}) + \frac{1}{2}h^1_k - y^{reg}_{o,d,k} < z_{o,d,k}$ **then**
        $z^{\tau}_{o,d,k} \leftarrow y^{rail}_{o,\alpha,k} + \min(y^{pt,\tau}_{\alpha,d}, y^{walk}_{\alpha,d}) + \frac{1}{2}h^1_k - y^{reg}_{o,d,k}$
      end if
      if $\min(y^{pt,\tau}_{o,\alpha}, y^{walk}_{o,\alpha}) + y^{rail}_{\alpha,d,k} + \frac{1}{2}h^2_k - y^{reg}_{o,d,k} < z_{o,d,k}$ **then**
        $z^{\tau}_{o,d,k} \leftarrow \min(y^{pt,\tau}_{o,\alpha}, y^{walk}_{o,\alpha}) + y^{rail}_{\alpha,d,k} + \frac{1}{2}h^2_k - y^{reg}_{o,d,k}$
      end if
    end for
  end if
end for
return $z^{mp}_{o,d,k}, z^{ap}_{o,d,k}, z^{re}_{o,d,k}$

3.5. Objective function and mathematical program

The goal of the objective function is to find a crossover combination set that minimizes the total delays of all passengers, for a given number of crossovers that can be used in the design. This yields an objective function (6) that minimizes the monetized delay minutes of all passengers per year. Since Function (6) minimizes passenger delay, the model is called the Unreliability Cost (UC) model.

$$\min \quad \beta \cdot \sum_{k=1}^{|K|} \left[r_k v_k \sum_{o=1}^{|O|} \sum_{d=1}^{|O|} \left(j_{o,d} \cdot \left(\frac{\theta}{2}\mu^{mp} z^{mp}_{o,d,k} + \frac{\theta}{2}\mu^{ap} z^{ap}_{o,d,k} + (1-\theta)(1-\mu^{mp}-\mu^{ap}) z^{re}_{o,d,k} \right) \right) \right] \tag{6}$$

$$\text{s.t.} \quad \sum_{i=1}^{|I|} x_i = \gamma \tag{7}$$

$$x_i \in \{0,1\}, \forall i \in I \tag{8}$$

For a given crossover combination strategy $\mathbf{x}$, the total disruption cost are calculated in the objective function (6). The function is a summation of all disruption scenarios k, and all station-to-station combinations o to d. The Function consists of three factors: morning peek, afternoon peek and the rest of the time, with their corresponding demand and time percentage. The disruption minutes per year ($r_k \cdot v_k$) are multiplied by the delay minutes for the o,d-pair and the average demand per minute. The total delay minutes are multiplied by a Value Of Time factor β. The first constraint controls the total number of crossovers. The second constraint makes sure that a crossover is a binary value: $x_i = 1$ if the i-th crossover is applied in the design, and $x_i = 0$ if the i-th crossover is not applied in the design. Objective Function 6 is an integer non-linear black box function. All combinations of crossovers are independent, so the best setting of $\mathbf{x}$ can only be found by running all possible combinations of $\mathbf{x}$. If γ is fixed, the number of combinations can be determined using Formula 9. This is the standard Formula for *combinations with repetition not allowed.*

$$\text{potential solutions} = \frac{|I|!}{\gamma!(|I| - \gamma)!} \qquad \text{(Arsham, 2015)} \tag{9}$$

The computation time might be high when the value for γ is high. A higher value for γ does not always results in lower disruption costs in Function 6, because the extra crossovers cause disruptions as well. Experiments using different values for γ might be useful to investigate, to see the impact of adding or removing crossovers.

4. Exploration of the solution space and pruning

According to Formula 9, the number of potential solutions increases enormously if the number of crossovers in the design (γ) or the potential crossovers ($|I|$) increase. Therefore, it is useful to know how large the sets can be without the computation time getting too long. The estimated computation time for different set sizes are presented in Figure 11. The running time of an integer non-linear black box function increases enormously compliant to the sizes of the input sets. The running time of the model depends on the number of stops $|O|$ and the number of disruption scenarios $|K|$. However, the number of potential crossover locations $|I|$ and the desired number of crossovers in the design (γ) have the highest influence on the running time. Because of the 'combination-without-repetition' nature, the number of combinations for low and high values of γ, is low compared to $\gamma = \frac{1}{2}|I|$, which has the most combinations. When γ approaches $|I|$, the number of possible combinations becomes smaller. The computation time decreases when the number of combinations is smaller (Formula 9). For example, if one has $|I| = 10$ crossovers to evaluate, and one wants $\gamma = 10$ crossovers in the design, there is only one possibility. Therefore, the line is parabolic. For most purposes, the value of γ is relatively low. The running time is estimated using a computer with a Intel Core i5-6300 CPU @ 2.40 GHz 8.00 GB RAM processor. In this research, a relatively small case study line is chosen, so that the complete set can be evaluated for the low values of γ. Evaluating high values of γ is unnecessary, because the The results of the study can be used to determine how the set of potential crossover locations can be reduced in the future.

In this thesis all scenarios are run, because the line is relatively small. However, the following simple steps can be used to make the model suitable for larger networks:

- *Divide the line into areas and define a maximum number of crossovers per area*

  Consider a rail line with a length of 20 kilometers, with a potential crossover location every kilometer ($|I| = 20$). 3 crossovers are allowed ($\gamma = 3$). It is unnecessary to calculate the combination where all 3 crossovers are placed in the first half of the line. In this situation, the line can be split in two areas of 10 kilometers, with for example a maximum of 2 crossovers per area. The total number of crossover still remains 3. Without the extra constraint, the number of crossover combinations is $\binom{20}{3} = \frac{20!}{3!(20-3)!} = 1140$ (see Formula 9). Adopting this extra constraint, the number of combinations is reduced to 900. If more than two areas are used, the number of combinations is even less.

- *Include the requirements of the operator*

  The operator often has requirements for the design of a rail line. These requirements might make it possible to eliminate a part of the crossover locations. The railway operator might prefer one crossover type, often the crossover in the facing direction. This makes it possible to only evaluate one crossover type. There is a difference between crossover type 1 and 2, but it can never be gigantic. Consider a rail line with 10 potential crossover locations, where at each location two crossover types are evaluated: $|I| = 20$. 3 crossovers are allowed ($\gamma = 3$). The number of combinations to evaluate is then

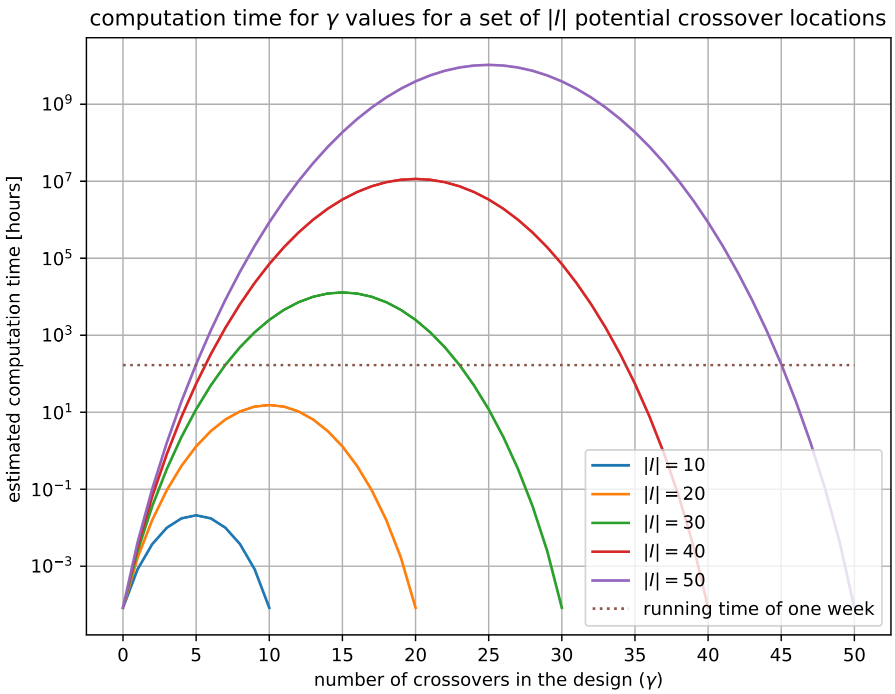


Figure 11: Estimated computational time for different γ and $|I|$ values

$\binom{20}{3} = \frac{20!}{3!(20-3)!} = 1140$ (see Formula 9). If only one crossover type is evaluated at each location, the potential crossover locations is twice as low: $|I| = 20$. In this situation, the number of combinations is: $\binom{10}{3} = \frac{10!}{3!(10-3)!} = 120$.

Overall, the exploration of the solution space experiments indicate that the model has limitations in set sizes, these will be reached quickly if the network is enlarged, because of the high number of combinations. However, the set sizes can be decreased very easily by applying the proposed methods, so that a larger network can be evaluated as well.

5. Numerical case study experiments

The UC model is set up to optimize crossover locations for double track rail lines. The model is tested for a light rail line in Bergen (Norway). This line is suitable as a case study for our model because:

- This line is independent from other lines, detours via other lines are not possible
- The headway is 5 minutes. Therefore, the transition phases can be neglected

5.1. Case study area and input data

The case study line is shown in Figure 12. This paper considers the line from Kaigaten to Fyllingsdalen (Turquoise), and consists of 9 stops. The construction of this line started recently. The line does not exist yet. The red line is another tram line that is already in use. The dark blue line is planned for the future, there are no implementation plans for this line yet. The following information is needed to define the parameters for the model:

1. Rail line design properties: slope, railway components, stop locations, speed, schedule, crossings, crossovers, switches

2. Average origin and destination passenger numbers of all stations on the line, and the percentage of the trips that is made during rush hours
3. Morning and afternoon rush hour times
4. Alternative mode travel times, for walking and PT modes other than the case study line
5. Rolling stock properties (acceleration, deceleration, length, maximum speed)
6. Expected disruption frequency and duration for the main disruptive event classes
7. The Value Of Time in the case study area

Figure 12: Bergen light rail line design

Slope, station locations and maximum speed information is gained from the design reports of the line, made by Sweco (2019). The location of crossings, switches and crossovers are gained from these documents as well. The demand matrix **J** is gained from Mortensen (2017). They calculated the expected number of passengers using transport models. In this document, the expected percentage of demand traveling during rush hours is $\theta = 60\%$. The new rail line will be operated 19 hours per day. The morning rush hour is from 07:00 AM until 09:00 AM, 5 days per week, and the afternoon rush hour is usually from 3:00 PM until 6:00 PM, 5 days per week. Therefore, $\mu^{mp} = 7.5\%$ and $\mu^{ap} = 11.3\%$.

The travel times for the alternative public transport lines are calculated with a Google Maps Python plugin. $\mathbf{y}^{pt,mp}$ is defined at 8:00 AM, $\mathbf{y}^{pt,ap}$ is defined at 4:30 PM, and $\mathbf{y}^{pt,re}$ at noon. Two bus lines will be abolished when the new tram line is finished: line 3 and line 9 between Kronstad and Bergen Sentrum (Mortensen, 2017). The travel times between Kronstad and Mollendal are adjusted manually in $\mathbf{y}^{pt,mp}$, $\mathbf{y}^{pt,ap}$ and $\mathbf{y}^{pt,re}$. The travel time from Haukeland Sykehus to the Kronstad and the city center stays the same, because bus line 2 is still being operated in the new schedule. Moreover, the new tram line facilitates pedestrian tunnels as well, in the Fyllingsdalen tunnel as well as the Haukeland tunnel. The travel times in $\mathbf{y}^{walk}$ are manually changed.

The frequency and duration of disruptions are gained from the RAMS study of the project. This RAMS study uses values from the existing line in Bergen and a light rail line in Oslo. From this document, switch, tunnel, power and road crossing failure probabilities are gained. For vehicle breakdowns, the values from Yap (2014) are used. There is one type of rolling stock ordered for this line: 38 Variobahn seven-car (42 m) vehicles from Stadler. The length, acceleration and deceleration properties of this rolling stock type are used.

Schematically, the line looks like Figure 13. For both directions, one track is designed. Those two tracks are horizontally drawn in black. For the first and last stop, a crossover is needed to turn in the other direction (location 70, 300 and 8800). Therefore, these crossovers cannot be left out the design. Moreover, a crossover is needed at Kronstad (at location 3700 m) to make it possible to move rolling stock to the maintenance building. The rail line splits at 700 metes. At this point, the line to Flesland branches off from the line (see Figure 12). Therefore, there is not considered to remove the crossover at 700 meter, because this has impact on the other rail line as well. In this case study, the crossovers between Lungegardskaien and Fyllingsdalen are optimized. This is a new to build rail line. The delay minimization model can be determined to define the optimal crossover strategy for this part of the line. The designers decided to add extra crossovers to use in case of disruptions. These crossovers are drawn in pink in Figure 13. However, the crossovers drawn in black can be used for degraded operation modes as well.

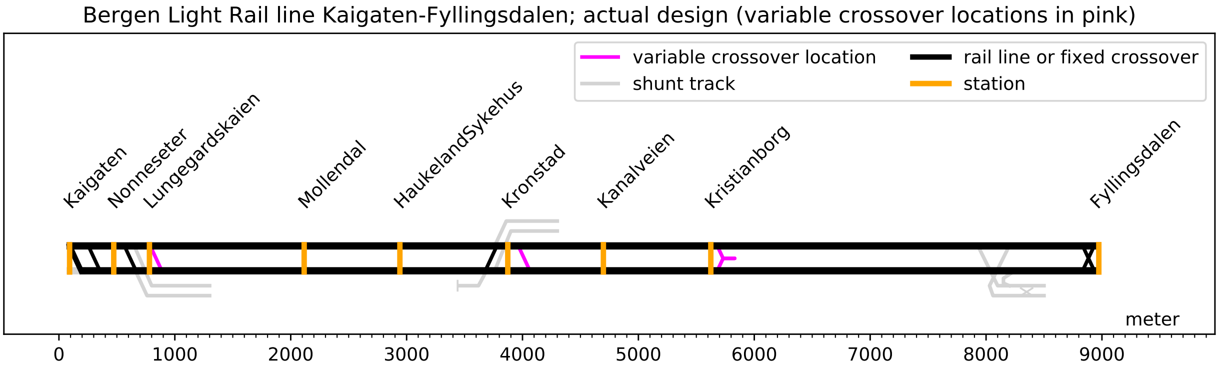


Figure 13: Bergen light rail line actual design

In existing light rail lines, crossovers are mostly placed ahead and beyond stations. When the operational strategy in case of disruptions is to split the line in two circuits, it makes sense to place crossovers ahead and beyond stations, because those crossovers make it possible to turn in the other direction when the station has been reached. The single track ride time matrix $\mathbf{B}$ can be filled by simulating the acceleration and deceleration of the rolling stock over the line, using the simulation model of Janssen (2018). Matrix $\mathbf{Y}^{cross}$ can be filled with this information as well. All 20 potential locations are drawn in pink in Figure 14. The crossovers look like diamond crossovers, but they are considered as two regular crossovers (in the two possible directions: facing and trailing) at the same location.

The actual design has three crossovers extra than the necessary crossovers to operate the line in regular circumstances ($\gamma = 3$). Two of them are regular crossovers (type 2), but one of the crossovers is a tail track crossover (type 3). Tail tracks are not considered in the optimization process, because regular crossovers do have the same functionality for turning. Tail tracks do have the extra functionality to shunt rolling stock. However, the optimization model does not include this. There can be decided to extend a regular crossover with a tail track. A tail track between the inbound and outbound track is not preferred, because using the crossover for turning is only possible at one of the two sides. However, the current design uses a tail track between the inbound and outbound track (Figure 13, 5600 m). This is probably done because it was

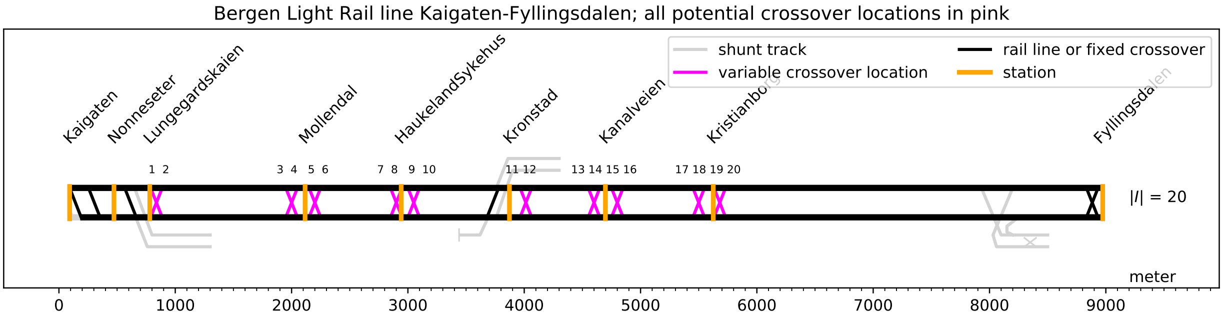


Figure 14: The line with potential crossover locations beyond and above stations; with crossovers in the two possible directions

easier to implement than a crossover at the (as done at 3600 m). However, the optimization model in this thesis does not consider the difficulties of fitting crossovers in the construction space. The advantage of a tail track crossover is that it can be used to shunt a (broken) vehicle. Tail tracks are not considered in the UC optimization model. In the UC model, regular crossovers have the same functionality as tail track crossovers, because only the turning purposes of crossovers are considered. Regular crossovers can be used for vehicles in two directions, so they have more possibilities for turning (Figure 15). There is an advantage of a tail track crossover compared to a regular crossover with a side track. A tail track crossover is better for turning, because the tram does not have to cross the wrong-way track to move to the shunting track. For the passengers there is no difference, because turning the tram is done without passengers. Therefore, it is not needed to evaluate tail tracks in the UC model, because they will in all circumstances perform worse than regular crossovers in the model.

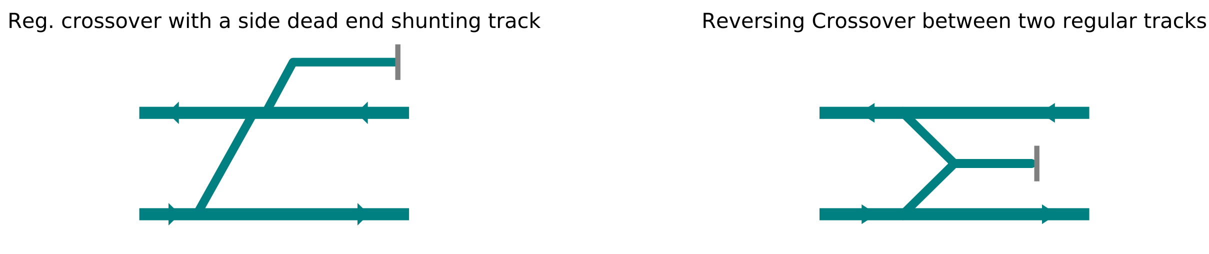


Figure 15: Regular crossover with a side shunting dead end track compared to a reversing tail track crossover

The Value Of Time (β) is gained from a study on behalf of the ministry of transport (Ramherdi et al., 1997). For delay, the Value Of Time is mostly assumed to be the same for business and non-business passengers (122 NOK). Therefore, there is no distinguish made between business and non-business passengers. Corrected for inflation between 1997 and 2020 Trading-Economics (2020), which is 59%, the Value Of Time for delay is 194 Norwegian Krones ($\pm$ 20 EUR). This means that the societal cost for one hour delay for one passenger are 194 Krones for a rail line in Norway. The disruption list is created using a Reliability-Availability-Maintainability-Safety (RAMS) study (Isaksen, 2019; Musæus, 2019a,b,c). Vehicle breakdowns are not included in these documents, so these values are gained from Yap et al. (2015).

With these data sources, the UC model can be executed. The model is verified by calculating some of the disruption scenarios manually. The model plots the disruption schedules and shows the disruption cost of that scenario. The output of some random and some complicated scenarios are checked manually.

5.2. Optimal crossover location strategy

The optimal crossover combination strategy according to the UC (Unreliability Cost) model is provided in Figure 16. This design is gained by minimizing objective Function 6. The running time for the different γ

values are provided in Table 6. The cost for passengers for the optimal crossover location combination for different values of γ are determined and plotted in red. The disruption cost for the actual project design are calculated as well, and is plotted in green. With the same number of crossovers in the design, the UC design performs 9.8% better than the actual design. There are three crossovers used in the actual design. The difference between zero, one and two crossovers is large (resp. 14% and 16%). Adding a few more crossovers leads to lower disruption cost, but the benefit of adding a third, fourth or fifth crossover is much lower (2%). Adding much more crossovers even results in higher unreliability cost, because the extra crossovers break down as well. The effect of the extra breakdowns is apparently higher than the benefits in functionality for degraded modes.

An important influencing parameter on the shape of Figure 16 is the breakdown frequency of the crossovers. If the extra crossovers fail a lot more than expected, the Figure would look more like a bath tube. The unreliability cost would be much higher for high γ values, because these designs have more crossovers with a failure probability. The optimal locations for crossovers for $0 \leq \gamma \leq 7$ according to the UC model can be found in Figure 17.

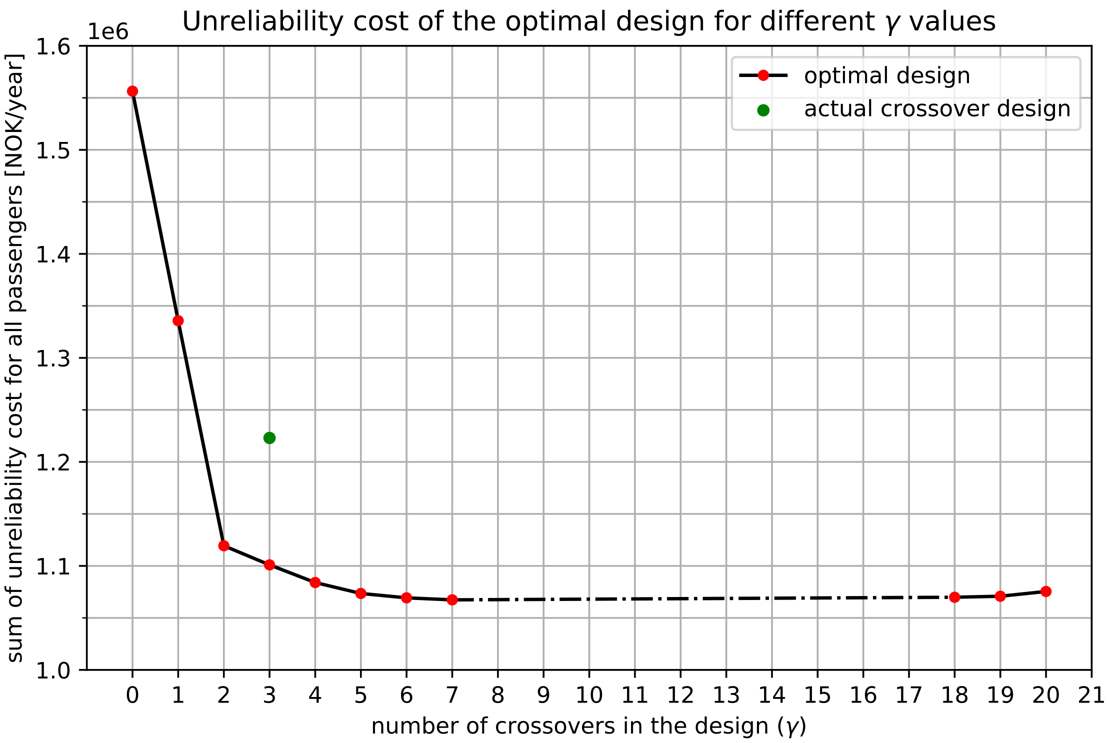


Figure 16: Passenger delay cost of the actual design (green dot) and passenger delay cost of the optimal crossover combination according to the UC model for different values of γ (red dots)

These results suggest that the UC model is able to find a better design than the actual design. In the next sections, we investigate how the unreliability cost behave in relation to the investment and maintenance cost.

Nr. of Crossovers γ	Unrelability Cost *NO Krones/year*	Running Time *minutes*
0	1556370	0.02
1	1335731	0.31
2	1119358	3.50
3	1100983	22.38
4	1084011	99.58
5	1073484	328.15
6	1069287	844.88
7	1067345	1706.75
18	1069854	6.12
19	1070835	0.68
20	1075417	0.33

Table 6: UC model outcome for different γ and running time

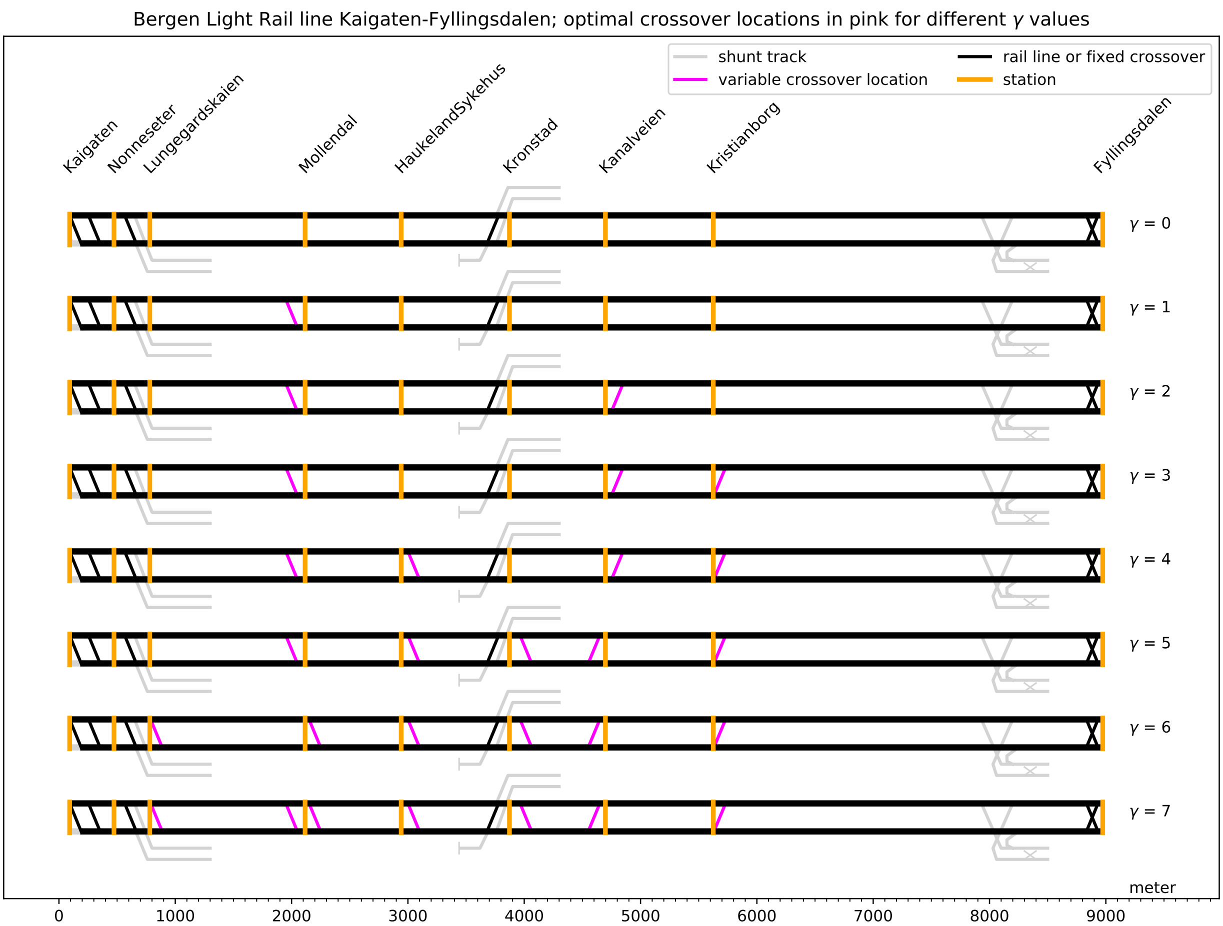


Figure 17: Optimal crossover location design strategy for different values of γ according to the UC minimization model

5.3. Investment strategy

The UC model optimizes the location for a given number of crossovers. Another aim of this study is to determine how many crossovers have to be placed in an optimal design. Extra crossovers leads to higher project investment cost and higher annual planned maintenance cost. Therefore, the financial reliability benefits of an extra crossover should weigh up to the cost of the crossover. To do this, the lifespan, purchase cost and scheduled maintenance cost of a crossover must be known. The economical lifespan is determined by the number of vehicles driving on the tracks and the weight of the vehicles. If the tracks are used by freight trains, the lifespan is often shorter than tracks for passenger transport only. In Table 7, the crossover purchase price, lifespan and maintenance cost are gained from Baumgartner (2001). The prices are corrected for inflation in Norway, which is 50% between 2000 and 2020 (Trading-Economics, 2020). The values used to calculate the economical lifespan, purchase cost and maintenance cost of a crossover on a high-frequency light rail line are given in Table 7. The range of crossover economical lifespan varies, depending on the maintenance strategy. The economical purchase cost varies a lot, for example because of variation in the extra components needed for the safety system and the cost for subsurface works. Maintenance cost are often expressed in percentage of purchase cost. The cost values are the prices for a new to built line. For crossovers added to existing lines, the prices might be higher. Consultancy work and contractor startup cost have to be added, existing rails have to be removed, existing foundations might have to be changed and control wires have to be added.

			extreme values	
	unit	**average**	**min**	**max**
Purchase cost	Norwegian Krones	$1.6 \cdot 10^6$	$1.3 \cdot 10^6$	$2.6 \cdot 10^6$
Maintenance cost	% of purchase cost	10	5	15
Lifespan	years	13	8	20

Table 7: Crossover LCC information: lifespan, purchase and maintenance cost, from Mubeka (2013) and Baumgartner (2001)

To determine if it is beneficial to add a crossover, the crossover Life Cycle Cost are compared to the monetized delay cost (unreliability cost). To do a fair comparison, the unreliability cost must be calculated for the total life span of the crossover, to include it in the Life Cycle Cost of a crossover. In Figure 18, the Life Cycle Cost of the variable crossovers are drawn for different values of γ. For example, the Life Cycle Cost for the value of $\gamma = 4$ on the black line is a summation of the average purchase and maintenance cost per year of the four crossovers over the total life span of the crossovers. The dotted lines are the upper and lower limits of the Life Cycle Cost of the crossovers. There is a lot of variation in the Life Cycle Cost, mainly because of the location of the crossover and because of construction circumstances. A complex location can make a crossover very expensive, and the weather and the use of the crossover determines the variation in maintenance cost. There is not worked with inflation or interest over the lifespan of the crossover in these calculations, because there is assumed that they cancel each other out. In reality, the Life Cycle Cost are more complex, because the maintenance cost per year are not a constant number per year. The cost of the unreliability (delay) cost per year for all passengers, for the best design according to the UC model, is drawn in the figure as well in red. The values are relative to the situation without crossovers. For example, if the total delay cost for all passengers per year without crossovers is 1.56 million, the total delay cost for all passengers per year with two crossovers is 1.10 million, the value at $\gamma = 2$ is 1.56-1.10=0.46 million. In this way, we can see if the monetized delay benefit for an extra crossover is as much as the investment cost of the crossover. If the red value lies under the black value for a certain γ value, it means that the cost of γ crossovers is not worth the money. If the red value lies above the black value for a certain γ value, it means that the monetized flexibility benefits of γ crossovers are higher than the crossover cost.

From Figure 18, one can note that the monetized delay benefit for one or two crossovers is comparable to the LCC cost of the crossover. However, they are slightly lower than the average crossover price. The monetized delay benefit for a third, fourth or fifth crossover is very low compared to the first and second crossover. When the red line lies below the gray area, it means that even when the crossover LCC are very low, the delay benefit of a fourth or fifth crossover are lower than the crossover cost. Because of the high variation of the crossover price, it cannot be said exactly to what extent one, two or three disruption crossovers are worth the investment. However, there can be concluded that more than three disruption crossovers are not worth the money. Location-specific research is needed for every possible crossover location to say more about the optimal number of crossovers.

Clients of rail line construction projects could decide to add different weights to the crossover cost and the reliability cost. The crossover cost are for the operator or the maintenance contractor, while the unreliability cost are for the passengers. A government may consider the purchase and maintenance cost of a crossover to be more important than the cost of delay, or vice versa. Because the costs are not paid by the same party, there are different interests. This makes it a political consideration to add weights to the comparison of crossover Life Cycle Cost and unreliability cost. However, because both cost factors are translated in the same currency, the trade-off can be viewed from a societal point of view in this way.

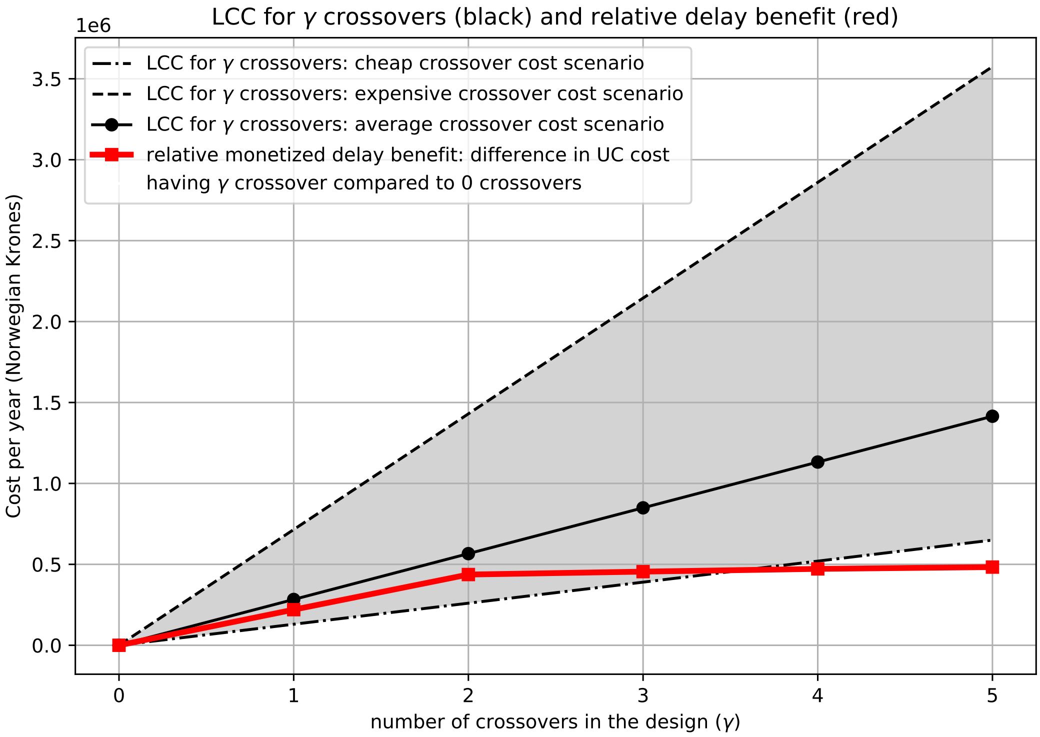


Figure 18: LCC cost for γ crossovers relative to the delay benefits. Black: LCC cost (purchase and scheduled maintenance cost) of γ crossovers: a cheap, expensive and average crossover cost scenario is drawn. Red: Passenger delay benefit of γ crossovers relative to 0 crossovers. The optimal design with γ crossovers according to the UC model is used.

5.4. Benefit/loss analysis per o, d-pair

The UC model uses the delay of all passengers to determine the performance of a design strategy. However, this does not mean that this design is the best design choice for all passengers. For some origin-destination pairs, the average delay might be higher. In Table 8, the percentage of relative delay minutes for the optimal design according to optimization function 6 (with $\gamma = 3$, Figure 17) relatively to the actual design (Figure 13) is provided for all origin to destination stations. A value of -1.00 means that the average delay for passengers traveling from station o to station d is 1.00% lower compared to the actual design. If the value is positive, it means that the actual design is better than the UC design for passengers traveling between those stations. In the optimal design according to the UC model, the average delay is higher for passengers traveling from Haukeland Sykehus to Kronstad and Kanalveien in both directions. In the actual design, a crossover is included between Kronstad and Kanalveien. In the optimal design, there is no crossover between those stations. Therefore, there are less turning possibilities there, so the average delay during disruptions is higher. The biggest delay benefit in the optimal design is for travelers between the city center (Kaigaten, Nonneseter, Lungegårdskaien) and the hospital (Haukeland Sykehus). Those passengers have on average between 20% and 40% less delay during non-recurrent disruptions. The reason for this benefit is the crossover between Møllendal and Lungegårdskaien. This crossover creates more options to reach the hospital in case of a disruption in the tunnel area. For passengers traveling from Kaigaten, Nonneseter and Lungegårdskaien to Kronstad and vice versa, an alternative tram line is available. Therefore, the delay is low, even when no service is possible.

origin	*destination*								
	Kaigaten	Nonneseter	Lungegårdskaien	Møllendal	Haukeland Sykehus	Kronstad	Kanalveien	Kristianborg	Fyllingsdalen
Kaigaten		0.00%	0.00%	-2.96%	-26.40%	-6.03%	-5.30%	-7.66%	-3.32%
Nonneseter	0.00%		0.00%	-4.58%	-27.32%	-1.90%	-3.17%	-8.83%	-4.48%
Lungegårdsk.	0.23%	0.46%		-17.24%	-35.59%	-6.07%	-9.16%	-10.97%	-5.98%
Møllendal	0.56%	-0.41%	-12.03%		-37.96%	-17.05%	-11.34%	-10.89%	-9.81%
Haukel. S.	-22.25%	-24.27%	-32.52%	-37.96%		6.78%	5.30%	-8.66%	-8.49%
Kronstad	0.04%	-0.25%	-3.14%	-14.31%	7.19%		-3.07%	-20.69%	-8.09%
Kanalveien	-2.05%	-2.58%	-5.52%	-7.58%	4.03%	-7.85%		-34.89%	-10.27%
Kristianborg	-1.38%	-3.57%	-2.81%	-8.80%	-7.14%	-18.95%	-36.12%		0.15%
Fyllingsdalen	-2.72%	-6.72%	-6.68%	-8.01%	-6.97%	-7.22%	-10.19%	-0.00%	

Table 8: Percentage of delay time loss (positive values) or benefit (negative values) for the optimal design according to the UC model (Figure 17, $\gamma = 3$) relative to the actual design (Figure 13)

Taken together, these results suggest that the design created by the UC model performs well compared to the actual design, for most o, d-pairs. The next section moves on to the validation, to perform tests with variable input parameters.

6. Validation

The unreliability cost model minimizes passenger delay. However, this indicator is based on a passenger point of view (demand). The railway operator and local authorities want a reliable line as well, but they often use other indicators for the performance of a rail line. Moreover, delay is not the only indicator for the performance from a passenger point of view. There are several indicators to determine the performance of a public transport line. To compare different crossover location strategies, a selection of indicators from past works are used. Firstly, another optimization model is introduced: the Crossover Performance model. Thereafter, experiments are done to check if the UC design performs better than the actual design and the Crossover Performance model when different random and fixed input values are used.

6.1. Crossover performance minimization problem

The Crossover Performance (CP) model is used to generate a design to compare to the UC model design. The Crossover Performance method is developed by Hoeffelman (2012). In this work, historical data about the number of times that a crossover is used for disruption schedules is summed. The number of times that the crossover was used determines performance of the crossover. However, for future rail lines, expectations have to be used to determine the crossover usage. The UC model sums the total delay of all passengers, while the CP model sums the crossover usages. Therefore, the main difference between the models is that the UC model is passenger based, and the CP model is network based. The advantage of the CP model is that passenger demand numbers, Value Of Time values and travel times for other transport modes are not required. However, the UC model has a fairer optimization aim, because rerouting a tram does not indicate how beneficial it is for passengers. Hoeffelman (2012) did not consider it as an optimization problem, but the method of counting crossover usage can be considered as a optimization problem when rewriting it as done in Formula 12. To count the expected crossover usage for a given crossover setting $\mathbf{x}$, we introduce the binary arrays δ^1 and δ^2 with length $|K|$:

$$\delta_k^1 \triangleq \begin{cases} 1, \text{ if a crossover is used for the circuit ahead the disrupted rail segment} \\ \quad \text{in degraded schedule for disruption } k \\ 0, \text{ otherwise} \end{cases} \qquad \forall k \in K \tag{10}$$

$$\delta_k^2 \triangleq \begin{cases} 1, \text{ if a crossover is used for the circuit beyond the disrupted rail segment} \\ \quad \text{in degraded schedule for disruption } k \\ 0, \text{ otherwise} \end{cases} \qquad \forall k \in K \tag{11}$$

If the degraded operation mode uses a circuit ahead the disruption for disruption k, and a crossover is needed for this degraded schedule, variable δ_k^1 is 1. If there is a circuit beyond the disruption for disruption k, and a crossover is needed for this degraded schedule, variable δ_k^2 is 1. The expected number of rail vehicles using the crossover depends on the expected frequency and duration for disruption k, which is calculated by the expected frequency per year times the average disruption duration $(r_k \cdot v_k)$. The number of minutes of disruption can be divided by the headway of the circuit ahead (h_k^1) and beyond (h_k^2) the disruption to determine the how many vehicles are using the crossover during k. Doing this for all $k \in K$, the total expected crossover usage of the complete rail line can be calculated (Optimization function 12).

$$\max \quad \sum_{k=1}^{|K|} \left(r_k \left[\delta_k^1 \frac{v_k}{h_k^1} + \delta_k^2 \frac{v_k}{h_k^2} \right] \right) \tag{12}$$

$$\text{s.t.} \quad \sum_{i=1}^{|I|} x_i = \gamma \tag{13}$$

$$x_i \in \{0,1\}, \forall i \in I \tag{14}$$

The first constraint makes sure that the number of crossovers in the design is equal to the preferred number of crossovers (γ). The second constraint makes sure that all elements in the decision array have a binary value. The output of the Crossover Performance (CP) model can be found in Figure 19.

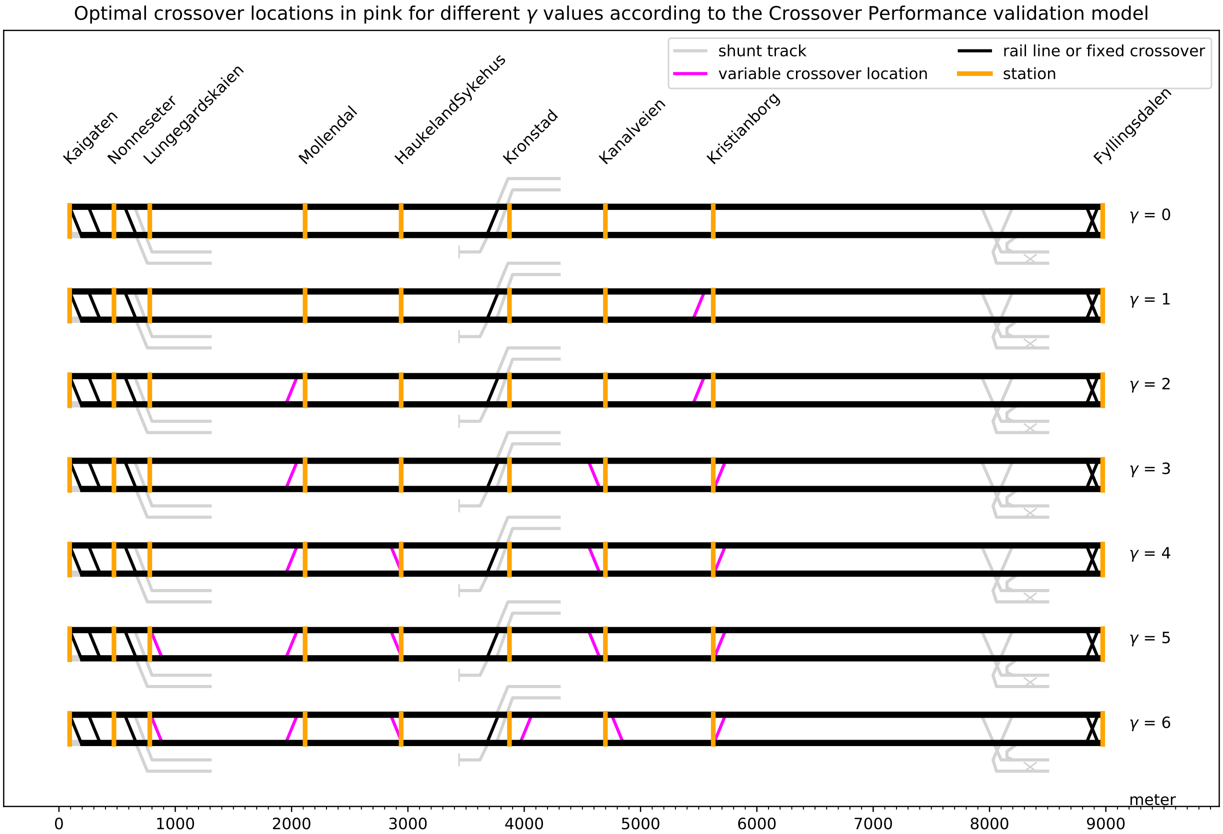


Figure 19: Optimal crossover location strategy for different values of γ according to the Crossover Performance validation model

6.2. Validation scenarios

Sensitivity of the input variables is evaluated by comparing the Unreliability Cost (UC) model to the Crossover Performance (CP) model for 50% lower and 50% higher input parameter values. Thereafter, a test with random input values for all disruption scenarios K is performed. The tests are done by comparing three crossover design strategies. The three crossover design strategies are presented in Figure 20. These three strategies are:

1. the optimal crossover location strategy according to the Unreliability Cost (UC) model
2. for the optimal crossover location strategy according to the Crossover Performance (CP) model
3. for the actual crossover location strategy in the final design that is currently being constructed in Bergen

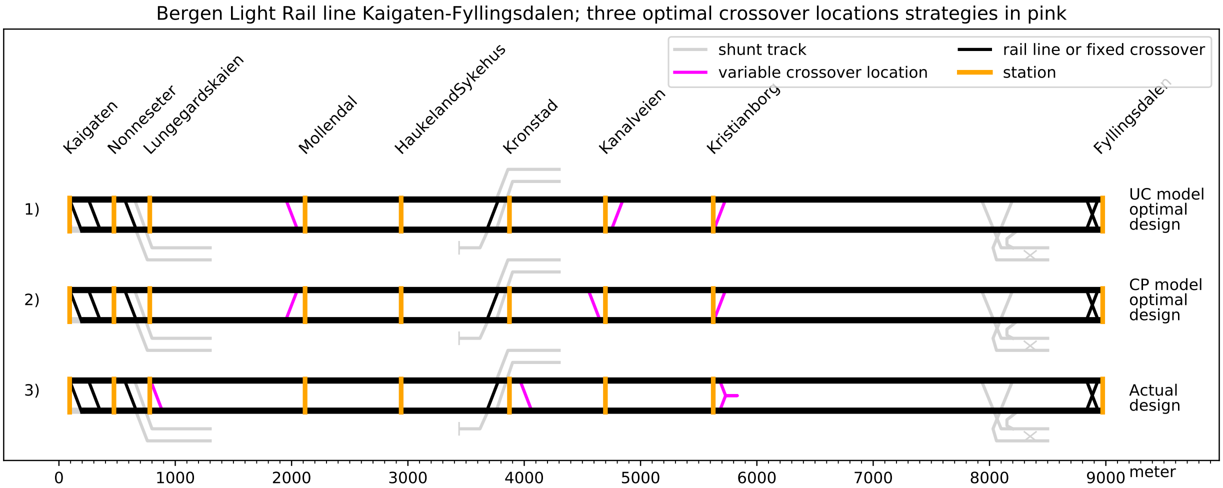


Figure 20: Optimal crossover location strategy according to the Unreliability Cost (UC) model, Crossover Performance (CP) model and the actual design

Two test are performed:

(T1) Fixed experiments

For all disruption types, a test is done to see the impact on the four performance indicators if the failure probability is 50% lower or 50% higher than the expected value gained from disruption probability studies. Moreover, test with a total passenger demand 20% lower or 20% higher than the expected numbers are done. With this test, the influence of all disruption types and the demand can be seen.

(T2) Random experiments

To test the sensitivity of all disruption scenarios, tests with random failure probabilities is done. For any disruption type at any location, a random value is randomly uniformly chosen between 50% lower and 50% higher than the expected value based on the disruption probability studies. The duration of all disruption scenarios is randomly selected as well. The passenger demand is randomly uniformly selected for each o, d-pair (station to station). The passenger demand on all these o, d-pairs has a value between 20% lower or 20% higher than the expected numbers.

Four performance indicators are used to compare the output of the scenarios of both tests:

(I1) Delay minutes

The sum of the delay of all passengers per year is an indicator for the performance of a rail line. This indicator is similar to the minimization problem used in the UC model. However, the sum of the delay minutes are multiplied by a Value Of Time factor in the UC model.

(I2) Crossover Performance

The Crossover Performance value is the expected usage per year of all crossovers, as explained in Section 6.1.

(I3) Network connectivity

The connectivity indicator of Nieminen (1974) is used to compare the scenarios (Formula 15). This indicator is the most suitable network performance indicator to use, because this indicator does not depend on the other lines in the network. The disadvantage of that is that the connectivity value cannot be compared to other lines. It is only useful to compare the same line under different circumstances.

$$C_D(p_k) = \sum_{i=1}^{n} a(p_i, p_k) \qquad \text{(Nieminen, 1974)} \tag{15}$$

where

$$C_D(p_k) : \text{Connectivity of station } p_k$$
$$n : \text{number of stations on the line}$$
$$a(p_i, p_k) = \begin{cases} 1, \text{ if and only if } p_i \text{ and } p_k \text{ are connected by a line} \\ 0, \text{ otherwise} \end{cases}$$

To determine the performance of a rail line during disruptions, the average connectivity of all stations on the line during all disruptions is calculated. Figure 21 shows the connectivity of all stations during a certain disruption. The average connectivity of the line in this example is (Mishra et al., 2012): $\frac{\sum_k C_D(p_k)}{|O|-1} = \frac{6+6+6+6+6+6+6+1+1}{9-1} = 5.5$. If the line is operated in regular circumstances, the maximum connectivity of 9 (number of stops) is reached.

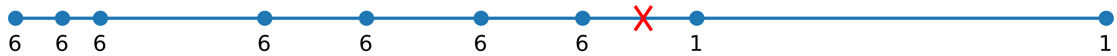


Figure 21: Example of line connectivity during a disruption

To compare the differences between the best design according to the UC model and the best design according to the CP model and the actual design, the connectivity value is calculated for all disruption scenarios K. The average connectivity value is calculated by taking the average of all these disruption scenarios, scaled by the average number of disruption minutes per year of k.

(I4) Passengers delayed more than 5 minutes

Another performance indicator is the number of passengers with a delay more than 5 minutes. The UC model sums the delay of all passengers. However, the perception of delay for passengers is not linear. Small delays of seconds or a few minutes are accepted by most people, while major delays are perceived as worse by travelers. Therefore, railway operators often indicate the performance of their lines by summing the number of passengers with a delay of more than x minutes. The Dutch Railways (NS) count the passengers with a delay more than 5 minutes (NS, 2020).

The output from the scenarios evaluated by the three models are given in Appendix C. The variable input parameters are the demand ($\mathbf{J}$) and the disruption risk ($\mathbf{r}$) and average disruption duration ($\mathbf{v}$). The output Key Performance Indicators are: I1: total delay minutes (a lower value is better), I2: Crossover Performance (a higher value is better), I3: Average Connectivity (a higher value is better) and I4: the yearly number of passengers delayed more than 5 minutes (a lower value is better).

From the results from T1 (Appendix C), one can conclude that the design is not sensitive for any of the failure types. If the frequency of one of the failure types is higher or lower, it does not mean that another of the three designs is better. This means that design choices are robust, the design is not sensitive for variations in the failure probabilities. Tunnel failures have a large impact on the unreliability cost, and relatively low impact on the crossover performance. This can be explained by the fact that a tunnel failure blocks both tracks over a large part of the line. Many travelers are involved in such a disturbance. If there is a broken vehicle, only one of the two tracks is blocked. The impact on passengers is therefore much lower than in the event of a tunnel failure. Because the crossover performance model does not take passenger numbers into account, this cannot be seen in the CP indicator (I2). The difference between the three designs according to the CP indicator is smaller than the difference in delay minutes. The CP indicator only responds to the differences in failure probability and failure duration, while the UC model also includes the impact on the passengers.

The results from test 1 are useful as an overview of changes in failure probability. However, it is also useful to know how the designs behave for different number of passengers, failure probabilities and failure duration at all locations. To do this, a second test is carried out. A random failure probability and failure duration has been generated for each failure scenario in K. This value is uniformly randomly chosen between a value that is 50% lower and 50% higher than the average value in the optimization models. The passenger demand is also randomly generated for each origin-destination pair. The value is uniformly generated between a value 20% lower and 20% higher than the average value in the optimization models. The results are presented in Appendix D. In this Table, the first two columns show the scenario number and design. The other four columns represent the four output key performance indicators: I1, I2, I3 and I4.

From the results of test 2 (Appendix D), one can conclude that for all scenarios, the UC design has the lowest delay, the best connectivity value and the lowest number of passengers with a delay more than five minutes. The CP design has a better Crossover Performance in most scenarios. The difference between the UC design and the CP design is very small in most scenarios, but there is a significant difference between the UC design and the actual design in all scenarios. Obviously, the Crossover Performance design is optimized for Crossover Performance. Therefore, this design is optimized to be able to use crossovers in as many as possible disruption scenarios. However, the impact on the network and on passengers is not included. Therefore, in some situations a crossover might be used, but it does not always mean that more stations are connected during the disruption. Moreover, in some disruption schedules, the impact on passengers may be small, because the delay gain for passengers is negligible compared to the situation without the crossover. The CP indicator does not consider connected stations and passenger impact.

Both experiments (fixed and random tests) show that the UC model created a robust design compared to the CP model and actual design. Three of the four indicators (passenger delay, connectivity, passengers delayed more than 5 minutes) have the best value for the UC design in all scenarios. The crossover performance is higher for the CP design in most scenarios, but the difference is very small, and it does not necessarily mean that a higher Crossover Performance is beneficial for passengers, operators and local authorities.

7. Discussion

This section provides some discussion of the main findings. An initial objective of the project was to analyze the trade-off of flexibility versus the cost of crossovers. Multiple indicators have shown that a robust design can be generated by minimizing passenger delay. Moreover, the costs of passenger delay are calculated and analysis is done to determine how they weigh up to the purchase and maintenance cost of crossovers.

Passenger delay is a fair indicator for a rail line, but clients might have a different opinion for rail line performance. As analyzed in this research, the proposed design is beneficial for the total delay, but there are o, d-pairs that would have an extra average delay when this design would be implemented instead of the actual design. For example, it is possible to minimize delays to certain important stations (for example stations close to a hospital). It may also be the case that a municipality wants the district with the worst mobility connections to be as reliable as possible. It is a social policy issue which objective function is better. Another optimization problem could be set up by minimizing the maximum delay from all o, d-pairs. Some policymakers prefer this, because budgets for public transport should be divided over city areas as fair as possible. Furthermore, policy makers may consider the monetized cost of delay to be more important than the LCC cost of crossovers, or vice versa. The interests of governments might conflict with the interests of PT operators. To tackle this problem, weights could be added to comparison of crossover LCC cost and passenger delay cost.

Some mayor assumptions are applied in the model to make it possible to create a fast-running model using data that is available for most new-to-build rail line projects. However, this might affect the reliability of the monetized delay cost. Time windows for the demand and alternative PT line travel times are used in the model, instead of distributions and variations over the year. This might have impact on the unreliability cost, if there are a lot of variations in demand over the day or over the year. Defining degraded schedules are case study specific, so one should be sure that disruptions are handled in the same way as done in this research before using the model. In reality, capacity constraints of Public Transport might have much influence on the delay time of passengers. In the UC model, capacity constraints are not considered. Therefore, the delay might be higher. Yap et al. (2015) experienced the same in their model outcome. The effect on the delay is the highest if the quickest alternative PT route is rarely used in regular circumstances. However, PT operators might use extra buses in such circumstances. Therefore, it is hard to model vehicle constraints, because operators are sometimes able to operate a line with extra vehicle capacity. For some rail lines, operators set up special bus lines between two unconnected stations in case of disruptions (bus bridging). There is many research about bus bridging, so it is better to use bus bridging models if the case study line always makes use of shuttle buses in case of disruptions. The UC model neglects transition phases from regular operation to degraded operation and back to regular operation. This has influence on the unreliability cost, because it takes a while before the trams drive according to the degraded schedule. In this transition phase, the delay is probably higher than during the degraded schedule. Because of this assumption, the unreliability cost might be higher in practice. Due to this assumption, the model is only useful for lines with a high operation frequency (a vehicle every 5-10 minutes). The UC model only considers case study line stations as origin and destinations in the transport model. In reality, people might have faster detour options, for example if they live closer to another bus stop. Therefore, the unreliability cost might be lower in practice. This effect is the same in all areas, so it will not have much influence on the model outcome. However, for transport models always yields that the results are more reliable if smaller zones are used. In contrast to Tahmasseby et al. (2008), the UC model does not use stochastic events. This is only possible if distribution fits from all input data are available. For new-to-build line, this is often not the case. Furthermore, if there is no alternative Public Transport connection between two stops, the delay cost will be enormously, because the model then assumes that people will walk the distance. In theory, it might even be infinite, if no route is available. For these type of case studies, bus bridging should be included in the model to get realistic output. Another possibility is to use a maximum number of delay minutes per passenger, which corresponds to a cancellation penalty for these passengers

Given these points, there are many factors and assumptions that affect the reliability of the monetized delay cost. On the other hand, the reliability of the analysis of the optimal design compared to the actual design is much better, because for this purpose only the relative differences in delay are important. Various tests and output indicators prove that the generated model performs well compared to the actual design. The model works to quantify the consideration of flexibility and crossover costs, but the uncertainty in crossover costs and delay costs must be kept in mind when making policy decisions.

8. Conclusion

The purpose of this study is to find the optimal crossover location design combination for rail lines by minimizing passenger delay. To do this, an algorithm had to be set up to define degraded schedules in case of disruptions automatically. Another aim of this study is to investigate the trade-off of flexibility of crossovers versus the purchase cost, maintenance cost and the extra breakdowns they provide. Moreover, analysis is done to determine the computational time compared to the set sizes.

An algorithm has been developed to automatically calculate disruption schedules. This algorithm has been developed using the disruption alternatives devised by the engineering firm during the design phase of the case study line. With a different type of railway, these routes might be different. For example if there is collision protection on the track, or if the track is shared with road vehicles. However, this algorithm can be used for any double-track railway line that does not share lanes with road traffic.

It is possible to optimize crossover locations for a rail line by minimizing unreliability cost (passenger delay). Past works already showed that monetized passenger delay can be used to evaluate design strategies, but this work proved that an optimization problem for crossover locations can lead to a more robust design. Estimated failure probabilities combined with an algorithm for the degraded schedule for all disruptions can be used to calculate the passenger delay cost. These delay costs can be used to determine the location and the number of crossovers that should be constructed in a new to build rail line. Experiments with predefined input scenarios and experiments with random input values showed that the optimized design is robust compared to the actual design. The UC design performs better for different key performance indicators as well: the crossover performance, average line connectivity and the number of passengers having a delay more than 5 minutes.

The unreliability cost can be used to determine if the Life Cycle Cost of a crossover are as high as the benefits for the passenger delay. However, there is a lot of uncertainty in the LCC of a crossover, and there is a lot of uncertainty in the delay costs as well, due to the assumptions associated to the UC model. The purchase and maintenance cost differ a lot, since the complexity of constructing them has a large influence on the purchase and maintenance cost. For example, a crossover that is hard to reach will be a lot more expensive than a crossover that is easily accessible by road. It is hard to estimate these cost for an optimization model, since there are a lot of locations. In fact, a separate estimate should be made for each potential location. Because of these variations, the delay costs should mainly be use to give a quick insight in the impact of a crossover design choice, and how the flexibility behaves relative to the purchase and maintenance cost. In the Bergen case, the same number of crossovers can ensure 10% less delay during non-recurring events, compared to the actual design.

The UC model has limitations for the set sizes, because the number of combinations to run rise enormously when an extra potential crossover location is added to the set. The maximum set sizes are large enough to evaluate a larger network than done in this project. However, it is not possible to optimize crossovers of a rail network of a complete country. Straightforward constraints can be added to reduced the number of runs. These constraints are based on requirements of operators, or by dividing the rail line in areas.

9. Recommendations

In this work, the UC model is created to optimize crossover location design strategies. The model can be improved for two reasons: 1) improve the reliability of the monetized passenger delay cost, and 2) make it possible to use the model for different purposes.

To make the model more reliable, more advanced models could be set up. If failure probability and duration distribution fits and extended passenger data is available from all transport modes and public transport lines in a city, it is possible to generate stochastic events and simulate the lifespan of the rail line. Doing this, it is also possible to model the failure probability during the entire life of a switch. For example, the risk of a breakdown failure slowly increases as the switch ages. If major maintenance is then carried out, this risk will be smaller again. Extended data analysis to crossover Life Cycle Cost should be done, to find out what determines the variation in crossover costs and with which parameters the costs can be estimated accurately.

There are more design issues that could be evaluated using the UC model than the optimal crossover location combination. For example, the effect of different maintenance strategies can be calculated with the UC model, if the difference in failure probability between those maintenance strategies is known. Moreover, track design choices can be evaluated. For example, the passenger delay effects of ballast tracks versus concrete rail beds can be evaluated, using failure probability data of both structure types. Constraints can be added to include more functions of crossovers. Crossovers needed for track maintenance vehicles are included as fixed in this work, but the model can be improved if these requirements are added as constraints. For example, a constraint can added to make sure that a facing crossover is needed between station a and station b, where the specific location is not important. In the current model, these crossovers have to be set as fixed.

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Appendix A. Flowchart to determine a disruption schedule for a disruption scenario

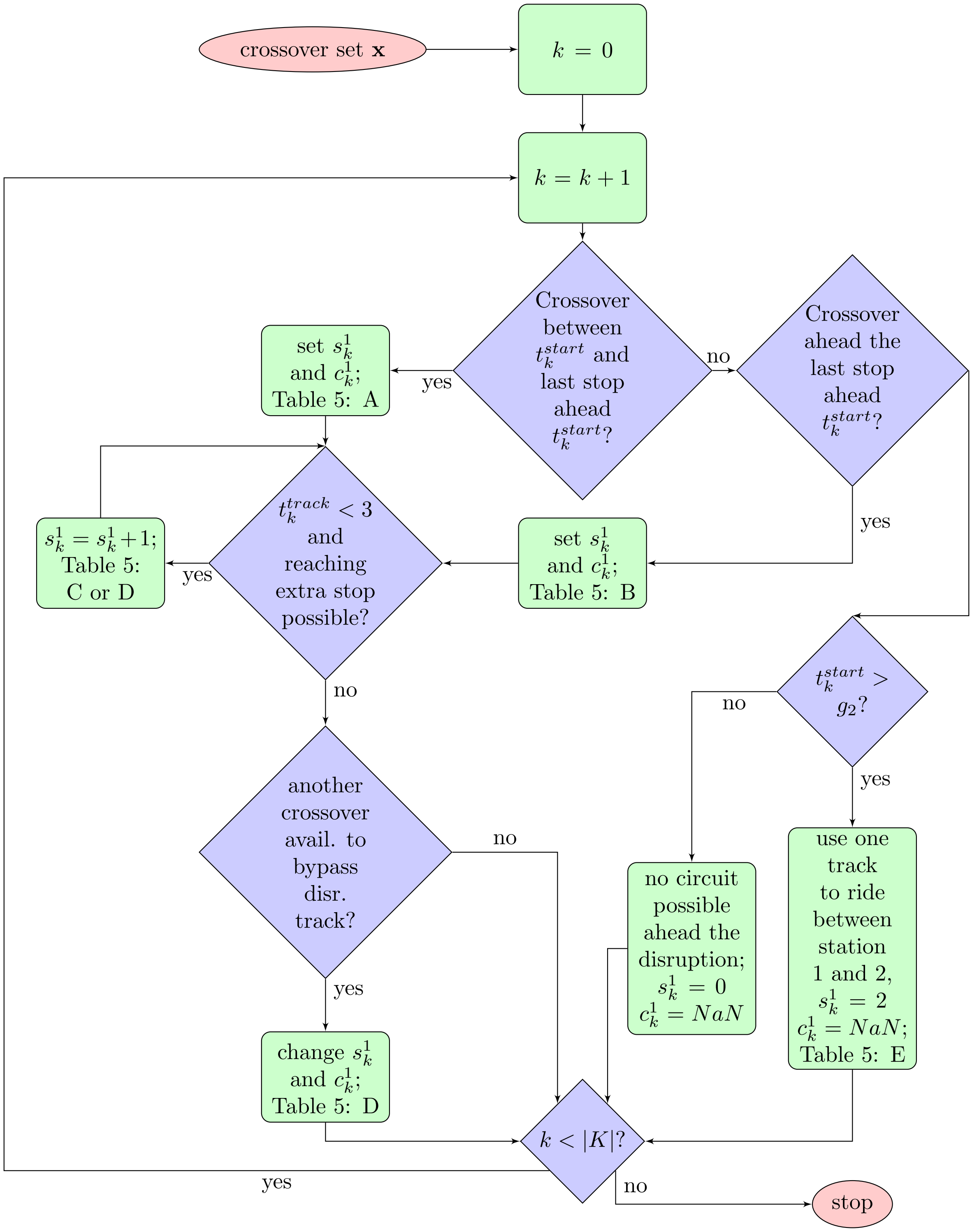

Figure A.22: Flowchart to define the disruption schedules for the circuit ahead the disruption for all disruption scenarios in K, for a given crossover set $\mathbf{x}$. The circuit beyond the disruption is calculated the same way, but in the opposite direction.

Appendix B. The difference between facing and trailing crossovers

As described in Figure 2, there are two possible placement directions for a regular crossover. In practice, the crossovers are mostly placed in the trailing direction (Type 2) on rail networks. This crossover has an advantage compared to the facing crossover: if the crossover is by mistake placed in the diverging direction, the tram or train still remains on the right track and forces the crossover to move in the right direction. It can damage the crossover if done with a high speed, but it is more dangerous if the tram by mistake rides to the diverging direction to the wrong-way track. Therefore, railway operators often prefer trailing crossovers. In Figure B.23, the optimal according to the UC model is presented, for the set $I^{trailing}$ that only contains trailing crossovers.

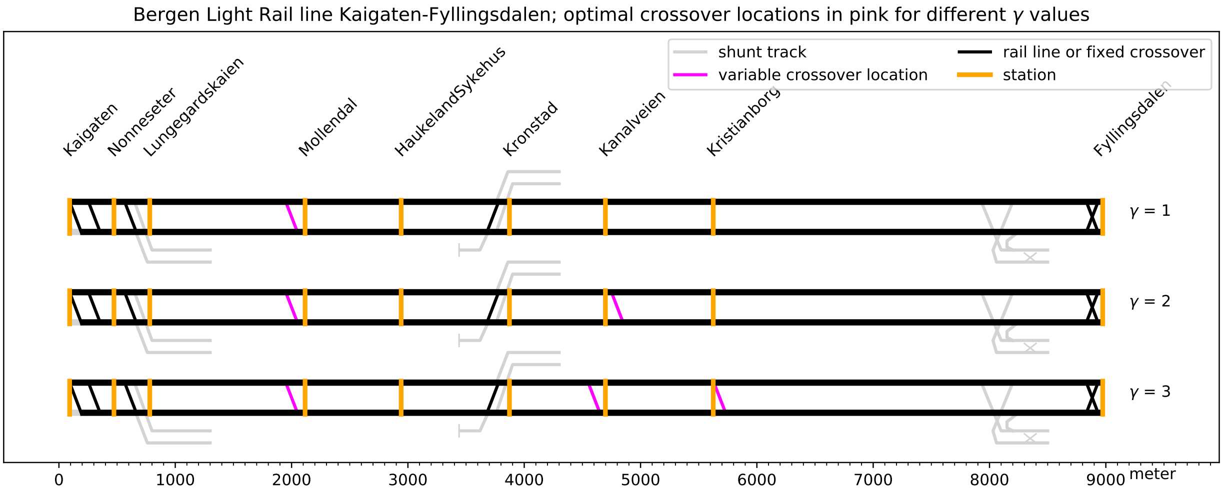

Figure B.23: Optimal crossover locations for $\gamma = 0, 1, 2$ and 3 according to the UC model, by only evaluating trailing crossovers (type 2)

In Table B.9, the difference between the optimal designs according to the UC model from the set $I^{trailing}$ containing only trailing crossovers is compared to the set I containing both facing (type 1) and trailing (type 2) crossovers.

Nr. of Crossovers γ	**Both facing and trailing crossovers** *NO Krones/year*	**Only trailing crossovers** *NO Krones/year*	**Percentual difference** *%*
1	1335731	1335731	-
2	1119358	1130057	0.96%
3	1100983	1110111	0.83%

Table B.9: UC model outcome for the optimal design containing only trailing crossover compared to the design containing both facing and trailing crossovers

From Table B.9, one can note that the difference between the two designs is very small. The difference in cost are mainly caused by the degraded schedule differences in Figure B.24 and B.25. if crossovers are placed close to each other, it is better to place them in the same direction. The design containing only trailing crossovers does not have service between Kronstad and Kanalveien in this situation (Figure B.24), while the UC design containing both facing and trailing crossovers does have service between Kronstad and Kanalveien in this situation (Figure B.25).

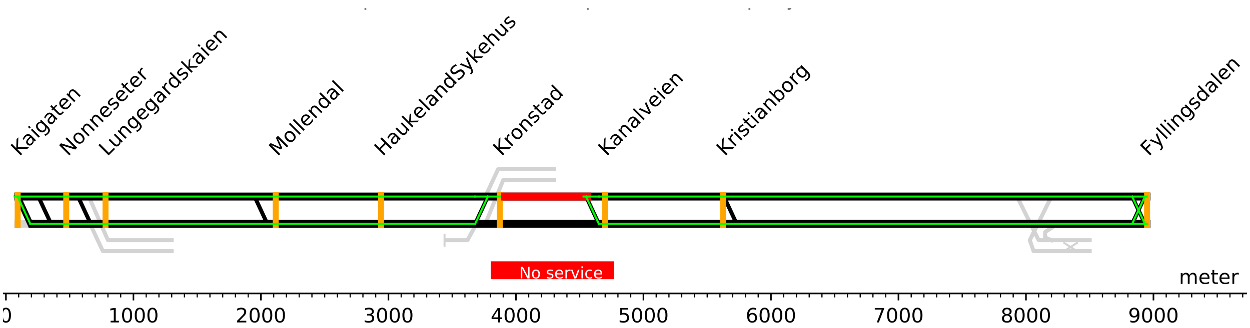

Figure B.24: Degraded schedule for the design that only contains trailing crossovers, for a disruption on the inbound track between Kronstad and the crossover ahead Kanalveien

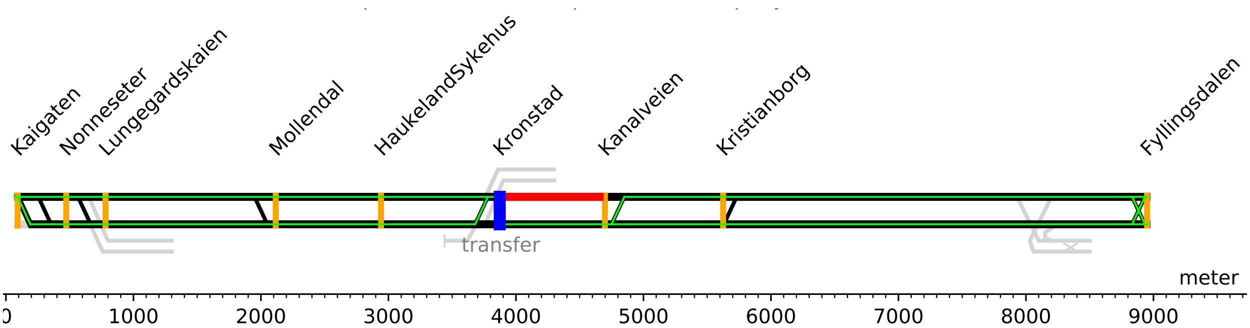

Figure B.25: Degraded schedule for the design that contains both trailing and facing crossovers, for a disruption on the inbound track between Kronstad and Kanalveien

Appendix C. Demand and failure probability validation output (T1)

Scenario	Design	(I1) Delay minutes	(I2) Crossover performance	(I3) Connectivity	(I4) Delay > 5 minutes
Base Scenario	UC Design	340510	914	5.32	22242
	CP design	347320	927	5.27	22951
	Actual Design	378201	871	5.16	25263
20% lower overall demand	UC Design	283759	914	5.32	18535
	CP Design	289433	927	5.27	19126
	Actual Design	315167	871	5.16	21052
20% higher overall demand	UC Design	408612	914	5.32	26690
	CP Design	416784	927	5.27	27541
	Actual Design	453841	871	5.16	30315
50% lower tunnel failure risk	UC Design	311937	863	5.29	20622
	CP Design	318751	876	5.24	21331
	Actual Design	349600	822	5.13	23643
50% higher tunnel failure risk	UC Design	383370	990	5.35	24671
	CP Design	390173	1003	5.30	25381
	Actual Design	421102	946	5.20	27692
50% lower vehicle breakdown risk	UC Design	330982	824	5.25	21758
	CP Design	335317	835	5.22	22205
	Actual Design	361894	786	5.11	24195
50% higher vehicle breakdown risk	UC Design	354802	1048	5.39	22968
	CP Design	365324	1064	5.32	24070
	Actual Design	402661	999	5.22	26864
50% lower road crossing failure risk	UC Design	327208	866	5.33	21139
	CP Design	334025	879	5.28	21852
	Actual Design	363682	833	5.17	24080
50% higher road crossing failure risk	UC Design	360464	986	5.30	23896
	CP Design	367262	999	5.25	24600
	Actual Design	399980	929	5.14	27037
50% lower infrastructure failure risk	UC Design	326179	880	5.31	21302
	CP Design	333008	893	5.26	22013
	Actual Design	362899	841	5.16	24251
50% higher infrastructure failure risk	UC Design	362007	964	5.32	23652
	CP Design	368787	977	5.27	24358
	Actual Design	401154	917	5.16	26780
50% lower switch failure risk	UC Design	334079	885	5.31	21499
	CP Design	341013	897	5.26	22225
	Actual Design	371668	841	5.15	24491
50% higher switch failure risk	UC Design	350156	957	5.32	23357
	CP Design	356779	972	5.27	24040
	Actual Design	387999	917	5.17	26420

50% lower power/catenary failure risk	UC Design	299172	859	5.39	19717
	CP Design	306031	872	5.34	20429
	Actual Design	333396	815	5.24	22495
50% higher power/catenary failure risk	UC Design	402517	995	5.22	26029
	CP Design	409252	1009	5.17	26733
	Actual Design	445408	956	5.05	29414

Table C.10: Comparing the output of the different models for different input values. The disruption types have a fixed lower/higher probability (50%), and a lower/higher (20%) demand scenarios are evaluated (for all o,d-pairs). The output Key Performance Indicators are the sum of all passenger's delay minutes per year (I1), crossover performance per year (I2), average connectivity during disruptions (I3) and the number of passengers with a delay higher than 5 minutes (I4)

Appendix D. Random input validation output (T2)

Scenario	Design	(I1) Delay minutes	(I2) Crossover performance	(I3) Connectivity	(I4) Delay > 5 minutes
Base Scenario	UC Design	340510	914	5.32	22242
	CP design	347320	927	5.27	22951
	Actual Design	378201	871	5.16	25263
Random input scenario 1	UC Design	369747	998	5.17	24206
	CP design	371836	1010	5.15	24680
	Actual Design	403761	951	5.04	26900
Random input scenario 2	UC Design	320597	910	5.22	21692
	CP design	327584	928	5.17	22543
	Actual Design	357303	877	5.05	24516
Random input scenario 3	UC Design	308632	867	5.54	19454
	CP design	317179	881	5.48	20338
	Actual Design	343757	825	5.40	22337
Random input scenario 4	UC Design	291912	846	5.26	19561
	CP design	298226	859	5.22	20301
	Actual Design	326879	808	5.11	22409
Random input scenario 5	UC Design	340848	899	5.46	21952
	CP design	350959	912	5.40	22921
	Actual Design	377138	851	5.31	24901
Random input scenario 6	UC Design	350017	967	5.59	22339
	CP design	353274	979	5.55	22688
	Actual Design	379125	917	5.48	24830
Random input scenario 7	UC Design	293745	859	5.29	20034
	CP design	298150	874	5.24	20576
	Actual Design	326360	820	5.15	22775
Random input scenario 8	UC Design	389441	1007	5.38	24441
	CP design	397142	1019	5.32	25095
	Actual Design	430395	962	5.23	27661
Random input scenario 9	UC Design	304076	940	5.64	19247
	CP design	309081	952	5.60	19744
	Actual Design	342003	900	5.49	22315
Random input scenario 10	UC Design	340254	920	5.25	22487
	CP design	347316	932	5.21	23231
	Actual Design	378706	875	5.09	25513
Random input scenario 11	UC Design	351958	907	5.23	23217
	CP design	353049	919	5.20	23315
	Actual Design	388825	870	5.08	26197
Random input scenario 12	UC Design	391443	970	5.20	25670
	CP design	399116	985	5.14	26464
	Actual Design	436475	927	5.02	29160

Random input scenario 13	UC Design	341763	908	5.25	22981
	CP design	348517	920	5.19	23463
	Actual Design	378228	863	5.08	25811
Random input scenario 14	UC Design	298289	840	5.27	20302
	CP design	307866	855	5.20	21324
	Actual Design	336094	795	5.11	23321
Random input scenario 15	UC Design	300841	797	5.12	20240
	CP design	303269	808	5.08	20632
	Actual Design	337350	753	4.95	23111
Random input scenario 16	UC Design	350495	954	5.50	22215
	CP design	358837	966	5.44	23001
	Actual Design	387848	910	5.35	25112
Random input scenario 17	UC Design	371769	963	5.25	23735
	CP design	380240	980	5.20	24781
	Actual Design	414509	926	5.09	27149
Random input scenario 18	UC Design	338003	950	5.44	21601
	CP design	343530	959	5.39	22153
	Actual Design	379492	905	5.27	25042
Random input scenario 19	UC Design	354573	929	5.31	23084
	CP design	357743	938	5.27	23447
	Actual Design	391865	882	5.16	26148
Random input scenario 20	UC Design	366133	989	5.33	23924
	CP design	379209	1005	5.24	25095
	Actual Design	415690	942	5.13	27920
Random input scenario 21	UC Design	343494	855	5.25	21480
	CP design	348985	865	5.21	22110
	Actual Design	381285	818	5.10	24477
Random input scenario 22	UC Design	327375	846	5.52	20546
	CP design	337089	859	5.46	21470
	Actual Design	364007	808	5.38	23660
Random input scenario 23	UC Design	356612	898	5.48	22456
	CP design	360899	909	5.45	22970
	Actual Design	388152	863	5.37	25055
Random input scenario 24	UC Design	348850	962	5.31	23213
	CP design	350225	970	5.28	23216
	Actual Design	384974	915	5.16	26010
Random input scenario 25	UC Design	354757	915	5.44	22414
	CP design	363900	929	5.38	23338
	Actual Design	393448	870	5.28	25450
Random input scenario 26	UC Design	319035	887	5.15	21835
	CP design	328762	900	5.08	22727
	Actual Design	361984	850	4.97	25158

Random input scenario 27	UC Design	315167	916	5.18	21648
	CP design	324759	931	5.13	22741
	Actual Design	358284	864	5.01	25089
Random input scenario 28	UC Design	353992	994	5.30	23886
	CP design	357645	1008	5.27	24283
	Actual Design	395197	941	5.16	27302
Random input scenario 29	UC Design	346351	896	5.41	21520
	CP design	357209	910	5.34	22589
	Actual Design	394398	853	5.22	25441
Random input scenario 30	UC Design	407811	1007	5.44	25821
	CP design	419177	1020	5.39	26922
	Actual Design	451604	963	5.30	29289

Table D.11: Comparing the output of the different models for random input values. All scenarios K have a random failure input value uniformly (r_k and v_k) distributed with a value 50% lower and 50% higher than the average value. The demand between each origin and destination stop ($j_{o,d}$) has a random input value uniformly distributed with a value 20% lower and 20% higher than the average value. The output Key Performance Indicators are the sum of all passenger's delay minutes per year (I1), crossover performance per year (I2), average connectivity during disruptions (I3) and the number of passengers with a delay higher than 5 minutes (I4)