Temporary Shuttle Services in Case of Major Disruptions of a Railway Network

Kees van der Knijff
312051
Erasmus University Rotterdam

Bachelor Thesis
June 2010

Supervisor:
Dr. D. Huisman

Abstract

Due to different circumstances, major disruptions on a railway network do frequently occur. When the problem that caused the disruption is solved, large amounts of passengers are gathered in the stations. Most railway companies start with running the initial schedule as soon as possible. To the best of our knowledge, until now no attempts have been made to establish a temporary shuttle service to disperse the passengers to the surrounding stations.

In this thesis, we will formulate a model that maximizes the total number of transported passengers from the station in which the initial disruption occurred to the stations around it. We focus on the allocation of rolling stock to the different directions using an Integer Linear Program (ILP) and we check whether the given solutions can be translated into a feasible timetable using a complete enumeration of the leaving orders of the trains.

We report some computational results on three different scenarios and discuss those results.

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Chapter 1 – Introduction

Every day all over the world millions of passengers are transported by train. Those of them who drive by train know that sometimes things go wrong and they miss their appointment. In some countries many even are prejudiced against the railway companies, saying that it is extraordinary when everything goes well. However, most people do not know what has gone wrong and what the role of the railway company in the solution of the problems is.

For example, in the Netherlands, every day approximately 1.2 million people are being transported by train without experiencing big troubles. However, every passenger that uses the train regularly has some experience with frustrating delays. A lot of those delays are minor delays, but on average three major disruptions (that block an entire route) occur per day. Many of those disruptions have causes that can be considered to be external factors and thus cannot be foreseen.

Because huge delays are one of the most annoying experiences for railway passengers and have a significant impact on passenger satisfaction, the Operations Research (OR) community develops methods to improve the so called railway disruption management process. At Netherlands Railways, thus far railway disruption management had as its primary goal to reschedule the original timetable.

In this report, we present an innovative idea to approach a totally new timetable for a given period in the case of a complete blockage of a major station. We introduce a timetable that will use the available rolling stock within the problem station at the moment of the disruption to transport huge amounts of passengers to the surrounding stations before returning to the initial timetable. In this report, we focus on the first step, the allocation of the different trains to the different directions and after a solution has been found, we show whether it could deliver a feasible timetable. In this initial stage of the research, many complicating factors are not considered in the model. Some of them will be discussed in the problem statement or in the conclusion.

The remainder of this report is organized as follows. In chapter 2 the problem will be explained in more detail and we give an overview of the assumptions we made while defining the exact problem. A brief literature overview on railway timetabling and disruption management is given in chapter 3. In chapter 4 we define a mathematical formulation, which we use to solve the problem. The scenarios we use for testing our approach are introduced in chapter 5. Computational results accompanied by some observations are given in chapter 6. We finish with some concluding remarks and directions for further research in chapter 7.

Chapter 2: Problem description

In this chapter we will define the problem we deal with. First, we will describe the situation in which the proposed model can be used, and then we define the objective of the research. Finally, we give an overview of the assumptions we have made in order to arrive at our specific problem.

Situation

Due to many different causes, many of which are the result of external, uncontrollable circumstances, it happens that a route between two stations or a station itself have suddenly to be closed for a considerable amount of time. In this thesis we focus on the situation that a major station (in the Netherlands, for example, these would include Utrecht, Rotterdam and Amsterdam) is not accessible for any train for a considerable amount of time. As a result of this, thousands of passengers will come together in the closed station, while many others have to wait to reach the particular station.

Until now, when the problem was solved, the objective was returning to the initial schedule as soon as possible. In this report we will take a look at an alternative, in which the available rolling stock and crew at the 'problem station' is used to transport the enormous amounts of passengers in a convenient way to one of the stations around the major station. Those stations should be those from which the passengers can continue their journey in different directions. That is, for example in the case that Rotterdam Central should be closed, the passengers are transported to Den Haag, Gouda and Dordrecht.

Objective

The objective of this research is to formulate a method to establish a temporary (acyclical) railway timetable that transports the passengers to the closest stations around the 'problem station'. There is no need for the timetable to be cyclical, because it will only be in use for a short period. The railway timetable should be able to divide the enormous mass of passengers over different stations in a given amount of time, for example an hour. For practical considerations, the calculations must be performed within only a few minutes. After some time interval, the objective is to return to the standard timetable, but that part will not be included in this research.

Assumptions

In order to be able to establish a temporary timetable, we made a number of assumptions.

We assume that when a problem appears, the following information can be considered to be available within a small amount of time:

- the estimated numbers of passengers that will pile up within the station until the moment the problem is solved
- the estimated numbers of passengers that will arrive at the station during the period that the alternative timetable is running
- the available rolling stock within the station with its capacity
- the infrastucture of the region with its restrictions
- the set of nodes that should be reached by the timetable
- the interval during which the timetable will be in use.

Furthermore, we make the following assumptions or simplifications of the otherwise complex problem:

- We leave the original timetable out of the model. That is, we do not take into account the trains that are stuck on a route between the major station and the stations that we try to reach. Furthermore, we do not try in this stage of the research, to make the temporary timetable in such a way that the connection with the standard timetable is optimal.
- When the first trains are going to drive, enormous amounts of passengers are set in motion. In order to minimize the chaos within the station there will be a period of at least five minutes between two consecutive train departures into a given direction.
- The planning within the station is a complex problem itself. Because it is not the objective of this research to implement that problem, we assume that it is possible in each major station to assign a number of inbound and outbound routes to the different directions, in such a way that no problem will occur between departures and arrivals of the different trains.
- We stated above that we take the available rolling stock and its capacity as given in the specific situation. Because the major stations often contain a crew depot, we assume that the required amount of train drivers and conductors is always available.
- We assume that the number of passengers that wants to leave the ´problem station´ is always bigger than the number that wants to reach it from one of the surrounding stations. As a result of that, a train that leaves in the direction of one of the minor stations has always enough capacity for the opposite direction.

Chapter 3: Literature Overview

Although the specific problem we consider in this report has to the best of our knowledge never been handled in the scientific literature, there are some results in literature that provide background information about railway timetabling, delay management and rerouting. In this chapter we will give a brief overview of some papers that are interesting for our own case.

Kroon et al. (2009) provide the background for the current research. They explain the way in which the current timetable in the Netherlands was established and introduced in December 2006. The objective of the introduction of this timetable was to facilitate the growth of the passenger and freight tranport on a highly utilized railway network and improve the robustness of the timetable, thus resulting in fewer operational train delays. They explain a number of subproblems that have to be taken into account when establishing a new timetable, like routing trains through stations, rolling stock scheduling and crew scheduling.

Hansen and Pachl (2008) present a wide range of issues relating to the modelling of a railway timetable. Especially the chapters about the analysis of train delays and about rescheduling provide some helpful information. However, these parts of their book focus on relative minor delays that require some adjustments to enable the system to return to its regular schedule. They do not mention options that can be considered when a major delay occurs due to problems on one of the important stations of the available infrastructure.

Huisman et al. (2005) provide a more general overview of all the areas in which Operations Research is of value in the processes concerning the timetabling for passenger railway transportation. They present state-of-the-art models and techniques. They show the usefulness of results in the strategical, tactical and operational stages of the planning process. Furthermore, they provide some helpful ways for reliability analysis and some suggestions for improvements. They use the situation at NS Reizigers for showing the ways the models they present are implemented in practice.

These are all pretty general with respect to the problem we have under consideration in this report. Potthoff et al. (2008) are somewhat more specific, focusing explicitly on problems related to major disruptions. They provide helpful information on the occurrence of disruptions that are not within the control of the railway organisation. The point of their article is, however, not related to the passenger side of the disruption problem, but to the crew side. They present an innovative approach to reschedule the crew, where we are looking for an innovative approach to reschedule a part of the timetable in order to solve the passenger side of the problem.

Another article focusing on major disruptions and related problems is Jespersen-Groth et al. (2009). These authors describe the roles of the different actors in the disruption management proces. Furthermore, they discuss the three main subproblems, namely timetable adjustment, rolling-stock and crew rescheduling. Finally, they give some remarks about the integration of these three re-scheduling processes.

Although all the literature forementioned provides us with information about part of the situation we handle, the main problem with most of them is that they use results for cyclical timetables. Therefore, the most relevant article for our current research is the one from Caprara et al. (2002). They describe a model for solving the train timetabling problem using an acyclical approach. They propose a graph theoretic formulation using a directed multigraph. This formulation is then used to derive an integer linear programming model that is relaxed in a Lagrangian way.

Chapter 4: Model Formulation

In this chapter we will present the model we use for establishing an acyclic timetable for a given time interval. In the model two major parts are to be integrated: The allocation of trains to destinations and the times on which the different trains will leave in the various directions, that is, the actual timetable. Combining those two parts in one model would be optimal, but because we have to deal with a very complex problem when we want to do both parts in one single model, we decided to divide the problem into two parts. This makes the model and corresponding calculations somewhat easier. As a result, however, we are likely to arrive at a suboptimal solution. In the first part of the model, we formulate a model to allocate the available rolling stock to the different destinations. Then with the obtained allocation, we try to establish a timetable for the different sets of trains and destinations. However, we focus on the first part of the problem and will use an easy solution to show whether a feasible solution exists. Furthermore, we will give some suggestions for solving this second part more exact. In Chapter 6 we will show the results and we will provide some remarks about the supposed suboptimality.

4.1 Rolling Stock allocation

In this first part of the problem, we have to find a way to allocate the available rolling stock to the different destinations. The objective is to find an allocation for the different trains with their given capacities to the different groups of passengers.

In order to formulate a model we define the following sets:

- The set of destinations D.
- The set of passengers P, with p_d denoting the total number of passengers in the direction of destination d. That is, both passengers with destination d and passengers for the stopping train in the direction of d are included in p_d.
- The set of stopping train passengers S, with s_d denoting the number of stopping train passengers in the direction of destination d. This group of stopping train passengers is defined as homogeneous, that is, the exact destination of the passengers is not taken into account. By definition, for every $d \in D$ it follows that $s_d \leq p_d$.
- The set of available trains T characterized by their capacities.

Furthermore, we have two vectors u_d and v_d with the total travelling times from the major station to each of the destinations *d* for stopping trains and intercity trains, respectively.
The parameter c_t denotes the capacity of train *t*. Furthermore, we know the length *l* of the time interval in which the alternative timetable is to be used. The parameter c_t denotes the capacity of train t.

Now, in order to be able to formulate a model that takes all this information into account, we have to make a decision about the following important issue:

In practice, there is the possibility that passengers that are on their way to the final destination (and thus 'should' make use of the intercity train) will use the stopping train when a stopping train leaves before an intercity. This would result in a lot of complexities in the formulation of both the objective function and the constraints. Therefore we have to make an extra assumption, assuming 'reasonable behaviour' of the passengers. That is, we model an optimal situation in which a stopping train is first filled by stopping train passengers, and only when a fraction of the capacity remains, those places will be filled by intercity passengers. With this assumption, we can include the two different passenger groups in the model, but we do not have to make the model more complex or make the two problems disjoint.

In order to formulate the model we introduce the following decision variables:
- y_{td} is the number of times train $t \in T$ travels towards destination $d \in D$ as a stopping train.
- z_{td} is the number of times train $t \in T$ travels towards destination $d \in D$ as an intercity train.
- x_{td} is 1 if train $t \in T$ travels towards destination $d \in D$, 0 otherwise. In the model, x_{td} is split up in q_{td} for stopping trains and r_{td} for intercity trains. By definition (all are binary variables) it should hold that $x_{td} = r_{td} + q_{td}$.
- The variables g_d, h_d and j_d denote penalty variables for the various restrictions and will be explained in more detail below.

Now the model can be formulated as follows:

Objective function:

$$\min \sum_{d \in D} (\alpha g_d + \beta h_d + \gamma j_d) \tag{1}$$

Subject to the following constraints:

$$\sum_{t \in T} c_t y_{td} + g_d \geq s_d \qquad \forall d \in D \tag{2}$$

$$\sum_{t \in T} c_t (y_{td} + z_{td}) + h_d \geq p_d \qquad \forall d \in D \tag{3}$$

$$y_{td} \leq M_d q_{td} \quad \forall t \in T, d \in D \quad with\ M_d = 0.5(\frac{l}{u_d + 5} + 1) \tag{4}$$

$$z_{td} \leq N_d r_{td} \quad \forall t \in T, d \in D \quad with\ N_d = 0.5(\frac{l}{v_d + 5} + 1) \tag{5}$$

$$x_{td} = q_{td} + r_{td} \qquad \forall t \in T, d \in D \tag{6}$$

$$\sum_{t \in T} x_{td} + j_d \geq 1 \qquad \forall d \in D \tag{7}$$

$$\sum_{d \in D} x_{td} \leq 1 \qquad \forall t \in T \tag{8}$$

$$x_{td}, q_{td}, r_{td} \in \{0,1\} \qquad \forall t \in T, d \in D \tag{9}$$

$$y_{td}, z_{td} \in \mathrm{Z}^+ \qquad \forall t \in T, d \in D \tag{10}$$

$$g_d, h_d, j_d \in \mathrm{Z}^+ \qquad \forall d \in D \tag{11}$$

The objective function (1) is defined as the sum of the penalties for the differences between the total capacity that goes to a destination and the amount of passengers that want to go in that direction plus an additional penalty when no train heads in a given direction. By definition, those differences all are non-negative. The parameters α, β and γ can be varied according to the weights that are given to the different situations. Intuitively, α should always exceed β, because passengers for destination *d* can use both stopping and intercity trains, but stopping train passengers can only use the stopping trains. Furthermore, in some cases it can be helpful to define α and β in such a way that the objective function is piecewise linear. In chapter 6 we will show which options we tried to obtain optimal results.

Constraints (2) impose that for every destination d the sum of the total capacity of the stopping trains leaving towards that destination plus the penalty for the number of passengers that cannot reach their destination is at least equal to the total amount of stopping train passengers towards the destination.
Constraints (3) are quite similar to constraints (2), the difference being that this one states that the capacity of all trains plus a penalty are at least equal to the total number of passengers towards each destination.

Constraints (4) and (5) state that, for stopping trains and intercity trains respectively, the number of times a train *t* drives towards destination *d* is smaller or equal to a factor M_d or N_d times a binary variable x_{td} indicating whether the train *t* leaves for destination *d* at all. M_d and N_d denote the maximum that the combination of the total interval time and the travelling time from the major station to a destination impose on the number of times a given train *t* leaves for a destination *d*. The factor 0.5 denotes that a train will have to get back before leaving again. As a result, each train will be either at the central station or at one of the destinations at the end of the period *l*.

Constraints (6) state that the variable x_{td}, denoting whether train *t* leaves towards destination *d*, is the sum of the variables q_{td}, denoting whether train *t* leaves towards destination *d* as a stopping train, and r_{td}, denoting whether train *t* leaves towards destination *d*. Thus, a train can leave towards a given destination being either a stopping train or an intercity train.

Constraints (7) impose that for every destination the sum of all trains that reach it plus a penalty should be at least equal to one. This means that a penalty is imposed when a destination is never reached within the solution.

Constraints (8) impose that every train is able to reach only one destination.

Finally, constraints (9) – (11) denote the range of the variables.

4.2 Piecewise Linear variant

The model presented in the previous section is a linear model, minimizing the total number of passengers that is not transported in the given solution. However, it is possible that more than one solution gives the same minimum. In that case, we have to choose between different options, but the given model will give only one solution.

In the case of two equally good solutions with respect to the minimization, we prefer the one with the lower variance in the undercapacities. For example, when we have an undercapacity of 1000 passengers, we prefer the solution with undercapacities of 400 and 600 in two directions to the one with undercapacities of 0 and 1000 passengers. This is because the given capacities of the trains are in practice somewhat lower than the total numbers of passengers that fit within the train when people do not know how long they have to wait for a better option. Thus spreading the undercapacity will reduce the total number of passengers that is not transported.

We can formulate the model to achieve this using a piecewise linear objective function. This could be done, for example by introducing dummy variables that are related to α or β (the weights of g_d and h_d, respectively) in the following way:

Suppose that the dependence of the objective function on g_d is continuous and piecewise linear with slope α for $g_d \leq a$ and with slope $\alpha + \delta$ for $g_d > a$. This can be formulated as follows. Let D be a dummy variable with $D_d = 0$ if $g_d \leq a$ and 1 otherwise; then the objective function becomes

$$\min \sum_{d \in D} (\alpha g_d + \delta (g_d - a) D_d + \beta h_d + \gamma j_d)$$

Of course, it is possible to split up the values of the slope into more parts, using various breakpoints. The same could be done for β, and the weights and ranges can be changed when the scenario changes.

4.3 Timetabling

In this stage the objective is to establish a way to obtain a feasible timetable between the major station and the surrounding stations, based on the results of the previous section. Because we know which trains drive which number of times in a certain direction, we can split up the problem for each of the directions. Because we assumed as given that we use one route to reach a given destination and one to get back, the problem in this stage is a relatively easy one. We just have to find the order in which the trains leave and the optimal times at which they leave.

Because we know how long a certain train will take to reach its final destination (given that it is used as an intercity or an stopping train), the minimum time the trains have to wait at the

different stations and the minimum distance that should at each moment on the route exist between two consecutive trains, this problem can be solved using a number of different methods.
In this section we will suggest three ways to obtain a (optimal) feasible solution, of which we will use only the first, because of the small scale problems we investigate.

<u>Complete enumeration</u>

The most straightforward way for solving the problem for a given destination and the corresponding set of trains is the complete enumeration of the orders in which the trains can leave and checking whether a certain order is feasible. In small scale problems, this could be done by hand within a few minutes and by a computer within a few seconds. This method will by definition find the optimal solution whenever a solution exists. However, in practice it possibly takes too much time when the number of trains and trips increases. We use it in this report as a means to show whether the results of the first half of the problem are usable for obtaining a feasible solution.

<u>Heuristic methods</u>

Another possibility is the use of a greedy heuristic. In our case, the heuristic could be based on ordering of the trains based on the gap between the total interval time and the total time needed for performing the given amount of trips, on the capacity of the trains (the bigger one first), or on the type of train (an intercity before a stopping train). Using a few simple steps, it should be fairly easy to check whether a feasible solution exists. However, we most likely add to the suboptimality because the solution will itself again most likely be suboptimal. In case of small scale problems, this solution will almost be identical to complete enumeration.

<u>Linear Programming</u>

When the size of the problem increases, the number of possibilities within the complete enumeration increases very fast. Therefore, modelling the problem using an (integer) linear program is perhaps the best solution. That way, it will be also possible to obtain an optimal solution in this part of the problem, based on the results of the previous part. We suggest using a simplified version of the graph theoretic model Caprara et al. (2002) introduce. Using a graph $G = (V, A)$ with V the set of the central station and the destinations and A the set of arcs between the central station and the various destinations at every (discretized) moment of time.

Chapter 5: Scenarios

In order to be able to test our model, in this chapter we will introduce three quite different scenarios in which the model will be tested. First, we will check how the model works in an 'easy' scenario, that is, a scenario in which the capacity of the trains exceeds the amount of passengers that is to be transported. The second scenario will be an 'impossible' scenario, in which the number of passengers will greatly outnumber the capacity of the trains. This way, we can see whether the model indeed maximizes the total number of passengers that are transported. The third scenario we will introduce will be the most 'tight' one. That is, in this scenario the total capacity within the planning horizon will be almost as much as the total number of passengers to be transported.

In this chapter we define the different scenarios. First we will give a few general facts that hold in all cases. After the framework is introduced we will split up between the different scenarios.

General framework

In all three scenarios we will use for our calculations in this report, some parts of the situation will remain stable.

First of all, we will use the same problem station in every scenario. We will name this central station A from now on. Furthermore, we will use a set of destinations containing three stations, named B, C and D. As a result of this, in station A we will have six groups of passengers. For each of the stations B, C and D we have passengers heading towards that station itself, and groups of passengers for the stopping trains in that direction.

Following our earlier assumptions, there are two paths between A and each of the other stations, one in the direction of those stations, and one back in the direction of station A.

For all of the destinations we know the running times for stopping and intercity trains, respectively. The running times for the stopping trains are inclusive the dwelling times at the intermediate stations. Table 1 reports the running times.

Destination	**B**	**C**	**D**
Stopping train	18 minutes	20 minutes	12 minutes
Intercity	14 minutes	16 minutes	9 minutes

Tabel 1: Running times

Furthermore, in all cases we will use a time period of two hours in which the trains can be used for the alternative timetable.

Finally, at the moment the disruption occurs the following set of trains (table 2) is available at the station. Capacities denote de sum of seating and standing places.

Train number	Train type	Capacity
1	ICM_3+4	830
2	ICM_3+4	830
3	ICM_4+4	900
4	VIRM_6	900
5	DDAR_4	750
6	SLT_4+4	800
7	SLT_4+6	1000
8	SGM_3+3	1000
Total capacity		**7010**

Tabel 2: Trains and Capacities

This way, we consider the total infrastructure and rolling stock constant over all the scenarios and we will define the different scenarios by giving specifics about the amounts of passengers for the different directions.

Scenario 1

The first scenario will be a relatively easy one, in which all passengers can reach their destination. The problem that caused the disruption was solved within an hour, and so the amounts of passengers are not extraordinary high. Table 3 shows the numbers of passengers that are stuck in the central station A for each of the destinations.

Destination	B_s	B_tot	C_s	C_tot	D_s	D_tot
# Passengers	1500	4500	2250	6000	1200	3500

Tabel 3:Passengers Scenario 1

So, a total of 14,000 passengers is to be transported, of which 4,950 are stopping train passengers.

Scenario 2

The second scenario will be the one in which we know beforehand that it will be impossible to transport all passengers. In that case, we will be able to check whether the model indeed maximizes the number of passengers transported. Furthermore, we will have the opportunity to check what influences the changes in α, β and γ in the objective function have and which preferences result in the best outcome.

In order to obtain a difficult situation, we use the same set of rolling stock that we used in scenario 1, but we double the amounts of passengers. This results in the following passenger-flows (table 4) towards the different destinations.

Destination	B_s	B_tot	C_s	C_tot	D_s	D_tot
# Passengers	3000	9000	4500	12000	2400	7000

Tabel 4: Passengers Scenario 2

Thus, in this case a total of 28,000 passengers have to be transported within the set period of two hours, of which 9,900 are stopping train passengers.

Scenario 3

The third scenario is the hardest one, because we try to make things tricky in this case. The groups of passengers and the total number of passengers are chosen in such a way that we do not know beforehand whether the model will succeed in transporting all passengers or not. In this way, varying α, β and γ will perhaps give possibilities for the problem just to be solved, or just to fall short.

In this scenario, the following numbers of passengers are to be transported.

Destination	B_s	B_tot	C_s	C_tot	D_s	D_tot
# Passengers	2250	6750	3200	9000	1800	5250

Tabel 5: Passengers Scenario 3

So, in this case the total amount of passengers to be transported is 21,000, of which 7,250 are stopping train passengers.

Chapter 6: Results

In this chapter we will present the results of testing our model in the scenarios we introduced in the previous chapter. We test the model using AIMMS 3.9. In all scenarios we tested the program was finished within a single second running on a Intel Celeron processor with 2 GB RAM clocked at 2GHz.

In our description of the results we will start with the most obvious choices for α, β and γ. In the different scenarios we will explain our choices when we try out other specifications or when we make changes in the initial model.

Results scenario 1

In scenario 1, which is by definition an easy one, the following results are obtained.

First, we show the case in which $\alpha = \beta = \gamma = 1$, so that every part of the objective function gets equal weight.

Scenario 1	B	C	D
Total Capacity	4980 (+480)	9700 (+3700)	4000 (+500)
Stopping train cap.	4980	6700	4000
Total trips	6	11	4
Total stopping trips	6	8	4

Tabel 6: Results Scenario 1

The numbers in brackets show the over- or undercapacities. Positive numbers denote overcapacities, negative numbers undercapacities. As is perfectly clear from those results, all passengers can be transported and the total overcapacity amounts to 4680 places. The only problem will perhaps be the schedule towards destination C. However, using complete enumeration it can be shown that this solution can be translated into a feasible schedule.

Because the objective function has a value of 0 in this solution, any change in α, β and γ will have no influence on the results.

Even though a solution is found, the enormous overcapacity in this solution suggests that there are options for improvements. A first and most intuitive try would be the reduction of the interval length *l*. Although we suppose this works fine, within the scope of our research it will be hard to say anything about it, because we do not know the influence of this interval reduction on the total amounts of passengers that are to be transported.

In scenarios like these, another option is an addition to the objective function. Although in the other cases minimizing the total number of trips is no goal, in this case it will reduce the over-capacity and thus the unnecessary 'empty kilometers'.

This way, the objective function can be defined as

$$\min \sum_{d\in D}(\alpha g_d + \beta h_d + \gamma j_d) + \sum_{d\in D}\sum_{t\in T}(y_{td} + z_{td}) \tag{12}$$

Scenario 1_expanded	B	C	D
Total Capacity	4800(+300)	6020(+20)	4000 (+500)
Stopping train cap.	4800	3320	4000
Total trips	5	7	4
Total stopping trips	5	4	4

Tabel 7: Results Scenario 1 (expanded version)

This way, the overcapacity is reduced from 4680 places to 820 places and the total number of trips is reduced from 21 to 18. It is clear that in a situation with relatively low amounts of passengers, this addition to the objective function proves to be helpful.

Results Scenario 2

In scenario 2, which beforehand will never result in travelling possibilities for all passengers, we will investigate how the model behaves with only a small capacity in comparison to the total number of passengers to be transported. In order to get an impression which choices for α, β and γ might be helpful we give the same results as in scenario 1, that is, with $\alpha = \beta = \gamma = 1$.

Scenario 2	B	C	D
Total Capacity	6000 (-3000)	7460 (-4540)	6920 (-80)
Stopping train cap.	6000 (+3000)	4760 (+260)	6920 (+4520)
Total trips	6	9	8
Total stopping trips	6	6	8

Tabel 8: Results Scenario 2

For this outcome, feasible schedules are easy to obtain, again by using complete enumeration of the possible leaving orders. However, only 72.8% of the total passengers are transported within this solution. It appears that relatively many stopping trains are chosen in comparison to the fraction of stopping train passengers. This is because the stopping train passengers that are not transported are both accounted for in the penalties g_d and h_d. Thus raising β should improve the solution.

Indeed raising β to 2 (or any case in which α and β have a relation of 1:2) results in an extra capacity of 500 passengers, raising the total transported passengers to almost 75%. In al those solutions, changes in γ have no influence, because all destinations are reached. All β's that exceed the relation 2:1 result in lower amounts of passengers transported due to neglected stopping train passengers.

Results Scenario 3

The third scenario promises to be the most interesting for testing, because it should somehow be possible to transport all passengers. In order to find out which improvements will be helpful, we first present the results for the 'standard' case with α = β = γ = 1.

Scenario 3	B	C	D
Total Capacity	6000 (-750)	8720 (-280)	6200 (+950)
Stopping train cap.	6000 (+3750)	5120 (+3120)	6200 (+4400)
Total trips	6	10	8
Total stopping trips	6	7	8

Tabel 9: Results Scenario 3

This is actually quite a nice result, with more then 95% of the 21,000 passengers being transported. Furthermore, the undercapacity (maximum of 750 passengers in total on six trips) will in practice most likely be solved.

However, in the result some things are remarkable and need further explanation or research. First of all, the total capacity in the initial solution exceeds the total capacity in scenario 2. This can be due to a different combination of destinations and trips, resulting in higher numbers of trips for bigger trains for example.

Another result, one which perhaps will give room for improvements, is the fact that the overcapacity to destination D is almost equal to the undercapacity towards the two other destinations.

In this case, raising the β does nog change anything. Furthermore, all destinations are reached, so changing γ will have no influence.

However, there is another option for improvement. With the current model, all differences are weighed equally. However, it is better to have to undercapacities of 300 passengers than one of 600 and one of 0 passengers, because the given capacities are not absolute maxima. When it is really busy people will prefer travelling uncomfortable to not travelling at all. This way of spreading the undercapacities could possibly be implemented into the model by making the objective function piecewise linear in the way declared in section 4.2.

We implemented this by trying various combinations of breaks and weights, especially on the value of β and thus the influence of g_d. For example, the case with break points at values of 200 and 500 for g_d turned out to reduce the variance of the undercapacities. However, in all cases we considered, this resulted in a considerable increase of the objective value. This is the result of the sum of small differences in capacities over a number of trips. In order to obtain a standard on which increase of the objective function is allowable in return for a decrease of the variance of the undercapacities, more research would be needed.

In practice, we suggest to make a manual change in the solution by deleting a trip to D and rescheduling it towards B. In the given formulation, the model is unable to allocate a train to different directions.

Chapter 7: Conclusion

In this final chapter we will summarize this thesis and derive some conclusions, remarks and points of discussion.

The model we defined in this report seems to be able to solve the problem we defined in the second chapter. That is, given the list of assumptions we gave, we established a method for allocation of the trains to the different directions which seems to result in a solution that maximizes the number of transported passengers in such a way that a feasible timetable remains possible. Furthermore, all those solutions can be obtained within seconds after the needed information is gathered. We suggest that different scenarios, based on the relations between available capacity and waiting passengers, are pre-programmed.

Within the solution, there is one crucial choice we have made, by splitting the allocation of rolling stock and the establishing of a timetable for each of the directions. This way the program will most likely end up in a suboptimal solution. We suggest further research on a graph-theoretic model like the one of Caprara et al. (2002) for combining the two stages. The most difficult difference with their model will be the combination of stopping train and intercity passengers that will result in a totally different cost function.

Furthermore, we made a number of simplifying assumptions because we are in the first stage of thinking about this particular problem. However, a number of those assumptions should be changed or integrated into the model.

First and most important is the assumption about the original timetable. We assumed that no trains were stuck underway in between the problem station and the surrounding station. In practice, at every moment of the day somewhere a train will be halfway its route or just about entering a station. The model should be adjusted in such a way that those can be taken into account. Furthermore, one of the extra goals of the model should be to allocate the trains and numbers of trips in such a way that they will end up at the end of the given interval l in the station that fits best into the original timetable. Also, the influence of the temporary timetable in a given area on the timetable in the surrounding area should somehow be measured.

We made a few additional assumptions about rolling stock, available crew, infrastructure and the planning inside the station that should in reality be made part of the programming process.

However, methods for those subproblems exist for the planning of the regular timetable and can be used in the given situation.

We conclude that the model we formulated works quite well given the assumptions we made, but that a lot of work is still to be done before a real comparison with the regular ways of railway disruption management will be possible.

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