# Design of a robust railway line system for severe winter conditions in The Netherlands 

Maarten L. Trap ${ }^{1} \quad$ Dennis Huisman ${ }^{1,2}$<br>Rob M.P. Goverde ${ }^{3}$<br>${ }^{1}$ Process quality and Innovation, Netherlands Railways, P.O. Box 2025, 3500 HA, Utrecht, The Netherlands<br>${ }^{2}$ Econometric Institute \& ECOPT, Erasmus University Rotterdam, P.O. Box 1738,3000 DR Rotterdam, The Netherlands<br>${ }^{3}$ Department of Transport and Planning, Delft University of Technology, P.O. Box 5048, 2600 GA, Delft, The Netherlands maarten.trap@ns.nl, huisman@ese.eur.nl, R.M.P.Goverde@tudelft.nl

Econometric Institute Report EI2016-08


#### Abstract

Winter weather has a major impact on railway operations in The Netherlands. To stay in control, the number of trains is reduced by half in a special "winter timetable". This results in a more robust network, but an insufficient amount of transport capacity. Adapting the line system can result in more transport capacity without losing robustness. This paper therefore focuses on the performance of a line system under extreme weather conditions. We define several criteria to assess the performance of the line system in terms of robustness and transport capacity. A case study has been conducted on the railway network in The Netherlands, which indicates that all alternatives are more robust and yield more transport capacity than the current winter timetable.


## 1 Introduction

The winter of 2009/2010 was one of the most extreme winters in The Netherlands in decades. With a mean temperature of $1.1^{\circ} \mathrm{C}$, it was the coldest winter since 1996. Excessive snowfall caused the snow cover to break the record of 1979 multiple times. On several days, the operations got "out-of-control". In such a situation, the operational control organizations are no longer able to control the train traffic due to the many disruptions. The subsequent winters in 2011, 2012 and 2013 were similar, with more or less the same weather conditions. Low temperatures and heavy snow have had a major impact on daily life, especially on transport.

During these winters, the operational control of the Dutch railway network has been completely disordered multiple times. The extreme weather circumstances resulted in broken trains and malfunctioning infrastructure, often at the same time and at multiple locations. Recovery from these disruptions is very difficult due to the intensive use of the Dutch rail infrastructure. The interdependencies between routes, rolling stock and crew make that delays are easily propagating through the whole network. The normal approach to disruption management consists of rescheduling the timetable based on predefined contingency plans (Jespersen-Groth et al, 2009; Louwerse and Huisman, 2014). Each contingency plan corresponds to a specific disruption scenario at a specific location like a fully or partially blocked track or station area. However, the actual situation always differs from a predefined disruption scenario so that traffic controllers have to adjust or combine plans to find a suitable solution which is an intensive task. Hence, multiple simultaneous disruptions quickly lead to out-of-control situations.

Since the first problems in 2009/2010, Netherlands Railways (Nederlandse Spoorwegen, NS) and infrastructure manager ProRail have been working on a comprehensive programme of measures to cope with winter weather and prevent out-of-control situations in the future. The main focus is therefore to increase the robustness of the transport network. One of the most important elements of the winter programme is the alternative timetable. Since the first winter programme in 2010, different timetables have been deployed to increase the robustness and limit the impact of disruptions. The current alternative winter timetable in The Netherlands is the National Reduced Timetable (Landelijke Uitgedunde Dienstregeling, LUD). The LUD is largely based on the regular line system with some mutations in line length and frequency. The LUD is therefore seen as a degraded version of the original timetable. About $20 \%$ of the train trips is canceled throughout the day, effectively reducing the frequency of the train service nationwide to 2 trains/hour. In the busy Randstad area this results in about $50 \%$ less trains.

The LUD can be deployed within a relative short time frame, because it only requires mutations in the regular plan. As a result, the LUD has more or less the same pattern of arrival and departure times which makes that passengers and crew is easily familiarized with the alternative plan. As of this moment, the LUD has proven to be the most successful timetable regarding the robustness of the network. Consequently, the severity of winter-related problems has decreased and the preventive measures have converged to a stable solution.

Decreasing the frequency of train services results in extra allowances and less delay propagation in case of a disruption, but limits the transport capacity. Analysis in both theory and practice shows that the transport capacity of the LUD is not sufficient. Lengthening the operating trains with additional rolling stock is a complex process and is not always possible due to platform constraints. Moreover, for numerous lines the trains cannot be extended since their length is already at maximum. Lengthening trains to yield more capacity is therefore not always possible, which calls for additional measures. Reducing the nuisance caused by crowded trains is therefore one of the main objectives of NS. Hence, another alternative must be found to reduce crowding in the trains while the robustness is conserved. Since the regular timetable is the foundation of the LUD, it might be useful to use a different foundation.

The main foundation of a timetable is the line system. A more robust timetable may thus be obtained for an alternative line system rather than just changing the frequencies of the existing line system. However, an alternative line system requires a new detailed timetable, rolling stock assignment and crew planning. This paper focuses on the changes to the line system and the implications for the assignment of rolling stock, as the latter greatly influences the transport capacity of the railway network. The objective is to reduce the nuisance of crowded trains while conserving robustness, such that train controllers can appropriately respond to disruptions. To achieve this, multiple alternative line systems, along with a corresponding distribution of rolling stock, are designed and evaluated to assess their robustness and transport capacity.

The scientific relevance of this study lies within the development of a novel approach of designing a line system, often called the Line Planning Problem (LPP). Many researchers have written about this problem, often proposing mathematical methods and models to optimize the line planning. Most models are aiming to minimize the costs while maximizing the utility for the passenger (Claessens et al, 1998; Bussieck, 1998; Goossens, 2004). In this paper the cost factor is intentionally left out of scope, as the deployment of an alternative timetable is incidental and not intended to save costs. The main


Figure 1: The railway planning process
contribution of this paper is a new line planning approach, where robustness (in terms of a controllable timetable) and transport capacity (in terms of available seats) are the key decision factors.

Section 2 proposes the new design methodology, which is applied in Section 3 to the railway network of the Netherlands Railways. Section 4 gives conclusions.

## 2 Design methodology and approach

The goal of this study is to design a robust line system with sufficient transport capacity. An iterative design methodology has been used to do so, presented in Figure 2. Several alternative line systems have been suggested, each with an own underlying principle to initiate the design process. The length and frequency of the lines determine the number of trains required to operate each line in the line system. The composition of the trains depends on the number of passengers per train. This is calculated using an OriginDestination Matrix (O-D Matrix) of the Dutch railway network. Using an allocation model, all passengers in the O-D Matrix are allocated to the trains resulting in a list of the travel demand per train composition. Based on the demand, the available rolling stock is assigned to the trains in order to cal-
culate the transport capacity of the line system. If the demand is larger than the capacity of a train, there is a capacity shortage. Adapting the line system could result in less shortage, for instance by increasing the frequency. This is visualized by the feedback loop in the design process. The succeeding sections elaborate further on the steps in the methodology.


Figure 2: Methodology to design an alternative line system

### 2.1 Designing alternative line systems

There are many different possible line systems, all based on an underlying principle or objective. Common recurring approaches in literature are for instance cost reduction (Claessens et al, 1998; Goerigk et al, 2013; Schöbel, 2012), minimization of transfers (Bussieck, 1998; Kaspi and Raviv, 2013; Bussieck et al, 1997), service improvement (De Keizer et al, 2013; Van Oort and Van Nes, 2009) or a combination of these (Goossens et al, 2006). Our methodology suggests to create a line system based on a robust perspective. The robustness of a line system is depending on multiple factors, such that it is not possible to take all factors into account simultaneously. To overcome this, multiple alternative line systems are created, all with their own underlying principle.

If the layout of the line system is complete, the frequencies for the lines are set. The result of this step in the design process is a complete list of all lines in the line system, consisting of their type (for instance InterCity or Regional train), frequency and the commercial stops per line. For all lines, the maximum train length can be determined by the stations the train serves. The shortest platform length of the served stations is the maximum train length.

### 2.2 Passenger allocation

In order to calculate the transport capacity of a line system, the number of passengers per line and per train has to be determined. An OriginDestination Matrix (O-D Matrix) is used to estimate the travel demand $D_{i j}$ from origin $i$ to destination $j$. Alle passengers in the O-D Matrix must be allocated to the lines in the line system. In this paper, the allocation of
passengers is performed using an allocation model called TRANS (Warmerdam, 2004), which determines the line(s) a passenger uses to travel from origin to destination. This is straightforward if there is only one possibility, but requires a discrete choice once there are more travel options, especially when a transfer is required. First, TRANS allocates the passengers to the different lines in the line system. Subsequently, the passengers are allocated to the trains on that line.

### 2.2.1 Allocation to lines

To allocate passengers to the lines, TRANS uses two phases. The first phase is the generation of all possible travel options. In similar studies, these options are also called itineraries. For every origin $i$ to destination $j$ (called O-D pair), TRANS generates a large set of possible travel options. Subsequently, TRANS determines which travel options are realistic by comparing two options with each other regarding travel time, transfers and frequency. Ticket price is not considered since it is assumed that a trip from $i$ to $j$ has the same price for all possible travel options. If one of the options is classified as "unrealistic", it is deleted from the set of options. This happens for instance if the difference in travel time between two options is greater than a certain threshold ( 20 minutes), while having the same number of transfers. This threshold and other parameters for the comparison have a default value based on research by NS. The result of the first phase is thus a set of travel options per O-D pair.

The second phase allocates the passengers to the travel options corresponding to the O-D pair using a discrete choice model. This is a mathematical function to predict the choice of a passenger based on the utility of the travel option (Akiva and Lerman, 1985). The utility of a travel option describes the preference of the passengers to use this travel option, based on multiple observable factors like the travel time and the number of transfers. The allocation is calculated using a Multinomial Logit (MNL) model, included in TRANS. Such a model incorporates the theory of utility maximization, which means that most passengers will choose the travel option with the largest utility (Dow and Endersby, 2004). Normally, a stochastic error is added to the utility function to account for possible preferences that cannot be observed. Since TRANS does not account for this preference, it is assumed that travel options with the exact same utility will have an even amount of passengers. The utility $U_{q}$ of each travel option $q$ is calulated using the following function:

$$
\begin{equation*}
U_{q}=\beta_{1} \cdot T_{t_{q}}+\beta_{2} \cdot O_{q}+\beta_{3} \cdot T_{O_{q}} \tag{1}
\end{equation*}
$$

The different elements used in this equation are:

- The travel time $T_{t_{q}}$, being the travel time from origin to destination using travel option $q$. This is calculated by multiplying the length of each attended edge $b$ with the average speed on that edge and adding a dwell time $T_{d}$ for each station the line serves. The dwell time includes the additional time required for deceleration and acceleration before and after the actual stop.
- The number of transfers $O_{q}$, determined via a path finding algorithm in TRANS.
- The transfer time $T_{O_{q}}$, determined via the same algorithm and the frequency of the transfer.
- Coefficients $\beta_{1} \ldots \beta_{3}$ are used to weigh the parameters.

Once the utility of all travel options per O-D pair is calculated, the share of passengers using each travel option is determined. Equation (2) gives the used function, which calculates the share $S_{q}$ of passengers using travel option $q$. Here, $f_{q}$ is the frequency for travel option $q$.

$$
\begin{equation*}
S_{q}=\frac{f_{q} \cdot e^{U_{q}}}{\sum_{r} f_{r} \cdot e^{U_{r}}} \tag{2}
\end{equation*}
$$

Multiplying $S_{q}$ by $D_{i j}$ yields the actual number of passengers traveling from $i$ to $j$ using travel option $q$. TRANS calculates the utility of the travel options for all O-D pairs in the O-D Matrix, such that the passenger load $P_{i j}^{l}$ can be calculated as well. This is the number of passengers on line $l$ between stations $i$ and $j$. The values of $D_{i j}$ originate from the O-D Matrix.

### 2.2.2 Allocation to trains

Every line requires a minimum number of train compositions to operate with the given frequency. The total number of trains $W_{l}$ per line $l$ is depending on the complete round-trip time $T_{c}^{l}$ and the headway $H_{l}$, rounded up using the following function:

$$
W_{l}=\left\lceil\frac{T_{c}^{l}}{H_{l}}\right\rceil
$$

Once the number of passengers and trains per line is known, the passengers are allocated to a specific train. This yields the travel demand per train between all stations the train serves, hence the travel demand per edge. The busiest edge a train encounters is the edge with the largest demand. The train must at least have enough capacity to transport these passengers. On
a specific line, the busiest edge is different for each train since the demand depends on the time of the day. Moreover, there is a notable difference in travel demand within the peak hours. TRANS therefore differentiates between the busiest hour, the second busiest hour and off-peak hours. This is because a busy edge can have a higher demand during off-peak hours, than another edge during the busiest peak hour.

This is best explained using an example. Figure 3 shows an imaginary line with the travel demand shown in Table 1, where the first hour of the morning peak is the busiest. The line is operating between $s_{0}$ and $s_{5}$ with intermediate stops $s_{1} \ldots s_{4}$. The trips between stations, including the dwell time at the stations, are all taking 30 minutes and so are the layover times at the terminal stations. This results in a round-trip time of 360 minutes. A frequency of 2 trains/hour yields that there are $\lceil 360 / 30\rceil=12$ trains required to operate this line. During operation, the 12 trains are spread evenly over the line.

Let train 1 depart from station $s_{0}$ just at the start of the busiest hour. This means that train 1 will operate from $s_{0}$ to $s_{2}$ in the 1st hour, from $s_{2}$ to $s_{4}$ in the 2 nd hour and from $s_{4}$ it will encounter off-peak demand. In the 1st hour, the busiest edge is between $s_{1}$ and $s_{2}$ with a demand of 315 passengers. During the 2nd hour, however, the busiest edge is between $s_{2}$ and $s_{3}$ with a demand of 340 passengers. Train 1 should therefore have capacity for at least 340 passengers. Another train in the circulation will attend the edge between $s_{2}$ and $s_{3}$ in the 1st hour of the peak, resulting in a required capacity of at least 510 passengers. This indicates that the length of all trains in the circulation of one line can vary. The desired length of a train depends on the largest demand, which depends on both the time and the location.


Figure 3: A line between terminal stations $s_{0}$ and $s_{5}$ with running- and layover times

Table 1: Passenger demand belonging to the example in Fig. 3

| From | To | 1st hour | 2nd hour | off-peak |
| :--- | :--- | ---: | ---: | ---: |
| $s_{0}$ | $s_{1}$ | 300 | 200 | 140 |
| $s_{1}$ | $s_{2}$ | 315 | 210 | 147 |
| $s_{2}$ | $s_{3}$ | 510 | 340 | 238 |
| $s_{3}$ | $s_{4}$ | 480 | 320 | 224 |
| $s_{4}$ | $s_{5}$ | 360 | 240 | 168 |

Table 2: Sets, parameters and decision variables for the rolling stock assignment model

| Sets | $W$ | Set of all trains |
| :--- | :--- | :--- |
|  | $C$ | Set of all possible train compositions |
| Parameters | $D_{w}$ | Set of all train types |
|  | $L_{w}$ | Number of passengers on train $w$ |
|  | $c a p_{c}$ | Capacity of composithen $c$ |

The result of the allocation per train is a list of all trains required to operate the line system, along with the maximum demand the train will encounter during the day. If all trains have enough capacity to at least accommodate this demand, there is sufficient transport capacity.

### 2.3 Rolling stock assignment

Once we know the required number of trains and their minimum capacity, the actual train units can be assigned to these trains. There is a fixed number of train units available which can be coupled to form a train composition, consisting of one or more train units of the same type. Each possible composition has its own length and capacity.

The assignment of compositions to the trains can be seen as an optimization problem with the objective to match the composition capacity with the number of passengers. In other words: the shortage of train capacity must be minimized. There is a shortage of capacity if not all passengers can be transported, for instance if the train is too short. The resulting shortage is expressed as the number of passengers that is unable to be transported in a decent way. An integer linear optimization model has been formulated to assign train compositions to every train on the network. This model is based on similar models presented by Abbink et al (2004) and Fioole et al (2006) and is adapted for the purpose of this study. Table 2 lists the sets, parameters and decision variables required for the model.

The rolling stock assignment model can be formulated as follows:
Minimize:

$$
\begin{equation*}
Z=\sum_{w \in W} z_{w} \tag{3}
\end{equation*}
$$

Subject to:

$$
\begin{align*}
z_{w} & \geq \sum_{c \in C}\left(D_{w}-\operatorname{cap}_{c}\right) \cdot x_{w, c} & & \forall w \in W  \tag{4}\\
\sum_{c \in C} x_{w, c} & =1 & & \forall w \in W  \tag{5}\\
\sum_{c \in C} l_{c} \cdot x_{w, c} & \leq L_{w} & & \forall w \in W  \tag{6}\\
\sum_{c \in C} \sum_{w \in W} n_{c, s} \cdot x_{w, c} & \leq N_{s} & & \forall s \in S  \tag{7}\\
x_{w, c} & =\{0,1\} & & \forall w \in W, c \in C  \tag{8}\\
z_{w} & \geq 0 & & \forall w \in W \tag{9}
\end{align*}
$$

The objective function (3) aims to minimize the total shortage of capacity over the complete network. Constraints (4) define the shortage per train if and only if the demand is larger than the capacity of the assigned composition. Constraints (5) ensure that every train is assigned exactly one composition. Constraints (6) limit the length of the assigned composition to the maximum allowed train length. The constraints in (7) limit the maximum number of assigned train units to the fleet size for each train type.

### 2.4 Evaluation of the line system

Once the capacity shortage has been calculated, the alternative line system can be evaluated. We evaluate both the transport capacity and the robustness of the alternatives, and adapt the line system if necessary.

### 2.4.1 Assessment of robustness

Several criteria and corresponding indicators have been determined to assess the robustness of the alternative line systems. The values of these indicators are subsequently used to calculate the robustness index, which is the measure for the robustness of the alternative.

The first criterion is the line length, expressed in the number of major stations a line serves. This is calculated by counting the number of "major" stations for every line, and taking the average.

The second criterion is the traffic intensity. This is measured by determining the number of trains and lines on a railway track between two stations, called an edge. The following indicators are used:

- Average frequency per edge
- Number of edges with frequency $>4$
- Average line density per edge
- Number of edges with $>2$ lines

The values of these indicators are calculated by listing all edges on the main railway network and determine the number of lines that attend each edge. The average line density and the number of edges with more than 2 lines is directly derived from here. The frequency on every edge can be calculated in a similar way by taking the sum of the frequencies of the lines that serve the respective edge.

A third criterion is the controllability of the line system. This criterion determines the number of trains in the operational control regions. We distinguish between traffic control regions of the infrastructure manager and the transport control regions of the railway operator.

- Number of trains per transport control region
- Number of trains per traffic control region
- Average served transport control regions per line
- Average served traffic control regions per line

The values of these indicators are calculated by listing all lines and determining which transport and traffic control regions they serve. The average number of attended regions can be derived from here. The number of trains per region is calculated by taking the sum of the frequencies of all lines that serve the respective region.

The last criterion is the infrastructural disruption risk, which relates to the possibility of a disruption due to failing infrastructure. This could for instance be a bridge, special switches or level crossings. We define two indicators regarding critical switches. These indicators illustrate the number of operational high-speed switches and the average number of switch movements per hour. The values are calculated by listing all edges with a high-speed switch and determining if attending this edge triggers switch movement. If
one switch is for instance controlling the junction between stations $A, B$ and $C$ as shown in Fig. 4, the switch is considered operational if both edges $A-B$ and $A-C$ are attended. Switch operation is estimated using the frequency and assuming an equal pattern over the hour. If $A-B$ is attended once per hour and $A-C$ twice/hour, the assumed order during the hour is $\{A-B, A-C, A-C\}$. This implies two switch movements per hour.


Figure 4: Example of a junction where attendance of both edges implies an operational switch

Once the values of the indicators are known, a Multi-Criteria Analysis (MCA) is performed to calculate the robustness index. A weighted sum of the above mentioned indicators determines the robustness of the alternatives. To make sure that all indicators are contributing on the same scale to the robustness index, the values of all indicators are standardized. The zero-alternative is used as a reference here, which means that the indicator values of each alternative are divided by the corresponding value of A0 and multiplied by 100 to create a new value that is relative to A0. For all indicator values holds: lower is better. This implies that a lower robustness index is preferred over a higher index as well, which makes that that the robustness index of 100 is considered as the upper bound.

The weights are used to prioritize certain criteria and indicators over others, since not every aspect is of equal importance. Weights are determined using an Analytic Hierachy Process (AHP), which makes it possible to systematically structure a decision-making problem with multiple criteria (Saaty, 1990). This is done by creating a hierarchy which divides the problem into different levels. The idea is to estimate how much more important one criterion is, compared to all other criteria. This yields a weight for all criteria, where the most important criterion gets the largest percentage. The sum of all weights is $100 \%$.

## 3 Case study

In this section, we present the results of our case study regarding the capacity shortages and the robustness of three alternative line systems for the Dutch railway network. First, we present the three alternatives and their underlying
principles. Subsequently, we discuss the capacity shortages of each alternative as calculated using the methodology presented in Section 2. The results are compared with the current winter timetable, the LUD. Afterwards, the robustness of each alternative is determined using the robustness index. A sensitivity analysis on this robustness index is presented in Section 3.3.

The following principles have been used:
A1: An alternative with short lines, such that the number of major stations a line serves is constrained to a maximum. This alternative aims to reduce the impact of disruptions on the network.

A2: A control-based alternative, such that lines are bound by a maximum number of (traffic) control regions. This alternative aims to reduce coordination between control regions.

A3: An infrastructure-based alternative where the operation of high-speed switches is evaded by locking the switch in one direction. This alternative aims to reduce the risk on disruptions at all.

The LUD is the current winter timetable and therefore used as reference, i.e. the zero-alternative (A0). In addition, we compare the transport capacity and robustness with the regular timetable.

### 3.1 Calculation of capacity shortage

The capacity shortage of each alternative has been calculated using the models presented in the previous section. The model has been implemented in AIMMS 3.14 using CPLEX 12.6. The used hardware is a Pentium i7 processor with 3.40 GHz and 16 GB RAM. Per alternative and line type, between 120 and 140 trains have been assigned a composition which gives a model with about 2,900 decision variables and 600 constraints. Solving the model takes less than 0.1 seconds.

Figure 5 gives an overview of the capacity shortage per alternative per train composition. The shortages have been sorted in descending order to present the individual differences. The regular line system does not have a capacity shortage, which explains its absence in this chart.

Figure 5 clearly shows the large capacity shortages during the LUD. Some trains require more than 700 additional passenger places, which indisputably results in passengers left behind on the platform. All new alternatives are providing a considerably better transport capacity. A2 is the worst of these, since three trains have a serious lack of capacity and many other trains have small shortages due to the insufficient fleet size.


Figure 5: Capacity shortages for all alternatives per composition in a descending order

### 3.2 Assessment of robustness

To assess the robustness of our alternatives, the indicators have been further specified. A list of major stations, control regions (called DVL for the infrastructure manager ProRail and RBC for the railway operator NS) and other details can be found in Trap (2014). Using the AHP, we have weighed our criteria and indicators. First, the four criteria have been evaluated. The importance of the groups (hence, their weight) has initially been estimated in accordance with an experienced transport controller. In a second stage, weights have been varied to verify the impact of the weights on the robustness index. This will be further elaborated on in Section 3.3. Line length is considered less important than all other criteria, since the line length cannot be expressed in a very structured way. Traffic intensity is considered the most important criterion. The busier the network is, the more dependencies between trains and lines. Since less trains will give more slack, this has been the most important reason to deploy the LUD for instance. The control region attendance and disruption risk are positioned in-between.

Secondly, all indicators within the criteria have been compared using the AHP. This is, again, initially done in accordance with a transport controller. The number of served major stations is the only indicator within its parent criteria group and therefore has a weight of $100 \%$. Within the traffic intensity group, the number of edges with a frequency $>4$ is the most important

Table 3: Initial AHP weights for the criteria

| Criterion | Weight |
| :--- | ---: |
| Line length | $9.7 \%$ |
| Traffic intensity | $36.5 \%$ |
| Control region attendance | $28.5 \%$ |
| Disruption risk | $25.3 \%$ |

Table 4: Initial AHP weights for the indicators

| Indicator | Weight |
| :--- | ---: |
| Major stations served | $9.70 \%$ |
| Frequency | $3.43 \%$ |
| Edges with Frequency > 4 | $20.95 \%$ |
| Line density | $3.69 \%$ |
| Edges with > 2 lines | $8.43 \%$ |
| Trains in RBC Randstad Noord | $1.25 \%$ |
| Trains in RBC Randstad Zuid | $1.25 \%$ |
| Trains in RBC Utrecht | $1.25 \%$ |
| Attended transport control regions | $1.48 \%$ |
| Trains in DVL Amsterdam | $4.96 \%$ |
| Trains in DVL Den Haag | $2.74 \%$ |
| Trains in DVL Rotterdam | $2.74 \%$ |
| Trains in DVL Utrecht | $4.96 \%$ |
| Attended traffic control regions | $7.92 \%$ |
| High-speed switches in use | $10.12 \%$ |
| Switch operation ratio | $15.18 \%$ |

indicator because this is more than the basic train service. A frequency of at most 4 trains/hour is considered safe and can be controlled well in case of a disruption. Regarding the control region attendance, the number of trains in RBC regions is considered less important than the number of trains in DVL regions. This is because the traffic controllers are the first to respond in case of a disruption. The number of trains in DVL Amsterdam and DVL Utrecht is considered more important than in the regions Den Haag and Rotterdam. This is due to the size of these regions and the fact that the largest stations Utrecht Centraal and Amsterdam Centraal are located in these regions. All other DVL regions are not considered, since they have much less traffic to control. For the RBC regions, a similar reasoning holds. The operation ratio of the high-speed switches is furthermore considered more important than the number of operational switches itself. Multiplying the indicator weight
by the weight of its parent (i.e. the criterion) yields the total weight. These initial weights are shown in Table 4. Section 3.3 describes the sensitivity of the robustness index to these weights. When we calculate the weighted sum of the indicators for all alternatives, we obtain the scores presented in Table 5

Table 5: Results of the MCA with initial weights and standardized indicator values

|  |  | Standardized values |  |  |  |
| :--- | :--- | ---: | ---: | ---: | ---: |
|  | Indicator | A0 | A1 | A2 | A3 |
| Line length | Major stations served | 100.00 | 73.41 | 56.01 | 77.51 |
| Traffic intensity | Frequency | 100.00 | 91.52 | 88.78 | 93.40 |
|  | Edges with Frequency > 4 | 100.00 | 82.08 | 79.25 | 95.28 |
|  | Line density | 100.00 | 71.81 | 69.95 | 70.32 |
|  | Edges with > 2 lines | 100.00 | 33.79 | 28.97 | 26.90 |
| Control region attendance | Trains in RBC Randstad Noord | 100.00 | 97.50 | 112.50 | 97.50 |
|  | Trains in RBC Randstad Zuid | 100.00 | 118.75 | 106.25 | 96.88 |
|  | Trains in RBC Utrecht | 100.00 | 102.08 | 100.00 | 104.17 |
|  | Attended transport control regions | 100.00 | 82.71 | 76.28 | 88.76 |
|  | Trains in DVL Amsterdam | 100.00 | 91.67 | 102.78 | 91.67 |
|  | Trains in DVL Den Haag | 100.00 | 116.67 | 122.22 | 105.56 |
|  | Trains in DVL Rotterdam | 100.00 | 121.43 | 100.00 | 85.71 |
|  | Trains in DVL Utrecht | 100.00 | 102.78 | 88.89 | 105.56 |
|  | Attended traffic control regions | 100.00 | 77.99 | 64.42 | 83.68 |
|  | High-speed switches in use | 100.00 | 74.29 | 74.29 | 11.43 |
| Disruption risk | Switch operation ratio | 100.00 | 49.99 | 47.59 | 8.86 |

The results indicate that A3 is the most robust alternative, followed by A2 and A1. All three alternatives are, according to these criteria, by far more robust than the zero-alternative. As a reference, we also calculated the robustness index of the regular line system, being 118.6. This indicates that the LUD line system is more robust than the regular line system, which is in accordance with the expectation. The succeeding sections will elaborate further on the validity of these results and how the robustness index relates to the capacity shortage of all alternatives.

### 3.3 Sensitivity analysis

The initial weights used in the MCA are estimated using subjective judgement. To assess the impact of the weights on the calculated robustness index, a sensitivity analysis is performed. By changing the weights of the criteria and the indicators, the robustness index of the alternatives will change as well. The zero-alternative will always have the same index of $\approx 100$.

The varying of weights is performed using different scenarios. Each scenario has a different distribution of weights, such that it is possible to focus on specific criteria or exclude indicators from contributing to the robustness index. Table 6 shows the scenarios that have been drafted.

Table 6: Scenarios for sensitivity analysis

| Scenario | Description |
| :--- | :--- |
| S1 | Default AHP weight as explained in section 3.2 |
| S2 | Equal weight for all criteria |
| S3 | Equal weight for all indicators within the same group |
| S4 | Equal weight for both criteria and indicators within the same group (no weight) |
| S5 | Line length is excluded from the analysis. Other criteria are reweighed |
| S6 | Traffic intensity is excluded from the analysis. Other criteria are reweighed |
| S7 | Attended control regions is excluded from the analysis. Other criteria are reweighed |
| S8 | Disruption risk is excluded from the analysis. Other criteria are reweighed |
| S9 | Line length is excluded from the analysis. Other criteria are of equal weight |
| S10 | Traffic intensity is excluded from the analysis. Other criteria are of equal weight |
| S11 | Attended control regions is excluded from the analysis. Other criteria are of equal weight |
| S12 | Disruption risk is excluded from the analysis. Other criteria are of equal weight |

All scenarios are based on the default scenario (S1), which means that unchanged weights are the same as in S1. Scenarios S2-S4 are used to determine the robustness index if the criteria and/or the corresponding indicators are weighted equally. Scenarios S5-S8 exclude one of the criteria from the analysis by changing its weight to $0 \%$ to assess the impact of the respective criterion on the robustness index. The other criteria are reweighed in order of importance using the AHP process. A third group of scenarios (S9-S12) excludes one of the criteria as well, while the other three groups are weighed equally.

Figure 6 presents the results of the sensitivity analysis. The lines in the figure indicate the robustness index for each alternative for each scenario. The robustness index of the regular line system is added to indicate that the LUD is more robust than the regular line system in all scenarios, which is in accordance to the expectations.

The chart in Figure 6 also shows that the ranking order between the alternative line systems is very stable. In almost all scenarios, A3 has the lowest robustness index, followed by A2 and A1. In S8 and S12, however, A3 is less robust than both A1 and A2. In both scenarios, the criterion "disruption risk" is excluded from the analysis. We therefore conclude that the low value of the robustness index of A3 is mainly caused by this criterion. This is also visible in Table 5, as the scores of the indicators in this group are very low. Since A3 becomes the least robust alternative in S8 and S12, the usefulness of the number of operational switches and their operation ratio, or at least their weight, in the MCA is questionable.


Figure 6: Robustness index of all alternatives using different weight scenarios

Based on this sensitivity analysis, we can conclude that all alternative line systems are in any case more robust than the LUD, and that the robustness index is only slightly sensitive to the applied weights.

### 3.4 Summary of the results

Figure 7 shows the relation between the robustness index and the capacity shortage. This clearly indicates that all three alternatives are better than the zero-alternative. The sensitivity analysis made clear that the robustness of A 3 is much depending on the weights in the MCA.

The following conclusions can be drawn based on the robustness index and the capacity shortage of the three alternatives:

- A1 and A3 have the least capacity shortage and no unacceptable shortage per composition. A1 is the best of these.
- A2 has a relatively large shortage and requires more rolling stock than in the operational fleet.
- Depending on the weight, A3 can be the best or the worst alternative regarding the robustness index, but is still more robust than A0
- A1 and A2 have a relatively stable robustness index.


Figure 7: Ranges of the robustness index over all alternatives and their capacity shortage

Based on these statements, we can conclude that A1 and A3 are considerably better than A2. Moreover, all alternatives score much better than the current winter timetable.

## 4 Conclusions

In this paper, we developed a methodology to design a robust line system and compute its transport capacity. The robustness of a line system is evaluated on several criteria, which are important on days with heavy weather conditions. To calculate the transport capacity, passengers from the O-D Matrix are allocated to the different lines and trains on the lines to estimate the travel demand per train. The difference between the demand and the train capacity determines the capacity shortage. We showed that there are several alternative line systems possible that score better than the currently operated winter timetable in both robustness and transport capacity.

## Acknowledgements

We would like to thank Timo van de Walle and Serge Hoogendoorn for their valuable input on an earlier draft of this paper.

## References

Abbink E, Van Den Berg B, Kroon LG, Salomon M (2004) Allocation of Railway Rolling Stock for Passenger Trains. Transportation Science 38(1):3341, DOI 10.1287/trsc.1030.0044

Akiva MEB, Lerman SR (1985) Discrete choice analysis: theory and application to predict travel demand, vol 9. MIT Press, Cambridge, MA

Bussieck MR (1998) Optimal lines in public rail transport. PhD Thesis, TU Braunschweig, Germany

Bussieck MR, Kreuzer P, Zimmermann UT (1997) Optimal lines for railway systems. European Journal of Operational Research 96(1):54-63, DOI 10.1016/0377-2217(95)00367-3

Claessens MT, Van Dijk NM, Zwaneveld PJ (1998) Cost optimal allocation of rail passenger lines. European Journal of Operational Research 110(3):474489, DOI 10.1016/S0377-2217(97)00271-3

De Keizer B, Fioole PJ, Van’t Wout J (2013) Optimalisatie van de lijnvoering op Railnetwerken. Colloquium Vervoersplanologisch Speurwerk. Rotterdam, The Netherlands

Dow JK, Endersby JW (2004) Multinomial probit and multinomial logit: a comparison of choice models for voting research. Electoral Studies 23(1):107-122, DOI 10.1016/S0261-3794(03)00040-4

Fioole PJ, Kroon LG, Maróti G, Schrijver A (2006) A rolling stock circulation model for combining and splitting of passenger trains. European Journal of Operational Research 174(2):1281-1297, DOI 10.1016/j.ejor.2005.03.032

Goerigk M, Schachtebeck M, Schöbel A (2013) Evaluating line concepts using travel times and robustness. Public Transport 5(3):267-284, DOI 10.1007/ s12469-013-0072-x

Goossens JWHM (2004) Models and Algortithms for Railway Line Planning Problems. PhD Thesis, Maastricht University, The Netherlands

Goossens JWHM, Van Hoesel CM, Kroon LGL (2006) On solving multi-type railway line planning problems. European Journal of Operational Research 168(2):403-424, DOI 10.1016/j.ejor.2004.04.036

Jespersen-Groth J, Potthoff D, Clausen J, Huisman D, Kroon LG, Maróti G, Nielsen MN (2009) Disruption Management in Passenger Railway Transportation. In: Ahuja RK, Möhring RH, Zaroliagis CD (eds) Robust and Online Large-Scale Optimization, no. 5868 in Lecture Notes in Computer Science, Springer Berlin Heidelberg, pp 399-421

Kaspi M, Raviv T (2013) Service-Oriented Line Planning and Timetabling for Passenger Trains. Transportation Science 47(3):295-311, DOI 10.1287/ trsc.1120.0424

Louwerse I, Huisman D (2014) Adjusting a railway timetable in case of partial or complete blockades. European Journal of Operational Research 235(3):583-593, DOI 10.1016/j.ejor.2013.12.020

Saaty TL (1990) How to make a decision: The analytic hierarchy process. European Journal of Operational Research 48(1):9-26, DOI 10.1016/ 0377-2217(90)90057-I

Schöbel A (2012) Line planning in public transportation: models and methods. OR Spectrum 34(3):491-510, DOI 10.1007/s00291-011-0251-6

Trap ML (2014) The Dutch Winter Timetable: Assessment of Alternative Line Systems for the Dutch Railway Network during Winter Weather. Master Thesis, Delft University of Technology, Delft, URLhttp://resolver. tudelft.nl/uuid:10ed75ca-76dd-4293-aeb1-f2005a1d30e1

Van Oort N, Van Nes R (2009) Line Length Versus Operational Reliability: Network Design Dilemma in Urban Public Transportation. Transportation Research Record: Journal of the Transportation Research Board 2112(3):104-110, DOI 10.3141/2112-13

Warmerdam J (2004) Specificaties TRANS toedeler. Internal Document, QQQ Delft, Delft.

