A model for Robust Rolling Stock Scheduling

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Short summary

Major disruptions render the schedules of public transport operators infeasible. The majority of the recently developed algorithms for updating these schedules assume the duration of the disruption is known when they occur. However, in practice, this is generally untrue. This paper compares three different models for Rolling Stock Rescheduling under uncertainty: an optimistic approach, a strict-robust model inspired by the definition of disruption of Ben Tal et al, and a Light-Robustness approach that aims to provide a middle way between the two.
The models are evaluated on a realistic case study of the Netherlands Railways. Initial results indicate that building robustness against different disruption durations is worthwhile when alternative scenarios are associated with a sizable probability mass. The best approach depends on the probability distribution over the different scenarios.
Keywords:public transport, passenger train rolling stock rescheduling, robust optimization, mathematical combinatorial optimization

1 Introduction

Railway operators all over the world transport millions of passengers on a daily basis. During actual operations, railway operators may face major *disruptions* as a result of, e.g., a system malfunction, an accident, or the complete blockage of a track segment by a fallen tree. In such cases, the current operational plan becomes infeasible, and needs to be rescheduled. Research on effective disruption management has led to many algorithmic tools for rescheduling the timetable, rolling stock and crew schedule (see Cacchiani et al. (2014)). These types of advances support operators in increasing the reliability of their operations' reliability, hopefully positively impacting their passenger volumes.
Our work focuses on robust rolling stock rescheduling assuming the duration of the disruption is uncertain. Previous research on this topic, such as Nielsen (2011), Løve et al. (2002), and Wagenaar (2016), have always assumed the duration of the disruption is known. Although such algorithms could be used in a rolling horizon setting, this means that in practice they will often have either over or underestimated the disruption duration.
Considering only a single disruption duration when rescheduling the rolling stock could result in myopic, irreversible decisions that may negatively impact passenger comfort. For example, it might be impossible to provide capacity for all passengers on a trip if the disruption lasts longer or shorter than expected, trips may have unnecessarily been cancelled, or additional trips need to be cancelled due to unforeseen shortages of rolling stock. If disruption duration variability is considered when rescheduling the first time, then the quality of the service that the operator is able to provide can be improved. Moreover, a minimization in the number of required updates has a practical advantage. At many operators, the updating of the schedule requires manual updates and communications, and the risk of errors is minimized when the frequency of these changes is minimized.
The main contribution of this paper is a model that is able to reschedule the rolling stock schedule in a robust way. This means that the rolling stock schedule requires no or small additional changes in case the disruption duration turns out to be longer than orignally expected. Depending on the level of robustness required, our model is able to give a full robust or a semi-robust solution. In case of a full robust solution all important trips and all composition changes are robust against different

disruption durations and in case of a semi-robust solution at least a given percentage of the trips must be robust against different disruption durations. We also demonstrate that robustness comes at a price and show what this price is for different practical settings.

2 Methodology

Problem definition

We consider the variant of the rolling stock scheduling problem as defined in Fioole et al. (2006), with the additional complication that, in contrast to (Fioole et al., 2006), the duration of the disruption is uncertain. Rolling stock scheduling thus entails finding a minimum cost assignment of train *compositions* (a specific ordering of specific rolling stock type units) to a set of timetabled *trips*. A trip refers to the movement of a train between two successive stops. It is assumed that both the departure time and the arrival time of any trip are known. Associated with each trip is a known, forecast demand that indicates the number of passengers who wish to make the trip. A *service* refers to the movement of a train between two terminal stations and comprises a sequence of trips. For any trip, its predecessor trip and its successor trip are specified in the timetable. Figure 1 illustrates an example timetable, adjusted after a major disruption. Stations are depicted as vertical layers, and time runs from left to right. A total of 44 trips is depicted, examples of which include t_1, t_2, and t_3. The sequence $t_1 - t_2 - t_3$ provides an example of a service between Amsterdam (Asd) and Arnhem (Ah).
The general objective of the rolling stock rescheduling problem is to minimize a weighted combination of the number of cancelled trips, the number of additional composition changes and shunting movements in comparison to the planned rolling stock schedule, carriage kilometers, seat-shortages, and end-of-day imbalances in rolling stock depot inventories.

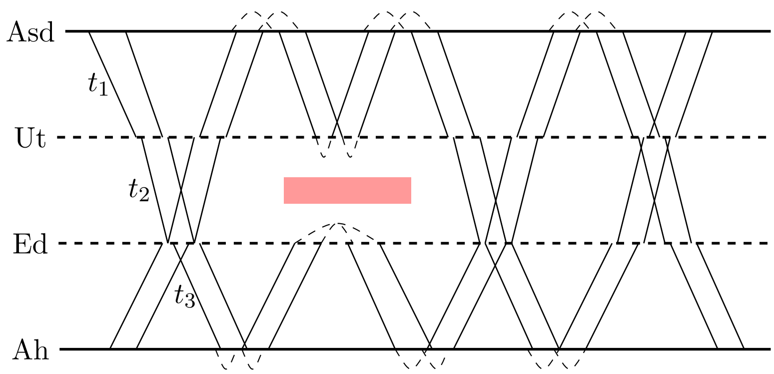

Figure 1: Timetable with disrupted area and short-turning.

Three approaches to robust rolling stock rescheduling

We propose three approaches for rolling stock rescheduling under uncertainty: a hopeful approach (HOPE) that always assumes the shortest-possible disruption duration and updates the rolling stock schedule step-by-step whenever this assumption is incorrect; a strict composition robust approach (STR), inspired by robustness as defined in Ben-Tal & Nemirovski (2002); and a light trip robust approach (LTR), inspired by light robustness as defined in Fischetti & Monaci (2009). All models are mixed-integer-programming models customized for rolling stock rescheduling under uncertainty. Unfortunately, the length of the abstract does not allow us to present them in detail here.

3 Results and discussion

Case study

2 depicts our Netherlands Railways(NS) based case study, spanning with 3 lines a signifcant and busy part of the network consisting or 1094 trips. We consider 16 different compositions, and thus

223 different composition changes, and assume that composition changes may occur after every trip.

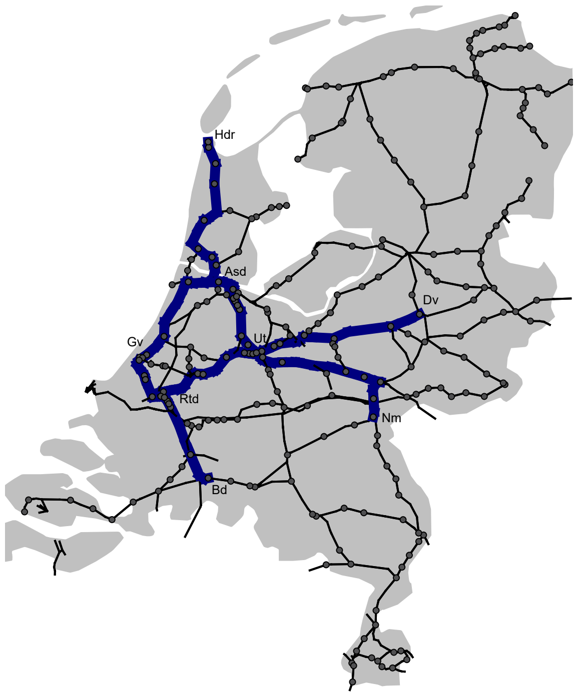

Figure 2: Train lines in the Netherlands. The lines in blue are the ones considered in the case study.

Evaluation function

The quality of a schedule is defined, for each possible disruption scenario, by the weighted sum of schedule changes. Table 1 gives an overview of the objective coefficients that we use in our experiments to evaluate the rescheduling approaches, set in discussion with NS. We make a distinction between rescheduling the first time (update λ_0) and rescheduling thereafter again (update λ_i for $i \geq 1$).

Costs	λ_0	λ_i for $i \geq 1$
Seat shortages: **SS**	0.1	0.1
Carriage costs p km: **Carr.**	0.01	0.01
Unplanned Shunting	10	100
Cancelled Shunting	5	20
Difference in end of day balance: **EOD**	10	10
Change in composition type: **Composition**	5	10
Cancellation of trip: **Cancel**	100000	100000

Table 1: Overview of costs

Detailed discussion of a single instance

There is a disruption between Utrecht (Ut) and Amsterdam (Asd) starting at 7:00 in the morning. We have the scenario set $\mathcal{S} = \{[(7:00, 9:00)], [(7:00, 9:00), (9:00, 11:00)]\}$. We show and compare results of four of our rescheduling approaches; the HOPEapproach, the LTR approach with $\alpha = 0.4$ and $\alpha = 0.8$, and the STR approach.
The results of our comparison regarding the different cost components and the overall objective are given in Table 2. Here, the columns denote the total penalty paid for each different components of the evaluation. Only 'Shunting' denotes a combination of the penalties for both unplanned and cancelled shunting movements. The first three rows of the table show the evaluation value

and its components when rescheduling the original rolling stock schedule at time $\lambda_0 = 7:00$ for disruption end time $d_0 = 9:00$, that is, for update $u_0 = (7:00, 9:00)$. In the second set of rows we see the rescheduling costs that we incur if we need to reschedule for a second time, that is, for update $u_1 = (9:00, 11:00)$. The third set of rows depict the total costs for scenario $S_1 = [(7:00, 9:00), (9:00, 11:00)]$. The final set of rows shows the expected evaluation value and its cost components for the scenario set $\mathcal{S} = \{S_0, S_1\}$ with $S_0 = [u_0]$ and $\pi_0 = \pi_1 = 0.5$.

Evaluation	Approach (A)	Evaluation value	SS	Carr	Shunting	EOD	Cancel	Comps
	$HOPE$	3066	1285	1181	65	100	0	435
	$LTR^{0.4}$	3199	1280	1184	140	100	0	495
'disr. ends at 9:00'	$LTR^{0.8}$	3470	1300	1180	185	100	0	705
	STR	3658	1231	1183	150	200	0	894
	$HOPE$	4468	1385	1175	600	100	0	1210
'rescheduling costs'	$LTR^{0.4}$	3908	1310	1178	260	100	0	1060
	$LTR^{0.8}$	3054	1150	1174	140	100	0	490
	STR	2664	1281	1183	0	200	0	0
$GC(A, R_0, S_1)$	$HOPE$	4968	1385	1175	665	100	0	1645
'disr. ends at 11:00'	$LTR^{0.4}$	4543	1310	1178	400	100	0	1555
	$LTR^{0.8}$	3944	1150	1174	325	100	0	1195
	STR	3708	1281	1183	150	200	0	894
$GC(A, R_0, \mathcal{S})$	$HOPE$	4017	1335	1177	365	100	0	1040
'expected value'	$LTR^{0.4}$	3875	1300	1180	270	100	0	1025
	$LTR^{0.8}$	3707	1225	1177	255	100	0	950
	STR	3683	1256	1183	150	200	0	894

Table 2: Evaluation values and their components for the single instance considered in Section 3.

For short disruption lengths, the robust approach provides a cost that can be avoided using the HOPEapproach. The main difference in schedules stems from the penalty for having more changed shunting operations and the number of different compositions appointed. However, when the disruption last long (second scenario) the rescheduling for the HOPE approach is much more expensive, in particular with respect to using different shunting operations and different compositions than in the initial schedule. Whether building in this robustness is worthwhile, depends on the probability on each of the two scenarios occuring.
The last set of columns denotes the expected evaluation value assuming a probability of 50% for each scenario, indicating the STR approach as optimal in this example. Figure 3 shows the expected evaluation values depending on the probabilities that we assign to the two scenarios 'disruption is over at 9:00' (π_0) and 'disruption is over at 11:00' ($\pi_0 = 1 - \pi_1$). As can be seen, in this example, each of the strategies is optimal for a certain range of probabilities: for a low probability of a later disruption end time, i.e., $\pi_1 \leq 0.22$, the HOPEapproach is best, for $0.22 \leq \pi_1 \leq 0.0.3$ $LTR^{0.4}$ is best, for $0.3 \leq \pi_1 \leq 0.45$ $LTR^{0.8}$ is best, for $\pi \geq 0.45$ the STR approach should be used.
In general, we observe that the penalty for the additional canceling of trips is chosen so high that the model avoids this measure completely. Composition changes, changes in the shunting movements, and in the end of day balance, which are penalized moderately in the model, have most influence on the evaluation. Seat shortages and costs for operating the carriages play a minor role for this parameter setting.
Experiments concerning multiple scenarios, and different ways of dealing with uncertain disruption length, are underway. Preliminary results indicate that whether the build-in of initial robustness against a longer disruption length is worthwhile when the probability of longer disruption lengths represents a significant probability mass.

4 Conclusions

We proposed three approaches to rolling stock rescheduling under uncertainty: HOPE, LTRand STR. The first represent current approach, the second a Light-robustness approach, and the latter a

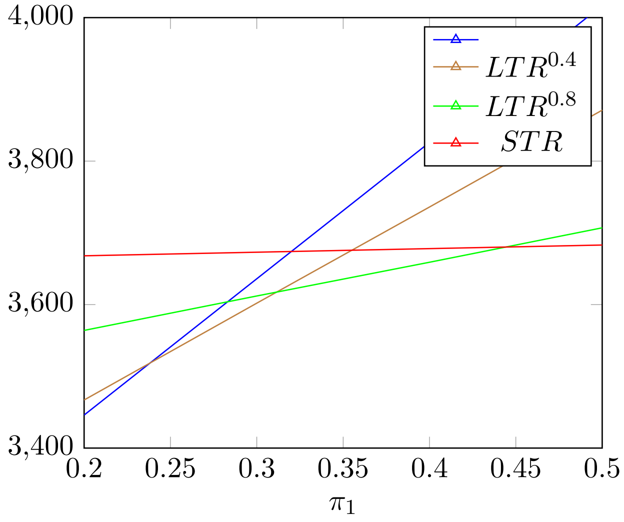

Figure 3: Expected evaluation values. The figure zooms in on the interesting part between $0.2 \leq \pi_1 \leq 0.5$

strict robustness version in the spirit ofBen-Tal & Nemirovski (2002). Mixed-Integer programming formulations have been developed for all three, that within a reasonable time can be solved with a commercial solver like CPlEX, Gurobi,etc. These approaches are evaluated on a realistic case study for Netherlands Railways. The results indicate that it is worthwhile to build in robustness for multiple possible durations of the disruption when there exists a reasonable probability for an alternative scenario. Which approach in expectation is best depends on the probabilities associated with each disruption scenario.
Current work is evaluating the model for multiple cases and multiple scenarios. Moreover, a sensitivity analysis for the selection of objective-parameters is on its way.

References

Ben-Tal, A., & Nemirovski, A. (2002). Robust optimization–methodology and applications. *Mathematical Programming*, *92*(3), 453–480.

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

Fioole, P.-J., Kroon, L., 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.

Fischetti, M., & Monaci, M. (2009). Light robustness. In *Robust and online large-scale optimization* (pp. 61–84). Springer.

Løve, M., Sørensen, K. R., Larsen, J., & Clausen, J. (2002). Disruption management for an airline—rescheduling of aircraft. In *Workshops on applications of evolutionary computation* (pp. 315–324).

Nielsen, L. K. (2011). *Rolling stock rescheduling in passenger railways: Applications in short-term planning and in disruption management* (No. EPS-2011-224-LIS).

Wagenaar, J. (2016). *Practice oriented algorithmic disruption management in passenger railways* (No. EPS-2016-390-LIS).