A Robust Rolling Stock Rescheduling Approach

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1 Introduction

Railway operators all over the world transport millions of passengers on a daily basis. These railway operators schedule the timetable and associated resources during an extensive planning period. The most common resources are the rolling stock and the crew schedule. All three schedules are often an optimized trade-off between passenger service, efficiency and robustness.

During actual operations, railway operators are faced with all kinds of unforeseen incidents having a negative effect on the railway schedules, which are named disruptions. For example, a system malfunction, an accident, or the complete blockage of a track segment by a fallen tree. In such cases, the timetable, the rolling stock schedule, and the crew schedule might be rendered infeasible. Effective disruption management is currently an active research area in Operations Research. This has lead to many papers on algorithmic tools for rescheduling the timetable, rolling stock and crew schedule (see Cacchiani *et al.* (2014)).

The focus in this paper is solely on rescheduling the rolling stock (RS) schedule, scheduling the timetable and crew is outside the scope. Many researchers (e.g. Nielsen (2011), Wagenaar (2016)) have already conducted research on this topic. However, all these models assume the duration of a disruption to be known at the time of rescheduling. Unfortunately, in practice the duration of a disruption is often uncertain.

Assuming that the disruption duration is known may lead to new problems if the realized duration of the disruption differs from what was assumed. Not considering the variation in disruption duration will result in a situation in which the rescheduling must be performed all over again. Some decisions could turn out to be very costly in terms of i) operating costs, ii) passenger service, and iii) possible communication problems.

In practice, an estimation on the disruption duration is made as soon as a disruption occurs. This estimation gives, among other information, a minimum and maximum duration. The main contribution of this paper is a model that is able to reschedule the RS schedule in a robust way. This means that the RS schedule created for the minimum disruption duration requires no or small additional changes in case the disruption duration turns out to be longer. A fully robust solution might come at an high expense. To that end, a second contribution is that we have developed a model to create a semi-robust rolling stock circulation, which includes a given level of robustness required.

2 Methodology

Algorithm 1 presents the current common approach to deal with an uncertain disruption duration. It starts with solving the nominal (deterministic) RS rescheduling model M^0, described in, among others, Fioole *et al.* (2006), Wagenaar *et al.* (2017), and Haahr *et al.* (2016), that assumes the disruption duration to be known and equal to the assumed minimum duration (denoted by d^{min}). In the first iteration the planned RS schedule (R_0) and the rescheduled timetable T_{λ_0} are provided as input and a new RS schedule $R^0_{\lambda_0}$ is constructed, allowing changes in composition assignments from the start of the disruption. When the disruption lasts longer, e.g. to λ_1 (or other durations $\lambda_2, \cdots, \lambda_n$), the RS schedule is updated, where changes to the previous RS schedule ($R^0_{\lambda_0}$) are only allowed after communicating λ_1, which is strictly after the time of communicating λ_0. This is repeated until no updates on the disruption duration take place. As M^0 does not consider any information on possible alternative durations of the disruption, it cannot anticipate on these alternative scenarios.

Algorithm 1: Nominal Approach

1 $M^0(T_{\lambda_0}, R_0) \rightarrow R^0_{\lambda_0}$
2 **for** i = *1*: n **do**
3 $\quad M^0(T_{\lambda_i}, R^0_{\lambda_{i-1}}) \rightarrow R^0_{\lambda_i}$
4 **end**

Algorithm 2 presents the strict composition robust approach to deal with a disruption. As additional input, the model requires the maximum duration (T_+) of the disruption in order to produce a new RS schedule $R^s_{\lambda_0}$, which is robust against all possible disruption durations in between the minimum and maximum duration.

The strict RS rescheduling model (M^s) is an extension of the nominal model existing in the literature, which creates an RS schedule for the minimum duration (λ_0), but restricts the composition assignment such that if the disruption takes longer, only very small changes are required, namely the trains that travel over the tracks hit by the disruption need to be cancelled. This is represented in Algorithm 2 by the method M^{cancel}. Such a change is easy and fast, as major additional shunting movements, which need to be communicated, are avoided. In order to achieve this, the M^s model has additional constraints, making sure that for all possible disruption updates in between the minimum and maximum duration of the disruption, all trips have the same composition and composition changes. A resulting disadvantage is that the model could be restrictive, as it needs to be robust for all possible disruption lengths, and may as a result be expensive in terms of operating costs.

Algorithm 2: Strict Composition Robust Approach

1 $M^s(T_{\lambda_0}, R_0, T_+) \rightarrow R^s_{\lambda_0}$
2 **for** i = *1*: n **do**
3 $\quad M^{cancel}(T_{\lambda_i}, R^s_{\lambda_{i-1}}) \rightarrow R^s_{\lambda_i}$
4 **end**

A third method has been developed which is more robust than the nominal approach, but less restrictive than the strict approach. Algorithm 3 presents the light trip robust approach. This method provides the possibility to specify a level of robustness α that defines α percentage of trips that must receive the same composition irrespective of the disruption duration when rescheduling with M^α, resulting in a new RS schedule $R^\alpha_{\lambda_0}$. A difference with M^s is that new composition changes are permitted to ensure this consistency. Therefore, even with $\alpha = 1$, this method is less restrictive than the strict approach, but it will likely need more changes in case of a disruption duration update. As it does take into account a possible different disruption duration, the expectation is that fewer changes will be required in case of an update λ_i in comparison with the nominal approach, at less operational costs than the strict approach.

Algorithm 3: Light Trip Robust Approach

1 $M^\alpha(T_{\lambda_0}, R_0, T_+) \rightarrow R^\alpha_{\lambda_0}$
2 **for** $i = 1 : n$ **do**
3 $\quad M^\alpha(T_{\lambda_i}, R_{\lambda_{i-1}}, T_+) \rightarrow R^\alpha_{\lambda_i}$
4 **end**

3 Results and Discussion

The three approaches were tested on a case study from Netherlands Railways, where there are 1078 trips in the Western part of The Netherlands. There are three different disruption locations tested; between Utrecht and Amsterdam (Ut-Asd), between Rotterdam and The Hague (Rtd-Gv), or between Haarlem and Amsterdam (Hlm-Asd) causing no trains being able to travel between those stations during the disruption. At every location, the minimum disruption lasts from 06:00-08:30, 07:00-09:00, or 09:30-12:00 in the morning. Furthermore, each disruption has a maximum duration either one, two, three, or four hours longer than the minimum duration.

In the first case study, we test all approaches where we reschedule for the minimum duration, where the robust approaches take into account the maximum duration. Then, we compare the results in case the minimum duration (λ_0) turns out to be true or in case the maximal duration (λ_1) turns out to be true. In the latter situation, rescheduling takes place at the start of the disruption and at time λ_0. Table 1 presents results for the light robust approach with $\alpha = 0.4, 0.8$ and the strict robust approach. Each entry represents the relative objective difference with the nominal approach. For example, the strict approach is on average 22% better than the nominal approach in case λ_1 turns out to be the true disruption duration for the disruptions between Utrecht and Amsterdam.

The last three rows represent the expected costs in case there is a 50% probability that λ_0 is the correct disruption duration and a 50% probability that λ_1 is the true disruption duration. As can be seen, in case there is a 50% probability on either of the disruption durations to be true, a robust approach outperforms the nominal approach. Furthermore, the strict robustness approach seems to be best in case it is probable that the disruption could take longer than the minimum duration.

Disruption	Model	Ut-Asd	Rtd-Gv	Hlm-Asd	600-830	700-900	930-1200	All
	0.4	0.03	0.01	0	0.01	0.03	0.01	0.01
λ_0	0.8	0.10	0.07	0.12	0.10	0.09	0.07	0.09
	Strict	0.14	0.13	0.15	0.16	0.13	0.11	0.13
	0.4	**-0.05**	**-0.02**	**-0.06**	**-0.05**	**-0.06**	**-0.04**	**-0.04**
λ_1	0.8	**-0.07**	**-0.05**	**-0.09**	**-0.05**	**-0.08**	**-0.07**	**-0.06**
	Strict	**-0.22**	**-0.18**	**-0.17**	**-0.17**	**-0.19**	**-0.20**	**-0.19**
	0.4	**-0.02**	**-0.01**	**-0.04**	**-0.02**	**-0.02**	**-0.02**	**-0.02**
Expectation	0.8	0	0	0	0.02	**-0.01**	**-0.01**	0
	Strict	**-0.07**	**-0.05**	**-0.04**	**-0.03**	**-0.06**	**-0.08**	**-0.05**

Table 1 – *Results for two disruption durations. Every number represents the relative total costs difference between rescheduling using the nominal approach and one of our approaches in case the corresponding disruption duration turns out to be true.*

In the second setting, we first reschedule again for the minimum duration, where the robust approaches consider a maximum duration of four hours longer. Then, every hour an update could be given that the disruption lasts one hour longer or that the disruption is over. After four hours the disruption is always over. Thus, we reschedule the rolling stock potentially five times. Table 2 presents the results in case the disruption would be over after each of the potential durations. Again, the strict robust approach performs on average best.

Disruption	Model	Ut-Asd	Rtd-Gv	Hlm-Asd	600-830	700-900	930-1200	All
	0.4	0.03	0.02	0.01	0.01	0.03	0.02	0.02
λ_0	0.8	0.14	0.09	0.08	0.06	0.16	0.13	0.10
	Strict	0.30	0.21	0.18	0.17	0.27	0.33	0.23
	0.4	0.03	0.02	0	0.02	0.01	**-0.01**	0.02
λ_1	0.8	**-0.02**	0.03	0.03	0	0.03	0.03	0.02
	Strict	**-0.04**	0	0.06	**-0.02**	0.02	0.06	0
	0.4	0.03	**-0.02**	0	0.02	**-0.01**	**-0.03**	0
λ_2	0.8	**-0.05**	**-0.02**	**-0.02**	**-0.01**	**-0.05**	**-0.04**	**-0.03**
	Strict	**-0.14**	**-0.09**	**-0.05**	**-0.08**	**-0.14**	**-0.06**	**-0.09**
	0.4	0	**-0.02**	0.02	0.01	**-0.02**	**-0.01**	0
λ_3	0.8	**-0.09**	**-0.05**	**-0.04**	**-0.03**	**-0.09**	**-0.09**	**-0.06**
	Strict	**-0.23**	**-0.15**	**-0.09**	**-0.13**	**-0.19**	**-0.17**	**-0.16**
	0.4	0	**-0.03**	**-0.02**	0	**-0.04**	**-0.03**	**-0.02**
λ_4	0.8	**-0.13**	**-0.13**	**-0.11**	**-0.10**	**-0.15**	**-0.15**	**-0.13**
	Strict	**-0.30**	**-0.26**	**-0.19**	**-0.22**	**-0.28**	**-0.27**	**-0.25**
	0.4	0.01	**-0.01**	0	0.01	**-0.01**	**-0.01**	0
Expectation	0.8	**-0.05**	**-0.03**	**-0.02**	**-0.02**	**-0.04**	**-0.05**	**-0.03**
	Strict	**-0.12**	**-0.08**	**-0.03**	**-0.07**	**-0.10**	**-0.07**	**-0.08**

Table 2 – *Results for five disruption durations. Every number represents the relative total costs difference between rescheduling using the nominal approach and one of our approaches in case the corresponding disruption duration turns out to be true.*

In general, we can conclude that the robust approaches work better in case uncertainty is present. When the estimation of the disruption duration is uncertain, the robust approaches perform better in comparison with the nominal approach.

In future research, a sensitivity analysis must be performed in order to see whether these results apply in general or only in our specific case study setting.

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