Generation and Evaluation of Passenger-Oriented Railway Disposition Timetables in Case of Severe Disruptions

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Abstract
Delays are one of the major reasons for passenger dissatisfaction in the railway industry. Depending on the gravity of the delay, timetables, crew schedules or rolling stock may be affected. In this research, we address the issue of timetable recovery in case of severe disruptions. Once an initial delay has occurred, the original timetable needs to be updated to a so-called disposition timetable. This new timetable has to be conflict-free in terms of operational constraints (e.g., trains cannot use the same track section at the same time) and as convenient as possible for the passengers. The recent scientific literature on recovery models mainly focuses on the operational point of view, thus paying less attention to the impact of passenger dissatisfaction in case of disruptions. This observation is the motivation for introducing a hybrid methodology that takes the satisfaction of both parties (i.e., passengers and railway companies) into account. Our model focuses mainly on severe disruptions and can evaluate several recovery strategies (e.g., partial train cancellation, complete train cancellation, train addition, train replacement), based on a number of key performance indicators, such as passenger delay, number of connections and departure time shift. This model will assist train operating companies when evaluating the trade-off between economic and infrastructural feasibility of recovery schemes on the one hand side and passenger satisfaction on the other.

Keywords
Train recovery problem, Passenger behavior modelling, Choice-based simulation, Disposition timetable

1 Introduction

On a daily basis, delays occur for a number of reasons in public transportation networks, e.g., a fallen tree obstructing the tracks or a temporarily unavailable track due to maintenance work. Once an initial delay has occurred, the original timetable needs to be updated to a so-called disposition timetable. This new timetable has to be conflict-free in terms of operational constraints (e.g., trains cannot use the same track section at the same time) and as convenient as possible for the passengers. The current practice in the field still heavily relies on predetermined "what-if" scenarios and personal experience of the train traffic controllers. However, due to the high utilization rate of modern railway networks, a decision made at one location in the network can have domino effects on the whole network. Up to date, no comprehensive tool assessing all consequences of train controllers' decisions exists to assist in their decisions, hence possibly leading to unforeseen additional conflicts as well as sub-optimalities in the network.

The recent scientific literature on recovery models mainly focuses on the operational point of view, thus paying less attention to the impact of passenger dissatisfaction in case of disruptions — see Section 2 for an overview of the current state of research. This observation is the motivation for introducing a hybrid methodology that takes into account both parties' satisfaction. In this paper, we present a formulation that addresses the problem by a realistic choice-based simulation model that computes passenger flows for a given timetable. Different factors, such as avoidance of additional transfers or earlier departures, are taken into account by the model to determine the flows. The result of the model is the evaluation of a set of passenger-oriented key performance indicators (KPIs), such as total passenger delay, number of transfers and departure time shift.

The main contribution of our approach is to introduce a framework that evaluates a timetable from the passenger perspective. Hence, several recovery strategies that are relevant in case of major disruptions in railway networks (such as train cancellations, partial train cancellations, train re-routings or additional train or bus services) can be assessed not only from the operational point of view, but also from the customer side. A key asset of the model is the flexibility of the choice-based passenger routing. We introduce a linear disutility function for every passenger path from origin to destination (encompassing travel time, waiting time and penalties for transfers and early/late departures) and assume that passengers minimize this generalized travel time. Passengers can therefore easily be re-routed through another part of the network or update their departure time in case of a disruption. Finally, our model deals with a railway network, instead of a single railway line, as the existing timetable evaluation methods do. It therefore allows to assess the effects of recovery strategies on a network level.

The remainder of this paper is structured as follows. Section 2 reviews the current state of research in the train timetable rescheduling area, as well as in the domain of passenger demand assignment models for schedule-based transportation systems. Section 3 then presents the proposed passenger-oriented timetable evaluation tool in detail. Based on the western part of the Swiss railway network, a case study with different disruption scenarios is presented as an illustrative example in Section 4. Finally, Section 5 concludes the paper and provides directions for future research.

2 Literature review

The literature review presented in this section focuses on two main topics. First, recent contributions to the Train Timetable Rescheduling (TTR) problem are reviewed extensively (Section 2.1). The publications are classified according to three criteria that facilitate the identification of gaps where contributions can be made to the TTR literature, hence justifying the relevance of this work. Second, schedule-based passenger assignment models are reviewed in Section 2.2.

2.1 Train timetable rescheduling

The review paper by Cacchiani et al. (2014) notes that the recent TTR literature exhibits three main differences that distinguish recovery models:

Disturbance / Disruption In a railway network, a disturbance is a primary delay (i.e., a process that takes longer than initially scheduled) — or a set of primary delays — that causes secondary delays that can be handled by rescheduling the timetable only, without rescheduling the resource duties (such as crews and rolling stock). On the other hand, a disruption is a (relatively) large external incident strongly influencing the timetable and requiring resource duties to be rescheduled as well.

Microscopic / Macroscopic representation In a microscopic approach, the railway infrastructure is modelled very precisely, sometimes at the switch or track section level, in order to compute detailed running times and headways between trains. In a macroscopic approach, the infrastructure is considered at a higher level where stations and tracks are represented by nodes and arcs in a graph, respectively. Details such as signals or track sections are ignored.

Operations-centric / Passenger-centric model Operations-centric models focus on minimizing parameters related to the train company operations, such as delays or the number of cancelled trains, whereas passenger-centric models focus on minimizing the negative effects of disruptions and disturbances for passengers.

The thorough review of railway recovery models presented in Cacchiani et al. (2014) shows that the major part of the recent scientific literature deals with disturbances rather than disruptions. Further, in most papers, the railway network is represented at the microscopic rather than at the macroscopic level. Most papers also have an operations-centric approach to railway timetable rescheduling, instead of a passenger-centric view. However, in reality, passenger reactions play a significant role in recovery policies. This is why the present work focuses on passenger satisfaction indicators to evaluate timetables in case of severe disruptions and proposes to assess the impacts of recovery strategies on a network level. The literature presented in this section thus focuses on the works that are most relevant to our case, i.e., that deal with disruptions at a macroscopic level (for a complete overview of the TTR literature, refer to Cacchiani et al. (2014), and references therein). First, operations-centric models are presented. Then, passenger-centric works are reviewed and the differences with the present work are pointed out.

Narayanaswami and Rangaraj (2013) develop a MILP model that detects and resolves conflicts because of a disruption that blocks part of a single track railway line. Disrupted train movements are rescheduled in both directions of the line for a small instance, with the objective of minimizing the total delay of all trains. The model does not allow trains to be cancelled. Albrecht et al. (2013) consider the problem of disruptions due to track maintenance, arising when maintenance operations take longer than scheduled and thus force to cancel additional trains. A disposition timetable including track maintenance is constructed using a problem space search meta-heuristic. This heuristic is also used to generate quickly disposition timetables in case of a disrupted system. Louwerse and Huisman (2014) consider the case of partial and complete blockades in case of a major disruption. They develop a mixed-integer programming model to generate the disposition timetable. Two disruption measures are applied: train cancelling and train delaying. Schedule regularity constraints (e.g., operating approximately the same number of trains in each direction during a partial blockade) are included in the formulation in order to take the rolling stock problem into account implicitly. In case of a complete blockade, both sides of the disruption are considered independently (i.e., trains will reverse before the disrupted area but no coordination with the other side is considered).

Kanai et al. (2011) develop a model that simulates train traffic and passenger flows simultaneously and define several functions to measure passengers' disutility. A tabu search algorithm is used to decide if passenger connections are to be maintained or not. The model only considers a single railway line (i.e., not a network) and evaluates the effects of small disturbances. Kunimatsu et al. (2012) also define disutility functions in order to evaluate different timetables from the passenger perspective. The disutility function encompasses travel times, waiting times and penalties for transfers and congestion. Again, only a single railway line is considered by the model. Cadarso et al. (2013) consider an integrated timetabling and rolling stock problem that accounts for passenger demand by splitting it up into two steps. In the first step, anticipated disrupted demand is computed using a multinomial logit model. As demand figures are estimated before the timetable is adjusted, they are based on line frequencies in an anticipated disposition timetable, rather than on actual arrival and departure times. In the second step, the timetabling and rolling stock rescheduling problem is formulated and solved as a MILP model, subject to the anticipated demand calculated in the first step.

The formulation coming closest to the present work is the one by Cadarso et al. (2013), where the effects of disruptions on the passenger demand is explicitly dealt with. However, the main difference between the two approaches is that, in Cadarso et al. (2013), the passenger demand is evaluated on an expected timetable before solving the timetable and rolling stock rescheduling problem, whereas in our case, the passenger demand is assigned on an actual timetable (with determined departure and arrival times for every train) in order to evaluate passenger satisfaction indicators. Furthermore, the interaction between demand and supplied capacity is ignored in Cadarso et al. (2013).

2.2 Passenger assignment models

In order to determine which approach is most relevant to our case, we review passenger assignment models for transit systems in this section. The literature is either frequency-based or schedule-based. In the former approach, transit services are represented by lines with travel frequencies and single vehicles are not explicitly considered. Single vehicle loads can therefore only be approximated. As this work is interested in exceptional events such as passenger demand peaks in case of severe disruptions, an explicit modelling of the remaining available capacity of the (presumably irregular, and therefore not frequency-based anymore) vehicles is necessary. The frequency-based approach will therefore not be reviewed here.

In the schedule-based model, each vehicle is considered individually with its capacity, either implicitly or explicitly. The implicit approach is similar to road network modelling, where link costs are related to link flows through non-decreasing functions. This method has the main disadvantage that the effects of congestion (represented by a general discomfort increase) are equal for all users of a train run, whereas they should be different for passengers already onboard and passengers trying to board a congested train at a station. The explicit schedule-based model deals with this issue by introducing vehicle capacity constraints, thus letting waiting passengers board the arriving train according to its residual capacity. The following papers use the explicit schedule-based approach to assign passengers on transit networks.

Tong and Wong (1999) formulate a stochastic transit assignment model on a dynamic schedule-based network, where passengers are assumed to travel on paths of minimal generalized travel cost, consisting of in-vehicle time, waiting time, walking time and transfer penalty time, weighted by a sensitivity coefficient. Stochasticity is included in the formulation by allowing these sensitivity coefficients to be randomly generated instead of being constant for every passenger. For given values of the sensitivity coefficients, the passenger demand is loaded onto the transit network by means of an all-or-nothing assignment process.

Nguyen et al. (2001) consider the case where timetables are reasonably reliable, and the number and frequencies of transit vehicles are low. For this kind of networks, departure time and route choice are both equivalently important decisions that passengers face. It is the first paper that is not limited to a single origin-destination pair and that considers both departure time choice and route selection simultaneously. Further, the concept of path available capacity is introduced in order to capture the flow priority aspect (i.e., giving priority to passengers already onboard the transit vehicles with respect to passengers waiting at the station). A traffic equilibrium model of the assignment problem is presented, and a computational procedure based on asymmetric boarding penalty functions is suggested to avoid the explicit enumeration of all paths connecting origins and destinations.

Poon et al. (2004) propose a model that explicitly describes the available capacity of every vehicle at each station, as well as the queuing time for every passenger (assuming a First-In-First-Out queue for passengers waiting at the station). The paper focuses on the route choice problem, ignoring other choice dimensions, such as departure time or departure station. In their formulation, route choice for every passenger is modelled by selecting a path that minimizes a generalized cost function consisting of in-vehicle time, waiting time, walking time and line change penalties. The network is loaded (i.e., user equilibrium is achieved) by using a Method of Successive Averages algorithm.

Hamdouch and Lawphongpanich (2008) also propose a user-equilibrium transit assignment model that explicitly considers individual vehicle capacities. For every O-D pair, passengers are divided into groups according to their desired arrival time intervals. It is assumed that every passenger group has a travel strategy resulting, at each station and each point in time, in a list of subsequent travel options that are ordered according to the passenger groups' preferences to continue their trip. Passenger preferences are described by the minimization of expected travel costs, made of in-vehicle time, fare and costs associated with early departures from home and/or arrivals outside the desired arrival time interval. Travel strategies can therefore be adaptive over time. When loading a vehicle at a station, onboard passengers continuing to the next station remain in the vehicle and waiting passengers are loaded according to the available remaining vehicle capacity. If the vehicle is full, passengers unable to board need to wait for the next vehicle. Demand-supply interactions are defined by a user equilibrium approach and a solution method based on successive averages is proposed.

Nuzzolo et al. (2012) propose a new schedule-based dynamic assignment problem for congested transit networks, explicitly considering vehicle capacities. It is new in the sense that more complex behavioral choice models are used for passengers (including updating of departure time, access stop and transit vehicle run), especially in the case of failure-to-board experiences. A learning process for the passengers is also included in the model. In this formulation, passengers are characterized by their origins and destinations, as well as desired departure or arrival times. They are also assumed to be flexible (in a certain range) in order to avoid congestion effects.

3 Passenger assignment model

This section describes the evaluation tool that is used to assess the performance of different timetables in terms of passenger satisfaction. First, the time-expanded network representing the supply side of the problem is described. Then, the passenger routing process is explained in detail, considering cases both with and without constraints on the transport capacity. Finally, the passenger-oriented key performance indicators are presented and their relevance is discussed.

3.1 Time-expanded network

In the passenger assignment problem, many elements are time-dependent, such as train occupation rates or passenger flows. One also needs to distinguish events taking place at different times at the same location, such as passengers leaving their origin or trains starting on a train line. One way to incorporate this kind of temporal information is by using a time-expanded network (TEN) — see, e.g., Ahuja et al. (1993); Nguyen et al. (2001); Hamdouch and Lawphongpanich (2008).

Let $[0, T]$ represent the daily operating interval of the railway system (i.e., T stands for the end time of the last operation of the day). In a time-expanded network, the operating interval is discretized into a set of points in time. A node stands for a train arrival event at or a departure event from a station. In other words, every train is represented by an alternating sequence of train departure and train arrival nodes. Thus, a node s_t^e in the TEN incorporates three pieces of information: (i) s represents the station where the event takes place, (ii) e is the type of event (a for arrival, d for departure), and (iii) t is the time when the event takes place. Additionally, for every passenger origin-destination pair, two time-invariant nodes are included: one for the origin and one for the destination. The set of all time-expanded nodes will be denoted by $N^T = N^* \cup O \cup D$, where N^* is the set of space-time nodes of the form s_t^e, and O and D are respectively the sets of time-invariant origins and destinations. Further, there are four types of arcs in the time-expanded network: train driving arcs, train waiting arcs, connection arcs and passenger walking arcs. They will be denoted by A_1^T, A_2^T, A_3^T and A_4^T, respectively.

- *Train driving arcs* of the form $(s_t^d, u_{t+tt_{s,u}}^a)$ represent a train moving between stations s and u, leaving station s at time t and arriving at station u at time $t + tt_{s,u}$. The travel time is $tt(s_t^d, u_{t+tt_{s,u}}^a) = tt_{s,u} \geq 0$.
- *Train waiting arcs* are included in the TEN in order to link the arrival of a train at a station with its subsequent departure. A train waiting arc representing a train arriving at station s at time t_a and leaving at time t_d is of the form $(s_{t_a}^a, s_{t_d}^d)$. The waiting time on this arc is given by $wt(s_{t_a}^a, s_{t_d}^d) = t_d - t_a \geq 0$.
- *Connection arcs* of the form $(s_t^a, s_{t+\tau}^d)$ are included in the TEN to model passengers arriving at a station s at time t and connecting to another train leaving station s at time $t + \tau$, with $\tau \in [\tau_{\min}, \tau_{\max}]$ in order to allow only reasonable connection times. The waiting time on this arc is the connection time: $wt(s_t^a, s_{t+\tau}^d) = \tau$.
- Finally, *passenger walking arcs* of the form (o, s_t^d) or (s_t^a, d) model passengers walking from their origin $o \in O$ to their first station at time t and passengers walking from

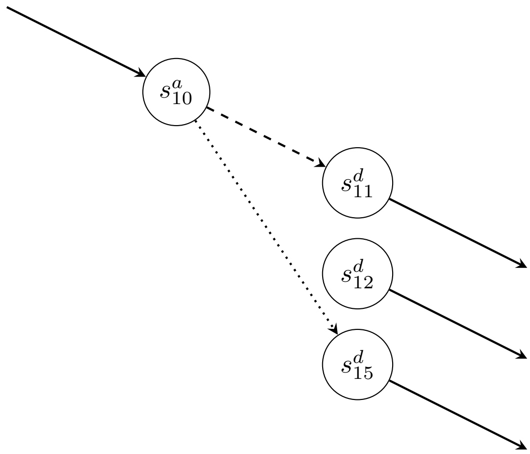


Figure 1: Example representation of station s in the time-expanded network, with $\tau_{\min} = 3$. Solid, dashed and dotted arrows stand for train driving, train waiting and connection arcs respectively. For ease of representation, walking arcs are omitted.

their last station to their destination $d \in D$ at time t. The walking time is assumed to be zero.

Together, the four types of arcs form the set of time-expanded arcs, i.e. $A^T = \cup_{i=1}^{4} A_i^T$. Every arc in $A^T \setminus A_4^T$ is weighted by its respective waiting or driving time. Passenger walking arcs are weighted in order to model penalty costs for early or late departures (see Section 3.2). Further, every arc in $A_1^T \cup A_2^T$ has a passenger capacity, defined by the capacity of the train run it represents (connection and walking arcs have infinite capacity). The passenger flows on the arcs in A^T are determined in the assignment process described in Section 3.2, taking these arc capacities into account.

Figure 1 shows an example representation of station s with three trains: the first one arrives at time 10 and departs at time 11 from station s, the second one starts its journey from station s at time 12 and the last one at time 15. The four solid arrows represent the train driving arcs corresponding to the train movements. The dashed arrow stands for the train waiting arc of the first train, between its arrival at time 10 and its departure at time 11. Passengers arriving on the first train can connect to any other train departing from the station, as long as the connection time is in the interval $[\tau_{\min}, \tau_{\max}]$. In this example, we assume $\tau_{\min} = 3$, thus there is a connection arc (dotted arrow) between s^a_{10} and s^d_{15}, but no connection arc between s^a_{10} and s^d_{12} (as the connection time of 2 minutes is shorter than $\tau_{\min}$).

3.2 Passenger routing

The TEN framework lists all possible passenger paths, for all passenger origin-destination pairs, in the supplied train route network. The question that needs to be answered in the next step is the assignment of passengers to the different arcs in the network, i.e. to model passenger decisions regarding departure time from origin as well as path choice.

In contrast to the road network case, where it is commonly assumed that travel times on a link increase with the number of passengers (vehicles) on the link, the number of passengers aboard a train usually does not have a direct influence on the length of the train trip. Nevertheless, congestion on the train network (i.e., lack of available capacity) may force a passenger to wait for the next available train, thus extending his journey time. This might particularly be the case when a major disruption appears in the network and trains are cancelled. It is therefore necessary to focus on train capacity constraints in order to model the asymmetric passengers inter-influence between passengers already onboard and boarding passengers. Also, the seating capacity of the additional services that are provided to mitigate the disruption (such as buses) is lower than the capacity under normal circumstances, thus capacity constraints need to be considered.

Departure time choice

We assume that passengers have a desired departure time (DDT) from their origin[1]. For every origin-destination pair, the passenger demand is subdivided into groups (indexed by g) by desired departure time from origin: the set of passengers with origin $o \in O$, destination $d \in D$ and desired departure time $t_g \in [0, T]$ are grouped together in group g. It is possible that there is no train leaving station o at time t_g. We thus allow passengers to change their departure time, by including a penalty if the actual departure time differs from the desired departure time (see next section).

Generalized travel time

To model a passenger's route choice in the TEN, a linear disutility function is associated with every path between pairs of origin and destination nodes (see, e.g., Nguyen et al. (2001); Poon et al. (2004); Tong and Wong (1999)). This disutility function encompasses four components: in-vehicle driving time, in-vehicle waiting time, connection time and potential penalty costs. The inclusion of penalty costs for undesirable passenger path properties (such as transfers or early/late departures) allows a flexible passenger routing, in the sense that it is possible for a passenger to choose the path that minimizes these inconveniences, instead of being forced to keep his original path.

For every passenger group g, a generalized travel cost is thus defined for a path $p \in P_{o,d}$, where $P_{o,d}$ is the set of all paths in the TEN between nodes $o \in O$ and $d \in D$, as a weighted combination of these four components:

$$\begin{aligned} C_p(g) \quad = \quad & \sum_{(i,j)\in A_p \cap A_1^T} tt(i,j) + \beta_2 \cdot \sum_{(i,j)\in A_p \cap A_2^T} wt(i,j) + \\ & + \beta_3 \cdot \sum_{(i,j)\in A_p \cap A_3^T} wt(i,j) + \eta_1 \cdot M_p + P_{(o,s_t^d)}(g). \end{aligned} \tag{1}$$

$A_p \subset A^T$ is the set of time-expanded arcs that path p uses. Here it is assumed that the weights of the various components of the disutility function are defined relative to the in-vehicle driving time of the path, and β_2 and β_3 denote the weighting factors for in-vehicle waiting time and connection time, respectively (usually, $1 \leq \beta_2 \leq \beta_3$). $\eta_1 > 0$

[1]In some representations, passengers with desired arrival times at destination are also considered, for instance to model passengers commuting to work in the morning. However, it is possible to traverse the TEN in reverse topological order (see, e.g., Nguyen et al. (2001)) in order to compute their (free-flow) latest possible departure time from origin L. We assume that the latter is their desired departure time, i.e., $t_g = L$.

is the transfer penalty in weighted time units (see, e.g., Guo and Wilson (2011); Wardman (2004) for values for η_1) and M_p is the number of transfers along path p. $P_{(o,s_t^d)}(g)$ denotes the penalty cost associated with early or late departures for path p and passenger group g. Similarly to Nguyen et al. (2001), the penalty cost of early or late departures from the passenger's origin is modelled by weighting the passenger walking arcs of the form (o, s_t^d) using the following arc penalty costs:

$$P_{(o,s_t^d)}(g) = \begin{cases} 0 & \text{if } t = t_g, \\ \delta_1(t_g - t) & \text{if } t_g > t, \\ \delta_2(t - t_g) & \text{if } t_g < t, \end{cases} \tag{2}$$

where δ_1, δ_2 are positive scalars. Note that the weighting factors $\beta_2, \beta_3, \eta_1, \delta_1, \delta_2$ are user-defined parameters and can differ from one passenger to the next. Tong and Wong (1999) for instance introduce stochasticity in the assignment procedure by randomly generating the sensitivity coefficients from known density functions instead of keeping them constant for every passenger.

Assignment procedure

The aim of the passenger assignment model is to determine the passenger flows on every arc of the TEN, taking train capacity constraints into account. A time-dependent shortest path-type algorithm associated with the above network is proposed. It consists of three main phases:

1. Assign passenger groups on the least expensive path according to $C_p(g)$.
2. If an arc capacity is exceeded, decide which passengers need to be re-assigned. Otherwise, stop.
3. Re-assign unassigned passengers on a reduced network, then go to step 2.

In the first phase, it is assumed that all passengers have full predictive information about present and future network conditions, and every group of passengers selects the path from origin to destination that minimizes its generalized travel cost function $C_p(g)$. A Dijkstra-type algorithm is used to determine the shortest path form origin to destination, then the passenger flows on the arcs of this shortest path are updated accordingly. However, passengers do not know about future train occupancy levels, and passenger flows are therefore updated without taking arc capacities into consideration. At the end of this phase of the assignment process, all passengers are assigned on the shortest path (in terms of $C_p(g)$) between their origin and their destination (and thus on the corresponding arcs in A^T), but this assignment might not be feasible as arc capacities were not yet considered.

The second phase of the assignment procedure deals with infeasibilities in terms of arc capacities, i.e., for every train waiting and driving arc, the algorithm checks if the passenger flow assigned in the previous phase exceeds the arc capacity. If no arc capacity is exceeded, the assignment is feasible and every passenger reaches his destination by the shortest path (in terms of $C_p(g)$). Otherwise, the surplus passengers are removed from the infeasible arc one by one until its capacity constraint is verified. In that case, priority rules are applied in order to decide which passengers are allowed to remain on the infeasible arc and which are not.

- The passengers with highest priority are those who are already onboard when new passengers try to board the train. In the TEN, these passengers were assigned (during the first phase of the algorithm) on a previous train waiting or driving arc representing the same train run as the infeasible arc. Highest-priority passengers can only be removed from the infeasible arc if the latter is the first train driving or waiting arc of a train run.
- Among passengers that are boarding the train, passengers that are in a group with higher OD passenger flow get higher priority. That is, for two passengers that want to board the same train, the passenger kilometres (taking Euclidian distance between stations) for the two passenger ODs is computed, and the one with higher OD passenger flow gets higher priority.
- Among passengers that are boarding the train and that have the same OD passenger flow, who can board the train and who cannot is decided randomly.

Starting from the ones with lowest priority, passengers are thus removed one by one from the passenger flow on the infeasible arc (as well as on following arcs on their path), until the passenger flow does not exceed the arc capacity anymore.

In the third phase of the assignment procedure, passengers that were removed from the passenger flows because of the arc capacity constraints in the second phase are re-assigned on a reduced TEN. For every unassigned passenger, the reduced TEN is constructed by removing the infeasible arc from A^T. The assignment procedure of the first phase is then re-run on the reduced TEN for every unassigned passenger.

The assignment procedure iterates between the second and third phases, until all passenger flows are feasible in terms of arc capacities or the set of unassigned passengers remains constant between two iterations, meaning that additional passengers cannot be assigned on the network because of capacity constraints.

3.3 Key performance indicators

To evaluate the performance of a given timetable, key performance indicators in terms of passenger satisfaction are derived from the model, once the assignment is completed. The following indicators are proposed:

- *Travel time indicators* are one of the most important indicators, if one assumes that passengers minimize their travel time. It is necessary to take into account that each origin-destination pair has a different minimal travel time, hence the difference between actual travel times and minimal travel times are computed.
- *Transfer indicators* are included as it is assumed that passengers try to minimize the number of transfers they need to make to arrive to destination.
- The *departure time shift*, i.e., the difference between the desired departure time and the actual departure time is reported.
- Finally, the *number of disrupted passengers*, i.e., the number of passengers that cannot reach their destination because of the saturation of the network, is a measure of the experience of passengers that are worst-off.

4 An illustrative example

In this section, we apply our methodology on an instance with eight train stations. The example is described below, and the key performance indicators are reported thereafter.

4.1 Case study description

The train network of the illustrative example is inspired from the Western part of the Swiss federal rail network. It consists of eight stations: Geneva (GVE), Renens (REN), Lausanne (LSN), Fribourg (FRI), Bern (BER), Yverdon (YVE), Neuchâtel (NEU) and Biel (BIE). The available tracks as well as the minimal travel times between stations are shown in Figure 2.

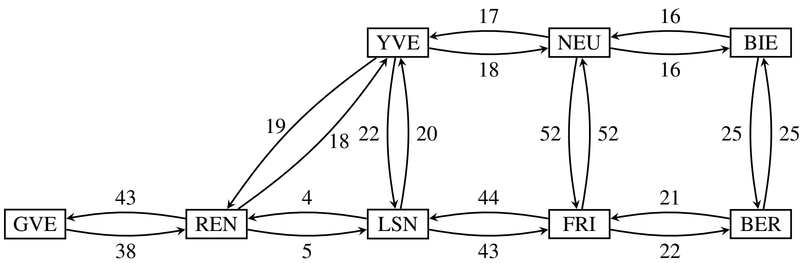


Figure 2: Rail network of the illustrative example, with minimal travel times (in minutes) between stations.

The timetable of the 941 trains running during a regular weekday on this network were downloaded from `http://www.sbb.ch`. Passenger origin-destination demand matrices were generated by periods of 15 minutes. The demand values are assumed to be random but incorporate a morning and an evening peak period, based on a report by the Swiss National Railways (2013), in order to be as realistic as possible. A total of 175,990 passengers are generated.

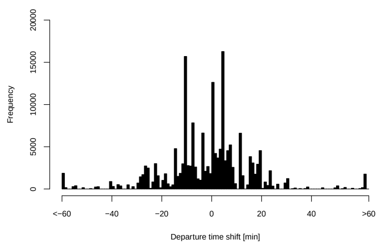
In order to assess the performance of the given timetable in case of disruptions, four different scenarios were defined. The first scenario, *Base*, represents the undisrupted state of the system. In the three disrupted scenarios (*Minor*, *Moderate* and *Severe*), respectively 10%, 30% and 50% of the trains available in *Base* are cancelled. The passenger demand remains identical throughout the scenarios.

4.2 Results for different scenarios

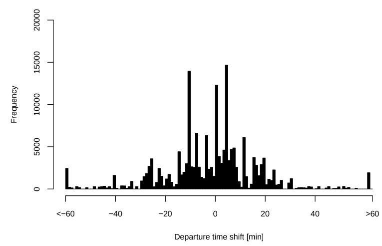
This section presents the values of the key performance indicators for the four different scenarios. Table 1 presents transfer indicators as well as the number of disrupted passengers. Some interesting implications of the results are as follows. One can observe that in the case of a minor or moderate disruption, there are no disrupted passengers, meaning that the transit network is not used up to its full capacity in the undisrupted case. In the case of a severe disruption (cancellation of 50% of the trains), 3.4% of the passengers cannot reach their destination because of the saturation of the network. The percentage of direct passengers (i.e., passengers with $C = 0$) decreases as the severity of the disruption increases. On the other hand, the percentage of passengers with at least one transfer increases as the severity of the disruption increases. In particular, there is a significant number of passengers with more than three transfers in the case of a severe disruption. However, a journey with more than three transfers is very unlikely to happen in a network the size of our example.

Table 1: Percentage of disrupted passengers and of passengers whose number of transfers equals C, for each scenario.

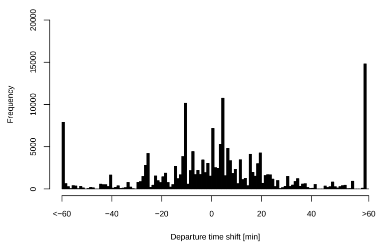
Scenario	Base	Minor	Moderate	Severe
Disrupted passengers [%]	0	0	0	3.4
$C = 0$ [%]	76.7	75.8	68.7	67.2
$C = 1$ [%]	22.7	23.5	27.3	24.1
$C = 2$ [%]	0.6	0.7	3.1	4.0
$C = 3$ [%]	0	0	0.9	0.8
$C > 3$ [%]	0	0	<0.1	0.5



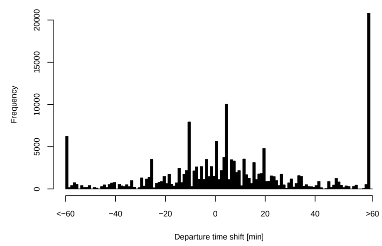
(a) Scenario: Base



(b) Scenario: Minor



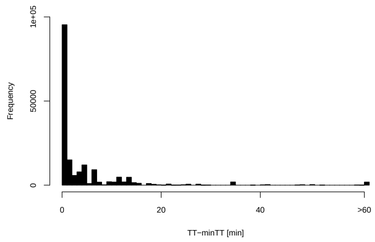
(c) Scenario: Moderate



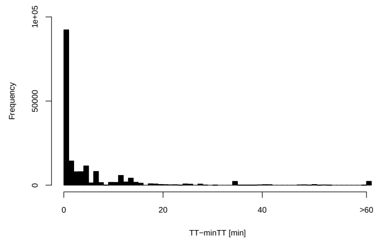
(d) Scenario: Severe

Figure 3: Departure time shifts, for each scenario.

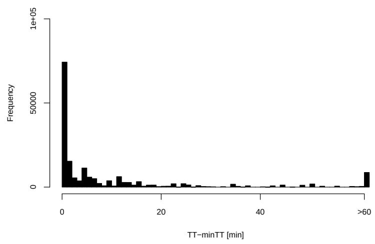
Figure 3 presents the histograms of departure time shifts, for each scenario, up to one hour before or after the desired departure time. Departure time shifts over one hour after (respectively before) the DDT are grouped in the category > 60 (respectively < -60). In the undisrupted case, 90% of the departure time shifts lie in the interval $[-28, 22]$, meaning that only 10% of the passenger demand needs to shift its departure time more than 28 (respectively 22) minutes prior to (respectively after) the desired departure time. As the severity of



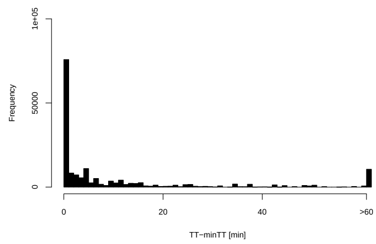
(a) Scenario: Base



(b) Scenario: Minor



(c) Scenario: Moderate



(d) Scenario: Severe

Figure 4: Difference between actual travel time and minimal travel time, for each scenario.

the disruption increases, the size of this interval increases to $[-32, 24]$ (minor disruption), $[-58, 247]$ (moderate disruption) and $[-53, 595]$ (severe disruption). In the case of a severe disruption, about 16% of passengers need to shift their departure time more than one hour after their DDT.

Figure 4 presents, for every passenger, the histogram of differences between the actual travel time and the minimal travel time for the passenger's origin-destination pair. Travel time differences above one hour are grouped in the category > 60. The number of passengers that have an actual travel time equal to the minimal travel time decreases with the severity of the disruption: 54.2% in the undisturbed case, and respectively 52.4%, 42.2% and 44.5% in the case of a minor, moderate or severe disruption. On the other hand, travel time differences of more than one hour appear respectively in 1.0%, 1.3%, 5.0% and 6.2% of the cases.

5 Conclusion

Motivated by the need for a passenger-centric framework for the train timetable rescheduling problem, this paper presented a timetable evaluation tool, that computes, for a given timetable, passenger satisfaction indicators, such as total passenger travel time, number of transfers and departure time shift. The evaluation tool is used to assess the performance of timetables in several disrupted scenarios.

Directions for further research include the generation of disposition timetables by including recovery strategies one at a time (on a trial-and-error basis) to be evaluated thereafter. This aggregation of recovery strategies to form a disposition timetable is based on the experience acquired in the evaluation phase. As this procedure only allows for the evaluation of a limited set of recovery strategies, it is not clear if it yields an optimal solution (in terms of passenger satisfaction), nor how close this solution is to an optimal solution. The subsequent step is the introduction of an optimization framework that integrates the train rescheduling problem with passenger routing.

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