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Recovery of Disruptions in Rapid Transit Networks with Origin-Destination Demand

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Abstract

This paper focuses on disruption management of Rapid Transit Rail Networks. We propose an integrated model for timetable and rolling stock rescheduling in order to minimize the recovery time, the passenger inconvenience and the incurred system costs. We introduce Origin-Destination demand formulation to the recovery problem in order to account for rerouting possibilities for passengers through the network, considering the presence of different transport modes. The computations presented are based on realistic problem instances of the Spanish rail operator RENFE. The tests have been accomplished using data from Madrid's rapid transit network.

Keywords: disruption management; integrated re-scheduling; timetable; rolling stock; passenger demand.

1. Introduction

Disruption management is the process of determining whether an incident produces a disruption or not and designing plans to recover from a disrupted situation. Such incidents may include infrastructure blockage, failing rolling stock, crew shortage, etc. In case of incidents the railway operations are said to be disrupted. A disruption imposes some new constraints to the railway operation (i.e.: canceling or delaying some trains).

The disruption management process includes the following major tasks: adapt the timetable according to the restrictions imposed by the disruption; re-schedule the rolling stock to cover the disrupted timetable; re-schedule the crew to serve the adapted rolling stock schedule; and re-schedule passenger.

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Defining recovery plans is a complex task since the presented resources have to be re-planned in near real-time. A disruption is in most cases addressed by solving the problem in a sequential manner. However, this approach will provide suboptimal allocation of resources, where the solution of one of the problems may restrict the set of feasible solutions of the problems solved sequentially.

A complicating issue in a disrupted situation is the fact that the duration of the disruption is usually not known exactly and that the status of the railway system is changing at the same time. That impact is generally in the form of a change in the system settings, a change in resource availability, or both. The response to a change in resource availability is to replan the current operations to apply only the available resources which may include giving up some of the planned services. A disruption may also cause a change in the system settings. Closing a station (or part thereof) temporarily is an example of a change in the system settings that affects the system's ability to operate.

A further change in the system environment is a deviation in demand because the passengers are free to choose their own itinerary in the network. In case of a disruption, some itineraries will not be available anymore and others may become less attractive. Passengers react to disruptions in different ways: either they reroute (within the network or with other modes of transport), or they wait for a train in their original itinerary, or they do not travel at all.

1.1. State of art

Jespersen-Groth et al. (2009) describe the disruption management process and the roles of the different actors involved in it. They discuss the three main subproblems in railway disruption management: timetable adjustment, rolling stock and crew re-scheduling. De Almeida et al. (2003) propose an approach for dealing with large scale disruptions where track capacity is greatly reduced. They propose a heuristic approach to re-building passenger transportation plan in real time. Kroon and Huisman (2011) describe models and algorithms for real-time rolling stock rescheduling and real-time crew rescheduling. Budai et al. (2010) state that in order to prevent expensive deadheading trips, it is attractive to modify the rolling stock schedules such that the rolling stock is balanced before the night. Nielsen (2011) formalizes the rolling stock rescheduling problem as the problem of adapting a set of rolling stock duties to a modified situation. The reschedule of the rolling stock considers a balance between the rescheduling effort and the service level. Almodovar and García-Ródenas (2011) deal with a special case of the vehicle re-scheduling problem for passenger railways in case of emergencies.

Sequential scheduling and re-scheduling have been common in the railway industry (see Cadarso and Marín (2010) and (2011) for examples in sequential planning). Cadarso and Marín (2012) demonstrate the benefits of integrated planning in timetable and rolling stock planning: the integrated approach leads to clearly superior solutions with regard to their efficiency and their robustness, while the integrated model is still solvable in reasonable time for real-life cases.

Cadarso et al. (2013) propose a two-step re-scheduling solution approach. First, they anticipate the passenger demand pattern using a discrete choice model. Then, they use an integrated optimization model for timetable and rolling stock recovery to minimize the recovery time, the passenger inconvenience and the incurred system costs. They report their computational tests on realistic problem instances of the Spanish rail operator RENFE.

1.1. Contributions

We present a new approach to deal with disruptions in rapid transit networks, where resources and capacities are limited and frequency values are high. For an undisturbed scenario we have full information on the timetable, rolling stock assignment and passenger demand. Once the disruption has started, we know the infra-availability of the network (with estimated time duration). We compute the expected passenger demand decisions according to a logit model. Finally, we run an integrated timetable, rolling stock and passenger use optimization model to deal with disruptions. Historically, disruption management has been addressed in a sequential manner. However, this sequential approach may produce suboptimal or even infeasible schedules. Therefore, we develop an optimization model to be applied in case of disruption that simultaneously deals with timetabling and rolling stock scheduling decisions.

The main contributions in this approach with respect the related literature are:

- We use itinerary based formulation instead of arc based formulation.
- Passengers make decisions about itineraries according to a logit model and then they try to board a train serving that itinerary.
- If passengers cannot travel with their first decision, they can change their mind and choose to travel in a different way.

This paper is organized as follows. In section 2 the problem is described. In section 3 the mathematical model is introduced. In section 4 is for computational experiments and section 5 is for conclusions.

2. Problem Description

First, the railway infrastructure is introduced. Next, we describe the timetable, train services and shunting in rapid transit networks. Finally, we explain how we treat the passenger demand for disturbed scenarios.

2.1. Railway Infrastructure

The railway network is studied as a graph composed of nodes and directed arcs linking different stations. It consists of tracks and two types of stations, namely passenger stations and depot stations. The first type is characterized by train services that only attend to passenger demand. In depot stations shunting operations can also be performed, that is, attached to the passenger station there is a depot where trains are driven to be parked or shunted.

Between two stations, two different arcs exist, one for each direction of movement. Therefore, every arc is defined by its departure and arrival station and by its length. The lines are defined in the network. Each line contains some arcs in the rapid transit network. However, there may be different train services within the same line. That is, a service may not attend all the arcs in the line in which is being operated.

As we are studying a real life problem, the railway infrastructure is not isolated from other modes of transport. We will consider the existence of the metro network. This metro network has several stations in common with the rapid transit railway network. Therefore, when a disruption occurs passengers may find an attractive itinerary using both, the railway and metro networks.

The planning time is discretized into time periods. Due to the high train frequencies, the duration of one time period is set to one minute. The existing physical network is replicated once for each time period existing in the planning period (e.g., 20 hours).

2.2. Timetable

There are two types of train services: the planned train services and the emergency services. The former are the trains scheduled for a regular situation and the latter are the trains inserted to the schedule during the disruption in order to alleviate its negative effects in passengers. There may be different services within the same line, services with different origins and destinations.

We mean by line a determined set of stations and tracks where services are performed. A planned train service is a passenger train traveling from a depot station to another depot station stopping at a number of intermediate stations. They are characterized by their departure depot station; their arrival depot station; every arc they travel on and their departure time.

Planned services may be canceled due to some disruption. We will not consider the possibility of changing the planned train services' departure times on a time window. In rapid transit networks the frequencies are on the order of headway times, so it does not make sense try to change departure times because changing them will mean to choose a departure time that already belongs to a different train service.

For emergency services, the model will decide whether they are used or not. An emergency service represents a feasible movement between depot stations, and it is defined by a departure station, an arrival station, every intermediate arc and the departure time. We define a feasible movement as a physical movement in the network once the disruption has started. For planned and emergency train services the headway must be maintained in every infrastructure they come through.

Rapid transit networks are characterized by high frequencies and a lack of capacity in depot stations. These facts make difficult to operate the network without empty movements. These are defined by an origin, a destination and a departure time. Empty movements can help satisfy both capacity and rolling stock material availability in depot stations.

2.3. Rolling Stock and Shunting

There are self-propelled train units of different type; they all have a driver seat at both ends. A composition of train units is a sequence of trains of the same type. Shunting operations complicate rapid transit networks because the performance time is on the order of the service frequency time. They are only performed in depot stations.

Train units of the same type can be aggregated or disaggregated to form different compositions. Although composition changes enable the network operator to use smaller fleet sizes, it is always a complicating operation, due to the necessity of human resources and the possibility of failure in the mechanical system governing the process.

2.4. Passengers

Once the disruption has occurred, passengers will have to use the new network topology to reach their destination. First, they will have to choose an itinerary in the modified network, wait for a train service and finally board the train if enough capacity is available.

The demand is characterized by an origin, a destination and a departure time. This information may be represented by passenger group w = (o; d; τ), where o is the departure station, d the arrival station, τ the desired departure time and $w \in W$ the set of passenger groups. The size of each group represents the number of passengers willing to travel.

The demand will be realized through available itineraries in the network. Each passenger group belonging to each market w will be able to choose an itinerary $i \in I_w$, where I_w denotes the set of itineraries attending it. Passengers within the same passenger group may travel by different itineraries, that is, passenger groups may be split.

As we are working in a rapid transit system, where different modes of transportation exist, we also will include itineraries containing these alternative modes. Moreover, we could also have itineraries composed of different lines in the railway network.

2.5. Passengers' reaction to the disruption

Rolling stock scheduling naturally needs information about the demand for each trip. These demand figures are, however, not available for a disrupted situation. To add to the complexity, the per-trip demand actually depends both on the timetable and on the rolling stock schedule. In this paper we propose a way to anticipate passenger demand's decisions before computing the schedules; these anticipated demand decisions are used to obtain the recovery plan. The anticipated demand's decisions are based on the assumption of assuming that the passengers choose their travel itinerary according to a multinomial logit model. If passengers are able to travel with this first decision they are done. However, it may occur to be impossible to complete the trip for many reasons. Consequently, we assume that passengers may change their initial decisions. Therefore, they may be recaptured in different itineraries with the same origin and destination. If they cannot be recaptured, they will be denied from the system.

The multinomial logit model allows us to capture how individuals are making choices. We must define the decision-maker and his/her characteristics, the alternatives as the possible options of the decision-maker, the attributes of each potential alternative the decision-maker is accounting for, and the decision rules describing the rules used by the decision-maker.

The utility of each alternative is a function of the attributes of the alternative itself and of the decision-maker. The utility function for every itinerary is calculated as the weighted sum of different terms: the traveling time (sum of the travel time of each of link of the itinerary), the transfer time and the waiting time:

$$v_i^w = \beta_1 ot_i^w + \beta_2 tt_i^w + \beta_3 wt_i^w, \forall i \in I_w, \forall w \in W,$$

where ot_i^w is the on-board time, tt_i^w is the transfer time and wt_i^w is the waiting time for each itinerary i attending demand w. $\beta_1, \beta_2, \beta_3$ represent the utility value of each of these different kinds of times. The probability of choosing a given itinerary i among the set I_w by the demand w will be given as a logit distribution, defined by the previous utility functions based on expected travel times for each itinerary.

3. Integrated Timetable, Rolling Stock and Passengers Rescheduling Model

The Integrated Timetable, Rolling Stock and Passengers Rescheduling Model (ITRSPRM) is a multiobjective model. It aims at computing the timetable and the rolling stock schedule for a disrupted rapid transit network accounting for passengers' decisions.

The ITRSPRM is based on the recoverability model proposed by Cadarso et al. (2013). They considered the timetable and rolling stock rescheduling problem for rapid transit networks. Compared to this paper, the novelties of the current paper are the following:

- Passenger demand is itinerary based: if a passenger is denied in any arc, he/she will be denied from the entire trip.
- Passengers make decisions according to a logit model: this demand is associated to itineraries and the timetable and rolling stock assignment are calculated at the same time.
- Passengers can make new decisions if their preferred decision is not available for any reason.

The most central decision variables are $x_{\ell,c} \in \{0,1\}$, defined for $\ell \in L, c \in C$. Their values indicate whether composition $c \in C$ is scheduled for service $\ell \in L$. $h_i^w \in Z^+$ are defined for $w \in W, i \in I_w$, to denote the number of passengers in itinerary i from passenger group w. $g_{i,i'}^w \in Z^+$ are defined for $w \in W, i, i' \in I_w$, to denote the number of disrupted passengers in itinerary i to itinerary i' from passenger group w. $y_\ell \in \{0,1\}$ are defined for $\ell \in L$, to indicate whether service $\ell \in L$ is canceled; $yt_{s,t}^c \in Z^+$ are defined for $s \in SC, t \in T, c \in C$, to denote the number of compositions c in station s at t period. $dp_{i,w} \in Z^+$ are defined for $w \in W, i \in I_w$, to denote the number of denied passengers in each itinerary i attending passenger group w; $em_{s,s',t}^c \in \{0,1\}$ are defined for $s, s' \in SC, t \in T, c \in C$, to indicate whether an empty movement is performed at t period from station s to s' with composition c; finally, $\alpha_\tau \in \{0,1\}$ and $\beta_\tau \in \{0,1\}$ are defined for $\tau \in IT$, to indicate which riding direction is opened in the line segment between two neighboring stations affected by the disruption; IT is the set of time periods during which the incident is active. If α_τ takes value 1, one of the riding direction is opened during τ and the opposite one is closed. Similarly for β_τ.

3.1 Objective Function

The multiobjective function of the model reads as follows.

$$\min z = \sum_{\ell \in L}\sum_{c \in C} oc_c km_\ell x_{\ell,c} + \sum_{s,s' \in SC}\sum_{t \in T}\sum_{c \in C} oc_c km_{s,s'} em^c_{s,s',t} + \sum_{\ell \in L^P} canc_\ell y_\ell + \sum_{w \in W}\sum_{i \in I_w} dpc_{i,w} dp_{i,w}$$
$$+ \sum_{w \in W}\sum_{i \in I_w}\sum_{i' \in RE_i} dpc_{i,w}\left(1-\phi_{i,i'}\right) g^w_{i,i'} + \sum_{\ell \in L^P}\sum_{c \in C}\kappa_\ell \left|x_{\ell,c} - \hat{x}_{\ell,c}\right| + \sum_{s,s',t \in S,T}\sum_{c \in C}\lambda_t \left|em^c_{s,s',t} - \hat{em}^c_{s,s',t}\right|$$

The objective terms, in the given order, penalize the following quantities.

- Operating costs of planned and emergency services; here oc_c is the operating cost per kilometer and km_ℓ is the distance in kilometers of service ℓ;
- Operating costs of empty movements; here $km_{s,s'}$ is the distance in kilometers from s to s';
- Cancelation of services; here $canc_\ell$ is the canceling cost for service ℓ;
- Denied passengers; here $dpc_{i,w}$ is the cost per denied passenger in each arc a during time period τ;
- Recaptured passengers; here $\phi_{i,i'}$ is the percentage of recaptured passengers. Therefore, $\left(1-\phi_{i,i'}\right)$ is the portion of denied passengers; RE_i is the set of itineraries compatible with itinerary i.
- Deviation from the schedule of commercial services; here κ_ℓ is the penalty for changing the RS assignment of a commercial service ℓ, while $\hat{x}_{\ell,c}$ indicates the RS assignment on a normal day;
- Deviation from the schedule of the empty movements; here λ_t is the penalty for changing the RS assignment of an empty movement, while $\hat{em}^c_{s,s',t}$ indicates the RS assignment on a normal day.

The last two terms of the objective attempt to minimize the length of the recovery period.

3.2 Passengers Constraints

$$h^w_i = P\left(i \mid w\right) d_w - \sum_{i' \in RE_i} g^w_{i,i'} + \sum_{i' \in RE_i} \phi_{i',i} g^w_{i',i} - dp_{i,w} \quad \forall w \in W, i \in I_w \tag{1}$$
$$\sum_{\ell \in L_a}\sum_{c \in C} cap_c x_{\ell,c} \geq \sum_{w \in W}\sum_{i \in I_w \cap I_a} h^w_i \quad \forall a \in A \tag{2}$$

Constraints (1) are demand constraints. Each passenger group demand is distributed through the different and available itineraries ($P\left(i \mid w\right)$). If there is no capacity for them in the desired itinerary, they may be recaptured in a different one or denied from the system (RE_i). Constraints (2) ensure that there will be enough capacity for passengers in each arc *a* of the network. cap_c is the passenger capacity in composition *c*. L_a are the services attending arc *a* and I_a the itineraries attending arc *a.*

3.3 Timetabling Constraints

The first set of timetabling constraints enforces the headway requirements.

$$\sum_{\ell \in L}\sum_{\substack{t1 \in LCS_{\ell,s}: \\ t1 \geq t, t1 \leq t+h}}\sum_{c \in C} x_{\ell,c} \leq 1 \quad \forall s \in S, t \in T \tag{3}$$

Constraints (3) say that any arc during any interval of length the headway time can accommodate at most one service. $LCS_{\ell,s}$ denotes the time period during which service ℓ comes through station *s.*

The second set of constraints deal with the riding direction on the disrupted link.

$$\sum_{c \in C} x_{\ell,c} \leq \alpha_\tau \quad \forall \tau \in IT, a \in INO \cap A_\tau, \ell \in L_a \tag{4}$$
$$\sum_{c \in C} x_{\ell,c} \leq \beta_\tau \quad \forall \tau \in IT, a \in ISO \cap A_\tau, \ell \in L_a \tag{5}$$

$$\alpha_\tau + \beta_\tau \le ain_\tau \quad \forall \tau \in IT \tag{6}$$

Constraints (4) and (5) make sure that services can use the disrupted arc only at those time periods when the arc is open for their riding direction. Constraints (6) express the infrastructure limitation to one direction at a time or to no traffic at all. The value ain_τ indicates the infrastructure limitation in time period τ. INO, ISO are the set of arcs which are affected by the disruption. The first set contains the arcs with a riding direction which is the opposite one to the riding direction in the second set. A_τ set of arcs which are active during time period τ.

3.4 Rolling Stock Constraints

$$\sum_{c\in C} x_{\ell,c} + y_\ell = 1 \quad \forall \ell \in L^p \tag{7}$$

$$\sum_{c\in C} x_{\ell,c} \le 1 \quad \forall \ell \in L^e \tag{8}$$

Constraints (7) state that each planned service $\ell \in L^p$ is either cancelled or it gets exactly one composition. Constraints (8) express that emergency services $\ell \in L^e$ get at most one composition.

$$yt^c_{s,t-1} + \sum_{\substack{\ell\in L \\ \alpha_{\ell,s,t}=1}} x_{\ell,c} + \sum_{s'\in SC} em^c_{s',s,t-et_{s',s}} = yt^c_{s,t} + \sum_{\substack{\ell\in L \\ \alpha_{\ell,s,t}=-1}} x_{\ell,c} + \sum_{s'\in SC} em^c_{s,s',t} \quad \forall s \in SC, t \in T, c \in C \tag{9}$$

Composition conservation constraints (9) ensure the train units' flow balance. The schedule is given by $\alpha_{\ell,s,t}$, which takes the value 1(-1)((0)), if train service ℓ arrives (leaves)((stays)) in station *s* at period *t*. $et_{s,s'}$ is the travel time between stations *s* and *s'*.

$$\sum_{s\in SC}\sum_{c\in C_m} tu_c yt^c_{s,t} + \sum_{\ell\in L}\sum_{c\in C_m} tu_c \beta_{\ell,t} x_{\ell,c} + \sum_{s,s'\in SC}\sum_{t'\in T}\sum_{c\in C_m} tu_c \xi_{s,s',t',t} em^c_{s,s',t'} \le \chi_m \quad \forall m \in M, t \in T \tag{10}$$

$$\sum_{c\in C} tu_c \cdot yt^c_{s,t} \le cap_{s,t} \quad \forall s \in SC, t \in T \tag{11}$$

Fleet capacity constraints (10) ensure that the number of train units used is limited by the size of the fleet χ_m. C_m is the set of compositions belonging to material type *m*. Depot capacity constraints (11) ensure that the total capacity is not overpassed. tu_c is the number of train units in composition *c*. Each train service time duration is given by $\beta_{\ell,t}$, which takes value 1, if train service is rolling at period *t*; 0, otherwise. Similarly, $\xi_{s,s',t',t}$ gives information about performance time of an empty train service, which departed from *s* during *t* and is going to *s'*.

Constraints denoting that the inventory during the initial and final period must be equal to the scheduled one during those time periods are also included in the model formulation.

4. Computational Experiments

All of our experiments are based on realistic cases drawn from RENFE's regional network in Madrid, also known as "Cercanías Madrid". This network is composed of 10 different lines with almost 100 stations. All data are from the year 2008. Approximately one million passengers use "Cercanías Madrid" every day.

Our runs were performed on a Personal Computer with an Intel Core 2 Quad Q9950 CPU at 2.83 GHz and 8 GB of RAM, running under Windows 7 64Bit, and our programs were implemented in GAMS/Cplex 12.1.

We will study the case where we have a blockage in a track between two stations. Consequently, the rolling stock can only go through one way between these stations. However, we must allow the rolling stock going through both ways in order to enable rolling stock in every depot station, that is, there is only one track available that needs to be shared between both directions. The disruption will start at 8:00 a.m. It is supposed that the duration of the disruption is known: 120 minutes.

Figure 1 shows the network topology after the disruption has started. A track is blocked in Line C5, so one unique track is available between two different stations: VIAL and OR. The following stations belong to Line C5: HU, FU, VIAL, OR, AT and MO. PA, VIAL, AT and CO to Line C4. Finally, AR and AT to Line C3.

The proposed model will decide depending on the different costs the schedule for the disruption period and the forthcoming recovery plan. During these two different periods of time train service cancellations may occur. However, there also exists the possibility of scheduling emergency services in order to maintain the offered capacity in the non-disrupted areas. The operator must account for passengers' new trips in order to reschedule the offered capacity in lines that were not originally affected by the disruption.

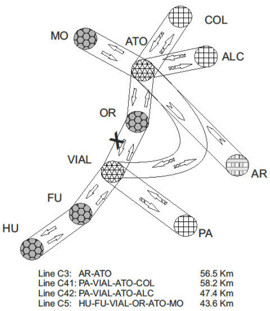

Fig. 1. Network topology while the blockage is active

Line C5 and Lines C3&C4 are independent in real life, that is, they do not share any rolling stock resources. Therefore, they are solved independently for rolling stock purposes. However, Lines C3&C4 are affected by passengers rerouting. Consequently, even though we have independent problems for rolling stock assignment, we have that the passenger problem must be solved in an integrated way. This fact mandates us to include all the lines (C5, C3&C4) in the same problem.

The total demand number in Line C5 for a day is 211985 for this study case. During the disruption period there were 47000 passengers willing to initiate their trip. From those passengers, 26.2% of the demand in line C5 chooses to stay in line C5; 44.3% will go through a combination of lines C5 and lines C3, C4; finally, 29.5% of the demand will go for a combination of line C5 and the Metro network.

The model formulation is based on itineraries. Consequently, if a passenger is denied in some arcs, he/she will be denied from the entire trip, not only from those arcs. Then, this demand is associated to itineraries and the timetable and rolling stock assignment is made at the same time. However, if passengers cannot reach their destination, they can change their mind and choose any different itinerary to try to get to their destination.

In Table 1 some passengers' re-routings are shown. In the first column we can see their origin station, in the second one their destination station, in the third one their departure time, in the fourth one their original itinerary, in the fifth one their alternative itinerary, in the sixth one the number of passengers that choose that alternative, in the seventh one the total demand for that origin, destination and departure time, in the eighth one the original travel time and in the last one the alternative travel time. For example, we can see how some passengers willing to travel from station FU to station MO at 9:04 a.m. cannot do it with their first decision. Their initial decision was to travel in itinerary i121. However, this itinerary is within Line C5 and contains the disrupted part of the line. Consequently, they have to change their mind and to choose a different itinerary. Some of them will choose the itinerary i19 and others the itinerary i80. These new itineraries contain different parts of the network. The first one comes through Line C5, metro and again Line C5 and it takes eight minutes more than the original itinerary to reach destination. The second one comes through Line C5, Lines C3&C4 and Line C5 again and it takes seventeen minutes more than the original itinerary to reach destination.

As we have explained above, passengers' decisions are modeled through the presented logit model. Once the disruption has started, passengers will make a decision for traveling. However, some of them will have to make a different decision because the first one is not feasible for reaching their destination. Consequently, 1550,94 passengers had to change their initial decision to be able to reach their destination. However, it is not always possible for passengers to re-route. Therefore, some passengers will be denied from the system. In this study case 784.08 passengers were denied from the system.

Table 1. Passengers' re-routings

Origin	Destination	Time	Original Itinerary	Alterative Itinerary	Passengers	Total Demand	Original Travel Time	Alterative Travel Time
HU	OR	8:46	i77	i119	1.57	4	32	35
FU	OR	8:06	i18	i122	22.02	42	16	52
FU	OR	8:06	i123	i122	13.35	42	31	52
FU	MO	9:04	i121	i19	18.5	33	28	36
FU	MO	9:04	i121	i80	6.52	33	28	45
VI-AL	OR	8:05	i21	i46	6.28	9	17	37
AT	FU	8:36	i60	i100	13.09	23	43	51
MO	FU	8:21	i156	i43	10.23	16	42	68

Table 2. Passengers flows through the arcs directly affected by the disruption

Time Period	VI-AL > AS	AS > OR	OR > AS	AS > VI-AL
8:00-8:10	713 - 1298	1473 - 1247	2870 - 394	2301 - 419
8:10-8:20	0 - 1336	0 - 1346	0 - 237	956.57 - 283
8:20-8:30	833.06 - 1789	0 - 1737	0 - 290	0 - 290
8:30-8:40	673.11 - 1399	349.28 - 1934	0 - 451	0 - 280
8:40-8:50	672.22 - 1282	564.93 - 1229	0 - 342	0 - 418
8:50-9:00	289.39 - 1059	1032.28 - 1439	995.23 - 308	0 - 357
9:00-9:10	0 - 693	0 - 597	1993 - 301	2605.18 - 289
9:10-9:20	0 - 704	0 - 763	2045.35 - 213	2096.73 - 210
9:20-9:30	0 - 599	0 - 770	335.72 - 163	1006.44 - 209
9:30-9:40	313.04 - 693	320.6 - 726	0 - 162	0 - 158
9:40-9:50	895.14 - 558	269.13 - 661	0 - 145	0 - 153
9:50-10:00	489.53 - 172	838.08 - 590	0 - 159	0 - 148

Although passengers can re-route to different itineraries, they will have to pay a price for it. This price is the travel time. They will probably travel in itineraries with longer travel times. For example, we may take a look at the average travel time per passenger. In the non-disrupted scenario this average travel time was of 12 minutes per passenger. However, for the disrupted scenario this average travel time is increased: it takes the value of 15.3 minutes.

In Table 2 passengers flows through the arcs directly affected by the disruption are showed. In Figure 1 we only can see that an arc is affected between two stations. However, in the real network there is an additional station (AS) between them. The issue is that in AS is not possible to perform any shunting operation. Therefore, the disruption affects two different arcs per riding direction. In the first column the time period during which the disruption is active are shown. The rest of the columns are the arcs directly affected by the disruption. That is, the arc going from station VI-AL to AS, the arc going from AS to OR, the arc going from OR to AS and the arc going from AS to VI-AL. The first number in each of the elements of the table is the passenger flow for the disrupted scenario. The second one is the passenger flow under normal conditions. For some cases, the disrupted flow is greater than the normal flow. However, as capacity is reduced in the arcs the disrupted flow will be lower than normal one.

5. Conclusions

A railway recovery problem has been presented in this paper. When facing a disruption different possibilities arise in order to fight against it. The operator wants to offer a good quality service while the system is being recovered to the original planning. The proposed approach for the system recovery accounts for a wide variety of operations during the disruption and the recovery period: planned train services, emergency train services, empty movements, adequate allocation of train units in the depots, etc. All of them must be taken into account in order to provide a feasible recovery plan.

The disruption and the recovery actions will surely change the network topology, and some passengers will have to face the fact that they are not able to reach their destination traveling with their planned itinerary for a common day. They will have to change their mind to choose a new itinerary for the disrupted scenario. In order to model the expected demand under the new topology a logit model is used. This model will represent the new demand mainly based on the expected travel times under the new situation. However, some passengers will not be able to travel due to train cancellations, lack of capacity, etc.

We show in the computational results a summary of how passengers re-route under the disrupted scenario in Line C5. These re-routings depend on the logit model's parameters provided by the operator. Many of them are done using the metro and the Lines C3&C4. This fact has an additional cost for passengers measured in travel time. As passengers re-route, passengers flows change compared to the undisturbed scenario and the rolling stock capacity is adjusted accordingly.

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References

Almodovar, M., & García-Ródenas, R. (2013). On-line reschedule optimization for passenger railways in case of emergencies. *Computers & Operations Research* (3): 725-736.

Budai, G., Maróti, G., Dekker, R., Huisman, D., & Kroon, L.G. (2010). Rescheduling in passenger railways: the rolling stock rebalancing problem. *Journal of Scheduling*, 13, 281-297.

Cadarso, L., & Marín, A. (2010). Robust routing of rapid transit rolling stock. *Public Transport* 2, 51–68

Cadarso, L., & Marín, A. (2011). Robust rolling stock in rapid transit networks. *Computers & Operations Research* 38 (8), 1131–1142.

Cadarso, L., & Marín, A. (2012). Integration of timetable planning and rolling stock in rapid transit networks. *Annals of Operations Research* 199 (1), 113–135.

Cadarso, L., Marín, A., & Maróti, G. (2013). Recovery of Disruptions in Rapid Transit Networks. *Transportation Research Part E: Logistics and Transportation Review*, (53): 15-33.

de Almeida, D., Trouve, F., & Hebben, B. (2003). A decision aid module for resources rescheduling when managing disturbances. Technical report, presented at the World Congress on Railway Research.

Jespersen-Groth, J., Pottho, D., Clausen, J., Huisman, D., Kroon, L., Maróti, G., & Nielsen, M. (2009). Disruption Management in Passenger Railway Transportation. In: Ahuja, R., Möhring, R. and Zaroliagis, C., editors. Robust and Online Large-Scale Optimization, *Lecture Notes in Computer Science*, Vol. 5868, pp. 399-421.

Kroon, L., & Huisman, D. (2011). Algorithmic Support for Railway Disruption Management. In: Nunen, Jo A.E.E., Huijbregts, P., Rietveld, P., editors. Transitions Towards Sustainable Mobility, Springer Berlin Heidelberg.

Nielsen, L. (2011). Rolling Stock Rescheduling in Passenger Railways. PhD. Thesis. Erasmus Research Institute of Management, Rotterdam School of Management (RSM). ISBN 978-90-5892-267-0.