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Integrated train and passenger disruption management for urban railway lines

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Abstract—**Urban railway transit systems in big cities operate at high capacity and represent the main arteries of city transport networks. In current operations, infrastructure failures occur occasionally causing severe disruptions. In this research, we propose a novel integrated disruption management methodology for automatically rescheduling trains and controlling passenger flows for a given disruption. Our framework incorporates a train traffic management model together with a model for adjusting flows of passengers and aims to minimize the total delay of passengers, the number of denied passengers, adjustments to train services, and recover time. On the train side, we short-turn, cancel and reroute train services. On the passenger side, we reflow passengers according to a disrupted timetable and control station gates. We test our integrated disruption management approach on real-life cases and discover dependencies between delayed/denied passengers and traffic management. Our goal is developing practical solutions to this critical transportation problem that will lead to establishing advanced decision support systems to assist metro dispatchers.**

I. Introduction

Urban rail transit systems take a significant share in public transportation systems, especially in large cities, where millions of passengers commute by trains and the passenger demand still increases. As such, they represent the main arteries of city transport networks. More and more urban rail transit lines are being operated with high frequencies at the maximal capacity. Under the current conditions, it is inevitable that infrastructure or vehicle failures occur occasionally such as a signal or train door malfunction. Even short disruptions of 10-15 minutes can cause significant deterioration of operations resulting in multiple trains being cancelled on one hand, and stations and trains being overcrowded on the other. In such cases, dispatchers have to react quickly to reschedule train services as promptly as possible as well as to inform and (re)direct passengers in the network. However, dispatchers can make decisions only locally, which may be of poor quality on the network level. As a result, passengers may spend drastically longer time in the metro system and many may have to be denied from the system due to extreme overcrowding in trains and stations which overall generates a great dissatisfaction among passengers. To support dispatchers in real-time operations and particularly during disruptions, mathematical optimization models and algorithms can bring great benefit to resolve these challenging problems efficiently and more effectively.

The goal of this paper is to develop a novel integrated methodology for train and passenger disruption management of busy metro systems. Our framework incorporates a train rescheduling model together with a model for adjusting and controlling passenger flows in the system. The aim is to minimize the total delay of passengers, the number of denied ones and the recovery to planned operations after the disruption is over. On the train side, we adjust arrival and departure times, change train routing, short-turn and, if necessary, cancel trains. In addition, we adjust rolling stock circulations during the disruption and insert extra services. On the passenger side, we adjust passenger routes through the system, and control station gates to limit the inflow of passengers entering stations. The framework considers important practical constraints like train and platform/station capacity which is extremely important when considering overcrowded metro systems such as in Beijing, Tokyo and New York. Combining train and passenger control brings multiple new dimensions in the integrated disruption management of metro systems.

The remainder of the paper is as follows. Section II presents literature review. Section III defines the considered problem. Section IV describes the proposed integrated disruption management framework and modelling details. Section V demonstrates the applicability of the framework and Section VI gives concluding remarks.

II. Literature review

Regarding disruption management of metro and railway systems, only limited research exists. Cacchiani et al. (2014) gives an extensive review of rescheduling and disruption management approaches in railway system, where most approaches consider only train traffic management. For instance, Xu et al. (2016) considered an incident in a subway line and formulated an optimization model to calculate the rescheduled timetables with the objective to minimize the total delay time of trains. However, passenger demand is not considered in this paper. Similarly, Ghaemi et al. (2017) proposed a microscopic train disruption management model deciding the optimal short-turning stations, platforms and routes based on the available capacity.

Railway planning and traffic management problems have been tackled recently in integrated or iterative setups in order to incorporate more practical constraints and/or generate better quality solutions. For instance, performance criteria like timetable feasibility, stability and robustness of original

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and rescheduled timetables were considered in Caimi (2009), Caimi et al. (2012), Bešinović et al. (2016), and Quaglietta et al. (2016). Corman et al. (2017) addressed a problem of solving train and passenger rescheduling during minor disturbances. They proposed a MIP model where trains and passengers were rescheduled/rerouted using an alternative graph-based model formulation. To solve this MIP, they further developed an iterative approach. Gao et al. (2016) proposed an optimization model to reschedule a metro line with an over-crowded passenger flow during a short disruption, where a stop-skip strategy is formulated in the model and an iterative algorithm is used to solve the model. Caimi (2009) and Caimi et al. (2012) modelled train scheduling and rescheduling problems introducing different variants of the conflict graph modelling formulation and successfully solved some real-life instances of busy corridors of Swiss railway networks. They concluded that the models are capable of considering many alternative routing possibilities and departure timings and, in particular, are applicable to real-time applications.

Detailed dynamic passenger assignment models (i.e. include timetable-dependent passenger behavior) are complex on its own (Zhu and Goverde, 2019). Until now, only a few train rescheduling models consider passenger demand in a dynamic way in case of disruptions. These models can represent passenger behavior more accurately, but this comes at the expense of higher computation time (Binder et al., 2017) that is usually not acceptable in practice. To efficiently address the challenging and complex railway problems that arise in practice simulation-based optimization approaches are needed (Bierlaire, 2015). In particular, these are useful for complex problems where issues are time-consuming and simulation is used. In our case, dynamic passenger assignment flow is reevaluated for each new optimized rescheduled timetable.

Several gaps in the current literature were identified. First, approaches based on conflict graph formulations have not been used for train disruption management. Second, existing passenger routing models always assumed that station platforms have sufficient capacity. Third, integrated approaches for train and passenger disruption management including train cancelation and controlling passenger flows do not exist in the current literature. In this paper, we address these challenges within our integrated passenger-oriented disruption management approach to urban railway lines.

III. Problem description

In this paper, we tackle a complete open-track disruption between two stations. Some practical examples for such cases are power outage of a local power station or a fire in the tunnel. If a track between two stations is blocked then, trains need to short-turn and circulate on shorter distances. Busy metro networks typically suffer from passenger overcrowding even during regular peak hour operations. Passengers often encounter the inability to board the first few departing trains as they may be already full and need long waiting time to get on board (Gao et al., 2016). Even more, particularly during disruptions, when less train services are provided, stations experience overflow of passengers and thus train operators may decide to control the number of incoming passengers due to the station capacity and in the most extreme situations even completely close a station (Xu et al., 2014). We focus on train and stations operations of one metro line while consider passengers originating/ending and traveling to other train lines in the network as well.

We consider a metro line as shown in Figure 1. Typically, one side of a station has a depot to park rolling stock during non-operating hours. During operating hours, this allows a train service to be cancelled and moved away to the depot. In addition, an additional reserve rolling stock unit may be stored in a depot to be potentially used due to a disruption (e.g. failed rolling stock).

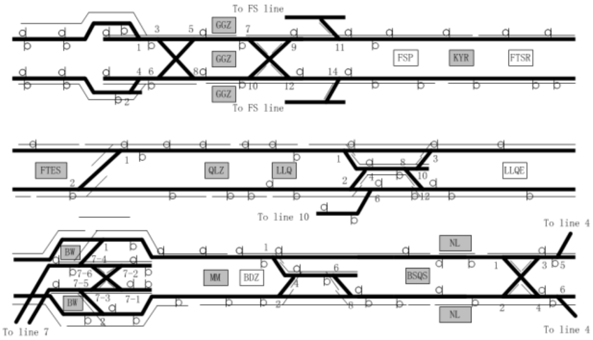

Figure 1. Layout of a metro line

We define a **train route** as a set of consecutive resources associated with running and dwell times. A **train service** is a train operating in one direction between origin and destination stations with a corresponding train route, and planned departure and arrival times. Each train service exclusively reserves a train route preventing its resources to be used by other trains.

Considered assumptions in the paper are: 1. If a train service is running when a disruption happens, it cannot be cancelled and will continue its running. 2. Running and dwell times are assumed fixed. 3. All platforms at all stations are island platforms. 4. All passengers that started their journey will end it, without leaving the system prematurely due to the disruption.

IV. Methodology

A. *Integrated disruption management (IDM) framework*

We propose a new integrated disruption management (IDM) framework for optimizing railway timetables and passenger flows during disruptions. The aim is to minimize cancelled and delayed trains as well as denied and delayed passengers. Figure 1 shows a conceptual IDM framework. Given are an original timetable, disruptions on a line, train-related input like infrastructure including signaling and train protection system, train dynamics and line characteristics, and passenger-related input such as original OD demand and passenger rerouting alternatives. The IDM framework includes two models:

1. a train traffic management (TTM) model based on a conflict graph formulation which reroutes, retimes, short-turns, and cancels train services, and

2. a passenger flow management (PFM) model based on the time-dependent OD passenger demand, where passengers could wait at platforms, board/alight trains, be on-board trains, or be denied by overcrowded stations (i.e. waiting outside due to station closure).

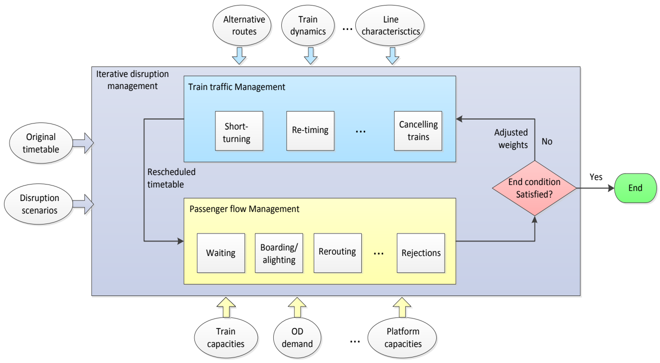

Figure 2. IDM framework

The framework starts by microscopically adjusting trains in the network (TTM). The original timetable should be adjusted by delaying, short-turning and cancelling train services. The objective of TTM is to find a new timetable such that train services are affected the least by a disruption. Output of TTM is a rescheduled timetable that satisfies the microscopic infrastructure capacity.

The new rescheduled timetable is given as input to the model for passenger flow management (PFM). Based on the rescheduled timetable and the passenger demand, the PFM model decides the number of boarding/alighting passengers, the number of waiting passengers, the number of passengers that are denied at stations, the number of passengers left the system without arriving at their destinations, etc. The objective of PFM is to minimize the delayed passenger (or total passenger delays) and the number of denied passengers. Over the iterations, the TTM delivers the departure and arrival times of train services at stations to PFM. The other way around, PFM produces rerouted passenger flows for TTM and passengers waiting at stations which are considered as input weights in the latter.

B. Train traffic management model (TTM)

The microscopic train **traffic management model (TTM)** aims to generate feasible rescheduled timetables while minimizing passenger dissatisfaction. The TTM is based on extended conflict graph models introduced by Caimi (2009). In the TTM, we decide on scheduling optimal routes for train services. Each train service has a set of alternative train routes over the remaining available infrastructure that incorporates traffic management measures such as rerouting and retiming and if necessary, cancellation. Given that a complete blockage is considered, all train services are short-turned in stations closest to the disrupted tracks. Due to limited infrastructure, trains need to satisfy safety constraints. Typically, a bigger minimum headway is necessary in short-turning stations as opposed to regular (non-disrupted operations). From every pair, only one route can be chosen. In this way, conflicts are prevented while ensuring feasibility of a route plan. Rolling stock connections are also considered to satisfy vehicle circulations in the system.

Rolling stock departs either from a depot or is cancelled and reinserted in service after a disruption ends. If a service from a terminal station is cancelled then a service in the opposite direction needs to be cancelled as well as a rolling stock is not available to run that service. Therefore, the number of services during a disruption in both directions should be equal to maintain a feasible rolling stock circulation.

When train service is cancelled then its rolling stock is stored in the depot until a disruption finishes. Then, it has to be reinserted to serve a train service in order to return to the planned operations. During a disruption, in the worst case all services n_s could be cancelled. Therefore, at most n_s services may need to be reinserted after a disruption finishes. In addition, extra rolling stock can be available to operate additional train services if needed.

Let us define a set of trains Z and a single train $i \in Z$. Train services in outbound direction are in subset Z_o and services in the inbound direction are in Z_i. Subset Z_b represents train services which are planned during disruption, and Z_r represents services which are planned after disruption. A set of routes is defined as J where a route $j \in J$. Subset J_i includes all routes available to train service i. Subset J_b are available routes during disruption and J_r - routes after disruption. Dispatching measures for adjusting train services are rerouting, altering rolling stock circulation, cancelling and inserting new train services. We define a decision variable x_{ij} for each train $i \in Z$ using a route $j \in J$. If a service x_{ij} is chosen, then $x_{ij} = 1$, otherwise equals 0. For cancelling a train service, a virtual route q is defined.

The objective of TTM consists of the model aims at recovering as fast as possible to the original train services. In addition, weights are assigned representing passengers' load for each alternative train route. We propose a mixed integer programming formulation for TTM as follows:

$$\text{Minimize} \sum_{i\in Z_b} w_{iq}x_{iq} + \sum_{i\in Z, j\in J_i} w_{ij}x_{ij} + \sum_{i\in Z, j\in J_i} p_{ij}x_{ij} \tag{1}$$

Such that

$$\sum_{i\in Z, j\in J_i} x_{ij} + x_{iq} = 1, \quad i\in Z, j\in J_i \tag{2}$$

$$x_{ij} + x_{kl} \leq 1, \quad i,k\in Z, j,l\in J, (k,l)\in C \tag{3}$$

$$\sum_{i\in Z_o} x_{iq} - \sum_{i\in Z_i} x_{iq} = 0, \quad i\in Z \tag{4}$$

$$\sum_{i\in Z_b} x_{iq} - \sum_{e\in J_r} (1 - x_{je}) \geq 0, \quad \forall i\in Z_b, \forall j\in Z_r \tag{5}$$

Objective function (1) minimizes the number of cancelled train services, timetable deviation and number of denied and waiting passengers. Equation (2) ensures that at most one train service is chosen or is cancelled if route q is selected, $x_{iq} = 1$. If a train service is cancelled it is assumed that it is moved to a depot. Equation (3) is an infrastructure constraint allowing to choose only one service from a conflicting pair of routes j and l. Set C is a set of conflicting pairs of train services. Equation (4) determines that the number of cancelled services in outbound direction $i \in Z_o$ is equalled the number of cancelled services in inbound direction $i \in Z_i$. Equation (5) defines that the number of cancelled train services during the disruption is considered for re-insertion in the recovery phase.

Parameter w_{iq} represents a cancellation penalty. Parameter w_{ij} defines the importance of train service x_{ij} (linear relation) to conform with the planned schedule and is computed as: $w_{ij} = 0.002 \cdot \frac{t_{ij}-s_T}{e_T-s_T} \cdot d_{ij}$, where $\frac{t_{ij}-s_D}{e_D-s_D}$ takes values from [0,1], t_{ij} is the departure time of service i with route j, d_{ij} is the time deviation from the planned timetable, s_D is the start time of a considered period and e_D is the end time of a considered period. Parameter p_{ij} represents the weighted passenger waiting time including: waiting onboard p_{ij}^{train}, waiting in stations $p_{ij}^{waitOut}$ and waiting out of stations $p_{ij}^{waitOut}$ over a train service x_{ij}. These waiting times are estimated by the PFM. The corresponding weights w^{train}, w^{wait} and $w^{waitOut}$ are defined, where $w^{train} < w^{wait} < w^{waitOut}$. Passenger weight p_{ij} is computed as $p_{ij} = w^{train}p_{ij}^{train} + w^{wait}p_{ij}^{wait} + w^{waitOut}p_{ij}^{waitOut}$. The TTM is implemented in Matlab with Yalmip toolbox and solved by optimization solver Gurobi.

C. *Passenger flow management model (PFM)*

The **passenger flow management** (**PFM**) model aims to describe different choices that can be taken by passengers themselves or by the train operator. On the passengers' side, the passengers may enter the station immediately when they arrived or may need to wait outside the station area if the station is too crowded. On the rail operators' side, the rail operators could adopt incoming passenger control strategies to limit the passenger flow in the rail system below a certain level, or to increase passenger flow by opening additional gates, and suggest passengers to taking alternative routes in the rail system or choosing other transportation mode. The PFM model is based on the passenger flow model used by Wang et al. (2015) and Gao et al. (2016) and the queuing models introduced by Xu et al. (2014). The PFM model here incorporates practical constraints such as the capacity of trains, capacity of stations (including platforms, station hall, etc.), alternative routes in the rail system, the reachability of the destinations of passengers and the tolerance of passenger to waiting times. Note that the decisions of the PFM model are highly affected by the rescheduled timetables generated by the TTM model. Based on the passengers' choices, the PFM model gives insights to the TTM model to re-adjust the train schedule to enhance the passenger satisfaction.

In this paper, the passenger arrival rate $\lambda_{m,m'}(\cdot)$ is a piecewise constant function with respect to the time intervals, i.e.,

$$\lambda_{m,m'}(t) = \begin{cases} \lambda_{m,m',1} & \text{if } t \in [t_1, t_2] \\ \vdots & \vdots \\ \lambda_{m,m',N} & \text{if } t \in [t_N, t_{N+1}] \end{cases}. \tag{6}$$

The gate control rate $\zeta_m(\cdot)$ is also defined as a piecewise constant function similar to (6). In addition, the passenger control rate has the same effect for all the passengers that have different destinations. Therefore, the number of passengers waiting outside the ticket gates can be computed by

$$w_m^{out} = \sum_{m'=1}^{M} \int_{t_{start}}^{t} (1 - \zeta_m(\tau))\lambda_{m,m'}(\tau))d\tau, \tag{7}$$

where $\zeta_m(\cdot) > 0$ since the passengers that have entered stations will not leave the system until they arrive at their destinations. In particular, $\zeta_m = 0$ represents that a station is completely closed, and no passengers are allowed to enter, $\zeta_m = 1$ represents that all the (newly) arrived passengers enter the station without interruption. If $0 < \zeta_m < 1$ then the passenger inflow is restricted, and $\zeta_m > 1$ represents that additional gates need to be open in order to let excessive passenger flow (e.g. due to the passengers that wait outside and have arrived newly at stations) to enter the station (typically after a disruption ended). The waiting time of the passengers waiting outside the gates can be computed by

$$t_m^{\text{out}}(t) = \sum_{m'=1}^{M} \int_{t_{\text{start}}}^{t} \int_{t_{\text{start}}}^{\tau_2} (1 - \zeta_m(\tau))\lambda_{m,m'}(\tau))\text{d}\tau_1\text{d}\tau_2. \tag{8}$$

The objective function of the PFM model is to minimize the total waiting time of the denied passengers that are waiting outside stations while satisfying the capacity constraints of trains and stations.

We propose an event-driven model similar to the one in Wang et al. (2015) to describe the behaviors of passengers (such as entering, waiting, boarding, alighting and leaving) based on the reschedule results of the TTM model. To describe the operation of trains from a passenger perspective, the event-driven model consists of the following three types of events: departure events, representing the departure of a train at a station, arrival events, representing the arrival of a train at a station, and short-turning events, representing the short turning operation of a train in an intermediate station.

The r-th event e_r occurring in the event-driven system is denoted as $e_r(\tau_r, y_r, i_r, m_r)$, where r is the event counter, τ_r is the time instant at which event e_r occurs, y_r is the event type, which has two possible values, i.e., 'd' and 'a' corresponding to a departure event and an arrival event, i_r is the train service index, and m_r is the station index. As mentioned before, all the events are known because the rescheduled timetable is provided by the TTM. When an event occurs, the state of the system, particularly the numbers of boarding, alighting and waiting passengers, should be updated. Specifically, during the boarding process of passengers, the number of passengers onboard trains is limited by the maximum capacity $C_{\max}^{\text{train}}$, i.e.,

$$\eta_{i_r,m_r}^{\text{board}} = \min\left(C_{\max}^{\text{train}} - \eta_{i_r,m_r}^{\text{before}}, w_m^{\text{before}}(\tau_r)\right), \tag{9}$$

where $w_m^{\text{before}}(\tau_r)$ is the number of passengers waiting at the platform and $\eta_{i_r,m_r}^{\text{before}}$ is the number of passengers that are already onboard before the boarding process. In addition, the number of passengers inside the station should be less than the maximum capacity at any time. Since here we consider an event-driven system, we only need to check the capacity constraints when an event occurs, especially when an arrival event occurs, i.e.,

$$w_{m_r}^{\text{before}}(\tau_r) + \eta_{i_r,m_r}^{\text{alight}} \le C_{m_r}^{\text{Station}}, \qquad (10)$$

where $C_{m_r}^{\text{Station}}$ is the capacity of station m_r and $\eta_{i_r,m_r}^{\text{alight}}$ is the number of passengers that alighted from the just arrived train.

The resulting passenger flow management problem is a nonlinear programming problem, which can be solved using e.g., sequential quadratic programming and interior-point method. In this paper, we use function fmincon in Matlab with the sqp algorithm.

To use adjusted passenger flows into TTM, for each train service x_{ij}, passenger waiting times (i.e. onboard, in station and denied/out-station) are summarized over all stations along that train service.

V. EXPERIMENTS

We demonstrate the IDM approach on real-life cases of Line 9 of Beijing Metro. We assume that the disruption occurs between QLZ and LLQ (see Figure 1) and lasts from 8:03 to 8:13, the time period for rescheduling considered is then from 8:03 to 9:13. Parameters of the IDM framework and the corresponding models are the following: number of iterations is set to 10, $w^{train} = 0, w^{wait} = 1, w^{waitOut} = 1.5, w_{iq} = 1{,}000{,}000$, the train capacity is set as 1440, and the station capacity is set as 2700. Moreover, the passenger arrival rates and the train schedule are constructed based on the data of Beijing Metro Line 9.

In the experiments, we compare variants with different numbers of maximum extra services that can be added in operations. In particular: with no extra train services, 2, 4 and 6 extra train services. The variant with 2 extra services corresponds to the TTM formulation (1)-(5). The variant with no extra services corresponds to the TTM formulation (1)-(4). The last two variants correspond to the TTM formulation (1)-(4) and an additional constraint $\sum_{e \in J_r} x_{je} = n_e,\ \forall j \in Z_r$, where n_e is the maximum number of extra services.

Table 1 reports the experimental results for 4 variants of the IDM: objective function value (OF), number of scheduled and cancelled train services, weighted train deviation (trainDev, computed as $\sum_{i \in Z, j \in J} w_{ij} x_{ij}$) and weighted passenger waiting times (paxDev, computed as $\sum_{i \in Z, j \in J} p_{ij} x_{ij}$). In all four cases, exactly 2 train services were cancelled during the disruption. These cancellations are mainly caused by a partial single-track operation from QLZ to GGZ which implied long headway and turnaround times and thus resulted in limited infrastructure capacity. When no extra services are used, the rescheduled solution reports a high OF being influenced by large passenger waiting times. Adding 2 extra services significantly reduces the passenger waiting time and thus also the OF. Further, adding extra services (4 and 6) brings smaller benefit to the performance of the system, i.e. paxDev reduces slightly. In fact, adding more extra train services means more adjustments to existing services, i.e. more services need retiming and rerouting (trainDev increases). On average, computation times per iteration over all scenarios were: 2 s for TTM and 240 s for PFM. The IDM framework typically converged to single solutions after 3 to 4 iterations.

Table 2 reports the number of waiting passengers in and out of the station (paxWaitIn and paxWaitOut) and the corresponding waiting times (timeWaitIn and timeWaitOut). It shows that paxWaitIn halves when adding 2 extra services, which also strongly reduces waiting time in stations timeWaitIn. However, increasing from 4 to 6 extra services, does not benefit the number of passengers waiting, but still reduces their waiting time to some extent. This is a consequence of most passengers accumulating at stations before the disrupted area, and with limited train capacity not all can board the first train after the disruption but need to wait for next ones.

Table 1. Experimental results for solving IDM

Max extra services	OF	Train services	Cancelled services	trainDev	paxDev
0	36208123	67	2	2162000	32207996
2	33629687	69	2	2160000	29629559
4	33101866	71	2	2166000	29101726
6	32987627	73	2	2202000	28987438

Table 2. Waiting passengers and waiting times

Max extra services	paxWaitIn	paxWaitOut	timeWaitIn	timeWaitOut
0	44439	709	10117948	45540
2	22690	709	7969067	45540
4	17964	709	7529202	45540
6	17964	709	7432595	45540

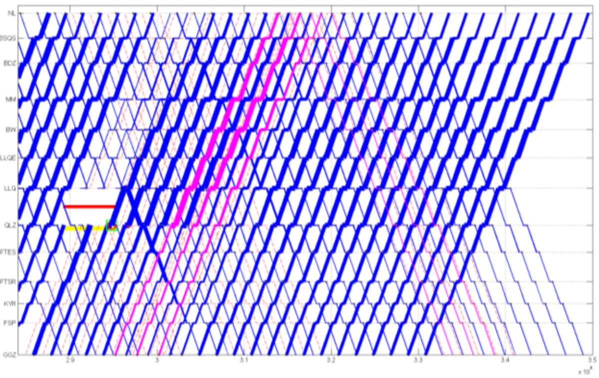

Figure 3. Adjusted timetable with 6 extra services

Figure 3 visualizes the disrupted time-distance diagram with 6 extra services. It shows adjusted existing train services (blue line), added extra services (purple line), number of passengers onboard (line width), passenger waiting time at each station (red circles at stations), number of passengers waiting outside of each station (green squares) and disruption duration (red line). As expected, most crowded are trains right after the disruption, as they collect all regular demand plus additional ones that have been denied and waiting out of stations during disruption, e.g. at QLZ. A limited positive effect of the third extra service is visible in Figure 3, i.e., it reduces some passenger waiting time but transports less passengers, and also causes the following 2 original services to operate with reduced occupancy.

Figure 4 shows gate control and passengers waiting, in and out of station QLZ for the scenario with 6 extra services. Before the disruption, gate control of value 1 represents that no passenger overcrowding is experienced, thus no measures are taken, and the arriving passenger flow can enter the station freely. During disruption, certain gate control measures are applied to manage inflow of passengers to the station. In particular, when a disruption happens, gates are first being partially closed (values smaller than 1) to reduce inflow of passengers and later on, completely closed (values equal 0). Accordingly, passengers accumulate in the station, as they arrive from other stations, and accumulate outside the station as they intend to start their journey. Once the disruption is resolved, all gates are re-opened, and furthermore, additional gates are open (values bigger than 1) to release an extra flow of passengers that accumulated out of the station.

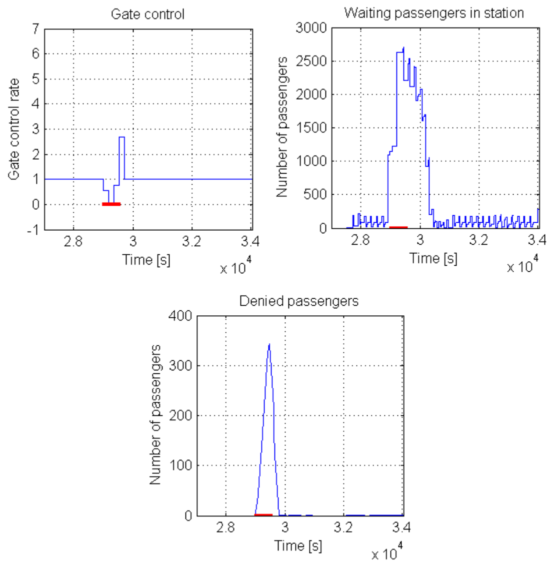

Figure 4. Station QLZ for scenario with 6 extra train services: gate control number of passengers waiting in and out of station

Table 3 reports gate control measures: time under (partial) closure (reported in min), weighted gate closure time (weightClose, computed as closure rate multiplied by the duration of the measure), time under additional gates are open, and weighted gate opening time (weightOpen, computed as open rate multiplied by the duration of the measure). For all cases, the gate control strategies are the same. Mainly, passengers that arrive during disruption are being accumulated first inside the station and then denied and need to wait outside the station. In order to restrict passengers entering a crowded station gates are closed for a certain time. In our considered cases, gates were closed for 12 min. After a disruption ends, additional gates are opened for 6 min.

Table 3. Gate control strategies

Max extra services	timeClose	weightClose	timeOpen	weightOpen
0	12	8,033	6	8,033
2	12	8,033	6	8,033
4	12	8,033	6	8,033
6	12	8,033	6	8,033

VI. CONCLUSIONS

We proposed a novel integrated disruption management methodology for automatically rescheduling trains and controlling passenger flows for a given disruption. Our framework incorporates a train traffic management model together with an event-driven passenger flow model and aims to minimize the total delay of passengers, reduce the number of denied passengers, minimize adjustments to train services and recover as quickly as possible. On the train side, we short-turn, cancel and reroute train services. On the passenger side, we reflow passengers according to a disrupted timetable and control station gates. We tested our integrated disruption management approach on real-life cases and discover dependencies between delayed/denied passengers and traffic management. The current model could support dispatchers in determining optimal train and station control measures as well as determine the necessary number of additional services to be inserted in order to minimize passenger waiting times and denied passengers.

As future work, we envisage new developments toward including train services with variable maximum speeds and/or more flexible short-turning possibilities. In addition, new simulation-based optimization approaches to solve efficiently the given integrated problem will be considered.

REFERENCES

[1] Bierlaire, M. 2015. Simulation and optimization: A short review. Transportation Research Part C: Emerging Technologies, 55, 4-13.

[2] Bešinović, N., Goverde, R.M.P., Quaglietta, E., Roberti, R. 2016. An integrated micro–macro approach to robust railway timetabling. Transportation Research Part B: Methodological, 87, 14-32.

[3] Binder S, Maknoon Y, Bierlaire M (2017) The multi-objective railway timetable rescheduling problem. Transportation Research Part C: Emerging Technologies 78:78–94.

[4] Caimi, G. C., 2009. Algorithmic decision support for train scheduling in a large and highly utilised railway network. PhD thesis, ETH Zurich, Switzerland.

[5] Caimi, G., Fuchsberger, M., Laumanns, M., & Lüthi, M., 2012. A model predictive control approach for discrete-time rescheduling in complex central railway station areas. Computers & Operations Research, 39(11), 2578-2593.

[6] Corman, F., D'Ariano, A., Marra, A. D., Pacciarelli, D., & Samà, M., 2017. Integrating train scheduling and delay management in real-time railway traffic control. Transportation Research Part E: Logistics and Transportation Review, 105, 213-239.

[7] Gao Y., Kroon L., Schmidt M., and Yang L., 2016. Rescheduling a metro line in an over-crowded situation after disruptions. Transportation Research Part B, vol. 93, pp.425-449.

[8] Ghaemi, N., Cats, O., & Goverde, R. M. P., 2017. A microscopic model for optimal train short-turnings during complete blockages. Transportation Research Part B: Methodological, 105, 423-437.

[9] Quaglietta, E., Pellegrini, P., Goverde, R. M., Albrecht, T., Jaekel, B., Marlière, G., & Giaroli, M., 2016. The ON-TIME real-time railway traffic management framework: A proof-of-concept using a scalable standardised data communication architecture. Transportation Research Part C: Emerging Technologies, 63, 23-50.

[10] Wang, Y., Tang, T., Ning, B., van den Boom, T., De Schutter, B., 2015. Passenger-demands-oriented train scheduling for an urban rail transit network. Transportation Research Part C 60, 1–23.

[11] Xu X., Li K. and Yang L., 2016, Rescheduling subway trains by a discrete event model considering service balance performance. Applied Mathematical Modelling, vol.40, no.2, pp.1446-1466.

[12] Xu X., Liu J., Li H., and Hu J., 2014, Analysis of subway station capacity with the use of queuing theory. Transportation Research Part C, vol. 38, pp. 28-43.

[13] Zhu, Y., Goverde, R. M. P., 2019. Railway timetable rescheduling with flexible stopping and flexible short-turning during disruptions, Transportation Research Part B Methodological, in press.