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A Matheuristic for the Integrated Disruption Management of Traffic, Passengers and Stations in Urban Railway Lines

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Abstract—In big cities, the metro lines usually face great pressure caused by huge passengers demand, especially during peak hours. When disruptions occur, passengers accumulate quickly at stations. It is of great importance for dispatchers to take passenger flow control into consideration for the traffic management to ensure passengers' safety and to maintain their satisfaction. This paper proposes an integrated disruption management model, which incorporates train rescheduling and passenger flow control. In this model, the train services can be short-turned, cancelled and rerouted, while the number of passengers entering a station is managed by controlling the station gates with consideration of the capacities of platforms and trains. Moreover, the number of passengers arriving at a station is calculated according to the origin-destination matrices. The objectives are to recover the train operation to the original timetable as soon as possible and to minimize the waiting time of passengers outside the stations. With the interaction between train services, passengers and station gates, an iterative metaheuristic approach is proposed to solve the integrated disruption management problem. Based on the data of a Beijing metro line, numerical experiments are conducted to test the proposed algorithm. The results demonstrate the importance of integrated disruption management and the effectiveness of our solution method.

Index Terms—Railway, disruption, resilience, passengers, trains, stations.

I. INTRODUCTION

URBAN rail transit systems are the main arteries of large cities and take a significant share in public transportation systems. Everyday, millions of passengers commute by trains and the passenger demand continues to increase. Urban rail transit lines are more commonly characterised with high frequency operations and maximum capacity use. Under such conditions, it is inevitable that failures in the system occur, such as a track blockage, signal failure or train door malfunction. Even short disruptions of 10-15 minutes can cause significant damage to operations including multiple trains being cancelled or heavily delayed, and stations and trains being overcrowded. In such cases, dispatchers have to react quickly to adjust train services as promptly as possible as well as to inform and (re)direct passengers in the network. However, dispatchers typically make decisions only locally, which may be of poor quality on the network level. Even more, train and platform capacity tend to become critical for disruption management. As a result, passengers may spend drastically longer time in the metro system and even many may have to be denied from the system due to extreme overcrowding in trains and stations which generates a great dissatisfaction to passengers. Therefore, these conditions raise the importance of combining train and station control in the disruption management of metro systems. To support dispatchers in real-time operations and particularly during disruptions, mathematical optimization models and algorithms can bring benefit to resolve these challenging problems efficiently and more effectively.

This paper presents an integrated methodology for transport disruption management of busy metro systems including jointly train services, passenger demand and station control, and we refer to it as an Integrated Disruption Management (IDM). The model formulation incorporates train rescheduling together with controlling passenger flows in the system, with the objective of minimizing the total delay of passengers, train service cancellations and the recovery to planned operations after the disruption ends. In particular, a phase-specific objective function is introduced that distinguishes between different phases of a disruption. On the train side, the arrival and departure times and routing of train services can be adjusted, train services can be cancelled and when necessary cancelled train services reinserted again. On the passenger side, taking system capacity constraints into account, passenger flows through the system are being adjusted, and station gates are controlled to manage the inflow of passengers entering stations. We solve this new problem by applying an iterative matheuristic approach. The approach is tested on a real-life metro line in Beijing.

The main contributions of the paper are fourfold. First, a new mathematical formulation for addressing integrated traffic, passenger and station management. Second, an iterative matheuristic for solving the integrated transport management problem. Third, the model combines two types of headways, namely frequency-based and schedule-based as required at metro systems. Fourth, we demonstrate the developed model on a real-life line at Beijing metro.

The remainder of the paper is as follows. Section II presents the literature review. Section III defines the considered problem. Section IV describes the proposed mathematical model of the integrated disruption management (IDM) problem Section V presents an algorithm for solving the IDM. Section VI demonstrates the applicability of the algorithm and Section VII gives concluding remarks.

II. LITERATURE REVIEW

Regarding disruption management of metro and railway systems, only limited research exists and most commonly papers tackle either traffic management, i.e. transport supply, or passenger assignment, i.e. transport demand. Cacchiani et al. [1] gave an extensive review of rescheduling and disruption management approaches in railway system, where most approaches consider only train traffic management. More generally, Bešinović [2] defined resilience of the rail transport systems as the ability to withstand disruptions as well as to recover as quickly as possible. It distinguishes between the transport phases during disruptions: survivability (from disruption occurrence to reaching the stable state, the first phase), response (a steady state with regular reduced services during disruption period, the second phase) and recovery (returning from disruption to regular conditions, the third phase). Resilience can be typically tackled both at planning level and operations level, while disruption management is part of the latter.

Some research focused exclusively on recovery – For example, Jespersen-Groth et al. [3] determined the best reinsertion strategies for cancelled services into the network after a disruption finished, survivability – Hirai et al. [4] tackled finding the best stop locations for trains that are cancelled due to a disruption and response – Van Aken et al. [5] solved adjusting timetables due to multiple planned disruptions. In [6], the authors 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. In addition, van Lieshout et al. [7] developed a new line plan to operate in an isolated disrupted area to address response in out-of-control situations. To solve all three sub-problems of disruption management together, authors considered rescheduling actions from a disruption start to returning to the original state again ([8]–[11]). Veelenturf et al. [8] proposed an integer linear programming model for solving the timetable rescheduling problem which minimizes the number of cancelled and delayed train services while adhering to infrastructure and rolling stock capacity constraints. Ghaemi et al. [9] proposed a microscopic train disruption management model deciding the optimal short-turning stations, platforms and routes based on the available capacity.

Ghaemi et al. [10] proposed a mixed integer linear programming model for the macroscopic rescheduling model covering all three phases of a disruption and the choice of short-turning station. In addition, Liu et al. [11] incorporated train circulations. Passenger demand is not considered in these papers. Some researchers took the passengers' behavior into consideration. Cadarso et al. [12] proposed a train rescheduling model accounting for the passenger demand behavior to minimize the operating costs and the number of denied passengers, where the probability that passengers choose different paths in the rapid transit network is considered. Considering the uncertainty of passenger demands, Yin et al. [13] proposed a stochastic programming model to minimize the passenger delay, passengers' traveling time and operating costs, where the energy consumption was also taken into consideration. In Veelenturf et al. [14], a train rescheduling model was proposed to minimize the total passenger delay with a waiting time limit for passengers. With the objective of maximizing passenger satisfaction, minimizing, the operational costs and the deviation from the undisrupted timetable, Binder et al. [15] formulated the train rescheduling problem as an Integer Linear Program. And ϵ-constraints were used to find the Pareto frontier. Ghaemi et al. [16] investigated the impact of railway disruption prediction and used a multinomial logit choice model to determine the passenger route choices together with the macroscopic MILP rescheduling model of Ghaemi et al. [10] in an iterative framework. Zhu and Goverde [17] proposed a schedule-based passenger assignment model to distribute passengers. Zhu and Goverde [18] used this model to determine passengers' paths and the passenger-dependent weights in the objective function, with the aim of minimizing the cancelled trains, number of skipping stops and passenger delays. Zhu and Goverde [19] extended this approach to an integrated timetable rescheduling and passenger reassignment model, and they proposed an Adapted Fix-and-Optimize algorithm to solve the MILP. During disruption, the large number of passengers in a metro line will cause severe congestion and increase the passengers' waiting time. To increase passengers' satisfaction, it is better to take passenger flow control into consideration. To our best knowledge, there are only several studies about train rescheduling in which the passenger flow control strategy is applied. Li et al. [20] proposed a state-space model to solve the train rescheduling problem, where the constraint of train capacity is considered and the passenger entering rate can be decreased by implementing a control strategy. In their model, when a train stops at a station, the number of alighting passenger is proportional to the number of onboard passengers, according to a proportionality factor estimated based on the passenger demand original-destination(OD) matrices. Model predictive control methodology was applied to solve the problem. Jiang et al. [21] proposed a skip-stopping strategy with coordinated passenger flow control. The constraints of train capacity and platform capacity are considered in this model. A Q-learning based approach was applied to minimize the frequency of passenger being stranded.

Railway 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. Caimi *et al.* [22] modelled train 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. Gao *et al.* [23] 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. Corman *et al.* [24] addressed the problem of solving train and passenger rescheduling during minor disturbances. They proposed a mixed integer programming (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. Recently, Bešinović *et al.* [25] presented the first attempt to address the IDM problem including station control. They proposed a heuristic approach, and a simple objective for recovering from disruption. In the current paper, we propose an exact mathematical model formulation, a phase-specific objective function to reinsert cancelled services and control station gates with the consideration of train capacity and station capacity.

Detailed dynamic passenger assignment models (i.e. include timetable-dependent passenger behavior) are complex and require particular attention [18]. Such models can represent passenger behavior more accurately. However, this comes at the expense of higher computation time [15] 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 [26]. In particular, these are useful for complex problems where issues are time-consuming and simulation is used.

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 [23]. 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 [27]. We focus on train and stations operations of one metro line while passengers originating/ending and traveling to other train lines in the network are considered as well.

In metro operations, operators aim at different objectives during survivability and response on one side, and recovery on the other. For the former, the main objective is to provide
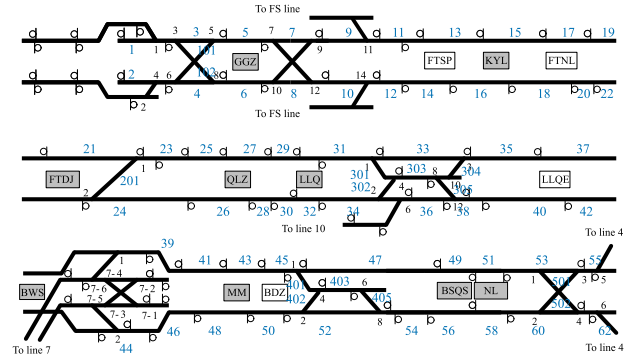

Fig. 1. Layout of the metro line.

regular/balanced services that are equally spaced in time without considering the original timetable, i.e. to (try to) balance demand peaks, and for the latter, the aim is to return to the original scheduled services (as soon as possible). We adopt and implement these two objectives in the model. Also, considered dispatching measures for adjusting train services are rerouting, retiming, replatforming, cancelling and reinserting (cancelled) train services.

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. A failed rolling stock).

A **train route** is defined as a set of consecutive resources associated with running and dwell times and planned departure and arrival times including platforms at origin and destination stations. A **train service** is a train operating in one direction between origin and destination stations with a corresponding train route. Each train service exclusively reserves a train route preventing its resources to be used by other trains. **Station gates** are important facilities for the station management. The passenger flow can be controlled via the opening and closing of gates. Each station gate has a maximum passing rate for passengers. When the passenger arrival rate is higher than the sum of maximum passing rate of opening gates, some passengers need to queue outside the station until more gates are opened or less passengers arrive at this station.

Considered assumptions in the paper are: 1. If a train service is running when a disruption occurs, 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. 5. The number of passengers is real-valued numbers to simplify the computation of passengers (because the number of passengers is usually big, the error introduced by this approximation is negligible).

IV. MATHEMATICAL FORMULATION

To solve the train rescheduling and passenger flow management problem, we propose the integrated traffic management (IDM) model. This section presents first a problem

formalisation including sets, parameters and decision variables (Section IV-A), as well as modelling related to train management (Section IV-B), station control (Section IV-C) passenger flows (Section IV-D), the objective function (Section IV-E). Finally, Section IV-F summarises the IDM model formulation.

A. Sets, Decision Variables and Parameters

Let us define a set of trains services $\mathscr{X}$ and a single train service $i \in \mathscr{X}$. Train services in outbound direction are in subset $\mathscr{X}_o$ and services in the inbound direction are in $\mathscr{X}_i$. The set of stations is defined as $\mathscr{M}$ and a single station $m \in \mathscr{M}$. The set of stations traversed by train service i, is defined as $\mathscr{M}_i$. A disruption time period is defined as $[T_{\text{start}}, T_{\text{end}}]$. The sets of train services are partitioned based on their scheduled timing relative to the disruption period to services during disruption $\mathscr{X}_b$ and services in recovery phase $\mathscr{X}_b$, i.e. after disruption ends. Services $\mathscr{X}_b$ are short-turned in stations closest to the disrupted link and represent the remaining parts of the original non-disrupted services on both sides of disruptions. Services $\mathscr{X}_r$ correspond to the original services. Also, an additional set of reinserting train services is denoted $\mathscr{X}_a$, which may be used as soon as the recovery phase begins. Finally, $\mathscr{X} = \mathscr{X}_b \cup \mathscr{X}_r \cup \mathscr{X}_a$. The planned departure and arrival times of train service i denoted by $\bar{d}_{i,m}$ and $\bar{a}_{i,m}$, where $m \in \mathscr{M}_i$. We note that if train service i is cancelled, then $\mathscr{M}_i = \emptyset$. For short-turned services, the planned departure and arrival times are assumed the same as for the original ones.

A set of routes is defined as $\mathscr{J}$ and a single route $j \in \mathscr{J}$. Subset $\mathscr{J}_i$ represents all routes available to train service i and includes different routing options (e.g. platform use) and/or timing options made by its alternative routes. The set $\mathscr{C}$ includes all pairs of conflicting routes, where $(j, l) \in \mathscr{C}$ if routes j and l are in conflict. For each train service i one route j can be used. We define a binary decision variable x_{ij} for each train service $i \in \mathscr{X}$ using a route $j \in \mathscr{J}_i$. If a service x_{ij} is chosen, then $x_{ij} = 1$, otherwise it equals 0. For cancelling a train service, a virtual route q is defined. The additional variables representing the actual departure and arrival times of train service i are denoted by $d_{i,m}$ and $a_{i,m}$, where $m \in \mathscr{M}_i$. In addition, each x_{ij} is associated with its departure time at the origin station τ_{ij}.

The passenger demand is described by a series of time-varying origin-destination matrices [28], [29]. The disruption period $[T_{\text{start}}, T_{\text{end}}]$ is discretized into a set of intervals, where the length of each interval is $|\Delta T|$ and $[T_n, T_{n+1})$ with $n \in 1, 2, \cdots N$. Based on that, we have $T_{\text{start}} = T_1$ and $T_{\text{end}} = T_{N+1}$. We use matrix Λ_n to denote the OD matrix for time interval $[T_n, T_{n+1})$. We denote the entering rate of station m in $[T_n, T_{n+1})$ for passengers that have station m' as their destination as $\zeta_{m,m',n}$ with $\zeta_{m,m',n} \geq 0$. To avoid the passenger congestion problems, a gate control strategy is adopted. Hence, decision variable $\beta_{m,n}$ is used to denote the gate control factor at station m in $[T_n, T_{n+1})$.

To calculate the passenger waiting times, we introduce an event-driven passenger flow formulation, where the events include train departure events, train arrival events and short-turning events. e_r is used to denote the r-th event, and τ_r is the time when the r-th event happens. To describe the

passenger alighting and boarding process, we use $w_{m_r,m'}^{\text{before}}(\tau_r)$ ($w_{m_r,m'}^{\text{after}}(\tau_r)$) to represent the number of passengers that are waiting inside station m_r and have destination m' immediately before (after) event e_r occurs. Parameter $C_{\max}^{\text{train}}$ is the maximum capacity of a train and C_m^{sta} is the capacity of station m. The number of passengers boarding train i_r at station m_r is denoted by $\eta_{i_r,m_r}^{\text{board}}$ and the remaining space on the train after the alighting process of passengers is denoted by $\eta_{i_r,m_r}^{\text{remain}}$. Finally, decision variable w_m^{out} represents the number of passengers outside the station m, and decision variable t_m^{out} represents the waiting time of these passengers.

The notation used in the paper is given in Appendix.

B. Trains

1) Routes Rescheduling: The train traffic management aims to generate feasible rescheduled timetables while minimizing passenger dissatisfaction. Train traffic management is based on the extended conflict graph formulation introduced by [30]. In essence, this model decides on scheduling optimal routes for train services. Each train service i 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. Each train service needs to satisfy

$$\sum_{j \in \mathscr{J}_i} x_{ij} + x_{iq} = 1, \quad \forall i \in \mathscr{X}. \tag{1}$$

Due to shared infrastructure, trains need to satisfy safety constraints. Therefore, For every conflicting pair in $\mathscr{C}$, only one service can be chosen as

$$x_{ij} + x_{kl} \leq 1, \quad \forall i, k \in \mathscr{X}, \; j, l \in \mathscr{J}, (j, l) \in \mathscr{C}. \tag{2}$$

In this way, conflicts are prevented while ensuring feasibility of the route plan. Typically, a bigger minimum headway is necessary in short-turning stations as opposed to regular (non-disrupted) operations.

Platform Selection: Given the limited station capacity, platform use and selection is considered in the model. Each route consists of a dedicated platforms at origin and destination stations. Platform choice is part of train routes $\mathscr{J}$ so no explicit modelling is required.

2) Rolling Stock Connections: Rolling stock connections are also considered to satisfy vehicle circulations in the system. If a service from a terminal station is cancelled then a service in the opposite direction needs to be cancelled as well since 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. To satisfy this,

$$\sum_{i \in \mathscr{X}_o} x_{iq} - \sum_{i \in \mathscr{X}_i} x_{iq} = 0, \quad \forall i \in \mathscr{X}, \tag{3}$$

which ensures that the number of cancelled services in outbound direction $i \in \mathscr{X}_o$ is equal to the number of cancelled services in inbound direction $i \in \mathscr{X}_i$.

3) Reinserting Cancelled Train Services: When a train service is cancelled then its rolling stock is stored in the depot

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until the disruption finishes. Once a blockage is over, then such rolling stock could be reinserted to provide additional train services in order to return to the planned operations and mitigate accumulated passenger demand as fast as possible. During a disruption, in the worst case all short services, i.e. short-turning services, denoted as n_s could be cancelled. Therefore, at most n_s services may need to be reinserted after a disruption finishes. Therefore,

$$\sum_{i \in \mathscr{Z}_b \cap \mathscr{Z}_o} x_{iq} - \sum_{e \in \mathscr{J}_r} x_{ke} \geq 0, \quad \forall i \in \mathscr{Z}_b, \forall k \in \mathscr{Z}_a. \quad (4)$$

which states that the number of (outgoing) cancelled train services during the disruption is considered for reinsertion in the recovery phase. $\mathscr{J}_r$ is the set of routes after disruption and $\mathscr{Z}_a$ is the set of available (outgoing) reinsertion services. If some services are cancelled in $\mathscr{Z}_b$, then they will be reinserted after the blockage is over.

Without loss of generality, it is sufficient to use reinserting train services after a disruption ends since the model formulation already minimizes the number of cancelled trains. and thus during the disruption, only the bare minimum will be removed, i.e. services will use the capacity in the best way possible. Therefore, no additional services could be inserted while a disruption is present. After that, spare capacity may exist only after the infrastructure network is brought back to its normal conditions, i.e. the blockage is fixed.

4) Train Arrival and Departure Times: The actual departure times of train service i depend on the selected train route x_{ij}. Therefore, the departure from the origin station $d_{i,1}$ takes the value of the selected route,

$$d_{i,1} \leq \tau_{ij} + M(1 - x_{ij}), \quad \forall i \in \mathscr{Z}, \forall j \in \mathscr{J}_i, \quad (5)$$
$$\delta_i = d_{i,1} - \bar{d}_{i,1}, \quad \forall i \in \mathscr{Z}. \quad (6)$$

Inequality (5) only holds for $x_{ij} = 1$, and otherwise, the associated big-M value is turned on and thereby eliminates the constraint. Since one of the objectives (defined in IV-E) is to minimize deviation from the original timetable, the actual departure time $d_{i,1}$ is driven to take values as close as possible to the original departure time $\bar{d}_{i,1}$. Therefore, the inequality in (5) is sufficient. Equation (6) defines the actual deviation δ_i from the original departure time from the origin for each route j of train i. Therefore, for the other stations, the arrival and departure times are defined as:

$$a_{i,m} = \bar{a}_{i,m} + \delta_i, \quad \forall i \in \mathscr{Z}, m \in 2, .., |\mathscr{M}_i|, \quad (7)$$
$$d_{i,m} = \bar{d}_{i,m} + \delta_i, \quad \forall i \in \mathscr{Z}, m \in 2, .., |\mathscr{M}_i| - 1. \quad (8)$$

C. Passenger Arrival Rate and Gate Control Strategy

Time-varying OD matrices denote the passenger demands. For a metro line with M stations, the OD matrix for time interval $[T_n, T_{n+1})$ can be written as

$$\Lambda_n = \begin{bmatrix} 0 & \lambda_{1,2,n} & \cdots & \lambda_{1,M,n} \\ \lambda_{2,1,n} & 0 & \cdots & \lambda_{2,M,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ & & & 0 & \\ \lambda_{M,1,n} & \lambda_{M,2,n} & \cdots & 0 \end{bmatrix}, \quad (9)$$

where $\lambda_{m,m',n}$ is the arrival rate of passengers that arrive at station m and have station m' as their destination in $[T_n, T_{n+1})$. The passenger arrival rate, i.e. the number of arriving passengers per second, for station m during the disruption period $[T_{\text{start}}, T_{\text{end}}]$ can be formulated as a piecewise constant function, i.e.,

$$\lambda_{m,m'}(t) = \lambda_{m,m',n}, \quad \forall t \in [T_n, T_{n+1}), \ n \in 1, 2, .., N. \quad (10)$$

A decision variable $\beta_{m,n}$ is defined as a gate control factor for station m and the time interval $[T_n, T_{n+1})$. Note that the gate control $\beta_{m,n}$ corresponds to controlling with respect to the passenger arrival rate, and not to the opening and closure of the physical gates explicitly. For $\beta_{m,n} > 0$, (some) passengers are allowed to enter the station. In particular, for $\beta_{m,n} = 1$, the entering rate is equal to the passenger arrival rate, which means that all the passengers can enter station m immediately after arrival and at the same time, the number of passengers queuing outside the station (if any) does not change. For $0 < \beta_{m,n} < 1$, some of the passengers cannot enter station m immediately after their arrivals during $[T_n, T_{n+1})$, but need to queue outside the station. In this case, the entering rate of passengers at a station is smaller than the arrival rate of passengers. More passengers would queue outside the stations. In addition, if $\beta_{m,n} > 1$, the number of passengers entering station m during $[T_n, T_{n+1})$ could be larger than the number of newly arriving passengers in this period, which means some or all the queuing passengers can enter the station. Finally, for $\beta_{m,n} = 0$, i.e., all the ticket gates of station m are closed, no passengers can enter station m during this time period, leading to a fully closed station.

The relationship between the passenger arrival rates and the passenger entering rates, i.e. controlled by $\beta_{m,n}$, at station m in $[T_n, T_{n+1})$ is denoted by

$$\zeta_{m,m',n} = \beta_{m,n} \lambda_{m,m',n}. \quad (11)$$

Note that the gate control strategy does not distinguish the destinations of passengers but treats them in the same way.

There exists a maximum entering rate, i.e., $\zeta_m^{\max}$, of station m for passengers when all ticket gates are open; so we have

$$\sum_{m'=1}^{M} \zeta_{m,m',n}(t) \leq \zeta_m^{\max}, t \in [T_{\text{start}}, T_{\text{end}}]. \quad (12)$$

With the introduction of the passenger arrival rates and entering rates, the number of passengers waiting (or queuing) outside the ticket gates is computed by

$$w_m^{\text{out}}(t) = \int_{t_{\text{start}}}^{t} \left(\sum_{m'=1}^{M} \lambda_{m,m'}(\tau) \right) d\tau$$
$$- \int_{t_{\text{start}}}^{t} \left(\sum_{m'=1}^{M} \zeta_{m,m'}(\tau) \right) d\tau, \quad (13)$$

where $\zeta_{m,m'}(\cdot)$ can be defined similarly as $\lambda_{m,m'}(\cdot)$ as given in (10). In the IDM model, one of the objectives is to minimize the total waiting time of the passengers queuing outside the stations. At time instant t, the waiting time of the passengers queuing outside station m is computed as follows:

$$t_m^{\text{out}}(t) = \int_{t_{\text{start}}}^{t} w_m^{\text{out}}(\tau) d\tau. \quad (14)$$

The total waiting time of the passengers queuing outside the stations is computed by

$$t^{\text{out,total}} = \sum_{m \in \mathcal{M}} t_m^{\text{out}}(T_{\text{end}}). \tag{15}$$

Remark: Note that the gate control variables can also be introduced to depend on the traveling directions or even depend on the destinations of passengers. However, this would require more assistance from the station staff and tend to be impractical for real-life application.

D. Passenger Flow

The numbers of boarding, alighting, and waiting passengers inside the stations highly depend on the departure and arrival times of train services, i.e., $d_{i,m}$ and $a_{i,m}$ for train service $i \in \mathscr{I}$ and station $m \in \mathcal{M}$. Even though the number of passengers changes continuously with time in practice, we ignore the detailed evolution process of passengers and present an event-driven passenger flow model, where the number of passengers varies suddenly when a train arrives at or departs from a station. However, these sudden changes can be simulated by e.g. a uniformly change over time. To describe the operation of trains from the passengers' perspective, we propose an event-driven model consisting 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,
- short-turning events: representing the short turning operation of a train at an intermediate station with turnaround facilities.

The r-th event e_r occurring in the event-driven system is denoted by a tuple as follows:

$$e_r = (\tau_r, y_r, i_r, m_r), \tag{16}$$

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 three possible values (i.e., 'd', 'a' and 's' corresponding to a departure event, an arrival event and a short-turning event), i_r is the train service index, and m_r is the station index. All the events for the event-driven passenger flow model are specified in the rescheduled timetable. Set $\mathscr{R}$ is the set of all events. The occurrence time of event e_r can be determined as follows:

$$\tau_r = \begin{cases} d_{i_r,m_r} & \text{if } e_r = 'd' \\ a_{i_r,m_r} & \text{if } e_r = 'a' \\ a_{i_r,m_r} & \text{if } e_r = 's' \end{cases}. \tag{17}$$

In the event-driven passenger flow model, the state of the system, particularly the numbers of boarding, alighting, and waiting passengers, should be updated when events occur. The number of waiting passengers needs to be updated when an event of any type occurs. The update of other states, e.g., the number of boarding passengers and the number of alighting passengers, depends on the event type of the occurring event. The updating process for the departure events, arrival events, and short-turning events is described in detail in the following sections.

1) Updates of Waiting Passengers for All Events: Before any event occurs, denoted by (τ_r, y_r, i_r, m_r), the number of passengers that are waiting inside station m_r and have destination m' is updated as follows:

$$w_{m_r,m'}^{\text{before}}(\tau_r) = w_{m_r,m'}^{\text{after}}(\tau_{r'}) + \int_{\tau_{r'}}^{\tau_r} \zeta_{m_r,m'}(t)dt, \tag{18}$$

where $\tau_{r'}$ is the event time of the predecessor event $e_{r'}$ that occurred at station m_r. The total number of waiting passengers at station m_r can be computed by

$$w_{m_r}^{\text{before}}(\tau_r) = \sum_{m'=1}^{M} w_{m_r,m'}^{\text{before}}(\tau_r). \tag{19}$$

However, we need to distinguish their destinations and to decide whether they take the train services in the up or down directions. The numbers of passengers waiting at station m_r for train services in the up and down directions are computed as follows:

$$w_{m_r}^{\text{before,up}}(\tau_r) = \sum_{m'=m_r+1}^{M} w_{m_r,m'}^{\text{before}}(\tau_r), \tag{20}$$

and

$$w_{m_r}^{\text{before,dn}}(\tau_r) = \sum_{m'=1}^{m_r-1} w_{m_r,m'}^{\text{before}}(\tau_r). \tag{21}$$

We use $t_{m_r}^{\text{wait}}(\tau_r)$ to denote the waiting time of passengers at station m_r when event e_r occurs, which can be calculated by

$$t_{m_r}^{\text{wait}}(\tau_r) = t_{m_r}^{\text{wait}}(\tau_{r'}) + \int_{\tau_{r'}}^{\tau_r} w_{m_r}^{\text{before}}(t)dt, \tag{22}$$

where $\tau_{r'}$ is the event time of the previous event $e_{r'}$ that occurred at station m_r.

2) State Updates for Arrival Events: When an arrival event occurs, denoted as $e_r = (a_{i_r,m_r}, 'a', i_r, m_r)$, then train i_r arrives at station m_r at time a_{i_r,m_r}. The number of passengers getting off train service i_r depends on whether station m_r is the first station of the train service or not.

- If station m_r is the first station of train service i_r, then there is no passenger getting off the train, i.e.,

$$\eta_{i_r,m_r}^{\text{alight}} = 0. \tag{23}$$

  Moreover, the number of passengers $\eta_{i_r,m_r,m'}^{\text{before}}$ that are on board train i_r at station m_r and have station m' as destination is also equal to zero, i.e.,

$$\eta_{i_r,m_r,m'}^{\text{before}} = 0. \tag{24}$$

- If station m_r is not the first station of train i_r, the number of passengers getting off the train can be computed by

$$\eta_{i_r,m_r}^{\text{alight}} = \eta_{i_r,\rho(m_r),m_r}^{\text{after}}, \tag{25}$$

  where $\eta_{i_r,\rho(m_r),m_r}^{\text{after}}$ is the number of passengers with destination m_r after the boarding process at predecessor station $\rho(m_r)$ has completed. Moreover, we have

$$\eta_{i_r,m_r,m'}^{\text{before}} = \eta_{i_r,\rho(m_r),m'}^{\text{after}}, \quad \forall m' \in \{m_r+1, \cdots, M\}, \tag{26}$$

if we consider train service i_r traveling in the up direction. Furthermore, the total number of passengers on board train i_r before the boarding process is

$$\eta_{i_r,m_r}^{\text{before}} = \sum_{m'=m_r+1}^{M} \eta_{i_r,\rho(m_r),m'}^{\text{after}}. \quad (27)$$

The equations for the calculations the train services in the down direction can be formulated in a similar way. Furthermore, the number of passengers waiting at the station to board train services immediately after the arrival events is the same as that immediately before, i.e.

$$w_{m,m'}^{\text{after}}(\tau_r) = w_{m,m'}^{\text{before}}(\tau_r), \quad (28)$$

because the boarding process of passengers is considered when a departure event happens.

3) State Updates for Departure Events: When a departure event occurs, denoted as $e_r = (d_{i_r,m_r}, {}'\text{d}', i_r, m_r)$, then train i_r departs from station m_r at time d_{i_r,m_r}. The number of passengers boarding train i_r (a train service, e.g., in the up direction) at station m_r is equal to the minimum of the number of waiting passengers $w_m^{\text{before,up}}(\tau_r)$ and the remaining space $\eta_{i_r,m_r}^{\text{remain}}$ on the train after the alighting process of passengers, i.e.,

$$\eta_{i_r,m_r}^{\text{board}} = \min(w_m^{\text{before,up}}(\tau_r), \eta_{i_r,m_r}^{\text{remain}}), \quad (29)$$

The remaining space $\eta_{i_r,m_r}^{\text{remain}}$ on train i_r is computed by

$$\eta_{i_r,m_r}^{\text{remain}} = C_{\max}^{\text{train}} - \eta_{i_r,m_r}^{\text{before}}, \quad (30)$$

where $C_{\max}^{\text{train}}$ is the maximum capacity of a train and $\eta_{i_r,m_r}^{\text{before}}$ is the number of passengers onboard train service i_r after the alighting process but before the boarding process at station m_r. The computation of $\eta_{i_r,m_r}^{\text{before}}$ is given in Section IV-D.2. The number of waiting passengers at station m_r should be updated as follows:

$$w_{m_r}^{\text{after}}(\tau_r) = w_{m_r}^{\text{before}}(\tau_r) - \eta_{i_r,m_r}^{\text{board}}. \quad (31)$$

In particular, since train service i_r is a train service in the up direction, so we also have

$$w_{m_r}^{\text{after,up}}(\tau_r) = w_{m_r}^{\text{before,up}}(\tau_r) - \eta_{i_r,m_r}^{\text{board}}. \quad (32)$$

We assume that the proportion of the passengers with different destinations with respect to the total number of waiting passengers does not change after the boarding process, i.e., the passengers with different destinations have the same probability to board the train service. So we have

$$w_{m_r,m'}^{\text{after}}(\tau_r) = w_{m_r,m'}^{\text{before}}(\tau_r) \frac{w_{m_r}^{\text{after,up}}(\tau_r)}{w_{m_r}^{\text{before,up}}(\tau_r)},$$
$$\forall m' \in \{m_r+1, \cdots M\}. \quad (33)$$

The number of passengers with destination m' that board train i_r at station m_r is

$$\eta_{i_r,m_r,m'}^{\text{board}} = w_{m_r,m'}^{\text{before}}(\tau_r) - w_{m_r,m'}^{\text{after}}(\tau_r), \quad (34)$$

and the number of onboard passengers with destination m' after the boarding process can be updated as

$$\eta_{i_r,m_r,m'}^{\text{after}} = \eta_{i_r,m_r,m'}^{\text{before}} + \eta_{i_r,m_r,m'}^{\text{board}}, \quad (35)$$

where $\eta_{i_r,m_r,m'}^{\text{before}}$ is the number of passengers that have station m' as destination immediately before the boarding process. Moreover, the total number of passengers onboard train i_r at station m_r can be calculated by

$$\eta_{i_r,m_r}^{\text{after}} = \eta_{i_r,m_r}^{\text{before}} + \eta_{i_r,m_r}^{\text{board}}. \quad (36)$$

It is noted that the number of boarding passengers at the final station of the train service is equal to zero.

4) State Updates for Short-Turning Events: When a short-turning event occurs, denoted as $e_r = (a_{i_r,m_r}, {}'\text{s}', i_r, m_r)$, then train i_r (a train service, e.g., in the up direction) arrives at station m_r at time a_{i_r,m_r}. This train will end its service at station m_r and turns around to the other direction. Hence, all the passengers that are on board this train should get off at station m_r. The alighting passengers that have not arrived at their destinations will wait at station m_r to board other train services heading to their destinations. So the number of alighting passengers is

$$\eta_{i_r,m_r}^{\text{alight}} = \sum_{m'=m_r}^{M} \eta_{i_r,\rho(m_r),m'}^{\text{after}}. \quad (37)$$

The number of passengers onboard train i_r before the boarding process is

$$\eta_{i_r,m_r}^{\text{before}} = 0. \quad (38)$$

In addition, the boarding process is not allowed for this short-turning train services. The number of waiting passengers at the station should also be updated as follows

$$w_{m_r,m'}^{\text{after}}(\tau_r) = w_{m_r,m'}^{\text{before}}(\tau_r) + \eta_{i_r,\rho(m_r),m'}^{\text{after}},$$
$$\forall m' \in \{m_r+1, \cdots, M\}. \quad (39)$$

5) Station Capacity Constraints: For simplicity, we assume that the type of platforms at all stations of the considered metro line is an island platform. This means that the passengers waiting for the train services in up and down directions are actually in the same area. Based on the event model proposed before, we only check the capacity of the station at the discrete times when the events occur. For the arrival events and the short-turning events, the constraint of station capacity can be written as

$$w_{m_r}^{\text{before}}(\tau_r) + \eta_{i_r,m_r}^{\text{alight}} \le C_{m_r}^{\text{sta}} \quad (40)$$

where $C_{m_r}^{\text{sta}}$ is the capacity of station m_r. For station j, from the time when an arrival event occurs to the time immediately before a departure event occurs, the number of passengers in station j will increase, because of the new passengers entering the station and passengers alighting from a train. For the departure events, there is also a constraint of station capacity, which can be formulated as

$$w_{m_r}^{\text{before}}(\tau_r) + \kappa \cdot \eta_{i_r,m_r}^{\text{alight}} \le C_{m_r}^{\text{sta}} \quad (41)$$

where κ is a coefficient used to denote the percentage of alighting passengers that are still inside the station when the train departs from the station.

E. Objective Function

The objective of IDM consists of both train- and passenger-related objectives. In the model, a distinction has been made between *response phase*, and *recovery phase* and phase specific objectives have been introduced. These different objectives are supported by planner requirements. Considering train-related objective terms, in the response phase, the focus is on cancelling the least number of train services, and balancing headways between consecutive trains, i.e. having frequency-based operations. In the recovery phase, after the blockage is over, the model aims at returning as fast as possible to the original train services, i.e. having schedule-based operations. Considering passenger-related objective terms, the 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 over both phases.

To model the objective function, we introduce additional notation. For the disrupted phase, parameter $\bar{H}$ represents a response headway for a given disrupted line. The rescheduled headway $H_{ij,kl}$ between two train services is defined as equal to a time duration between two departures, for a pair of train routes x_{ij} and x_{kl}. An auxiliary binary variable $y_{ij,kl}$ is introduced which is equal to 1 if both routes x_{ij} and x_{kl} are selected. Headway $\bar{H}$ is computed as the maximum of the minimum headway $h_{\min}$ and the scheduled/original headway h_{sch}. For example, in a busy line during a disruption, infrastructure often becomes limited, and thus the minimum headway tends to be more restrictive. However, on less busy lines, the scheduled headway tends to remain the preferable one. For the recovery phase, planned departure times $\bar{d}_{i,1}$ are to be achieved in the shortest possible time. Parameter τ_{ij} is the departure time from the origin station associated with a train route x_{ij}. Also, X_h denotes the summed headway deviation computed as:

$$X_h = \sum_{i,k \in \mathscr{Z}, j,l \in \mathscr{J}} |\bar{H} - H_{ij,kl} y_{ij,kl}| \tag{42}$$

The objective function of the IDM problem is then defined as follows:

$$\text{Minimize} \sum_{i \in \mathscr{Z}_\mathrm{b}} \omega_{iq} x_{iq} + \bar{\omega} X_h$$
$$+ \sum_{i \in \mathscr{Z}_\mathrm{d}} \sum_{j \in \mathscr{J}_i} \omega_{ij}^\mathrm{d} x_{ij} + \omega^\mathrm{out} t^{\mathrm{out,total}}. \tag{43}$$

In (43), the first term defines the number of cancelled trains, the second relates to regular services during the disrupted period, the third is the difference from the original timetable and the fourth is the total waiting time of passengers queuing outside the station during the considered time period. In the recovery phase, if a train route x_{ij} is not selected, then the corresponding departure time penalty becomes 0. Parameter ω_{iq} represents a cancellation penalty. Parameter $\bar{\omega}$ represents a weight for the irregular services. Parameter ω_{ij}^d defines the relative importance of train service x_{ij} to conform with the planned schedule, which 1) defines an increasingly higher importance to stick to the planned time as a train service is further away from the disruption end, and 2) sets a higher value for a bigger deviation from the schedule. To do so, we assume a recovery period that the schedule needs to recover to the original one. Such recovery period has a starting time s_T, which is equal the end of the disruption, and an ending time e_T. Then the weights ω_{ij}^d are computed as

$$\omega_{ij}^\mathrm{d} = \frac{|\tau_{ij} - \bar{d}_{i,1}|}{e_T - s_T} \bar{d}_{i,1} \tag{44}$$

where $|\tau_{ij} - \bar{d}_{i,1}|$ is an absolute time deviation from the planned timetable departure and train service departure from the origin station. Note that in a metro system, the actual departure/arrival times can occur both before and after the planned time, thus the absolute operator is needed. Multiplying by planned departure time $\bar{d}_{i,1}$ gives more importance to the train services departing later in time, i.e. to force them to return to their scheduled time.

In addition,

$$x_{ij} + x_{kl} \le 1 + y_{ij,kl}, \quad \forall i, k \in \mathscr{Z}, j, l \in \mathscr{J} \tag{45}$$

Equation (45) secures that an auxiliary variable $y_{ij,kl}$ becomes 1 when both train routes x_{ij} and x_{kl} are selected. Since the objective is to minimize a non-negative cost times the variable $y_{ij,kl}$, there is an incentive to set $y_{ij,kl} = 0$.

F. Overall IDM Model

The resulting integrated disruption management problem is a nonlinear programming problem. The model finds the optimal set of train-related decisions (cancellations, adjusted arrival and departure times), and passenger-related decisions (passenger flows through the system and station/gate closures) by solving the objective function (43) such that (1)-(4), (11)-(12), (18)-(41), (45) and $x_{ij} \in \{0,1\}, \forall i \in \mathscr{Z}, j \in \mathscr{J}$.

The IDM model is a nonlinear and computationally-expensive problem, which is hard to address.

V. Solving Integrated Disruption Management: Matheuristic Approach

We propose a new matheuristic approach for integrated disruption management (IDM) to optimize railway timetables and passenger flows during disruptions. First the models are introduced, and then the solution algorithm is presented. The matheuristic algorithm includes two mathematical models: a *train traffic management (TTM) model* and a *passenger flow management (PFM) model*.

The train traffic management (TTM) model is a mixed integer program (MIP) based on a conflict graph formulation which reroutes, retimes, short-turns, and cancels train services. The TTM minimizes the number of cancelled trains and schedule deviations, while considering fixed passenger flows in the network. The objective function of TTM is defined in (43), satisfying constraints (1)-(4). Objective function (43) minimizes the number of cancelled train services, headway irregularity during the disrupted phase, timetable deviation during recovery, and the number of denied and waiting passengers. The objective function of TTM is denoted as f.

The passenger flow management (PFM) model is a nonlinear programming problem based on the time-dependent OD

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passenger demand, where passengers could wait at platforms, board/alight trains, be on-board trains, or be denied by over-crowded stations (i.e. waiting outside due to station gates closure). The objective of the PFM model is to minimize the total waiting time of the passengers queuing outside the station. For the calculation of the PFM model, the train schedule is considered to be fixed by the TTM model. The PFM is defined as follows:

$$\text{Minimize} \sum_{m \in \mathscr{M}} \int_{t_{\text{start}}}^{t_{\text{end}}} w_m^{\text{out}}(t) dt, \tag{46}$$

while satisfying constraints (11)-(12) and (18)-(41). The resulting nonlinear passenger flow management problem can be solved using e.g., sequential quadratic programming (SQP) or interior-point methods. In this paper, we use function fmincon in Matlab with the SQP algorithm.

Algorithm 1 IDM Algorithm

Input: services $\mathscr{X}$, routes $\mathscr{J}$, stations $\mathscr{M}$, OD demand Λ_n, disruption $[T_{\text{start}}, T_{\text{end}}]$, $\bar{a}_{i,m}, \bar{d}_{i,m}, \omega_{iq}, \bar{\omega}, \omega^{\text{out}}, \omega_{ij}^{\text{d}}, \bar{H}$

Output: $x_{ij}^k, a_{i,m}^k, d_{i,m}^k, w_m^{\text{out},k}, w_m^{\text{before},k}, \beta_{m,n}^k$

Initialization. $k = 0$

Step 1. compute all $x_{ij}^0, a_{i,m}^0, d_{i,m}^0$, and f^0 running TTM with uniform number of passengers assigned to train services.

repeat

k=k+1;

Step 2. solve PFM and obtain new passenger flows, passengers waiting outside $w_m^{\text{out},k}$ and gate decisions $\beta_{m,n}^k$

Step 3. compute total waiting time of passengers outside the stations $t_k^{\text{out,total}}$

Step 4. solve TTM using weight $t_k^{\text{out,total}}$ and obtain f^k, and all $x_{ij}^k, a_{i,m}^k, d_{i,m}^k$

until $k = n_{\text{max}}$ **or** $f^k \geq f^{k-1}$

Return all $x_{ij}^k, a_{i,m}^k, d_{i,m}^k, w_m^{\text{out},k}, w_m^{\text{before},k}, \beta_{m,n}^k$

A. The Algorithm

The IDM algorithm is shown in Algorithm 1. Given are train-related input like train services $\mathscr{X}$, routes $\mathscr{J}$, the original timetable represented by the scheduled arrival and departure times for all train services $\bar{a}_{i,m}, \bar{d}_{i,m}$, train capacity $C_{\text{max}}^{\text{train}}$, stations $\mathscr{M}$, and passenger-related input such as original OD demand Λ_n and station capacity C_m^{sta}. Also, given are disruption start and end time $T_{\text{start}}, T_{\text{end}}$, the maximum number of iterations n_{max}, weights $\omega_{iq}, \bar{\omega}, \omega^{\text{out}}$ and ω_{ij}^{d} and the optimal headway $\bar{H}$. We define for a given iteration k: $x_{i,j}^k$ as the train services in iteration k, $a_{i,m}^k, d_{i,m}^k$ as a rescheduled timetable including arrival and departure times, $w_m^{\text{out},k}$ ($w_m^{\text{before},k}$) as passengers waiting outside (inside), $\beta_{m,n}^k$ as gates control strategy, and f^k as the objective value in iteration k.

In step 1, the TTM model is solved assuming a uniform number of passengers, since passenger flows and distribution are not known at this point. The original timetable is 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. In addition, the TTM assumes a fixed passenger distribution in the network.

In step 2, the new rescheduled timetable is given as input to the model for passenger flow management (PFM). Based on the fixed rescheduled timetable and the passenger demand, the PFM model decides gate controls and computes the number of boarding/alighting passengers, the number of waiting passengers and the number of passengers that are denied at stations. Output are gate control factor $\beta_{m,n}$ for each station, number of passengers waiting outside $w_m^{\text{out},k}$, and number of passengers waiting in the station m, $w_m^{\text{before},k}$ as

$$w_m^{\text{out},k} = \sum_{r \in \mathscr{R}} w_m^{\text{out},k}(\tau_r), \tag{47}$$

$$w_m^{\text{before},k} = \sum_{r \in \mathscr{R}} w_m^{\text{before},k}(\tau_r), \tag{48}$$

where $\mathscr{R}$ is the set of all events. In step 3, to use adjusted passenger flows into TTM, waiting passengers (i.e. onboard, in station and denied/out-station) are summarized over all stations along all train services. In each iteration k, $t_k^{\text{out,total}}$ represents the waiting times outside all stations. This waiting time is estimated by the PFM and thus, computed as:

$$t_k^{\text{out,total}} = \sum_{m \in \mathscr{M}} \int_{t_{\text{start}}}^{t_{\text{end}}} w_m^{\text{out}}(t) dt \tag{49}$$

In step 4, TTM is run again using new weighted passenger waiting time $t_k^{\text{out,total}}$. Over the iterations, TTM delivers the departure and arrival times of train services at stations to PFM.

After step 4, the algorithm terminates if n_{max} is reached or the objective function f^k, computed in iteration k by (43), does not improve. In essence, if n_{max} is not reached, then the new solution of TTM f^k is compared with the solution obtained in the previous iteration f^{k-1}. If the solution does not improve, i.e. $f^{k-1} - f^k \geq 0$, then the algorithm terminates. Within the algorithm, the convergence is not proven guaranteed. However, based on previous similar implementations and our experiments, the interaction of the two models terminate, i.e. stop improving the solution, in a few iterations (as shown for traffic management under disturbances in [24]).

The algorithm and models are implemented in Matlab with the Yalmip toolbox. The TTM is solved by the optimization solver Gurobi, while the nonlinear PFM is solved using function fmincon in Matlab with the SQP algorithm.

VI. EXPERIMENTS

A. Setup

We demonstrate the IDM approach on real-life cases of Line 9 of Beijing Metro. Line 9 consists of 11 stations. The total length is 16.5 km, and the average daily passenger volume is approximately 520,000 passengers. A depot for keeping cancelled rolling stock is at station GGZ. Figure 2 gives the layout of Line 9. The stations are numbered sequentially from GGZ to NL, e.g. GGZ is station 1 and QLZ is station 6.

We test the model against different durations of disruption as well as varied passenger demand. We assume that the

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Fig. 2. Line 9 layout.

disruption occurs between QLZ and LLQ (see Figure 2). Since metro services operate with high frequency, we assume a single starting time of a disruption. All disruptions occur at 8:03 and the time period for rescheduling considered is then from 8:03 to 9:13. We consider various test cases, where disruption duration is 10, 15 and 20 minutes, the relative ratio of passenger demand ranges from 60% to 125% in steps of 5%, and extra services can be inserted or not after the disruption. Hence, a scenario refers to a combination of these 3 parameters being duration, passenger demand and extra services. This resulted in 84 scenarios in total. In the results, each point represents an outcome from one scenario. In addition, we ran an IDM variant without gate control to determine the transport capacity limitations and use it as a benchmark to evaluate the benefits of IDM. Passenger demand represents a realistic demand in the network as multiple proportional demand variants are created representing 60% to 125% of the original one.

Parameters of the IDM algorithm and the corresponding models are the following: number of iterations is set to $n_{\max} = 10$, $\omega_{iq} = 1,000,000$, $\bar{\omega} = 1$, $\omega^{\mathrm{out}} = 2,000$, the train capacity is set as 1440, the station capacity is set as 2700 and κ is set as 0.7. The maximum entering rate $\zeta_m^{\max}$ is 10 persons per second for every station. The time interval is set as 180s. Moreover, the passenger arrival rates and the train schedule are constructed based on the data of Beijing Metro Line 9. During the considered time period in our case study, the passenger demand is constant, which is reasonable for peak periods. The values in OD matrices are shown in Table I. For generating alternative routes, a time granularity of 10 s is used. For each train service, the alternative routes are defined around the originally scheduled departure time and so they do not overlap with the alternative routes of neighbouring train services. The total number of alternative routes (without the dummy ones) is 1575, 1701 and 1827 for 10, 15 and 20 min disruption duration, respectively. In addition, for three extra reinserting train services, a total of 120 alternative routes has been included.

B. Results

In the following, the applicability of the developed algorithm is presented over the defined scenarios including number

TABLE I
THE PASSENGER DEMANDS IN THE CASE STUDY (PERSON PER SECOND)

| Origin | Detination | | | | | |
	GGZ	FTSP	KYL	FTNL	FTDJ	QLZ
GGZ	0	0.02	0.02	0.01	0.01	0.02
FTSP	0.01	0	0.002	0.002	0.004	0.006
KYL	0.018	0.018	0	0.01	0.01	0.018
FTNL	0.014	0.016	0.018	0	0.01	0.02
FTDJ	0.014	0.016	0.018	0.014	0	0.04
QLZ	0.02	0.04	0.02	0.02	0.02	0
LLQ	0.02	0.03	0.03	0.03	0.03	0.032
LLQE	0.02	0.03	0.03	0.03	0.03	0.03
BWRS	0.04	0.06	0.06	0.06	0.06	0.06
MM	0.02	0.03	0.03	0.03	0.03	0.03
BDZ	0.01	0.01	0.01	0.01	0.01	0.01
BSQS	0.04	0.06	0.06	0.06	0.06	0.06
NL	0.04	0.06	0.06	0.06	0.06	0.06

| Origin | Detination | | | | | |
	LLQ	LLQE	BWRS	MM	BDZ	BSQS	NL
GGZ	0.16	0.02	0.6	0.64	0.1	0.8	1.36
FTSP	0.01	0.01	0.018	0.02	0.01	0.024	0.06
KYL	0.02	0.01	0.024	0.028	0.01	0.04	0.06
FTNL	0.02	0.016	0.03	0.04	0.01	0.046	0.06
FTDJ	0.08	0.04	0.06	0.04	0.01	0.04	0.06
QLZ	0.04	0.04	0.18	0.14	0.04	0.24	0.4
LLQ	0	0.032	0.064	0.1	0.02	0.2	0.36
LLQE	0	0	0.064	0.08	0.02	0.24	0.3
BWRS	0.08	0.06	0	0.04	0.02	0.36	0.4
MM	0.04	0.04	0.04	0	0.04	0.26	0.24
BDZ	0.01	0.01	0.016	0.18	0	0.14	0.14
BSQS	0.08	0.06	0.1	0.1	0.02	0	0.24
NL	0.08	0.06	0.3	0.24	0.06	0.3	0

of passengers waiting inside and outside of stations, time under (partial) gate closures, and number of stations requiring gate control for different scenarios. In the end, we report the computational performance of the algorithm.

Without gate control, the system can operate and provide solutions only for limited demand and shorter disruption durations. In particular, when solving the problem without gate control, only disruptions of 10 min (except 120% demand) and 15 min with small demand (up to 65%) can be solved. As soon as the demand (and/or duration) increases further, a station (or more) becomes overcrowded, with the passengers ending up in a deadlock meaning that the station capacity is fully used and a full train is dwelling to alight the passengers. Then the solution of PFM, and thus IDM (without gate control), is infeasible. In such cases, the gate control is necessary to manage passenger flows in the system and prevent deadlocks at busy stations. Therefore, the gate control in IDM provides a higher passenger throughput of the network, i.e. allows more passengers to be transported.

Figure 3 shows the number of passengers waiting in stations during the disruption and recovery phase. Clearly, the number of affected passengers grows with increasing disruption length (3 line colors). It can be seen that reinserting train services (dashed lines) is beneficial in reducing the number of passengers waiting inside stations for disruptions of 15 and 20 min. In particular, when passenger demand exceeds 110% for the former, and 90% for the latter. Instead, for 10-min disruption, reinserting train services does not reduce passengers waiting time (solid and dashed lines overlap).
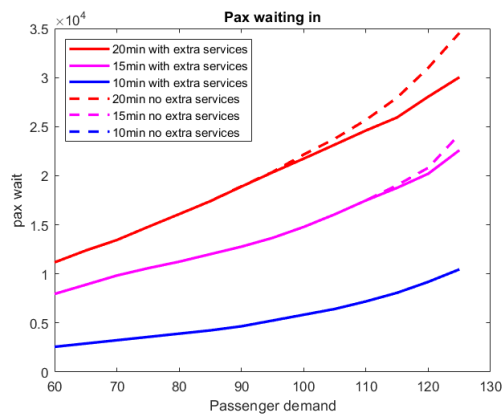
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Fig. 3.   Number of passengers waiting in stations.

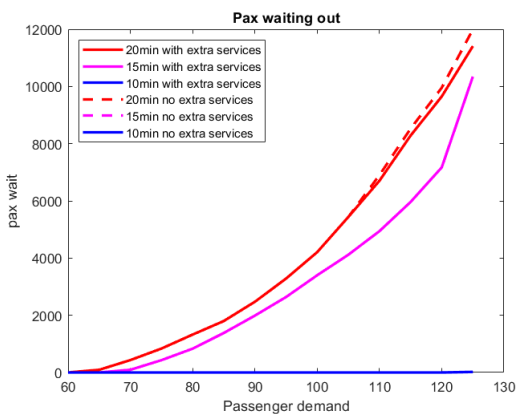Fig. 5.   Number of stations controlled.

Fig. 4.   Number of passengers waiting outside stations.

Figure 4 shows the number of passengers waiting outside stations during the disruption and recovery phase. It can be seen that for 10 min disruption no passengers are waiting outside, and thus, no gate control was required. For 15-min disruption, passengers start accumulating outside for demand bigger than 65%, while for 20-min disruption, only until 60% demand no passengers are waiting outside. For both 15 and 20-min disruptions, the increase in pax waiting is steep and seems quadratic/exponential. Clearly, the metro line cannot accommodate all passengers at its stations during disruptions and represents a significant bottleneck. Observed is also that reinserted services do not impact (much) the passengers waiting outside. This is due to the fact that passengers primarily queue during disruptions while reinserting services was possible only after the disruption was resolved. In general, passengers will queue outside the station if the gate control strategy is adopted. The reinserting services are scheduled only after the disruption is resolved, i.e. during the recovery phase. When the disruption duration is long and the passenger demand is large, there will be a large number of passengers accumulated in some stations. Without extra services, the gate control strategy is still adopted during the recovery phase for these stations, because there are many passengers in the stations and the station capacity is limited. So, the number of passengers waiting outside the station may keep increasing after the disruption phase. If there are extra
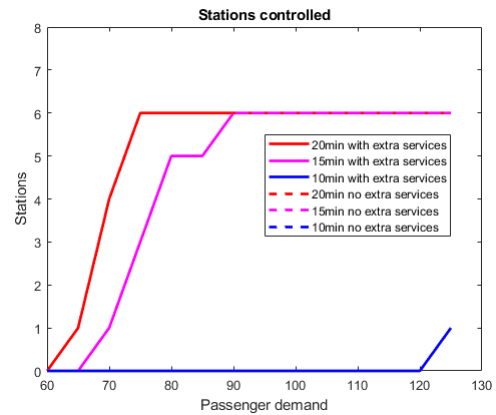
services, more passengers can be served, which means the number of closed gates can be smaller and more passengers can enter the station. However, for a disruption with short duration or small passenger demand, the number of passengers accumulated in the stations is not large. The gate control strategy is not required during the recovery phase. In this case, the extra services have no influence on the passengers waiting outside the station. In Figure 4, it can be seen that the extra services can decrease the number of passengers waiting outside the stations for the 20-min disruption with large passenger demand. Instead, for the 15-min disruption, the extra services do not affect the number of passengers waiting outside the stations.

It can be observed in Figures 4 and 5, while gates are not controlled, all passengers can enter the stations, i.e. the number of passengers waiting outside stations is zero. The numbers of passengers inside stations coincide to the ones obtained by the IDM. With increasing demand, in order to avoid deadlocks, station control is used and passengers start to queue outside. Note that the results for IDM that do not require gate control (e.g. 10-min disruption, except 125% demand), are equal to the ones of operations without gate control.

Figure 5 shows the number of stations applying gate control over the scenarios. It is seen that for 10-min disruption, only 1 station required to be controlled for demand of 125%, while for the rest, no gate control was needed, meaning that stations were able to withstand passengers arriving and waiting inside. For 15 and 20-min disruption instead, multiple stations required some sort of control, either complete or partial closure of station gates. More interestingly, in many cases it was required to manage not only the stations right next to the disrupted track section, but also further along the line. Such control of multiple stations allowed for the best (highest) flows of passengers in the network. For 15-min disruption, somewhat less stations were controlled for cases between 60 and 90% of demand scenarios. And for the rest, both 15 and 20-min disruptions required control of 6 stations. In fact all, 6 stations are on the same side of the disruption, on the segment GGZ-QLZ, while no stations on the segment LLQ-NL was closed. This is due to the fact that infrastructure on GGZ-QLZ becomes significantly reduced by the disruption (see Figure 1). At entering QLZ, only 1 track remains available
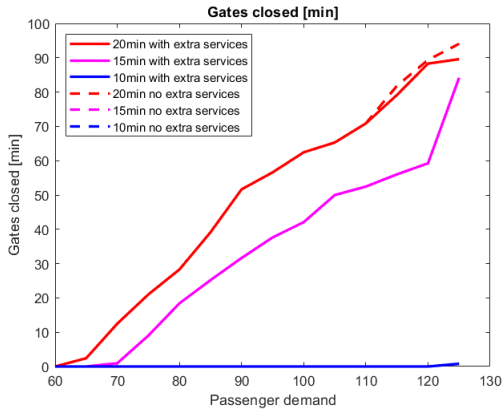
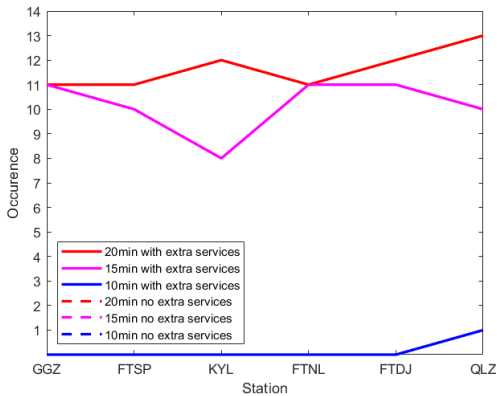This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

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Fig. 6. Gates closed.

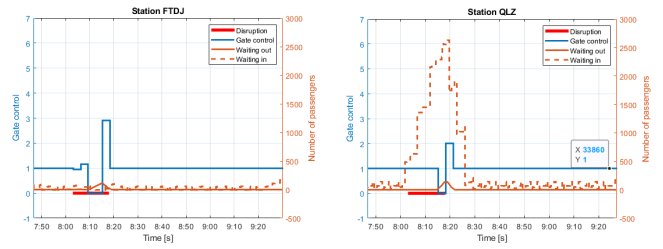Fig. 7. Occurrence of station control over demand scenarios.

Fig. 8. Gates control and passengers queuing at FTDJ (left) and QLZ (right) for 15-min scenario with extra services with 80% demand.

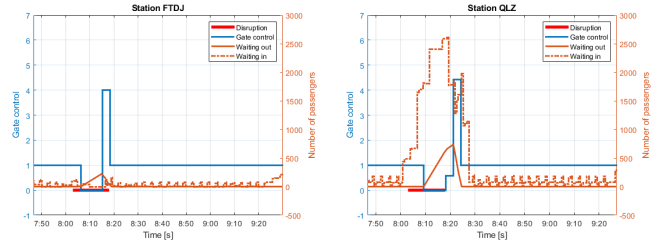Fig. 9. Gates control and passengers queuing at FTDJ (left) and QLZ (right) for 15-min scenario with extra services with 100% demand.

due to limited interlocking in the area. The dashed lines are below the solid lines of the same color, which means that the number of station controlled do not depend on the extra services.

Figure 6 reports gate control, computed as summed gate control factor $\beta_{m,n}$ multiplied by the duration of the measure. This way, complete gate closure is weighted more. It shows behaviour similar to passengers waiting outside in Figure 4. Due to the overcongested line, reinserting train services does not relief much passengers waiting outside of stations. For 20-min disruption, a slightly shorter gate control is required with extra train services. This is due to the fact, that passengers remain stranded in stations (one or more) for a longer time, and thus some are benefiting from (being transported by) inserted extra services. For 15-min disruption, that is not the case, as the passenger queues outside stations were resolved earlier.

Figure 7 visualises stations controlled along the line. It shows the occurrence of each station being controlled over demand scenarios, i.e. the number of scenarios in which each station had $\beta_{m,n} \neq 1$ at any point of time. Only stations on the segment GGZ-QLZ are given, as no other stations required to be controlled. For 10-min disruption only station QLZ, the closest to the disrupted track section, is controlled for demand of 125%. For 15 min, stations GGZ, FTNL and QLZ, are equally often used to control passenger flows. Station GGZ, the first station on the line, is relatively often chosen and thus passengers prevented from entering the network at this

station in order to allow passengers traveling between intermediate stations and avoid passenger deadlocks, i.e. excessive number of passengers in a station and onboard requiring to alight at the station. For 20 min, station QLZ is controlled most often, i.e. in all demand scenarios.

Figure 8 shows gates control and passengers queuing at the two consecutive stations just before the disrupted section FTDJ (left) and QLZ (right) for a 15-min scenario with extra services with 80% demand. It can be seen that in QLZ, gates are being closed completely ($\beta_{QLZ,n} = 0$) due to capacity constraints within the station, i.e. number of passengers in a station reaches the station capacity of 2500 at certain point and then, passengers start queuing outside the station. After the disruption is over, the gates are being open, including additionally available gates, $\beta_{QLZ,n'} > 1$ (time instance $n' > n$). And after some time, the passenger queue dissipates and the gate control returns to its normal gates rate $\beta_{QLZ,p} = 1$ ($p > n' > n$). Instead, in FTDJ, the station preceding QLZ, gates are being closed even though only limited number of passengers is present at the station and even for longer time than at QLZ. This is due to the limiting capacity at the station downstream. Thus, to prevent having a deadlock at QLZ, i.e. a full train arriving at the station at a fully occupied station, FTDJ is getting fully closed. Note that at the beginning of the disruption also a partial gate control is applied at the beginning of the disruption, followed by a limited opening of additional gates. Later on, a complete closure was required to limit passengers traveling to QLZ and avoiding a deadlock. Figure 9 shows gates control and passengers queuing for the 15 min scenario with extra reinserting services and 100% demand. Due to the higher demand, it depicts an extended gate control at QLZ, also after the disruption ends, and more passengers waiting outside for a longer period. At FTDJ, it shows a slightly longer gate closure and some more passengers waiting outside.

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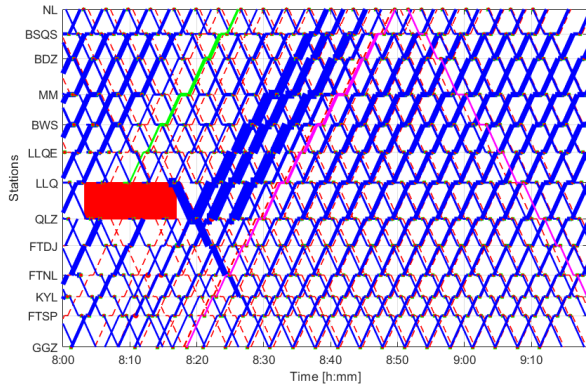BEŠINOVIĆ *et al.*: MATHEURISTIC FOR IDM OF TRAFFIC, PASSENGERS AND STATIONS
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Fig. 10. Rescheduled timetable for 15-min scenario with extra services with 80% demand.

Figure 10 presents the disrupted timetable for 15-min scenario with extra services with 80% demand. It shows retimed existing train services (blue line), rerouted train services (green line), added extra services (purple line), number of passengers onboard (line width), 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. Additionally, one extra train service helps to reduce overall delays to passengers.

Regarding the computational performance, the IDM algorithm typically terminated after at most 4 iterations. Looking at the computational time of the algorithm, per iteration, the PFM model takes on average 3 min, and the TTM model takes around 10 s. In total, the CPU time of the IDM algorithm was always under 13 min.

VII. CONCLUSION

We proposed a novel integrated disruption management model for simultaneously rescheduling trains and controlling passenger flows for a given disruption. Our IDM model incorporates train traffic management, station gate control, and an event-driven passenger flow model to simulate passengers moving through the network. The model aims to minimize the total delay of passengers, reduce the number of denied passengers, minimize cancellations and adjustments to train services, and recover as quickly as possible. Trains can be short-turned, cancelled and rerouted; stations can be closed partially/fully, or open additional gates; and passengers can wait at stations, depart later, or queue outside of stations according to a disrupted timetable and controlled station gates. To solve the IDM, an iterative heuristic approach is designed.

We tested our integrated disruption management approach on real-life cases of Beijing metro. The results showed the necessity of controlling station gates, by closing them partially or fully during a disruption in order to allow the best passenger flows through the line. The current model could support dispatchers in determining the best train and station control measures as well as determining the necessary number of additional services to be inserted in order to minimize passenger waiting times and denied passengers. Finally, IDM allows a higher passenger throughput of the network during disruptions.

TABLE II
NOTATION OF THE MODEL FORMULATION

Train-related decision variables, indices, sets, and parameters	
Symbol	**Description**
Decision variables	
x_{ij}	Binary decision variable depicting a route j of a train service i
$y_{ij,kl}$	Auxiliary binary variable to model interaction between x_{ij} and x_{kl}
$d_{i,m}$	Actual departure time of train service i at station m
$a_{i,m}$	Actual arrival time of train service i at station m
δ_i	deviation from original departure time from origin for each train service i
Indices	
i	Index of a train service
j	Index of a train route
q	Index of the dummy route for cancelling train service i
c	Index of a pair of conflicting train routes
m	Index of a station
Sets	
$\mathscr{X}$	Set of train services
$\mathscr{X}_i$	Set of inbound train services
$\mathscr{X}_o$	Set of outbound train services
$\mathscr{X}_b$	Set of train services during infrastructure blockage in disruption phase
$\mathscr{X}_r$	Set of train services in recovery phase
$\mathscr{X}_a$	Set of available (outgoing) reinsertion train services
$\mathscr{J}$	Set of train routes
$\mathscr{J}_i$	Set of train routes related to train i
$\mathscr{J}_b$	Set of routes during disruption
$\mathscr{J}_r$	Set of routes after the disruption
$\mathscr{C}$	Set of conflicting train routes
$\mathscr{M}$	Set of stations, i.e., $\{1,2,\ldots,M\}$ in a metro line
$\mathscr{M}_i$	Set of stations traversed by train service i
Parameters	
$\bar{H}$	Optimal headway time
$H_{ij,kl}$	Actual headway for train services x_{ij} and x_{kl}
$\bar{d}_{i,m}$	Planned departure time of train service i at station m
$\bar{a}_{i,m}$	Planned arrival time of train service i at station m
τ_{ij}	departure time from the origin station associated with a train route x_{ij}
ω_{iq}	A cancellation penalty
$\bar{\omega}$	A weight for the irregular services
ω_{ij}^d	A weight of train service x_{ij}
Passenger-related decision variables, indices, and parameters	
Decision variables	
$\beta_{m,n}$	Station gate control factor
$\zeta_{m,m',n}$	Passengers entering rate at station m for the passengers that have station m' as their destination at time interval n
w_m^{out}	Number of passengers queuing outside the ticket gates
$w_{m,m'}^{before}$	Immediately before event e_r happens, the number of passengers waiting at station m and have destination m'
w_m^{before}	Immediately before event e_r happens, the number of passengers waiting at station m
$w_m^{before,up}$	Immediately before event e_r happens, the number of passengers waiting at station m with up direction
$w_m^{before,dn}$	Immediately before event e_r happens, the number of passengers waiting at station m with down direction
$w_{m_r}^{after}$	Immediately after event e_r happens, the number of waiting passengers at station m_r
$w_{m_r,m'}^{after}$	Immediately after event e_r happens, the number of passengers waiting at station m_r and have destination m'

Due to the current computation times, the IDM algorithm could be used in the planning process to generate contingency plans, i.e. precomputed rescheduled timetables, before

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TABLE II

(Continued.) NOTATION OF THE MODEL FORMULATION

$t_{m_r}^{\text{wait}}$	The waiting time of passengers at station m when event e_r occurs
$t_{m_r}^{\text{out}}$	The waiting time of the passengers waiting outside the ticket gates
$\eta_{i_r,m_r}^{\text{alight}}$	The number of passengers getting off the train i_r at station m_r
$\eta_{i_r,m_r}^{\text{board}}$	The number of passengers boarding train i_r
$\eta_{i_r,m_r}^{\text{remain}}$	The remaining space on the train after the alighting process of passengers
$\eta_{i_r,m_r,m'}^{\text{before}}$	Immediately before the boarding process, the number of passengers waiting at station m_r that have station as destination m'
$\eta_{i_r,m_r}^{\text{before}}$	Immediately before the boarding process, the number of passengers waiting at station m_r
$\eta_{i_r,m_r,m'}^{\text{after}}$	Immediately after the boarding process, the number of passengers waiting at station m_r that have station m' as destination
$\eta_{i_r,m_r}^{\text{after}}$	Immediately after the boarding process, the number of passengers waiting at station
Indices	
n	Index of a time interval
r	Index of an event
$\rho(m)$	Predecessor of station m
Set	
$\mathscr{R}$	Set of events
Parameters	
T_{start}	Start time of the disruption time period
T_{end}	End time of the disruption time period
N	Number of intervals
$\lambda_{m,m',n}$	Arrival rate of passengers that arrive at station m and have station m' as their destination at time interval n
$\zeta_m^{\max}$	Maximum entering rate of passengers that can enter station m
$C_{\max}^{\text{train}}$	Capacity of a train
C_m^{sta}	Capacity of station m
κ	the percentage of alighting passengers that are still inside the station when the train departs

disruptions happen, but not yet as a real-life application. Planners could run the IDM algorithm multiple times for different times of day and different demands to determine effective strategies for controlling stations, trains and passengers. Alternatively, for using the IDM algorithm real-time, railway operators shall acquire a higher computation power by using cloud computing (e.g., [31]) or supercomputers (e.g., [32]).

As future work, computation times could be improved by applying advanced simulation-based optimization approaches or decomposition techniques such as rolling horizon. In addition, passenger demand could be approximated by clustering in passenger groups instead of modelling single passengers as in [19]. Moreover, linearizing PFM model can also be explored. Extensions toward more flexible short-turning possibilities and applying the model to metro networks could be considered. For the latter, passenger transfers shall be included as well. Finally, to deal with limited transport capacity in metro lines and networks during disruptions, new measures such as bus bridging services may be introduced.

APPENDIX
NOTATION OF THE MODEL FORMULATION
See Table II.

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