

Research Article

Modeling and Quantifying Interaction of Information and Capacity in Public Transport Disruptions

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Disruption in public transport networks has adverse implications for both passengers and service managers. To evaluate the effects of disruptions on passengers' behaviour, various methods, simulation modules, and mathematical models are widely used. However, such methods included many assumptions for the sake of simplicity. We here use multiagent microsimulation modules to simulate complex real-life scenarios. Aspects that were never explicitly modelled together are the capacity of the network and the effect of disruption to on-board passengers, who might need to alight the disrupted services. In addition, our simulation and developed module provide a framework that can be applied for both transport planning and real-time management of disruption for the large-scale network. We formalize the agent-based assignment problem in capacitated transit networks for disrupted situations, where some information is available about the disruption. We extend a microsimulation environment to quantify precisely the impact and the number of agents directly and indirectly affected by the disruption, respectively, those passengers who cannot perform their trip because of disrupted services (directly affected passengers), and those passengers whose services are not disrupted but experience additional crowding effects (indirectly affected passengers). The outcomes are discussed both from passengers' perspective and for extracting more general planning and policy recommendations. The modeling and solution approaches are applied to the multimodal public transport system of Zürich, Switzerland. Our results show that different information dissemination strategies have a large impact on direct and indirect effects. By earlier information dissemination, the direct effects get milder but larger in space, and indirect negative effects arise. The scenarios with the least information instead are very strongly affecting few passengers, while the less negative indirect effect for the rest of the network.

1. Introduction

Disruptions cause complex logistical rescheduling problems when they limit the availability of transport networks. Often disruptions result in the closure of specific links (i.e., due to accidents, infrastructure collapse, deterioration, etc.), which requires users to find an alternative plan to fulfil their desire for mobility. In public transport networks, disruptions have different impacts as the network provides mobility only at specified times (when a vehicle runs) and spaces (at stops), thus limiting available choices for replanning. Moreover, capacity in a public transport network is limited, and crowding or denied boarding phenomena are common, even in nondisrupted situation. Finally, users have only a

limited information of what is happening in the network, as those latter are complex with hundreds of stops and vehicles.

We aim to estimate comprehensively the effects of any disruption the potential of disposition timetable adjusting supply to the conditions, based on the reaction of the passengers as dependent on the limited information they might have. There is limited related data available about past disruptions; the supply side (identification of a disruption onset, estimation of its consequences, prediction of its duration, and actions taken) is very difficult to track, especially when the disruption is itself unexpected. Collecting data from passengers facing a disruption is even more complex (what do passenger choose, based on which information, and what outcome they finally experience); as

stated preference is subject to strong bias, revealed preference has too limited a view on the effectively available alternatives, and prompt recall studies are subject to filtering bias from participants; concluding, this approach is effectively insufficient to properly estimate impacts [1].

This limits the potential to use data about past disruptions to improve the management of future ones and limits the usage of survey methods. To be able to model the interaction and effects of a disposition timetable and the information that travelers have, during a disruption, and subject to realistic preferences of the travelers who are replanning their trips and limited capacity of the vehicles, we therefore resort to simulation approaches able to represent the most relevant dynamics; specifically, we use microscopic, multimodal, activity-based, and agent-based simulation. We first describe a mathematical formalization of the problem and further use a newly developed module in the agent-based simulation to show the potential of quantifying those mentioned effects. The contributions of the present paper are as follows:

- (1) We consider disruptions with replanning and represent realistic passengers' behaviour by means of a newly developed module for an agent-based simulation model. We simulate complex real-life conditions, such as long, unplanned disruptions, and also including informing onboard passengers and forcing passengers to alight if they are affected by the disruption. So far, in the literature, the analysis and simulation of the disruptions' effects have been subject to many simplifying assumptions. If disruptions are short enough (lasting less than 45 minutes, see [2]), the adjustment of plans and disposition timetable could be instead ignored.
- (2) We mathematically model and formalize the effect of capacity towards transit assignment in an agent-based model. Indirect effects are in fact caused by the interaction between the specific capacity of all vehicles and the flows of all passengers onboard. While this has been well studied for public transport in normal conditions, or in theoretical disruptions [3], its interplay with a managed disruption has not been investigated in detail.
- (3) We consider a comprehensive set of scenarios containing different passengers reactions based on different information strategies; passengers can be informed individually or in a group at any time and locations. We also consider possible reaction time of travelers as a waiting tolerance before they change their original plan.
- (4) We compute the effects of information towards global network dynamics and delays, which include that disruption or delays can positively affect some passengers to have earlier arrivals. We are among the

first to identify and quantify those effects; to the best of our knowledge, we refer to it as positive indirect effects.

In the rest of the paper, Section 2 reviews the literature. Section 3 describes the problem. Section 4 introduces our model and methodology. Section 5 reports on the case study. Results are presented in Section 6. Section 7 discusses the policy and planning suggestions and concludes the paper.

2. Literature Review

We organize the literature on the effects of disruptions on public transport networks, mediated by information and capacity, in four streams, as follows. In sequence, we report on the understanding of travelers choices under disruptions, capacity management, and disposition timetable; discuss the role of information in choices in public transport networks; and finally approach studying network dynamics.

The first category investigates behavioral aspects of the mode choice of passengers in the case of disruption. The most common approach is based on stated preferences to understand the choice of passengers, based on experimental data collected by surveys. Reference [4] studied how passengers react to planned engineering-based disruptions, by means of a survey. Reference [5] used a survey to understand passenger's perceptions and behavior during disruptions and indicated that informing passengers before the disruption can lead them to opt not to travel or choose different plans. Reference [6] reported, based on a survey, criteria such as socio-demographic attributes, personal attitudes, trip information, and built-environment which are critical in passengers' behaviour in case of unexpected disruptions. They also identify a waiting tolerance, as the length of time that agents need to think and find an alternative solution and/or are willing to wait for a disrupted transit service with the hope that it be restored before starting to replan. Reference [7] performed a mode choice analysis after a disruption employing a web-based survey. They showed that passengers are reluctant to alter mode or travel choice in a disruption.

Management of disruptions by optimizing public transportation capacity refers to supply-side choices able to mitigate the undesired effects. Reference [8] studied bus-bridging service as a recovery plan for public transportation under disruptions. They presented an algorithm to compute the optimal evacuation scheme. Reference [9] investigated the recovery of rapid transit rail networks under disruptions, combining changes in the timetable and the availability of rolling stock to satisfy passengers' demand. References [10, 11] developed optimization models for the computation of a disposition timetable, in the case of railway disruptions.

A third group quantitatively evaluated the role of information in the decision-making of the passengers, in public transport networks. Reference [12] reported how passengers exhibit flexibility in changing their decision

about the trip to adjust to the network facing some disruption. Reference [13] mentioned that passengers should be kept informed as soon as information is declared accurate and reliable in the disruption. Reference [14] emphasized that informing passengers as soon as possible about the disruption minimizes the negative effects of an unexpected disruption, by decreasing overall travel times and changes in travel lines.

The last group studied the network dynamics of public transport disruptions, related to the passengers' delays. Reference [15] did a vulnerability analysis for the public transport network to evaluate the consequence of a disruption on the passengers' travel time. Reference [16] studied the impact of the disruption length estimates in railways on the consequent delays of passengers. A few studies specifically investigated the propagation effect of a disruption through the public transport network considering the delay caused to the passengers. Reference [17] introduced a mathematical model to consider the propagation of the delay from a trip to a trip in a disrupted network. They estimated the changes in travel time and the delays caused by common disruptions (i.e., lasting less than 15 minutes) based on a survey. They reported how passengers can be affected by being delayed, missing their transport means or facing detours. With a similar goal, Yap et al. [18] identified the most vulnerable links in public transportation network considering the capacity impact. Reference [2] used the agent-based simulator BusMezzo to analyse the capacity vulnerability of public transport under a disruption, specifically focusing on a nonequilibrium situation. Recently, the authors of [19] were able to replicate the impact of information in a large agent-based instance, as a consequence of the information available to passengers. They identified few information levels and dealt with real-life operations, without a specific focus on large disruptions. In summary, agent-based models are based on an incremental, dynamic decision process which is shown to be appropriate in the study of dynamic events such as disruptions. Agent-based simulation has been shown to be able to replicate many realistic constraints, based on the assumption that input data reflect reality [20].

Compared to the literature, we are able to analyse quantitatively the effects of disruptions considering complex aspects of real-life such as capacity of vehicles, disposition timetable, and information. We are able to model mathematically how capacity and information result in equilibrium or nonequilibrium solutions in a public transport network under disruption. Based on an agent-based approach, we are able to quantify the resulting network dynamics and how delays spread through the network, by means of directly affected passengers (i.e., those whose intended public transport service is disrupted) and negatively and positively affected passengers (those who, respectively, suffer/benefit from propagation of effects mediated by crowding). For the first time in the literature, we identify and quantify heterogeneous positively affected passengers by the disruption. We show how network dynamics are greatly dependent on both information and capacity, which are

two aspects that have been not yet studied together with such detail, under disruption.

3. Problem Description

We assume a disruption is an event, mostly unexpected or unknown until shortly before, or even after its occurrence, which prevents some public transport services to be run as planned. Possible disruptions can be related, for instance, to operational limitations, failures, accidents, adverse weather conditions, etc. The impact of disruptions to public transport is large because they affect the network-wide availability of resources and limit the capacity of services offered. For instance, some services cannot run anymore, as the infrastructure, vehicles, or crew required are not available at the right moment, at the right place; some other services will be unable to face larger demands.

All those unavailabilities in the services directly affect some passengers. They would need to be informed about the details of the disruption, including the affected locations and lines, and, if possible, the end time of the disruption.

Having no information, passengers might be stranded at stops, wait for a public transport service which is not running, or not running on time, resulting in large delays, and related large disutility. A disruption might also result in the cancellation of activities due to too late arrivals (i.e., arrival at work with multiple hours of delay). We consider those delays and disutility as direct effects of the disruption.

When travelers receive information about the disruption and the alternative routes, we assume they look for an alternative, which maximizes their utility. The travelers using public transport are not assumed to be able to promptly change the mode to a private car, as they have no vehicle available right away. The travelers can instead use the public transport services, which are running despite the disruption. This might result in longer trips and/or more transfers and/or longer waiting times, to reach their destination. Specifically, travelers will use public transport services, which were not typically using compared to the undisrupted user equilibrium situation (i.e., a situation in which travelers have available a set of alternative ways to move in the network and they choose the one which maximizes a utility or score, related to their satisfaction). Therefore, they add to the travel demand of the other vehicle, which on a normal (undisrupted) day, would experience less travel demand. Consequently, due to the increased demand on the other lines, some passengers are not able to board and experience denied boarding due to the full capacity. We call the "indirect effect of a disruption" those effects of this different assignment of travelers in the network. Specifically, a public transport line running with different frequency, vehicle capacity, or being canceled will alter the occupancy level on the other lines, causing unexpected sudden changes in demand for other lines, which disappear quickly as the disruption ends. As a result, some passengers (which would be not directly affected by the disruption itself, i.e., their lines are actually undisrupted) will be denied boarding, due to those disrupted travelers sharing the same vehicles with them. In general, this effect will cascade to a delay for an even larger set of passengers further away from the specific disrupted location.

It is evident, earlier availability of information reduces the delay of directly affected agents. However, replanning of directly affected agents causes unexpected demand to the other part of the network. Therefore, there is a complex interaction and trade-off between positive and negative effects. A disruption on a specific public transport line may change, i.e., increase (negative indirect effect) but also decrease (i.e., positive indirect effect) the occupancy level on the other lines in the public transport network too. Those indirect effects are heterogeneous in their sign (i.e., positive or negative), magnitude (i.e., larger or smaller delays), exposure (i.e., affecting many or few travelers), space (close to the disruption location, or further away), and time (happening at the same moment as the disruption, but possibly with various intensity over time; and persisting also after the disruption ended). This heterogeneity brings about the complexity that we deal with in this paper to replicate all those processes in an agent-based capacitated simulation environment and relate the possible ways of disseminating information to travelers, with the impacts they face, in their direct and indirect circumstances.

4. Methodology

4.1. Modelling Capacity Effects in Agent-Based Simulation

4.1.1. Basics. We describe in the following the very basic concepts and formalize the agent-based transit assignment problem in capacitated networks. We note that, in Gentile and Noekel [21], this does not have the level of detail we need for the study proposed. This allows us to describe in this section the requirements for the information dissemination in case of disruption and the resulting implementation in the agent-based simulation software MATSim.

Agents spend their day performing activities and moving between them, by trips. As a general basic requirement to all agent-based models, we assume that activities and movements replicate the behavior observed in real-life, which for the dataset used was validated in [22]. We here describe formally how the agents choose the activities and trips they perform from a choice set. Specific focus is on public transport trips. Agents are categorized in a population $A = \{a_1, a_2, a_3, \dots, a_{|A|}\}$. Each agent $a \in A$ has a set S_a of potential $|K|$ plans, from which we choose $S_a = \{s_{a,1}, s_{a,2}, s_{a,3}, \dots, s_{a,k}, \dots, s_{a,|K|}\}$. The union of all potential plans of all agents is $S = \cup_a S_a$. Each plan is a sequence of daily activities (Ac) and trips (Tr), which starts with an activity (being at home in the night) and ends at the same activity at the end of the day. Formally,

$$s_{a,k} = \{Ac_1, Tr_1, Ac_2, Tr_2, \dots, Ac_{i-1}, Tr_{i-1}, Ac_i\}. \quad (1)$$

Activities are characterized by three elements: the location (l_i) in which the activity happens, the time that the activity starts ($t_{start,i}$), and the time that the activity ends ($t_{end,i}$). Trips are characterized by the chosen mode, routes, and duration. A trip is made up of one or multiple stages (continuous movements with one mode of transport), i.e., $Tr_i = \{St_1, St_2, \dots, St_j\}$. Stages can include, for instance, walking, riding bicycle, traveling by public transport, or private car [23]. We focus on public transport stages, but consider them within a multimodal network. Specifically, we consider each public transport Stage (St) as made up of many atomic stages (AS), which are movements with a single vehicle between two successive stops:

$$\begin{aligned} St &= \{AS_1, AS_2, \dots\}, \\ AS_i &= \left\{ (l_{start,i}, line_i, T_{start,i}) - (l_{end,i}, line_i, T_{end,i}) \right\}. \end{aligned} \quad (2)$$

A typical public transport stage would result in multiple atomic stages. Formally, each atomic stage AS is a connection between a starting and ending location (l_{start}, l_{end}), by a specific public transport line (line) between a starting and ending time (T_{start}, T_{end}). The set \mathcal{N} collects all possible atomic stages in a public transport network, i.e., describes the supply of the entire public transport network. In Figure 1, a simple example of an agent's daily plan is illustrated along with the illustrative time (vertical) and space (horizontal) axes. The agent wants to reach work from home, go to a leisure location, and finally, come back home at the end of the day. The agent starts in the morning by traveling from home (Ac_1) to work (Ac_2) by Trip (Tr_1), which includes one Stage (St_1) itself consisting of one atomic stage. The day continues after work by traveling from work (Ac_2) to leisure (Ac_3) by trip (Tr_2), which includes two stages (St_2 and St_3) taking public transport (specifically, two successive transit lines, with five atomic stages and two atomic stages, respectively). St_2 includes five atomic stages, A-B, B-C, C-D, D-E, and E-F, then agent a does a transfer in location F to change the stop for another transit line. Finally, the agent returns home (Ac_4) by trip (Tr_3). For the sake of simplicity, just one stage per each Tr_1 and Tr_3 is considered.

In Figure 1, agent a moves from A to F with a vehicle within a stage (St). An example of St is illustrated in equation (3), which describes the five atomic stages. For instance, the first atomic stage (AS_1) denotes the service of public transport line 80, leaving stop A, at 17:04, bound for the next stop B, arriving there 2 minutes later.

$$\begin{aligned} St = \left\{ \begin{array}{l} \underbrace{(A, 80, 17: 04) - (B, 80, 17: 06)}_{AS_1}; \\ (B, 80, 17: 06) - (C, 80, 17: 07); \\ (C, 80, 17: 07) - (D, 80, 17: 10); \\ (D, 80, 17: 10) - (E, 80, 17: 11); \\ (E, 80, 17: 11) - (F, 80, 17: 13). \end{array} \right. \end{aligned} \quad (3)$$

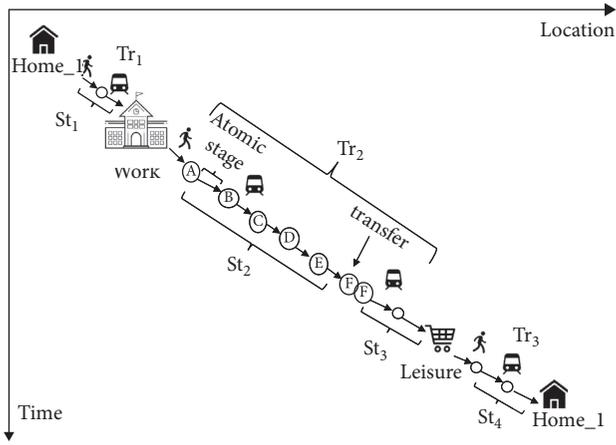


FIGURE 1: Explanation of traveling in agent-based simulation.

4.1.2. Choice of Plans. Agents choose one plan out of their possible choice set S_a . The chosen plan of an agent is denoted by \bar{s}_a , which represents a plan that has been ultimately performed at the end of the day. The set of chosen plan of all agents is denoted by $\bar{S} = \cup_a \bar{s}_a$. One interesting choice is the user equilibrium plan, we denote this plan by s_a^* ; conversely, the set of all equilibrium plans is $S^* = \cup_a s_a^*$. As we are interested in equilibrium and nonequilibrium solutions, we refer to \bar{S} as a generic solution, which can be an equilibrium, or not. Formally, the equilibrium plan s_a^* is the one maximizing the utility function U , over all plans $s_{a,k}$ of agent a , given the (equilibrium) choices s_b^* of all other agents b , where $b \in A \setminus \{a\}$:

$$s_a^* = \arg \max_{s_{a,k}} U(s_{a,k}, s_b^*). \quad (4)$$

4.1.3. Effect of Capacity towards Plans and Equilibrium. We define the maximum number of people that can fit onboard a vehicle as the vehicle capacity (C), and we link it to each atomic stage. For instance, if AS_i is the atomic stage $\{(A, 80, 17: 04) - (B, 80, 17: 06)\}$, its capacity $C_i = C(AS_i)$ can be equal to 120 persons, depending on the precise vehicle used.

The number of agents, given their choices \bar{S} , who are onboard a vehicle at any atomic stage i is described as the flow of agents f_i . Flow f_i is always no greater than the vehicle capacity $C(AS_i)$.

If an agent attempts to board a vehicle which has enough capacity (apart from other agents boarding and alighting), the flow of the atomic stage will increase by one unit. If an agent attempts to board a vehicle that is already full, then the agent will deny boarding. Therefore, flow f_i remains untouched. To describe this process formally, we distinguish here between the desired plan \hat{s}_a , belonging to S_a , where the agent assumes to board the vehicle, and the actual plan \bar{s}_a , where the agent is denied boarding. The mismatch between the desired and actual plan can be translated to a mismatch between an expected utility $\hat{U}(s_{a,k})$ and the actual utility U , already introduced. In general, both are a function of the choice of the agent and the choice of everybody else. Such a

mismatch could model aspects such as bounded rationality aspects. We use it for the sole purpose of including the effect of capacity in public transport vehicles.

4.1.4. Adjustment of Plans under Capacity Effects. When an agent following a plan $\hat{s}_a = s_{a,k}$ is denied boarding at an atomic stage AS_i , this means that the flow (f_i) at the start of atomic stage i , plus one (i.e., the agent under discussion) is larger than the $C(AS_i)$. We exclude in this discussion the competition between different agents, assuming that a suitable order of agents waiting at a stop could be derived, by which it is clear which agent is able to board and which one is denied boarding. As a result of the denied boarding, $\hat{s}_a = s_{a,k}$ is infeasible, and the agent has to resort to choosing (or in general performing without an active choice process) another plan $s'_{a,k}$. A simple choice for the default behavior of an agent-denied boarding at atomic stage i is to wait for the next service of the same line, departing the same stop, bound for the same direction (this is for instance implemented in MATSim). This will define a new atomic stage i' , included in $s'_{a,k} \in S_a$ for agent a . However, we will explain later that we extend the module such that when agents are denied boarding, they replan according to available specific information. The replanning may suggest waiting or switching to another public transport services. We also assume that people can get denied boarding only when they want to get onboard; people onboard a vehicle will not be forced to leave their place onboard to other boarding passengers, when capacity is reached.

We define y as the delay that agent a has to wait, as long as full vehicles are passing the current stop until a nonfull vehicle arrives, on which it is possible to board. This might be larger than a single headway of the transit line under discussion.

4.1.5. Capacity, Utility, and Equilibrium. In general $\hat{U}(s_{a,k}) \geq U(s_{a,k})$, i.e., the agents expect more utility from a plan $s_{a,k}$ than they actually experience; agents are optimistic to get onboard a vehicle. Suppose their expectation of utility of the desired plan $\hat{U}(\hat{s}_a)$ equals the actual utility of the actual plan $U(\bar{s}_a)$. In that case, we can identify that agents have a perfect understanding of the flows in the network, and/or the network has enough capacity, such that there are no unexpected denied boarding phenomena. However, if $\hat{U}(\hat{s}) \neq U(\bar{s})$, then at least one vehicle is full, and there is denied boarding.

Through learning and exploring the solution space aiming for the equilibrium solution, ultimately the agents will have \hat{U} which matches the actual U . Agents in the day-to-day process, useful to determine the equilibrium solution, choose their plan based on the perceived utility $\hat{U}(s_{a,k})$, learning the difference $\hat{U}(s_{a,k}) - U(s_{a,k})$, and updating their \hat{U} accordingly. At equilibrium, we assume that the learning process has been completed, $\bar{s}_a = s_a^*$, and also $\hat{s}_a = \bar{s}_a = s_a^*$. At equilibrium, the perceived utility $\hat{U}(s_a^*)$ of the equilibrium plan s_a^* corresponds to the actual utility $U(s_a^*)$:

$$s_a^* = \arg \max_{s_{a,k}} U(s_{a,k}, s_b^*) = \arg \max_{s_{a,k}} \widehat{U}(s_{a,k}, s_b^*). \quad (5)$$

At equilibrium, it is possible that some agents are denied boarding. By suitable $\widehat{U}(s_a^*)$, they are aware that a specific plan might result in denied boarding, and related disutility, but they choose it anyway.

4.2. Disruption

4.2.1. Disruption Description. We recall that \mathcal{N} represents a public transport network, i.e., all possible services, described by all possible atomic stages included in the supply. We

$$\begin{aligned} \text{St} = \{ & (A, 80, 17: 04) - (B, 80, 17: 06); (B, 80, 17: 06) - (C, 80, 17: 07); (C, 80, 17: 07) - (D, 80, 17: 10); (D, 80, 17: 10) \\ & - (E, 80, 17: 11); (E, 80, 17: 11) - (F, 80, 17: 13). \end{aligned} \quad (6)$$

A disruption can be further characterized by a start time $\mathcal{F}_{\text{start}}$, i.e., the start time of the earliest disrupted atomic stage; an ending time \mathcal{F}_{end} , i.e., the end time of the last disrupted atomic stage and a geographical extent, which describes all locations for which at least some atomic stages are disrupted.

4.2.2. Infeasible Plans and Their Effect on Agents. If a plan contains a stage which in turn contains an atomic stage which is disrupted, the entire plan is infeasible, as it cannot be performed by the agent. We identify such plans as $s_{a,k}^-$. In general, all infeasible possible plans, for all agents, are collected in \mathcal{S} .

We assume that agents have an equilibrium plan (s^*) before disruption occurs, for which we have $s^* = \bar{s} = \widehat{s}$. Agents with a desired plan $\widehat{s}_{a,k} \in \mathcal{S}$ cannot perform the plan and actually will perform some other feasible plan $\bar{s}_{a,k}$. The situation is similar to a denied boarding event as far as there is a mismatch between what the agents expect of a network and which supply is actually available.

We call affected agents (\mathcal{A}), all those agents who, due to a disruption, are not able to perform their desired plan because parts of it are not any more feasible. Formally, the following holds for affected agents: $\widehat{s}_a \in \mathcal{S}$. For those agents, the process of determining which actual feasible plan $\bar{s}_a \in \mathcal{S}$ is going to be performed by the agents defines a replanning problem. Similarly to the denied boarding, we could imagine that, without information, the agents will stick to the same line and wait until a vehicle of the chosen line will depart from the stop in which the denied boarding occurred, in the same direction. In reality, we want to investigate which better solutions are available and possible, i.e., the best plans in $\mathcal{S} \setminus \mathcal{S}$; which is the core topic of the present paper. In general, the replanning will affect the entire set of agents, but for the agents which are not affected, the original plan is already feasible. We graphically illustrate in equation (7) how among all possible plans $S_{a,k}$ for each agent a , there are some plans (displayed at the bottom of the vector) which are disrupted, while some plans are still available.

describe a disruption as a limitation of such a supply, i.e., a limitation of the network obtained by removing some atomic stages. Formally, a disruption \mathcal{A} is a set of locations, lines, and times, identifying all atomic stages, which are disrupted and do not run, under the disruption. For instance, reanalyzing the example already proposed, we could imagine a disruption blocking the area of stop C, such that no public transport service incoming/outgoing is possible. This would result in the two atomic stages (B, 80, 17: 06) – (C, 80, 17: 07) and (C, 80, 17: 07) – (D, 80, 17: 10) being not operated, thus unavailable for service, as follows:

$$S_{a,k} = \begin{pmatrix} s_{a,1} \\ s_{a,2} \\ s_{a,3} \\ \vdots \\ \bar{s}_{a,k-2} \\ \bar{s}_{a,k-1} \\ \bar{s}_{a,k} \end{pmatrix}. \quad (7)$$

It is possible that, for some agents, no plan is disrupted, and for some agents, the disrupted plans actually include the desired one \widehat{s}_a . We consider here, as we discuss a public transport disruption, only the stages can be disrupted; the activities cannot be disrupted. Of course, the activities can be delayed or be affected by a delay or disturbance caused by the disruption.

4.2.3. Relevant Points in a Disrupted Plan. To identify the feasible alternative plans, it is relevant to consider some critical points, which define the extent by which the initially desired plan \widehat{s}_a was feasible, and where/when the disruption actually triggers. We identify the following situations:

- (i) LNA: last nondisrupted activity, which is the last activity in \widehat{s}_a , before the disruption triggers.
- (ii) LNS: last nondisrupted stage, which is the last stage in the last trip in \widehat{s}_a , before the disruption triggers. In case there is no stage between the LNA and the disrupted stage, this might not be defined. In other terms, up to and including LNS, the travelers can still move without problems in the network.
- (iii) FAS: the first affected stage, which is the first stage in the disrupted trip, which is not feasible. In other terms, from FAS onward, the travelers will need to change their plan, to move in the network.

- (iv) FAA: the first affected activity, which is the first activity, after a trip which is not feasible. In other terms, from FAA onward, the effects of a disruption will be experienced.

The LNA (respectively, LNS) is the activity (stage), before which everything in \widehat{s}_a is feasible. After the LNA, the desired plan \widehat{s}_a and the actual plan \bar{s}_a will be different. This difference hints that the agents becoming aware of the disruption, at T_{info} . Depending on the possible cases of LNS/LNA, we can categorize all possible situations:

- (i) Becoming aware during an activity: the agents know of a disruption during an activity and they have the possibility to change their plans for the entire next trip. In this case, the FAS can be completely changed to another stage (in general, trip) in a public transport network.
- (ii) Becoming aware during a trip, at a transfer: the agents know of a disruption before boarding a vehicle, which was planned to perform an atomic stage, actually disrupted. All passengers can therefore avoid boarding the vehicle and continue in some other way.
- (iii) Becoming aware during a trip, at an atomic stage: the agents know of a disruption while being onboard a vehicle, bound to perform an atomic stage, which happens to be disrupted. All passengers onboard have to disembark the disrupted vehicle and continue in some other way.

For trips with a single stage, the first two cases might coincide. Depending on how the LNA, LNS, FAS, and FAA are organized, and which of the three cases of information timing happens, multiple cases are given when a plan has to be changed.

4.3. Within-Day Replanning Methodology. In an unexpected event agents cannot anticipate (i.e., a disruption), a user equilibrium (and iterative approach used for a day-to-day process, to find it) is not a logical choice and far from reality. Agents face a specific disruption only once and have no information on beforehand on the alternatives [24]. To avoid such a problem, within-day replanning is presented as the solution. In this research, to comprehensively simulate the effects of a disruption, we develop some theoretical foundations for within-day replanning, in capacitated networks. We start from its required principles; formalize it; identify relevant scenarios; and discuss its implementation in an agent-based simulation environment.

4.3.1. Within-Day Replanning Principles. We consider an approach which is able to fulfill the following principles and constraints, relevant to simulate and analyse disruptions in public transport networks:

- (1) To consider an entire multimodal network as solution space for the plans in case of the disruption and

starting from an equilibrium solution computed for the case without disruption.

- (2) To refer to a utility function of the users. The users aim to maximize the utility by choosing plans based on the available information.
- (3) To be able to disseminate information to agents (that is, determining T_{info}) by (3A) broadcasting methods, by which all agents have the same information at the same time (think about radio, or news) but also by individual communication (3B), at a specified time or (3C) place.
- (4) To be able to adjust the plan starting from a specific time T_{replan} , in general related to the T_{info} and the waiting tolerance of the agents ψ . The sensitivity of the outcome to various values of this parameter can also be determined.
- (5) To include effects of limited capacity of public transport vehicles and therefore include the realistic reaction of people who are denied boarding.
- (6) To cascade the adjustment of plans (replan of activities and trips) as far as those cannot take place as originally planned.

4.3.2. Role of Information in Within-Day Replanning.

The within-day replanning is performed for each agent, triggered when the agents become aware of the disruption or they are denied boarding. In general, it is different for each agent: $T_{\text{info},a}$ the time at which agent a becomes aware of the disruption. The within-day replanning module starts from the desired plan \widehat{s}_a of an agent, separating between past activities and trips already occurred, which cannot be replanned or changed, and those after a certain moment in time, which can be actually replanned or adjusted. We call this moment, the start of the replanning (T_{replan}), which is determined by its time, location, and situation of the agents. T_{replan} depends on a lot of practical situations. It can be at the same time as T_{info} , i.e., agents react very quickly when they become aware of the disruption. Moreover, ($T_{\text{replan},a}$) might be different and personalized per each individual agent a ; for instance, if this is related to reaching a specific location. A disruption reduces the set of plans S_a that agent a can perform. Therefore, we can identify a reduced set of plans $S_a \setminus \mathcal{S}$, which are feasible for replanning in general. Depending on T_{replan} , some of those plans are not possible anymore, as they would have different activities or stages in the past (i.e., before T_{replan}). We call \widetilde{S}_a the set of plans which can be chosen obeying a causality principle (i.e., those changes in the past cannot take place) given a T_{replan} . For the sake of clarity, we call \widetilde{s}_a the complete day plan, which is determined as the application of replanning until the end of the day. We will compare it with the complete day plan \bar{s}_a , which is performed during an undisturbed day.

Formally, the within-day replanning (see equation (8)) seeks for an optimal response which maximizes the perceived utility of each agent, assuming that other agents $b \in A \setminus \{a\}$ do not change their behavior from the planned, undisturbed case $\bar{s}_b = s_b^*$. In fact, agents do not know what

other agents would do in an unexpected situation. For instance, agents cannot anticipate the increased demand on the network due to the disruption and might be denied boarding due to full capacity.

$$\hat{s}_a = \arg \max_{s_{a,k} \in \mathcal{S}_a, \bar{s}_{a,k} \in \bar{\mathcal{S}}_a} \sim \hat{U}(s_{a,k}, \bar{s}_b). \quad (8)$$

In general, $U(\bar{s}_a)$ is different from $\hat{U}(\bar{s}_a)$, that is, agents are not able to properly estimate the utility of their choices, in a disruption. The output of the within-day replanning depends on three arguments, the set of possible feasible plans (depending on the disruption \mathcal{A} and possible actions taken by the operators), the old choices (depending on the solution without disruption $\bar{s}_a = s_a^*$), and an information strategy (embedding which information is actually available at T_{info} , and at what time (T_{replan}) replanning is actually performed).

4.4. Information Strategies. We call information strategy the way by which each agent has information and the possibility to adjust their behavior, i.e., their plan. The availability of information about alternative routes and the duration of the disruption plays a significant role in determining the consequences of public transport disruptions on agents' behavior.

Here, we assume that agents are aware of the disruption (i.e., they can pick a new plan, from their set $\bar{\mathcal{S}}_a$) at time T_{info} , and the new plan will differ from the current one starting from T_{replan} onward. T_{replan} can take place, in the plan of an agent, at some specific relevant points, namely, at the end of an activity; at the end of a stage; or during a stage. In any of those cases, T_{info} must be later than disruption start time ($\mathcal{F}_{\text{start}}$) in the case of an unexpected disruption. Disruption end time (\mathcal{F}_{end}) must be later than T_{info} so that ultimately when the disruption ends, agents know about it. T_{info} can be only before T_{replan} because agents cannot replan, if they do not know about the disruption.

Figure 2 illustrates the plan of an agent where Trip2, from work to leisure, is in the focus. The figure is organized over a time (vertical) distance (horizontal) axis. In the solution of an undisrupted day (reported green colour, top of the figure), the agent travels over the network, with Trip2 made up of 5 atomic stages (A-B, B-C, C-D, D-E, and E-F), reaching an intermediate transfer point at F, where a walking stage allows a transfer to another public transport service, to finally, reach the leisure activity. This is in fact the same example as in Figure 1. We consider a disruption, in Figure 2, assuming to disrupt all traffic coming and leaving from stop C, between the start time $\mathcal{F}_{\text{start}}$ and the end time \mathcal{F}_{end} . As a consequence, the atomic stages of Trip2 connecting B-C and C-D are not feasible anymore. This is identified in figure as a red-dotted line for the disrupted atomic stages B-C and C-D.

The agent therefore finds alternative plans in the public transport network. These alternative plans depend on the four variations (the first three already discussed in Section 4.2.3) in which agents become aware of the disruption and

the assumed set $\bar{\mathcal{S}}_a$, depending on the information strategy followed the following:

- (i) *Onboard.* If agents are already onboard a disrupted transit vehicle, when they become aware of the disruption, they have to leave the disrupted vehicle in the last served stop. From there, they replan their trip to the location of the next activity in the plan. Such a situation results in the plan illustrated in brown in Figure 2, where agents are leaving the disrupted service at stop C, and replan their trip, through the network, towards the leisure activity. In general, it might be the case that stop C is not well served. It is possible that agents will reach their next activity via a different path in the public transport network (for instance, via transfer at Q). In Figure 2, this condition is associated with a considerable delay (i.e., the brown plan is the second-latest).
- (ii) *Replan from LNA.* If agents become aware of the disruption while performing an activity, they can replan the affected trip already from the location of the current activity, i.e., the last nondisrupted activity LNA. In other terms, it is possible to reach the leisure activity with a completely different path in the public transport network, possibly starting from a different stop. Such a situation results in the plan illustrated as a purple line, in which the agent starts Trip2 from a different stop (L, instead of A). Given the largest degree of freedom in choosing the best starting stop, this condition can be often associated with the smallest delay.
- (iii) *Replan from FAS.* If agents become aware of the disruption at the beginning of an affected stage, i.e., when they already reached stop A, then the replanning starts from that stop towards the location of the next activity in the plan. In Figure 2, this is reported as the yellow line, starting from stop A, via a possibly different path in the public transport network (for instance via transfer at G).
- (iv) *Wait until Resolution.* Finally, we here discuss an extreme case of replanning, where there is no possibility to change the line chosen, and the path determined by replanning uses the same public transport line and visits the same stops, as the original one (without disruption considered). In this case, agents do not exploit any information about the disruption or the running services in $\mathcal{T} \setminus \mathcal{F}$. The only action they can perform is to wait at their starting station, until a first undisrupted service runs. We report this in Figure 2 as the solid, dark red line, starting after \mathcal{F}_{end} , and visiting the same stops A to F.

We consider multiple scenarios of information, which can partially result in the 4 conditions described above, depending on their choice of T_{info} , T_{replan} , and $\bar{\mathcal{S}}_a$. These scenarios are ordered by the decreasing size of $\bar{\mathcal{S}}_a$:

- (iii) Start of the disruption (SD): in this scenario, agents become aware of the disruption exactly when disruption starts, no matter where they are already traveling or in an activity. They perform a replanning which can start already at that same time. Therefore, in this scenario, T_{info} equals to the start of the disruption $\mathcal{F}_{\text{start}}$, and T_{replan} can be as small as T_{info} . We consider the reaction time of the public transport operators for informing agents negligible, as well as the reaction time of agents to the received information. In this case, the three scenarios—onboard, replan from LNA, and replan from FAS reported in Figure 2—are possible.

$$\widehat{s}_a(\text{SD}) = \arg \max_{s_{a,k} \in S_a, \mathcal{S}; s_{a,k} \in S_a, T_{\text{replan}} > \mathcal{F}_{\text{start}}} \widehat{U}(s_{a,k}, s_b^*). \quad (10)$$

- (iv) Start of the trip (ST): in this scenario, agents become aware of the disruption (T_{info}) at different times, in relation to the time they intend to perform their trip, which is actually disrupted. Specifically, this time coincides with the moment they begin the last nondisrupted stage, or LNS. This is different for every agent, i.e., agents become aware of the disruption at different times, when the last nondisrupted stage is finished and the first disrupted trip/stage is supposed to be performed. In this case, only the two scenarios—onboard and replan from FAS reported in Figure 2—are possible. For this plan, it is relevant to consider a waiting tolerance ψ , i.e., time the agents wait before replanning. In our analysis, this parameter is zero, if not otherwise specified.

$$\widehat{s}_a(\text{ST}) = \arg \max_{s_{a,k} \in S_a, \mathcal{S}; s_{a,k} \in S_a, T_{\text{replan}} + \psi > t_{\text{FAS}}} \widehat{U}(s_{a,k}, s_b^*). \quad (11)$$

- (v) No information (NI). In this scenario, agents do not have any information about the disruption, specifically on its location, affected lines, and the start/end time. The only possible reaction of the agents to the disruption is what has been identified before as wait until resolution: waiting at the public transport stop of FAS until arrival of the next vehicle of the public transport line they intended to take. This can be identified as a special case of \widetilde{s}_a , which contains only the lines and stages which differ from the planned ones by their starting time. The sequence of stops and the lines used are the same as in s_a^* . Agent a takes the earliest of such plans, departing after (\mathcal{F}_{end}), just after the disruption is over. Formally,

$$\widetilde{s}_a(\text{NI}) = \arg \max_{s_{a,k} \in S_a, \mathcal{S}; s_{a,k} \in S_a, T_{\text{replan}} > \mathcal{F}_{\text{end}}} \widehat{U}(s_{a,k}, s_b^*), \quad (12)$$

where \widetilde{s}_a is constructed in a similar way as the operator \mathcal{M} governing the default reaction to denied boarding.

We also consider some benchmark, determined by the cases without disruptions:

- (i) Equilibrium without disruption (EOD): this scenario corresponds to the equilibrium solution S^* on a normal day, i.e., on the full public transport supply \mathcal{N} . This is the base behavior, approximated through the standard iterative process of day-to-day replanning. We assume all scenarios starting from this solution.
- (ii) Replan when boarding denied (RBD): this scenario describes a normal day without any disruption. However, agents who are denied boarding due to a full capacity of vehicle will go through the within-day replanning and receive a new plan for the traveling. In this way, the comparison between the within-day replanning scenarios can precisely identify the agents, which face denied boarding also in the undisrupted situation and assess their (possible) changes, due to the disruption. This scenario quantifies the effects of public transport vehicle capacities and crowding into the base behavior and choices of agents.

The information on the disruption is assumed to be either none, or complete; and it is static, i.e., there is no flow of updates of information about an expected duration. In the scenarios SM and SD, the information is disseminated to all agents at the same time. Instead scenario ST has a different dynamic by which the information is disseminated to agents, based on their time and space. In the same public transport service, it can be that some agents are aware of the disruption, and others not.

During the within-day replanning, we assume activities cannot be dropped; therefore, the utility can be directly related to just the stages to be chosen. In all within-day replanning cases, the chosen plan maximizes the expected utility, assuming that other agents do not change their plan from the undisrupted choices. In fact, in capacitated networks, the actual utility U can be bigger or smaller than the expected one \widehat{U} . The difference has to do with network effects propagated through the limited capacity of the vehicles and phenomena of denied boarding. Generally, the result from any within-day replanning (\widetilde{s}_a) is worse than that of the equilibrium. This has to do with a restricted set of plans to choose from and an incorrect approximation of the utility function, especially concerning the choices of other agents.

The following cases are worth being discussed. Recall that U is the actual utility experienced; at the end of the day, \widehat{U} is the utility expected from a plan, at a certain moment; \widetilde{s}_a is the plan actually performed at the end of the disrupted day; $\bar{s}_a = s_a^*$ is the plan actually performed at the end of a normal day, again assumed to be the equilibrium solution.

If $U(\bar{s}_a) \leq \widehat{U}(\widetilde{s}_a)$, i.e., agents have a lower utility, at the end of the day, than expected, i.e., the capacity effects are actually delaying them further, during the disruption. Agents in this situation are for instance trying to take a line bypassing the disruption, where exceptionally higher demand is seen.

If $U(\bar{s}_a) < U(\bar{s}_a)$, then the agents have a lower utility than typically seen in the nondisrupted case. This is by far the most common case, for the affected agents, the unavailability of transport services (due to the disruption), and the strong competition of many agents for the fewer services still running (crowding and denied boarding) results in delay. We here distinguish between those agents whose ideal plan s_a^* is disrupted, i.e., $s_a^* \in \mathcal{S}$; which we call directly affected and those whose ideal plan is actually feasible, despite the disruption, but they experience delays only due to the capacity of the vehicles in the network. We call those latter indirectly negatively affected agents.

If $U(\bar{s}_a) > U(\bar{s}_a)$, then the agents have a higher utility than typically seen in the nondisrupted case. This is happening to those agents, whose ideal plan s_a^* is actually feasible, due to the disruption, and they experience less delay, as the disruption is preventing some demand to occupy the capacity of the services they wish to take. In this sense, those agents perceive the disruption as causing positive utility. We call those agents indirectly positively affected agents.

4.5. Implementation in Agent-Based Framework. We implemented the methodology described in MATSim. Appendix A reports graphically the flowchart of the methodology used. As a quick summary, we explain here the scientific contributions of our development in MATSim:

- (i) When an agent is denied boarding, the within-day replanning module produces a new plan based on the current situation, for instance, change the plan or wait for the next service
- (ii) Agents can be informed at any possible time and location. For instance, onboard services agents are also informed about the disruption. Besides, if agents are onboard and affected by the disruption, they have to alight and replan.

5. Case Study

We test our methodology and evaluate the direct and indirect effects of a disruption on a large multimodal network. We used the data of Zürich, as derived by Rieser-Schüssler et al. [22]. We model the entire transport demand in Zürich, and its public transportation system. However, the proposed methodology is not limited to any particular geographical situation. We represent the population of Zürich by means of agents, at 1% sampling rate. Each agent represents 100 persons in real life; capacities of road links and vehicles are scaled accordingly. This results in 12,072 agents.

We refer to a disruption affecting the core of the public transport network, namely, two largest stations Zürich HB and Zürich Oerlikon. A schematic view of the disrupted lines and stations is illustrated in Figure 3. The dotted lines in Figure 3 represent the disrupted sections of the rail lines; solid lines represent services still running. All other public transports and all road transport are not affected by the disruption.

During the afternoon peak hours (between 16:00 and 19:00), no train can run on the disrupted lines. The feasible disposition timetable is assumed to operate during the disruption, which is from 16:00 to 19:00:

- (i) For the lines via Zürich Hardbrücke and Zürich Wipkingen, all the trains scheduled are canceled between Zürich HB and Zürich Oerlikon. For the lines not stopping at those stations, the cancellation is extended until/from the first available stop (Schaffhausen for IC4; Zürich Flughafen for IR75 and IR 37)
- (ii) Between 16:00 and 19:00, the original train schedules beyond either Zürich HB or Zürich Oerlikon (apart for the exceptions just introduced for IC4, IR75, and IR37) are maintained
- (iii) Before 16:00 and after 19:00, the original train schedules are not affected

Some terms used in the upcoming section are defined as follows:

- (i) The disrupted line is a line for which not all its services are able to run due to the disruption. A list of these disrupted lines is shown in Figure 3.
- (ii) A disrupted vehicle is a vehicle used by a service, which cannot run due to the disruption.
- (iii) The disrupted stations consist of the two central locations which delimit the disruption (Zürich HB and Zürich Oerlikon) and the stations along the disrupted lines (Zürich Hardbrücke and Zürich Wipkingen), where services are canceled.

In the simulated test case, 140 agents (therefore corresponding to 14000 people in real-life) cannot perform a trip from their plan at equilibrium s^* , directly due to the disruption. These agents are called “directly affected agents,” and we analyse their behavior in detail. We later study in Sections 6.3 and 6.3 the indirect effects of the disruption on the “indirectly affected agents,” who face denied boarding due to the replanned directly affected agents. The execution of within-day scenarios SM, SD, and ST takes about 22 minutes, while NI is faster at just 6 minutes, on a standard laptop (Intel(R) Core(TM) i7-8650U CPU). A single day-to-day iteration takes about 3 minutes.

6. Results

6.1. Delay Analysis for Directly Affected Agents. This section quantifies the effects of the different information strategies on the arrival time of the directly affected agents to evaluate the effects of information strategies in mitigating the delay. To avoid adding more complexity, we assume that activities cannot be dropped; therefore, the utility is directly related to just the stages to be chosen and their travel time and delay. The different scenarios are evaluated based on the delay, as it has a more immediate physical meaning rather than utility. We study the activity-delay, which is the difference between the arrival time at activities in the EOD scenario and the arrival time at activities, in each disrupted scenario, for all

directly affected agents. For each scenario, the activity-delay for all directly affected agents for all activities taking place after $\mathcal{F}_{\text{start}}$ is computed. The cumulative distribution of activity-delay under different scenarios is shown in Figure 4. The X-axis shows the delay, in minutes, and the Y-axis shows the cumulative probability, varying from 0 to 1; the scenarios are represented in the legend with specific colours; the same colour scheme is used throughout the paper.

Activity-delay is reported with regard to (wrt) the EOD (EOD, not shown, would correspond to a 0 activity-delay). Figure 4 demonstrates how the EWD scenario (blue) corresponds to the least activity-delay (i.e., the one at the left-most side of the figure). After this (ideal) equilibrium scenario, the rank of scenarios in terms of increasing delays is SM (black) and SD (purple), with comparable values; further, ST (yellow) and NI (red), with the largest activity-delay. These results approve that earlier availability of information causes fewer delays for directly affected agents.

The NI results in large activity-delay, ranging from 0 to well above 300 minutes; this might be related to possibly stranded passengers. It can be seen in Figure 4 that some agents experience a negative activity-delay compared to EOD, corresponding to an earlier arrival. On the other hand, some other agents experience a positive activity-delay.

The detailed numerical results of activity-delay are reported in Table 1, presenting scenarios in columns (with two columns for EWD, see explanation later) and statistics (mean value; minimum value; 25, 50 75 and 90 percentile; and maximum value) of delay-minutes in rows. We also add the amount of agents affected and the total delay for all affected agents. The delay is calculated by grouping the activities of each agent which occurs after $\mathcal{F}_{\text{start}}$ and then aggregating the average of those arrival times for activities.

When no equilibrium is considered, but the disruption is still known well in advance, i.e., scenario SM, the delay is averagely around 3 minutes. This last gap between EWD and SM reports the significant degree by which agents interact with each other, possibly changing mode and causing unexpected congestion.

SD is resulting in almost 55% more delays than the SM. This gap is related to the anticipative character of SM, i.e., passengers know about the disruption before its occurrence. The ST scenario has a further 70% more delay. NI unsurprisingly results in by far the worse delay. From Table 1, it is also evident how EWD changes agents' plans, with a 90-percentile value of activity-delay lower than SM and SD. A larger degree of freedom that agents have to deal with a disruption leads to larger changes that the agents will experience, some in positive and some in negative. Figure 4 clearly highlights the large variability of EWD, though it has the lowest mean delay. Our results show that, in the EWD scenario, 33% of directly affected agents gave up using public transport during the disruption, through the day-to-day iterations, and switch to the car mode. Using car mode to reach their activity locations results in less travel time. Therefore, the average delay of all directly affected agents (both passengers who remain to keep the PT mode and those who switch to car mode) is negative. Therefore, we show the delay analysis

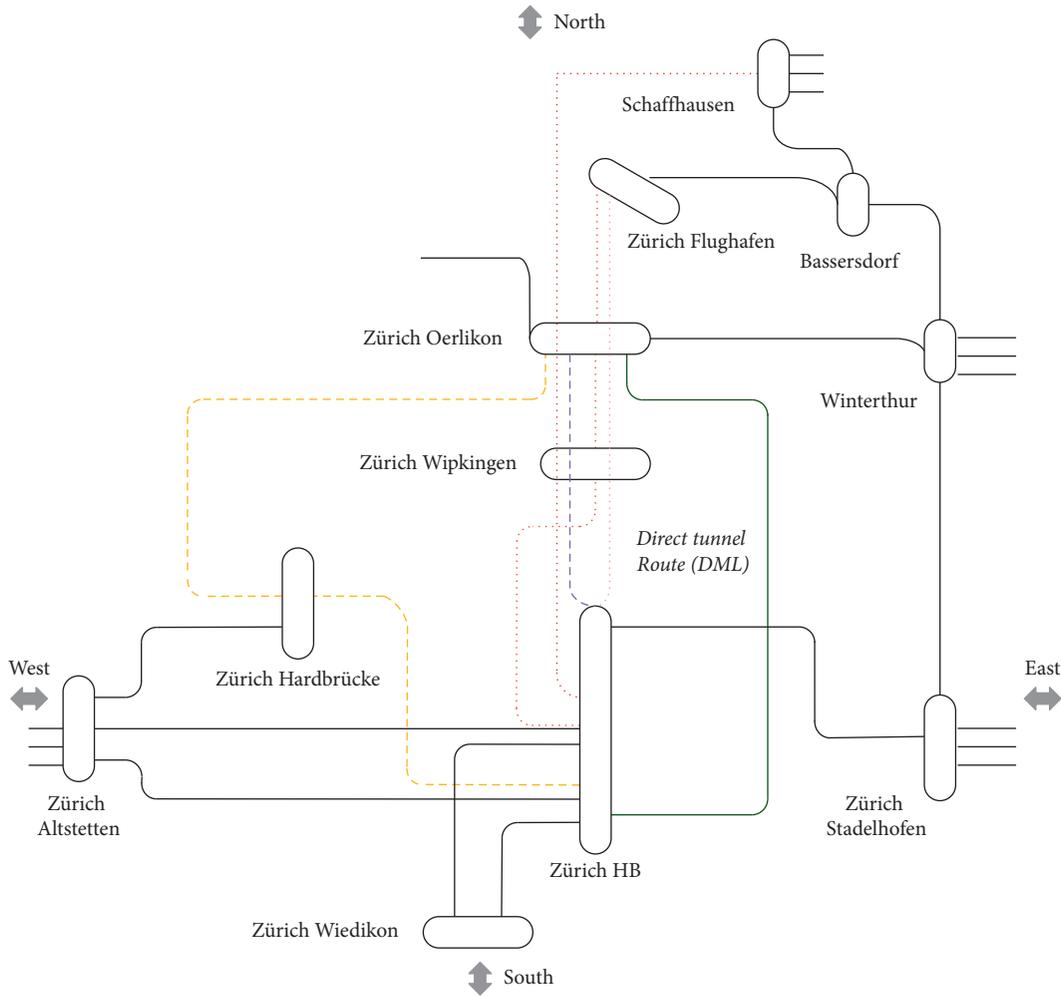
of EWD in two columns of all agents and those who keep using public transport after the disruption occurs.

140 agents are directly affected. In scenario NI, 115 agents could finish their plans, as 25 agents are unable to reach any activity after they are disrupted and remain stranded in the disrupted network. Their plan was to take a public transport service which runs only during peak hours and which is not scheduled to run anymore after 19:00 when the disruption is resolved. A few agents have a larger delay in scenario SM than scenario SD (comparing the maximum values). The reason is that the disrupted services in SD partially serve few agents who were already on-board when they are informed about the disruption. Then, they have to leave and search for a new plan. However, in the SM scenario, those agents replan their trips in such a way to avoid the disruption stations, and therefore, it results in a larger travel time for them.

6.2. Indirectly Affected Agents. We here quantify the indirect effect as a function of the information, resulting from variations (increase/decrease) in the occupancy level on other lines, due to a disruption happening somewhere in the network. Some lines which bypass the disruption will be more crowded and therefore result in more often in denied boarding to anybody willing to take them. The phenomena will lead to delay for a broader geographical and time dimension.

It can also happen that the disruption results in fewer loads in specific lines. For instance, those where people on the disrupted vehicles would normally transfer to will have less load and possibly cause less disutility for a restricted set of passengers (positively indirectly affected agents, experiencing a negative delay, i.e., an early arrival).

Figure 5 shows a map of the negative and positive indirectly affected agents, overlaid on the disruption area, that is, Zürich area, in the SM, ST, SD, and NI scenarios respectively, i.e., all those with within-day replanning. The number of negatively indirectly affected agents (overall amount of red) is the highest in the SD scenario and the second-highest in the SM scenarios, both larger than the NI scenario. Agents in the NI scenario will stay in the disrupted locations until the disruption is over; therefore, the occupancy level of the other parts of the public transport network will not change. The smallest amount of negatively indirectly affected agents occurs in scenario ST, in which directly affected agents become aware of the disruption exactly the time they attempt to board their planned (disrupted) public transport vehicle. As they become aware of the disruption late, compared to the other scenarios, they will resort less to use other lines of the network, therefore spreading less negative indirect effects throughout the network. They also avoid moving altogether when the disruption ends, i.e., what happens in the NI scenario. Thus, the results indicate a tradeoff between reducing delays for the directly affected agents (SM, ST) and increasing the spread of the delays in the network (more negatively indirectly affected agents), aiming for small generalized delays throughout the network. In the NI scenario, the directly affected agents suffer from



Direct tunnel Route (DML):
 Lines: IR36, IC1, IC5, IC8, S2, S8, S14, S19

 Lines: S6, S7, S9, S15, S16, S21

 Lines: RE, IR70

 Line: IR75, IR37

 Line: IC4

 Line: S24

FIGURE 3: Details of rail elements in the Zürich scenario for the considered example.

large delays; however, they do not spread the disruption to other travelers. Figure 5 also illustrates that, in the NI scenario, the negatively and positively indirectly affected agents are localized at the disrupted places. In scenarios SM and SD, agents are affected in a broader geographical dimension, effectively making the disruption impact a much larger area.

Figure 6 shows the negatively and positively indirectly affected agents, based on the time at which their delay occurs. The colour intensity refers instead to a timeline within the day, decreasing in intensity from the beginning of the disruption (strongest colour) towards the end of the day (lightest colour). The four maps in Figure 6 have the same

scale. The negative indirect effects are limited between 16:00 and 20:00 in SM, ST, and SD scenarios while lasting to 21:00 in the NI scenario. The positively affected agents are present until 21:00 in SM, SD, and ST scenarios and until 22:00 in the NI scenario. This is due to the replanning, effectively shifting their trips in time until the disruption is over, which keeps lighter loads in other parts of the public transport network for a longer time. In general, those indirect effects have complex dynamics. Positive indirect effects happen later than the negative indirect effects, i.e., it takes time for an unexpected load increase to propagate in the network.

The largest indirect effects of the disruption are well identified close to Oerlikon, in the first moments of

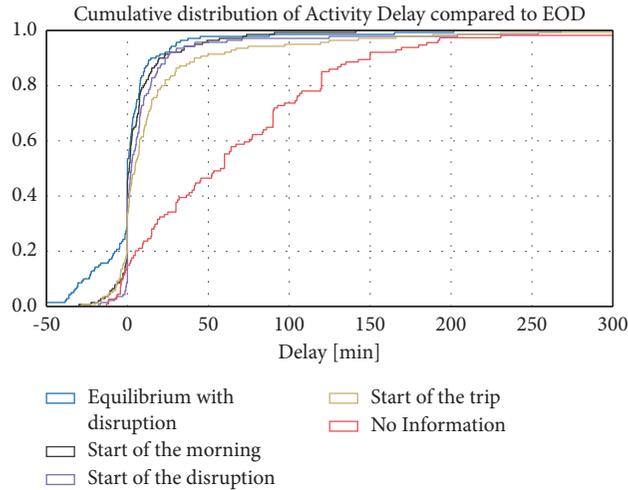


FIGURE 4: Cumulative distribution of activity-delay (delay wrt EOD) for directly affected agents.

TABLE 1: Activity-delay (minutes) wrt EOD, for scenarios, for directly affected agents.

	EWD-all agents	EWD + PT agents	SM	SD	ST	NI
Mean	-4	0.2	3.4	5.3	9	89.3
Min	-63.4	-63.4	-22.5	-20.4	-17.9	-32.2
25%	-8.7	0	0	0	0	30.1
50%	0	0	0	3	4.6	89
75%	3.3	5.5	5.2	8	11.8	129.1
90%	10.6	11.6	11.8	14.7	23.6	180
Max	87.7	45	62.2	49.2	90	300
Number of agents	140	109	140	140	140	115
Agents minutes	-553.7	18.7	479.4	736.3	1253.7	10269.6

disruption (16:00–18:00), which shows the vulnerability of this critical station, for the considered disruption. The affected stations have the largest share of negatively affected agents. Zürich central station has no positively affected agent; in fact, the station is very crowded already in undisrupted situations.

Figure 7 illustrates the data for negatively (Figure 7(a)) and positively (Figure 7(b)) indirectly affected agents, as a box plot. The amount of agents affected is reported at the bottom of the plot, and the mean value is presented as white circle. The EWD shows a large variation with roughly the same amount of agents experiencing a negative effect (19 minutes on average) and positive effect (16 minutes on average). In other terms, the search for a new equilibrium shakes the planning of many agents, which are affected in very heterogeneous manner. This was already evident from our analysis on the directly affected agents. The NI scenario results in negative and positive indirect effects, which are both smaller than EWD on average. ST has the smallest amount of negatively affected agents, as well as the second smallest amount of positively affected agents, and, moreover, the smallest magnitude of delays for both cases. Being ST the closest scenario to common situations, one can understand that the improvement in disruption management (for instance, if the situation becomes closer to SD, or even SM) might actually bring much more indirect effects than currently experienced in real-life networks. The large variability

in extreme cases for EWD depends on the computational process to compute the equilibrium. In absolute terms, the amount of agents indirectly affected in most scenarios is comparable with 20% of the directly affected agents.

6.3. Comparing the Direct and Indirect Effects. We finally review together direct and indirect effects to further appreciate the heterogeneity of the different information strategies in scenarios. We expand the study to include all scenarios introduced; in fact, in the EOD and EWD, there is no reaction to denied boarding or no within-day replanning at all. This refers to the fact that when agents are denied boarding in the EOD and EWD scenarios, the simulation does not trigger the within-day replanning for them, which causes less disutility. Instead, agents learn through day-to-day iteration to improve the utility of their plans. We moreover consider the Replan when Boarding Denied (RBD) scenario, which allows a direct fair comparison when within-day replanning is included (i.e., EOD + RBD is compared to SM, SD, and ST). Even in the ideal EOD situation, 670 agents are denied boarding due to some vehicles' full capacity. The user equilibrium solution includes this delay and discomfort though agents cannot avoid taking a crowded vehicle or the effects of the agents' interaction is within the approximation of the final user equilibrium. On the other hand, this shows how capacity effects are present

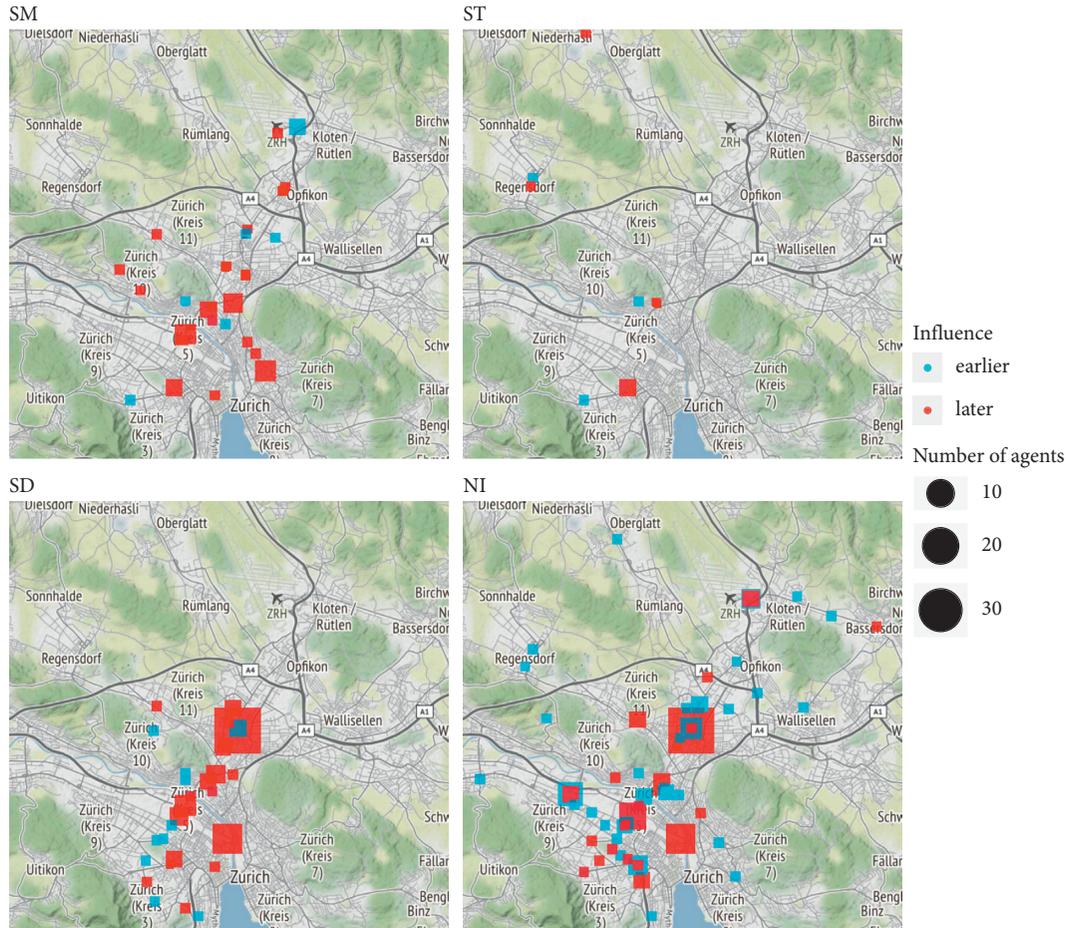


FIGURE 5: Location and amount of agents positively (arriving earlier at their activities) and negatively (arriving later at their activities) indirectly affected by the disruption. Map size is about 15 km (scenarios SM, ST, SD, and NI).

even in the user equilibrium, though in a minor form, and are greatly amplified by the disruptive event.

The grand total of the amount of agents directly and indirectly, positively, and negatively affected is reported in Table 2. The overall conclusions are that the equilibrium scenario EWD results in positive and negative effects spread over the largest amount of agents and the lowest total delay. In this case, the direct effect is actually much smaller than the indirect effects (refer to Section 6.1). The second smallest grand total is computed by the SM scenario, which is also an anticipative idealization of a possible reaction in a disruption. In this case, the direct effects, agents minutes, are much larger. The direct effects are actually experienced by the same amount of agents, but agents experience much more delay in SM rather than in EWD. Scenario SD is the lower bound (for delay) in case of an unexpected disruption, and the delay increases both in terms of direct and indirect delay compared with SM. Scenario ST further reports higher direct effects and lower indirect effects, for a grand total delay which is roughly double than SM. Finally, NI has very large direct effects, and the second smallest amount of indirect negative effects.

EWD manages to reach a very small average delay when the absolute magnitude of effects is divided by the very large

amount of agents affected (352 in the test case). Instead, the later the information is disseminated to agents and the smaller the effect of their within-day replanning is, the more the average effect increases. Therefore, a solution changing the plan of many agents results finally the best. From a practical point of view, it highlights the need to mobilize more people than the directly affected agents to decrease the effect of the disruption.

We summarize the effects also including the capacity, by running the agent-based models in configurations that allow to separate the effects of capacity, further differentiated in effects to directly affected people, and indirectly affected people, information, nonanticipativity (i.e., information is available at the start of the disruption or at the start of the morning) and reaction of other users (i.e., the gap between the user equilibrium EWD and SM). We further identify the supply reduction which unavoidably introduces delay and plot also the amount of delay due to denied boarding in normal conditions (in the bottom part of the plot). Figure 8 reports the absolute (Y -axis, in agents-minutes) and relative value (in percentage of the extra delays due to the disruptions, for the two/three important components) for the three configurations: NI, ST, and SD, respectively. The effect of

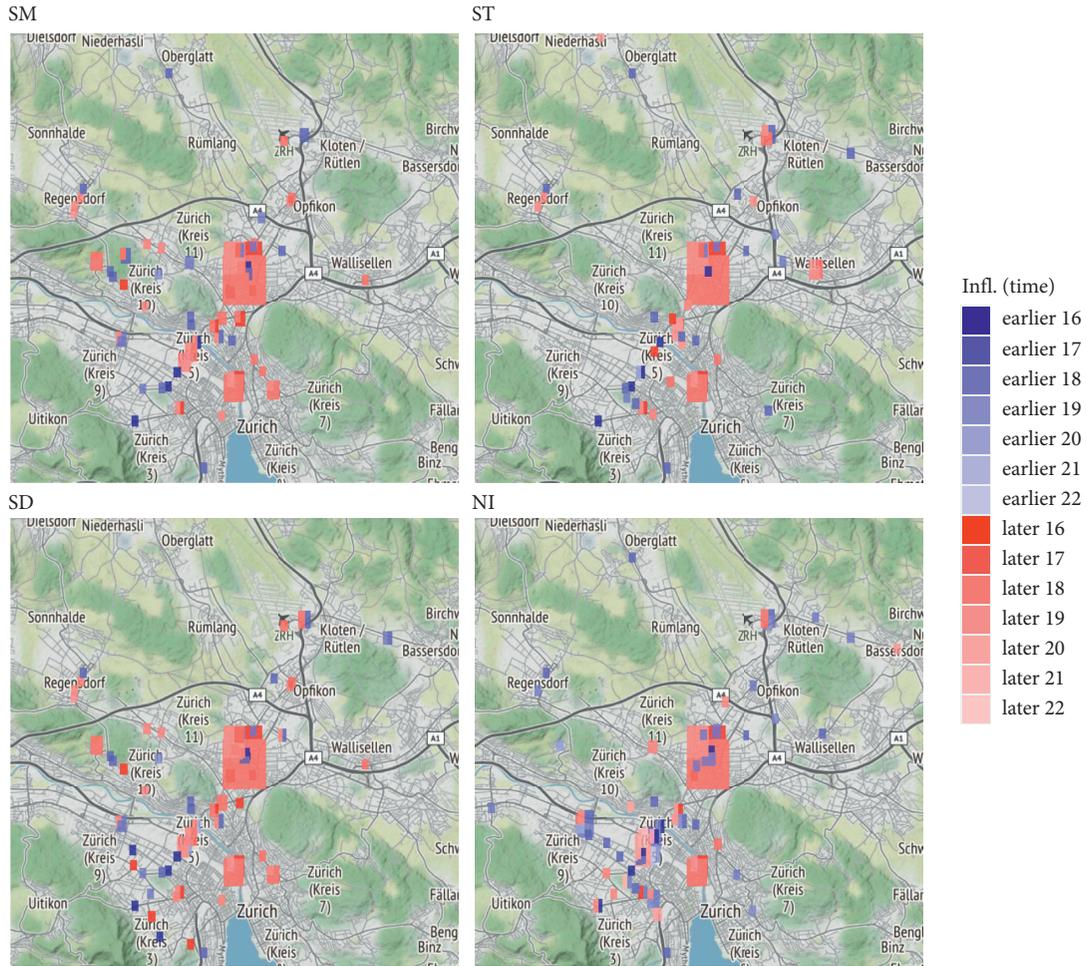


FIGURE 6: Time and amount of agents positively (arriving earlier at their activities) and negatively (arriving later) indirectly affected agents by the disruption; map size is around 15 km (scenarios SM, ST, SD, and NI).

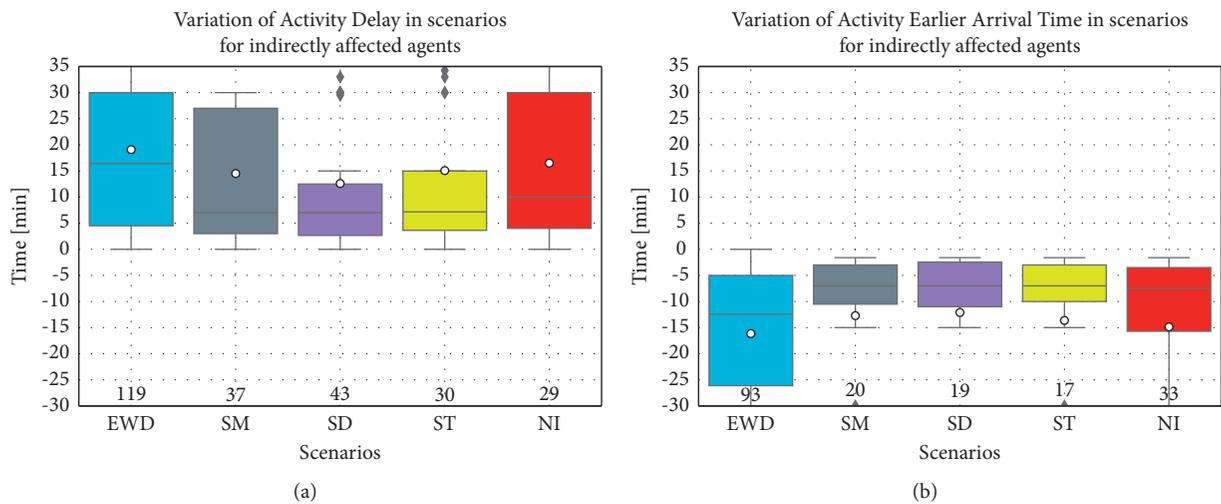


FIGURE 7: Activity-delay after disruption starts for negatively (a) and positively (b) indirectly affected agents.

TABLE 2: Summary of direct and indirect effects.

Quantification	EWD	SM	SD	ST	NI
Direct effect (activity-delay), avg minutes	0.2	3.4	5.3	9	89.3
Number of agents affected	140	140	140	140	140
Agents minutes	18.7	479.4	736.3	1253.7	10269.6
Negative indirect effect (activity-delay), avg minutes	19	14.9	12.9	15.6	16.6
Number of agents affected	119	36	42	29	29
Agents minutes	2265.5	536.9	541.9	452.1	481.5
Positive indirect effect (early arrival), avg minutes	-16.1	-12.7	-12.1	-13.6	-14.9
Number of agents affected	93	20	19	17	33
Agents minutes	-1501.5	-254.1	-229.8	-231.6	-490.6
Grand total delay, agents minutes	210.3	762.2	1048.4	1474.2	10260.5
Grand total, agents affected	352	196	201	186	177

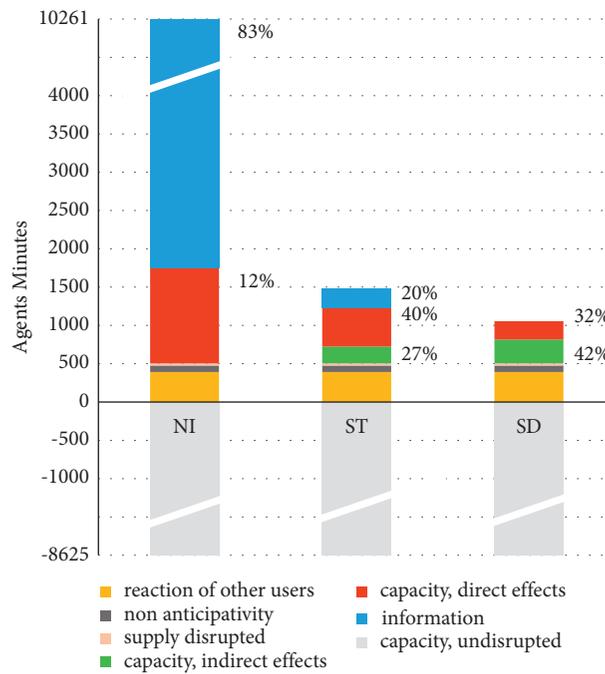


FIGURE 8: Summary of the effects and reason.

information for the NI case, and the effect of capacity in normal conditions are both out of scale.

The reaction of other users (yellow), effects of non-anticipativity (dark gray), supply disruption (pink), and undisrupted capacity (light gray) are the same in the three scenarios investigated. The effects of capacity towards directly affected people (red) is large, and for the scenarios ST and SD, comparable with the effects of information (blue). In other terms, investing in better disruption information can be as effective as providing unlimited capacity for the directly affected passengers (for instance, by bus bridging or similar solutions). The earlier information is shared, the smaller the direct effects of disruption, the larger (in absolute value, and even more in percentage) is the amount of indirect effects (green). It can be seen that the effects of the capacity, under normal conditions (light gray), are as adverse as a disruption, in terms of total minutes of delay, even though distributed among a much larger set of agents. Providing the best information possible, just after

the disruption occurred (i.e., SD), can reduce the effects of NI by as much as 83%.

6.4. Waiting Tolerance. We finally do some tests to identify the possible role of a waiting time tolerance ψ as in formula (11). The empirical existence of such a value was investigated by Rahimi et al. [6] by survey, and we here use it to estimate the realism of scenario ST, by including a sensitivity analysis on this parameter. Therefore, we consider a range of waiting tolerance ranging from 3 and 8 minutes (which are half of the headway for most of the urban public transport and the train lines, respectively) towards 20 minutes (as reported by Rahimi et al. [6]). We combine this waiting time tolerance with scenario ST. If agents become aware of the disruption at the start of their trip (scenario ST) while having 3 minutes waiting tolerance, the delay averagely increases by 38%, mostly corresponding to the extra 3 minutes. In other terms, the network is relatively dense,

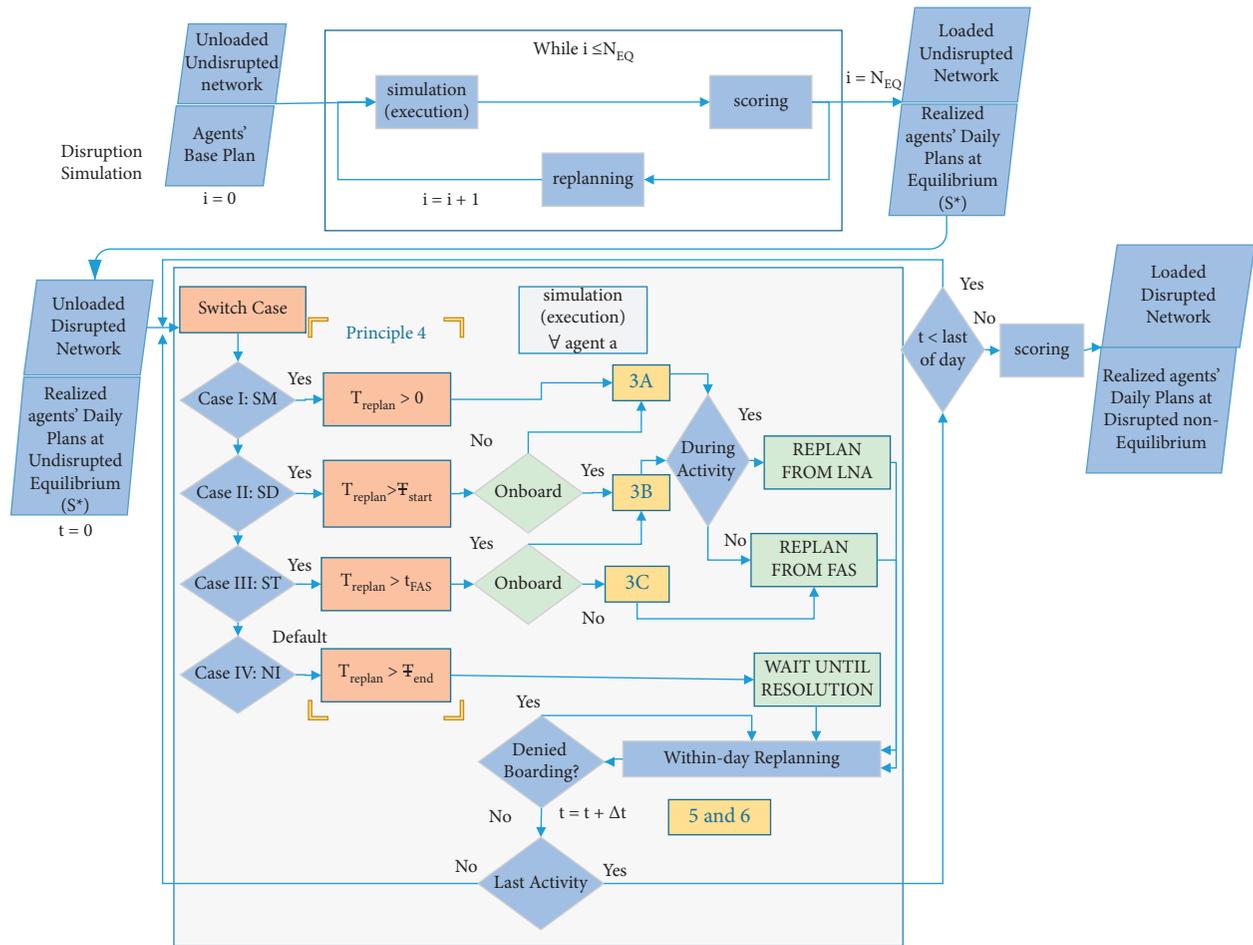


FIGURE 9: Flowchart of the developed module.

and people have sufficient alternatives by which they can move forward. If the waiting tolerance increases to 8 and 20 minutes, the delay rises by 61% and 140%, respectively. In absolute terms, this is actually a bit less than the value of ψ , respectively, for ψ equal to 0, 3, 8, and 20 minutes; average: 9, 12, 14, and 21 minutes; median: 5, 8, 11, and 16. We assume this smaller increase is due to different modes which can be chosen as a result. Overall, such results show the importance of quick decision-making and replanning for the agents.

The waiting time tolerance has minor impact towards indirect effects. Effectively, it acts as an accumulation of demand. And, the disruption in the afternoon peak hours delays the directly affected people. Overall, we can observe the negative effects increase by a few minutes, and the positive stay is mostly the same. The positive effects (early arrival) are estimated, respectively, for ψ equal to 0, 3, 8, and 20 minutes; average: -14, -12, -12, and -12 minutes; median: -7, -9, -9, and -9. The negative effects (delays) are estimated, respectively, for ψ equal to 0, 3, 8, and 20 minutes; average: 15, 15, 16, and 16 minutes; median: 7, 8, 10, and 8 minutes.

7. Conclusion

Due to the dynamic nature of the public transport system, passenger flows, and capacity limitations, the effects of a

disruption are not confined to the disrupted area and time but spread in a broader geographical and time dimension, mediated by the capacity of the vehicles in the network, and influenced by the information travelers have about the ongoing situation. So far, in the literature, the analysis and simulation of the disruptions' effects have been considered with some assumptions for the sake of simplicity. We here made the step forward to model those effects mathematically and develop accordingly a multiagent microsimulation module to simulate more realistic situations. These include long disruptions in which replanning is necessary to represent realistic passengers' behaviour; passengers can become informed individually or in a group, informing onboard passengers, forcing passengers to alight if they are affected by the disruption, and modeling waiting time tolerance effects. We start by formally modeling the effect of capacity towards transit assignment in an agent-based model. We then implemented this approach in the agent-based simulation MATSim, as a new within-day replanning module for public transport. For studying indirect effects, the specific capacity of all vehicles and the flows of all passengers onboard has been considered. Based on our result, we quantified how a disruption has pervasive effects, which could also positively affect some passengers, due to shifting of capacity bottlenecks.

We believe that such an approach is very useful for operators in their disruption management, as well as for planning and policy purposes, once a real-life situation can be comprehensively described by the agent based model discussed. In results, we show that different information dissemination strategies have a large impact on the direct effects, and even more on the indirect effects in terms of their network-wide delay. In general, by disseminating increasing information, the direct effects get milder, but the indirect effects get larger in space and more varied in positive and negative aspects. The scenarios with the least information instead are strongly affecting few passengers, with fewer impacts for the rest of the network.

The most important policy implications refer to the value that information has, in disruption situations. For instance, for the considered disruption, if agents become aware of the disruption in the transit stops, they face an average of 9 minutes delay. Instead, if they are informed about the disruption at start time and replan accordingly, their delay can be reduced by 41%, even without any investment in extra vehicles or additional services.

Due to the favorable computation speed, the proposed model can be used in both real time and planning stage. In the former case, it can help determining the network effects of an incumbent disruption. In the planning stage, the simulation model can help determine improved contingency plans, as in Corman and D'Ariano [25], and identify criticalities in the network. Furthermore, the model directly assesses how information can improve management of disruption, therefore helping in the design and management of disruption information systems and passenger advice.

Making it possible to have a good overview of the consequences, by the start of the disruption, it can result in effects which are comparable to capacity limitation for the network. In other terms, proper information could replace bus bridging. We are aware that the start time of the disruption communication is hard to be identified; the best effort could limit the delay in recognizing and transmitting proper information about disruptions, and that effect could be already very substantial in the dense networks of major cities. The earliest information dissemination about the disruption and offering alternative plans could reduce the delay of the directly affected passengers (refer to Table 1). However, such a strategy leads to significant indirect effects for possibly many other travelers. Some of those travelers might be better off, others might effectively face the negative effects of a disruption that should not affect them, but propagated by the capacity of the vehicles. Such results emphasize the importance of finding an optimal information strategy in which both, directly and indirectly, affected agents gain the lowest delay time. Assuming compliance of travelers, one can aim to steer their flow to reduce crowding.

Further research might consider including a more detailed quantification and identifying the essential network elements whose disruptions would cause the worst consequences in magnitude, or exposure, or further in the variation of effects (i.e., some lines face strong performance reduction, and others face a performance improvement). Timetable and vehicle scheduling can be designed,

considering the risk of disruptions, to decrease the likelihood of disruption and exposure (see Bababeik et al. [26]; Yan et al. [27], or adjusted as different disposition timetables (see Corman et al. [28]). The proposed approach improves the estimation of both aspects. The possible situations of information dissemination are in reality almost endless, based on their location, time, and the delay with which they might react. Suitable behavioral analysis could clarify which information scenario is the closest to the observed behavior. We expect that travelers might behave similarly, based on age, gender, job, etc., as well as affinity, with the public transport network. For instance, old travelers might prefer a direct, but longer trip, based on limited guidance from online route information available on mobile devices. Disruptions are often difficult to characterize and result in successive updates over time, about the magnitude and expected duration. Future research can study how partially wrong values for those two aspects can influence the result as well as a possible scheme with intermediate information updates as the disruption unfolds.

Finally, the simulation framework should be extended in the future by dropping activities, as a reaction to disruption. This would require that the utility for such a last-minute change could be determined.

Appendix

A. Implementation in Agent-Based Framework

The top part of Figure 9 illustrates the iteration process of MATSim, which produces the equilibrium scenario in the undisturbed case. The number of iterations is configurable, which we represent in the figure with N_{EQ} (fixed to 500 in our study). The output from the top part is used as the input for the down part of the figure, which describes the within-day replanning module and information strategies. In Figure 9, time $t = 0$ refers to the beginning of the day (at time 00:00), and the simulation checks the situation of agents every Δt , which we fixed to 4 seconds. We now explain how the principles from Section 4.3.1 apply to the chosen information strategies scenarios. Moreover, other possible choices of information strategies can be implemented, given the generality of the methodology. Principles 1 and 2 are, respectively, addressed by the comprehensive agent-based simulation used and the within-day replanning module as explained in Section 4.3. Figure 9 illustrates that, at the beginning of the simulation, we configure with the switch function, in which one of the four scenarios is going to be run. Based on the scenario that we configured, T_{replan} is varied. The simulation (execution) runs the plans of the agents and checks the situation of each agent. If an agent is affected by the disruption, then the simulation triggers the within-day replanning module based on the agents' situations. For example, when we configure the scenario as SD ($T_{replan} > \mathcal{F}_{start}$), the simulation checks the situation of agents, and if agent a is not onboard and performing an activity, then the situation "replan from LNA" calls the within-day replanning function. In such a process, we achieve principle 3A. All four situations of replanning and

principle are illustrated in Figure 9. If an agent is not affected by the disruption, the within day replanning will give back the same plan s^* , which is the output of the equilibrium situation (output from the top part of the figure).

In scenarios SM and SD in which broadcasting (3A) is used to distribute information, all agents have the same T_{info} . The passengers can know about the disruption before they begin the trip; therefore, avoiding starting a trip or a stage which ultimately will lead them to be waiting at a stop, where a disrupted service should have run. If agents become aware of the disruption when they attempt to take a disrupted line, such as in the ST scenario, each agent knows about the disruption at different times, based on the effective time at which agents attempt to board their planned public transport line and the specific stop where boarding is attempted. Such a situation is commonly determined by the available information systems at stations, stops, or other locations. The usual information systems at stations are speaker announcements, departure boards directly at the tracks, and general departure and arrival displays, which are abundant in the Zürich network, and actually used to disseminate information in case of disruptions. Such a situation is connected to principle 3C above. For the sake of simplicity, T_{info} is not illustrated in the figure, and only T_{replan} is shown.

T_{replan} is determined according to the methodology explained. In scenario SM, the within-day replanning function adjusts the plan starting from T_{replan} equal to LNA, which is by default “staying at home overnight.” In scenario SD, the within-day replanning function considers T_{replan} greater than $\mathcal{F}_{\text{start}}$ by ϵ , regardless of the state or location of the agents. At that time, two possibilities are given: agents can be performing an activity (during an activity) or performing a stage of a trip. In both cases, T_{replan} corresponds to the earliest possible time, after the ending of the current activity (replan from LNA) or ending of the current stage of the trip (replan from FAS). This relates to principle 4. In scenario ST, T_{replan} is greater than t_{FAS} by ϵ , i.e., the within-day replanning can adjust any further activity or trip, from the very moment they arrive at the stop where they attempt to board. Therefore, in ST, T_{replan} is time and space based.

In both SD and ST, there is the possibility that some agents are already onboard on a disrupted public transport vehicle when they know about the disruption through call announcements and/or displays. This case corresponds to principle 3B. In such a case, all passengers onboard will receive the information that their desired trip cannot be performed as planned, when the vehicle actually becomes disrupted. The agents will need to disembark and replan. In scenario NI, T_{replan} is greater than \mathcal{F}_{end} , again by ϵ , agents have no information and have to wait until the disruption is resolved and continue their plans.

The last trigger for calling the within-day replanning is the moment when agents are denied boarding due to a full capacity of a vehicle (identified by principle 5, shown as an if condition in Figure 9). In such a situation, T_{replan}

corresponds to the moment of being denied boarding. The within-day replanning determines an adjusted-plan from the time and location in which they are denied boarding.

Every time, the agents’ plans are first adjusted from T_{replan} until the next activity in their plans that does not require adjustment. A delay from the first disrupted trip might propagate through the entire plan. Moreover, a traveler might face multiple times replanning over a plan, especially in case of denied boarding. This relates to principle 6.

If an agent completes the plan and reaches the last activity, the simulation executes it till the end of the day. The simulation continues the execution for the rest of the agents. Finally, when the simulation is finished for all agents, the simulation is completed. The realized plans \bar{S} are available for analysis, and a scoring function can then calculate the utility.

Data Availability

The data supporting this paper come from previously reported studies and datasets, which have been cited.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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