Quantifying the heterogeneity of direct and indirect effects of a public transport disruption with agent-based simulation

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Abstract

This paper studies and quantifies the direct and indirect effects of a disruption in the public transport network on passengers using agent-based simulation. In particular, we study the behavior of agents in the network to measure the spatial and temporal extent of the impacts (delays, disutility) of a disruption. Due to the dynamic nature of public transport systems, disruption's impact on a particular part of the public transport network propagates through the network in both time and space dimensions. Besides, we attempt to evaluate passengers' behavior in as realistic as possible scenarios, where information about the disruption is scarce, or the disruption is even completely unexpected, and overcome the difficulties of a real-life passenger' behavior simulation. For such an aim, we add a new extension to the within-day replanning module in the agent-based simulation for public transport (MATSim). We apply our agent-based simulation to the case of the public transport system of Zürich, Switzerland. Our simulation approach quantifies precisely the number of directly and indirectly affected agents by the disruption, respectively those passengers who cannot carry their trip as planned because the services are disrupted and need to reroute their trip in the network; and those passengers whose services are not disrupted, but experience additional crowding effects due to the rerouted, directly affected, passengers. For both groups of travelers, we also study the delay that they experience, and the variation in their utility score of traveling. We prove how those effects relate to a large spatial and temporal heterogeneity, and moreover, they depend strongly on the information available, and replanning actions that the agents might undertake

Keywords

Disruption Management, Agent-based Simulation, Passengers' Behavior Simulation, Public Transport Disruption

1 Introduction

In the last years, research on the vulnerability of public transport networks received growing attention because of the repercussions that disruption can have on the passengers' satisfaction. In public transport disruptions, the travelers' choices are restricted to only the services that the network provides. Previous studies studied how to improve infrastructure, network, timetable, rolling stock, mode-choice, and capacity, to mitigate the negative impact of disruptions (Piner and Condry, 2017; Kiefer *et al.*, 2016). A few ones highlight the effect of the information strategies on passengers' behavior (Khattak *et al.*, 2008; Kattan *et al.*, 2013). Informing passengers as a solution for mitigating the downsides of disruptions in public transport is very attractive, as it does not need massive investments in the infrastructure, vehicle, or personnel resources. Information alone enables passengers to have better decision making in disruption cases, and thereby reducing their delays and inconvenience. One of the aims of this paper is to show to what extent informing passengers about the disruption can help them, by studying the replanning process of a daily-plan, based on some information available, to improve their satisfaction and reduce the delay that they may experience. We assume the satisfaction can be quantified in an economic term by a utility score. The delay and utility of the passengers vary according to the time they become aware of the disruption, and by the extent they can replan their desired trips and activities. The replanning has unavoidable negative effects, as some transport trips are unavailable due to the disruption itself. Moreover, due to the limited capacity of vehicles, indirect effects spread throughout the network in time and space, as the public transport network will experience different flows, triggering capacity limits at other moments and places. This will result in further cascading crowding, delays and inconvenience, i.e. indirect negative effects. In a complementary manner, some usual capacity limits might not be triggered at all, thus leading to limited positive effects for specific groups of passengers. We use agent-based modeling to study and quantify such effects. Starting from plans supposed to be optimal (i.e. user equilibrium in an undisrupted situation), passengers adjust their daily-plans, depending on the time that they receive information about the disruption. We analyze and compare the behavior of agents (representing passengers) in eight scenarios, evaluating scores and delays. We determine how indirect effects are characterized and depend on the information disseminated

The key contributions of this research are:

1. We analyze and compare passengers' behavior in disruption, referring to a comprehensive set of scenarios, including two benchmark scenarios, which represent ideal equilibrium solutions with, and without the disruption. Besides, we quantify

four scenarios under disruption situation, referring to a disposition timetable and different information strategies. We consider long disruptions, where replanning is necessary to represent realistic human behavior. Previous research studied the propagation effect of a disruption on the public transport network in short time disruption (lasting less than 45 minutes), where the adjustment of daily-plans could be ignored. For longer disruptions, the operator will implement corrective actions (disposition timetable), replanning infrastructure, vehicle and crew resources. The passengers will need to take this into account to adjust their daily-plan according to their wish to continue traveling with the maximum utility.

2. By using an agent-based simulation, extended by means of a new within-day replanning module for public transport, we quantify the number of involved passengers and their delay for the cases of directly and indirectly affected passengers and identify to which extent indirect effects are a heterogeneous combination of positive and negative aspects. Few studies evaluated such a comprehensive propagation of effects mediated by the occupancy level on the public transport network, which expands beyond a single disrupted event (Malandri *et al.*, 2018). To study indirect effects, the specific capacity of all vehicles, and the flows of all passengers onboard need to be considered and modelled.

The paper goes as follows. Chapter 2 describes the problem stated in this research. Chapter 3 consists of the literature review. Chapter 4 introduces our methodology for simulation, the critical features of disruption, and presents the different scenarios in relation to different information strategies. Chapter 5 reports on the case study utilized. Chapter 6 presents the result and quantifies the effects in terms of delays and score, discussing the heterogeneity in space and time between directly and indirectly affected passengers. Finally, Chapter 7 presents the conclusion.

2 Problem description

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, . . .), which requires users to find an alternative plan to fulfill their desire for mobility. Most commonly, disruptions are happening on road transport networks, and travelers have an available car, i.e. they can react by their own choices to the disruption by replanning or rerouting their trip over the infrastructure links still available.

In the case of public transport networks, disruptions have different impacts as a public transport network provides mobility only at specified times (when a vehicle runs) and spaces (at stops) thus limiting available choices for replanning. The vehicles resources are managed by an operator, which might not know or consider the specific wishes of the travelers. Typically, the operators react by a new plan of operations (a disposition timetable), canceling some services, possibly running additional services, or modifying the service in some ways to take into account unavoidable limitations (i.e. some infrastructure links are unpassable) as well as operational stability (i.e. short turning runs or inserting bridging services).

All those actions directly affect 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 available this information, they can look for an alternative path, compatible with the updated schedule of services in the disposition timetable, to fulfill their mobility desire. When all those steps are performed quickly, travelers might experience a minimal delay; but typically, the reaction time by the operators and the passengers is a slow and delay-prone process. From the passengers' point of view, during the disruption, they have choices to determine the best response, find the shortest alternative public transport lines to their destination, or leave the network in the disruption. They might change their route choice, mode choice, or adjust their departure time. In any case, when the disruption occurs, it causes inconvenience to the passengers, which can be quantified in delays, and a reduced utility score.

The goal of this paper is to analyze such real aspects and quantify the real-life impacts of disruptions. For analyzing the impact of a disruption, one could experimentally evaluate an occurred event, by collecting the data through surveying passengers who experienced it. Such an experimental study has been performed for mode choice analysis of passengers after a disruption (Currie and Muir, 2017; Murray-Tuite *et al.*, 2014). Their findings highlight the importance of improved information before the departure, and the fear of users to be stranded. However, for a reliable and comprehensive analysis of disruptions on public transport networks, one would need comprehensive coverage in data for all passengers, those affected, and those potentially affected, even for unexpected events. Finally, such an approach is limited only to experienced disruptions and not able to evaluate hypothetical ones.

another goal of this paper is thus to replicate the dynamics of disruptions in a simulation environment and quantify this way, their impacts on passengers. We believe that, to make the right decisions, as a reaction to a disruption, precise quantification of their effects is essential. This assessment needs a comprehensive model of the entire transportation system, in its interconnection within a specific mode, as well as from other modes, and related to the activities and desires of travelers. We resort to agent-based simulation, which has been shown to be able to replicate those constraints (Horni *et al.*, 2016), also for public transport networks (Bouman, 2017). In such simulation environments, travelers are represented by agents, which interact with each other. In general, one agent's choice affects another agent's choice and, finally, the whole environment. With a comprehensive and well-calibrated simulation model, one could assess the impacts of any potential disruptions on all the passengers on the network. To specifically perform such an analysis, we extend an existing agent-based simulation environment to incorporate the updates of public transport services as disposition timetables, as a consequence of the disruption; and the reaction of passengers, also mediated by the different degrees of information they have of those updates.

We assume a disruption is an event, 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. A disruption is typically associated with serious (multiple lines, multiple stops) and long (multiple hours) times of degraded service. 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.

This causes adjustments to the public transport service, which typically include a lot of canceled services; moreover can include and adjustment to the operating plan (timetabling), an updated rolling stock and crew allocation. Moreover, the public transport operator can activate alternative and bridging lines, increase the transport capacity (longer vehicles, more runs) of existing lines, which can help bypass the disruptive event. Such efforts can be all considered included in the concept of a disposition timetable, which differs from the planned timetable. Determining and effective disposition timetable is a complex task, to be performed very quickly, and with only approximate understanding on how the passengers might distribute along with the network, and/or react (Corman *et al.*, 2016). In any case, the transport performance of the network will be degraded from the planned one.

In case of no disruption, a typical way in which passengers distribute along the network can be computed by assignment procedures. Typical concepts used are referring to a user equilibrium solution, 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. Through a day-to-day process, travelers, for instance, learn that some lines are slower or faster and that some are close to capacity and the travelers might get denied boarding, incurring, therefore, longer travel times (typically a disutility). At the condition called user equilibrium, no traveler can improve their utility/score by their unilateral choice, without reducing the score of another traveler. A user equilibrium solution can be approximated by a variety of methods; we consider the often used day-to-day process by which travelers are assumed to learn the utility of all their possible choices by trying them and learning from the experienced outcome. Such a process can be easily implemented in a simulation model by means of an iterative convergent procedure, where each iteration corresponds to one day.

The concept of user equilibrium is not appropriate to model travelers' actions under disruptions (Dobler and Nagel, 2016). Disruption is such large, unexpected and non-recurrent events that move the system away from the equilibrium condition. In particular, the travelers can hardly anticipate the effects, i.e. most often, they know a disruption is taking place after it started, or even later, when it affects their planned trip. In such a case, the score (i.e. utility for all possible alternative choices available in the undisrupted network) that travelers might have learned through their past is not applicable to the new situation. As disruptions are not recurrent, travelers cannot learn from past experiences, and a day-to-day process looks illogical. As the disruptions are unexpected, travelers cannot be assumed to find the best alternative choice because they have limited information. In general, there is no information on the disruption itself, and the adjustments triggered in the public transport network, before the disruption itself starts. There is moreover no understanding or information about how all other travelers will react, whether everybody will try to board some specific line, for instance, triggering capacity limits. Some information will be available through time, for instance, disseminated by the operators, after the disruption started.

In an unexpected disruption, the behavior of the passenger is heavily reliant on the information they receive, in content and time. We assume at this moment that the operators are able to compute the disposition timetable that reacts the disruption in negligible time and focus only on the time at which information about this disposition timetable reaches the travelers. 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 (score). A disruption might also result in cancellation of activities due to too late arrival (i.e. arrival at work with multiple hours of delay). We consider those delays and disutility as direct effects of the disruption. Having available some information, travelers can react; specifically adjust their travel plan to the newly implemented disposition timetable, so as to maximize their utility, notwithstanding the disruption. Having available information very early can be assumed to result in fewer delays, as the set of alternative choices is larger, and allows for pro-active actions. Having information very late might result in larger delays, as there are little actions left to do. Therefore, the time at which travelers receive information is crucial. We identify a few relevant cases of the timing of information dissemination, which we will investigate in detail in this paper.

We assume travelers are rational, and as soon as they know about the disruption, they look for adjusting at best their behavior. After the sensitive analysis it can be seen, that the differences between the points in time (considering a few time for reaction) are small and does not affect the result. In general, the earlier the time at which agents would receive information, the better the reaction will be. In the case of a completely unexpected disruption, the best situation is to receive information right at the moment the disruption begins. We assume travelers can react in the following ways:

- They can become aware of the disruption at a specific time, equal for everybody (i.e. once an announcement is broadcasted to everybody at a given time).
- The time the travelers become aware of the disruption can be different for everybody, based on their time plan: think about when they finish their workday, they look for their public transport trip in a routing planner service (in this case, the time would be different for any different traveler, according to when they would finish work).
- The time the travelers become aware of the disruption can be different for everybody, based on their location: they can become aware of the disruption for instance, once they reach a station with a display.
- Special cases also include travelers who experience the disruption onboard a disrupted vehicle and thus are forced to exit the current trip and find another way of moving forward

When travelers received the information, we assume they immediately look for the 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 (i.e., compared to the undisrupted user equilibrium situation). In other words, passengers affected by the disruption, who cannot take their desire public transport vehicles, have to board to other public transport vehicles. Therefore, they add to the travel demand of the other vehicle, which on a normal (undisrupted) day, would experience less travel demand. As a result, due to the increased demand on the other lines, some passengers are not able to board, and they experience denied boarded due to the full capacity. We call the "indirect effect of a disruption" the 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 too. This results in 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.

A few studies have investigated this effect on public transport networks (Malandri *et al.*, 2018; Sun *et al.*, 2016). Such an indirect effect has been studied in (Malandri *et al.*, 2018) as "propagation effects" for the negative impact of the disruption on the higher occupancy level in the public transport network. We follow the more general way by which 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 a simulation environment, which relates the possible ways of disseminating information to travelers, to the impacts the travelers actually face, in their direct and indirect circumstances.

3 Literature review

The literature review on the effects of disruption on public transport networks is here reported, divided into four major categories. The first category investigates behavioral aspects of the mode choices of passengers in the case of disruption. Mostly, this is based on stated preferences to understand the choice of the passengers based on experimental data collected by surveys. (Currie and Muir, 2017) 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 daily-plans. (Murray-Tuite *et al.*, 2014) performed a mode choice analysis after a disruption based employing a Web-based survey. Its outcomes show that passengers are reluctant to alter mode or change travel choice in a disruption; women are more likely to make changes after the disruption rather than men. The limitations of stated preferences are in the realism of the results; and the limited realistic interactions between travelers and non-performance of the network that can be reasonably investigated.

The second focus of research studied the management of disruptions from the point of view of optimizing public transportation capacity. (Kiefer *et al.*, 2016) studied recovery plans for public transportation in the case of the disruption. Installing bus depots result useful in providing a timely alternative to the disrupted transit lines, and building additional rail capacity creates additional routes in case of a disruption. (Cadarso *et al.*, 2013) investigated the recovery of rapid transit rail networks in the case of disruption. The authors combined changes in the timetable and the availability of rolling stock to satisfy passengers' demand. They run their simulation in GAMS/Cplex 12.1, and they assumed that passengers keep their path choices, and cannot adjust their plans, even though they are aware of the disruption. Generally, the inclusion of passenger choices, and their sudden adaptation when they become aware of the disruption, which in reality might include forced alighting from a disrupted vehicle, and replan of multiple activities, is modelled partially or even not at all, due to the high complexity already in the optimization of operations. The third group quantitatively evaluates the role of information strategies in the decision making of the passengers, in public transport networks. (Khattak *et al.*, 2008) showed that the travel information delivery mechanism significantly affects the probability of passengers' travel decision adjustment, which could, for example, include changing the route, time, mode of traveling, or dropping the trip. (Kattan *et al.*, 2013) report how passengers exhibit flexibility in changing their decision about the trip to adjust to the network facing some disruption. For the given case, given enough information on the networks, public transit was found more often the travel mode of choice for the passengers, and passengers were reported to have different preferences to get updated information.

(Piner and Condry, 2017) mentioned that passengers should be kept informed as soon as information is declared accurate and reliable in the disruption. (Xiong *et al.*, 2017) used an agent-based model integrated with a simulation-based optimization model to evaluate the agents' behavior response to different information strategies under uncertainty on the transportation network under the equilibrium condition. (Leng and Corman, 2020) investigated the role of information strategies on the passengers' utility (score) in a public transport disruption under the equilibrium and non-equilibrium condition.

The last group studied the network dynamics of public transport disruptions, related to the delays that the passengers experienced. (Rodriguez-Núñez and García-Palomares, 2014) did a vulnerability analysis for the public transport network to evaluate the consequence of the disruption on the travel time of the passengers. (Ghaemi *et al.*, 2018) studied the impact of the disruption length estimates in railways on the consequent delays of passengers. A few studies specifically investigate the propagation effect of the disruption through the public transport network considering the delay caused to the passengers. (Sun *et al.*, 2016)introduce a mathematical model to consider the propagation of the delay from a trip to a trip in a network under a disruption. They estimated the changes in travel time and the delays caused by common disruptions based on the survey result. Common in their study means that the disruption lasts less than 15 minutes. They further refer to survey data to understand the implications of the disruption on travel times and delays. Passengers can be affected by being delayed, missing their transport means, or facing detours. With a similar goal, (Shelat and Cats, 2017) studied the distribution of passenger flow over the network under a user equilibrium condition, to find critical links in the network. Equilibrium simulation might result in incorrect or unrealistic results, when facing an unexpected event such as a disruption. (Malandri *et al.*, 2018) used an agent-based public transport simulator called BusMezzo to analyze the capacity vulnerability of public transport under a disruption, specifically focusing on a non-equilibrium situation.

The goal of this research is to replicate the impacts and dynamics of a real-life disruption by simulating appropriate scenarios of information dissemination and passengers' response. , we implement an agent-based simulation. We build on this state of the art, by contributing to mathematical quantification of effects, interconnected with network propagation and dynamics. The current work fills the existing scientific gaps, as follows:

- We compare the behavior of the passengers in a comprehensive set of scenarios, which include non-equilibrium conditions, and compare them to equilibrium conditions, to highlight the differences. This allows us to perform a rich comparison of passengers' behavior under disruption.

- We consider the realistic case, often neglected in the literature, that passengers become aware of the disruption onboard vehicles, such that they can (or must) adjust their daily-plans, leaving the disrupted transport vehicle along a new, adjusted, daily-plan. Moreover, we consider the capacity of public transport vehicles as a further determinant of disruption impacts.
- We consider long disruptions, for which the public transport operators will provide an alternative timetable, and the passengers will realistically update their daily-plans and replan for their travel. A long disruption also requires differentiating between information available and replanning at different moments in time, i.e. the beginning, or during the disruption, and pre-trip or en-route. Most previous research evaluating passenger delays and network dynamics under disruption (Sun *et al.*, 2016; Malandri *et al.*, 2018), chose a short (less than 45 minutes) disruption; which does not require a comprehensive modeling of the replanning process of adjustment of the daily-plans by the passengers.

4 Methodology

The simulation of the impacts and dynamics of a real-life disruption is performed by an agent-based simulation. We did a novel development in the within-day replanning module, which provides us with the possibility of simulating complex scenarios and realistic situations. This section explains some of the basic concepts of agent-based simulation, that include iterative replanning and within-day replanning, as well as some background terminology and concepts.

4.1 Agent-based simulation approach

The agent-based simulation analyzes individual behavior, by modelling each traveler as an individual agent who makes their own decisions according to predefined rules. Agents interact with each other in the simulation environment where one agent's choice affects another agent's choice and, finally, the whole environment. An agent-based model is built from three components:

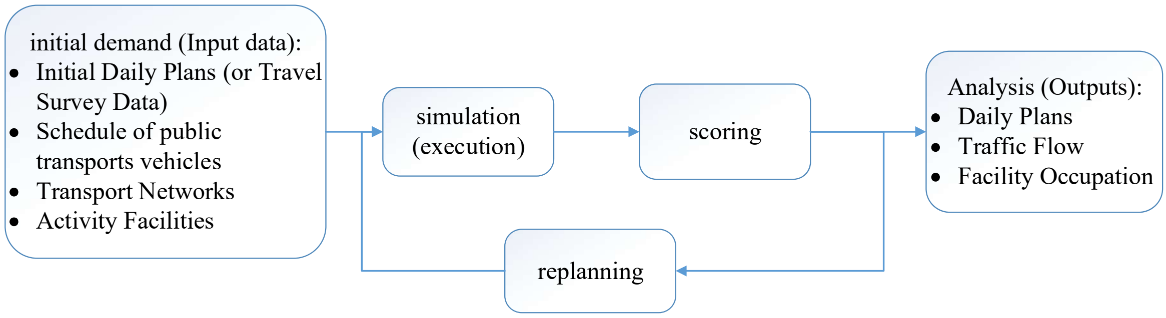
- The agents,
- The simulation environment,
- The rules are defining how agents move and interact with each other and through the environment.

Agent-based simulation models and techniques can help to formulate and evaluate the behavior of the agents in public transport research (Bouman, 2017). According to (Russell and Norvig, 2010), an agent is "anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators." Specifically for mobility studies, each traveler/agent makes their own decisions in terms of departure time, route chosen, according to predefined rules; for public transport, the specific vehicle of which line to take at which time, along which route to travel, including which transfer, etc. Performing the activities is the desired result for agents and brings them a positive benefit. The trip to reach an activity is essential that reduces the time available for the activity. Thus, the benefit of a trip is negative for the agent: the shorter, the better.

An agent-based simulation has the advantage, which is expandable as required. It supports a very high level of detail in the modeling. Each agent, for example, can be described with any number of attributes. They can have attributes such as age, gender, living place, workplace other something else. Depending on these attributes, the agents will behave differently. For example, an agent, who owns a car, prefers the car more likely than someone who does not own a car. It is also possible to modeling traffic with a high level of detail, and consider every means of transport simultaneously in one scenario. Each means of transportation is furthermore described with different attributes, also at the level of individual vehicles. It is also possible to simulate delays or a breakdown of the traffic system. An agent-based simulation, with suitable amount of agents and size of networks, and appropriate computation time, allows simulating large scenarios with arbitrary levels of detail.

Agent-based modeling attracts growing attention in the transport field. (Djavadian and Chow, 2017) Proposed an agent-based day-to-day modification process model to find the agent-based stochastic user equilibrium and its effects on operating policies. So far, several frameworks and simulation programs have been developed for simulating transport: TRANSIMS (TRansportation ANalysis and SIMulation System) was developed with the aim of forecasting travel demand (Smith *et al.*, 1995). (Javanmardi *et al.*, 2011) connected TRANSIMS to ADAPTS (Agent-based Dynamic Activity Planning and Travel Scheduling) (Auld and Mohammadian, 2009). The present research uses the software MATSim, described more in detail in what follows, which required specific extensions

Figure 1: MATSim framework, including input data, simulation run, and the output data



to include complex aspects of real-life dynamics and accurate analysis of the behavior as dependent on the information dissemination, which is so far missing in the literature. As we want to reflect on the heterogeneity of effects of disruptions, we explicitly look at the differences between agents. Agents have their daily-plans and their own attributes, including preferences regarding mobility.

4.2 MATSim

Researchers from ETH Zürich and TU Berlin have been developing MATSim (Charypar *et al.*, 2016). MATSim uses a microscopic description of demand (level of individuals) through the daily schedule and the synthetic travelers' decisions. MATSim is an activity-based and it enables an agent-based simulation of large-scale scenarios with all means of transport.

The simulation process of MATSim is an iterative day-to-day procedure to approximate the user equilibrium solution. Figure 1 illustrates the iterative procedure that primarily consists of three sections of Execution, Replanning, and Scoring. One loop corresponds to one day. The replanning step is executed at the beginning of each day. The number of iterations and thus, the number of simulated days is configurable. The individual elements are explained below as far as needed to describe the extensions proposed; we refer to (Horni *et al.*, 2016)for further details.

The demand is characterized by a set of agents, with their initial desires in terms of activities. Those desired activities could be, for example, stay at home, work, perform shopping in a specific location, spend the evening at home; each of those activities might result in a positive utility to the agent. Given those desires, people would take some actual choices, which result in a selection of activities to be performed in sequence, exploiting trips (which might result in negative utility, given the time lost travelling) to move along a network when the activities are performed at different places. A daily-plan is the actual sequence of activities (with location and duration) and trips (with mode chosen, routes, duration), in the example those allowing an agent to reach work from home; to reach the shopping location, and finally come back home at the end of the day. A trip is made up of one or multiple stages (continuous movements with one mode of transport), for instance, when agents have to transfer between two public transport vehicles. The initial demand is normally calibrated based on empirical data (Charypar *et al.*, 2016).

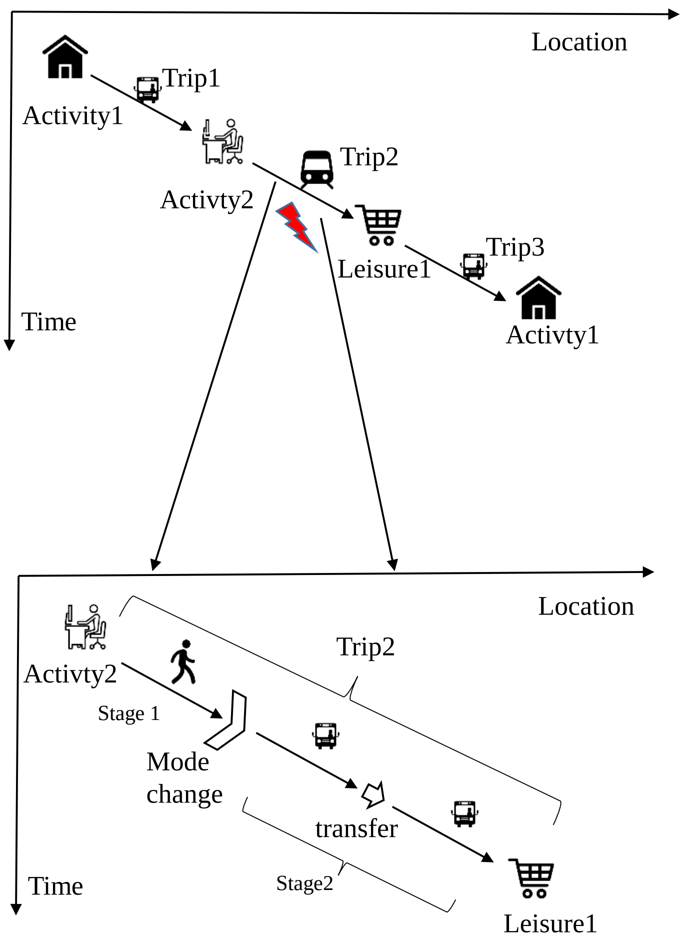
As an example, an agent can start in the morning by traveling from Home (Activity1) to Work (Activity2) by bus (Trip 1). The day continues after work by traveling to Shopping (Activity3) by train (Trip 2), and, finally, by returning Home (Activity1) by bus (Trip 3). These concepts are described in Figure 2, along with illustrative time (vertical) and space (horizontal) axes. For the sake of simplicity, in this example, just one stage per trip is considered.

The agent-based model executes the daily-plan of the agents, by updating at regular time location, possible activity being performed, possible trip being performed. The agents can interact with each other, for resources with limited capacities, for instance traffic jams might reduce the speed of road transport, crowding in a public transport vehicle might result in a denied boarding and related delay. For each daily-plan, the score can be computed at the end of the execution, based on econometric parameters. (Charypar *et al.*, 2016) developed the scoring function of MATSim, as corresponding to the sum of the utility of the activities and the travel utility, as in Formula (1) where n is the number of activities, q is an activity and S corresponds to the utility of activities ($S_{\text{act},q}$), trips ($S_{\text{trav},mode(q)}$), or daily plans (S_{plan}). The trip $S_{\text{trav},mode(q)}$, is the trip after the activity q.

$$S_{\text{plan}} = \sum_{q=0}^{n-1} S_{\text{act},q} + \sum_{q=0}^{n-1} S_{\text{trav},mode(q)} \tag{1}$$

The daily-plan are changed iteratively by the day-to-day replanning such that the utility, computed by a score function is maximized, given the choices of the other agents. Namely, based on the experienced traffic conditions of the current day, alternatives are generated

Figure 2: Explanation of traveling in agent based simulation

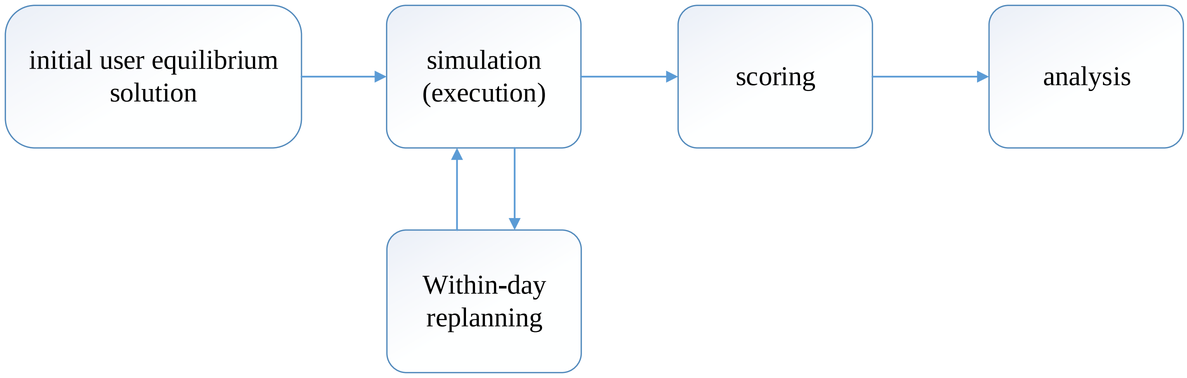


for the next day, for instance by rerouting a trip, changing the timeline of activities, choosing another means of transport, etc. Iteratively, better daily plans are chosen, and worse daily plans are discarded by the day-to-day iterative process, until an optimum is reached. When no agent can improve their utility without reducing the utility of another agent, a *user equilibrium* is reached.

4.3 Within-day replanning approach

An iterative (day-to-day) replanning approach is valid as long as the scenario describes a typical situation or day, where knowledge about the outcomes of choices are applicable and useful, to take a decision in the next days; for instance, avoiding traffic jams during rush hours by changing departure times, or using alternative routes. However, if unexpected

Figure 3: The Agent-based simulation approach (within-day replanning)



events happen, that the agents cannot anticipate, (i.e. the disruption investigated) a user equilibrium (and iterative approach used for a day-to-day process, to find it) is not a logical choice, as it is far from reality: agents face disruptions only once; and have no information on beforehand on the alternatives. (Dobler and Nagel, 2016)already reflected on the problems of illogical agent behavior in unexpected events. For instance, in a user equilibrium solution found (for instance by an iterative approach) considering the disruption, agents can start rerouting before the disruption occurs, based on the knowledge they have (from the previous iterations). However, in reality, in the case of an unexpected event, passengers do not have prior knowledge about the disruption and, therefore, they react to the disruption after they know about it. A clear solution to preventing such problems is using an alternative simulation approach which does not work based on the iterative optimization process. To this end, within-day replanning approach simulates only a single iteration, preventing problems resulting from an iterative simulation process (Dobler and Nagel, 2016; Rodriguez-Núñez and García-Palomares, 2014). Within-day replanning modifies agents' daily-plans using a single iteration (see figure 3). Therefore, it is crucial to incorporate all relevant aspects, including all information available to agents, in this single iteration. (Dobler and Nagel, 2016) developed the within-day replanning for road cars/traffic according to two parameters, the elements of the plan (activities and trips) and the time that those elements are replanned. We similarly propose that for the within-day replanning, trips can be updated in terms of stages, lines used, mode of transport, and departure time considered, while considering the same origin and destination of each trip between two given activities. The updates need to furthermore differentiate between future activities and trips, and current or past activities and trips, as some of those latter cannot be adjusted anymore because either already performed; and some can be adjusted in a limited manner because being performed, or in an immediate future which is actually unavoidable.

Figure 3 shows how such a situation can be simulated. Each agent adjusts their daily-plan by means of the within-day replanning module, which is called for each agent, at a specific time, triggered when the agents becomes aware of the disruption (we call $T_{\text{info,a}}$ the time at which agent a becomes aware of the disruption). At that moment, the decision-making process of an agent is particularly crucial. In an iterative approach, each agent has complete information and can consequently select the best updates to their daily-plan, based on a best-response principle. Due to the realistic limitation of available information, a within-day approach can only refer to a best guess, concerning the future conditions of the network. Moreover, the time and location in which agents receive the information affects the possible choices of activities and trips, which can be updated.

The within-day replanning module (WR) receives as input the daily-plan of an agent, separating between past activities and trips, which already occurred during the day can cannot be replanned or changed; and those after a certain moment in time (start of the replanning, T_{replan}) which can be actually replanned or adjusted. The start of the replanning is related to a trigger event, which represents the moment T_{info} that agents become aware of the disruption. A trigger is determined by its time, location and situation of the agents.

WR works by substituting activities and trips which can be replanned (i.e., after T_{replan}) with new ones, based on the available understanding of the status of the network, such that the total expected utility is maximized. In the first instance, we do not allow to drop or introduce new activities, but only temporally shifting them. Therefore, the only true change is regarding trips, which are connecting activities. For those, the shortest path, based on the services, which are known to be running in the disposition timetable during the disruption, is used to determine the trip with the maximum utility. For a trip, route, departure time, mode of transport, origin, and destination can be replanned. The utility of a trip can only be estimated as the reaction of other agents is unknown (for instance, many agents can be replanned within-day to a minor road, empty at user equilibrium, but that will cause large scale congestion in practice). Replanning one single trip might result in a chain of replan that cascade to later times. The WR continue to replan the daily-plans of the agents from the specific moment that it is called until the end of the daily-plan. The WR returns as output a complete daily-plan, in which the part to be replanned is adjusted. We call this output an adjusted daily plan.

(Leng and Corman, 2020) develop a first within-day replanning module for public transportation users in MATSim. Their model simulates the start time of the disruption as a trigger to use the within-day replanning module for agents. Their model identified two extreme information strategy scenarios: (1) all agents do not become aware of the disruption until the disruption is over (2) all agents become aware of the disruption at the start of the disruption. Moreover an ideal unrealistic benchmark was identified as (3) all agents are aware of the disruption, and they identify their best response in a user equilibrium case. Their model ignores capacity of public transport vehicles and therefore is unable to quantify the indirect effects of disruptions, which are the goal of this paper.

4.4 Information strategy

During a disruption, information about the details of the disruption and the possibility of alternative plans is essential for agents since the adjustment of their daily-plans is highly dependent on the information they have available. (Bouman, 2017; Kattan *et al.*, 2013; Khattak *et al.*, 2008; Piner and Condry, 2017) stress the importance of the pre-trip information dissemination in case of disruptions, to make passengers more likely to take the alternative trips' plans. We call information strategy the way by which each agent has information and the possibility to adjust their behavior, i.e. their daily-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. This research study agents' behavior in eight scenarios, schematically reported in Figure 4, further divided into 4 information strategies scenarios, and 4 reference scenarios (for comparison purposes; two of them are based on equilibrium assumption). These scenarios are:

1. No-Information (NI). Agents do not have any information about the disruption, specifically on its location, affected lines, and the start and end time of the disruption. Their reaction consists of waiting at the train station until arrival of the next vehicle, of the public transport line they intended to take.
2. Start of the morning (SM). Agents know about the disruption in the morning of the day, before they start their traveling. In this case, the disruption is not completely unexpected. Their reaction consists of replanning the entire daily-plan with the highest possible degree of freedom, even though they cannot anticipate the reactions of the other users.
3. Start of the disruption (SD). Agents become aware of the disruption exactly when disruption starts, no matter where they are already in their traveling, or in their activity location. At that time, they ask for a replanning.
4. Start of the trip (ST). Agents become aware of the disruption at different times, in

relation to the time they intend to perform their trip, which is actually disrupted. Specifically, agents affected by the disruption have by definition one or more trips in their daily-plan which cannot be performed. When the first disrupted trip is attempted to be performed, the agent becomes aware of the disruption, and asks for a replanning.

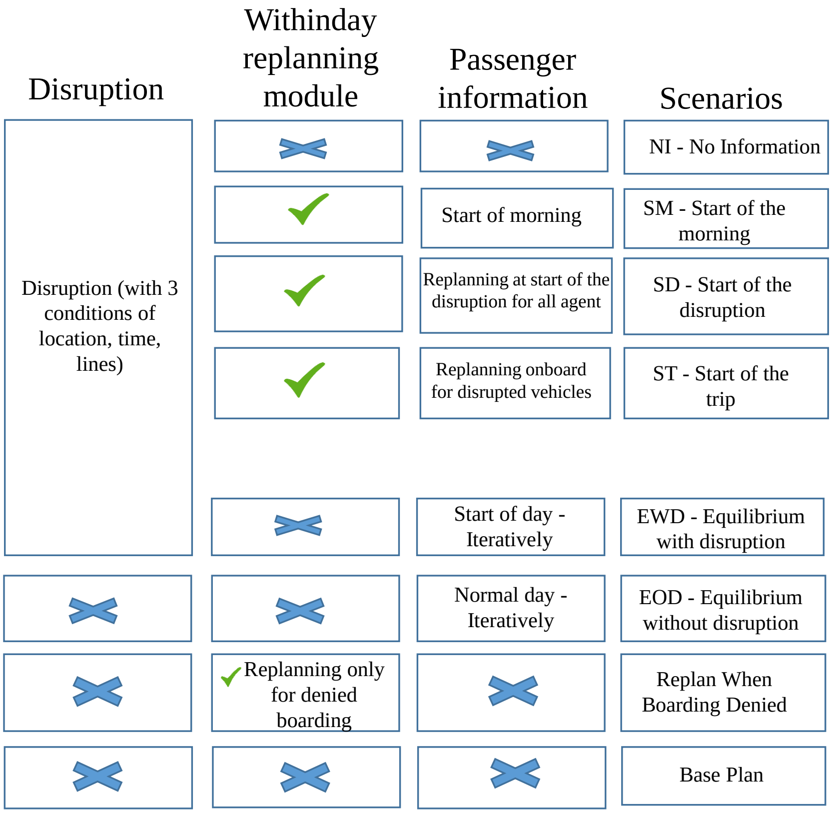
To be able to evaluate the absolute variations in score of the adjusted daily-plan of the agents in those scenarios, and relate to the delay that they experience, we simulate four other scenarios as reference cases, as follows.

5. Equilibrium without disruption (EOD). This scenario is a normal day (basic scenario) without any disruption. This corresponds to a normal daily routine for the passengers. This is the base behavior, the EOD for the agent that is approximated through the iterative process of day-to-day replanning in the agent-based simulation.
6. Equilibrium with disruption (EWD). This scenario has a disrupted timetable as the input data and runs through the iterative process. In this scenario, the agents are supposed to know the disruption, and discover by a day-to-day iterative approach the reaction of the other agents to the disruption. This results in a different user equilibrium, adapted to the disrupted situations.
7. Replan When Boarding Denied. This scenario is a normal day (basic scenario) without any disruption, but specifically quantifying the effects of public transport vehicle capacities and crowding into the choices of agents. In this scenario, agents who are denied boarding due to the full capacity, in an undisrupted day, will go through the within-day replanning module to receive a new plan for the traveling.
8. Base Plan. This is the desired plan described determined by the input data, and used a starting solution for the iterative day-to-day process. This scenario is used for quantifying the delay experienced by the agents.

4.5 Within-day replanning methodology and approach

In this research, to be able to simulate direct and indirect effects of a disruption, we develop a methodology for within-day replanning, and consequently extend the MATSim environment. The functional goals of the methodology and the newly proposed within-day replanning module are:

Figure 4: Description of the scenarios considered



1. to consider an entire multimodal network as solution space for the adjusted daily plans, and an equilibrium solution proving starting daily plans;
2. to refer to a utility function of the users, which is to be maximized by the choices made available by the 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, at a specified time (3B) or place (3C);
4. to be able to adjust the daily-plan starting from a specific time T_{replan}, in general related to the T_{info}.
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 daily-plans (replan of activities and trips) as far as those cannot take place as originally planned.

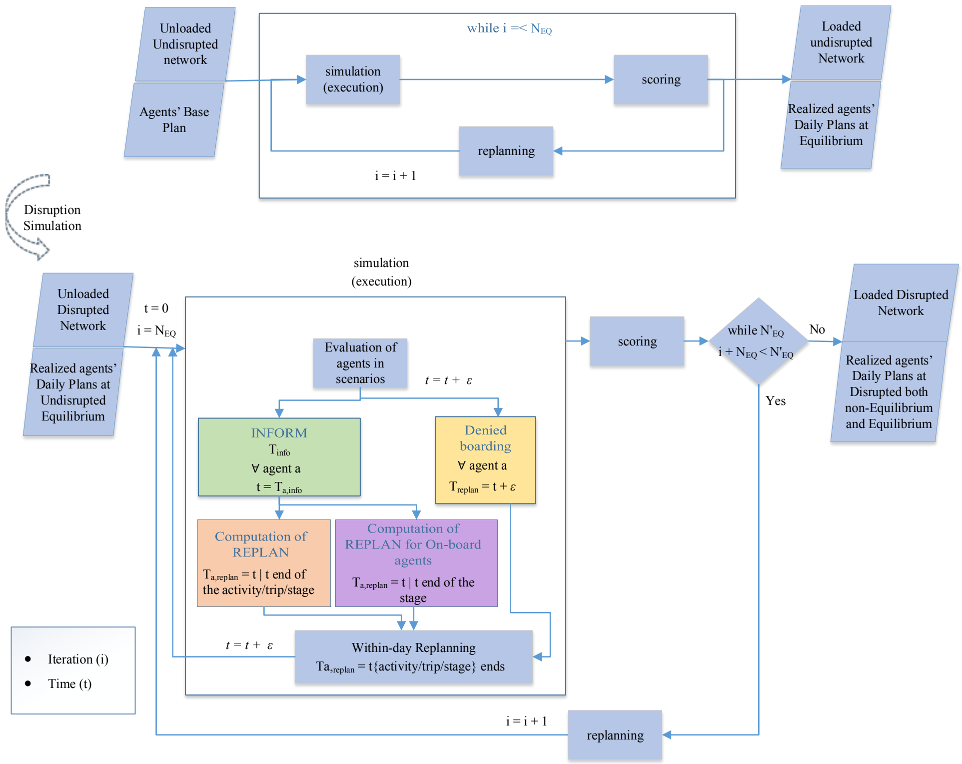
Figure 5 reports graphically the flowchart of the methodology used. We now explain how the four functional goals above categorize the chosen information strategies scenarios. Moreover, other possible choices of information strategies can be implemented, given the generality of the methodology. Functional goals 1 and 2 are respectively addressed by the comprehensive agent based simulation used, and the within-day replanning module as explained above. In scenarios SM and SD broadcasting (3A) is used to distribute information. In other words, 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. In general, the earlier T_{info}, the better the alternatives which could be chosen. The scenario SD has been already identified (but neglecting vehicle capacity and indirect effects) in (Leng and Corman, 2020).

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 covered by functional goal 3C above.

In scenario SM, the within-day replanning module adjusts the daily-plan starting from a T_{replan} equal to the end time of the first activity, which is by default is staying at home overnight. In scenario SD, the within-day replanning module considers a T_{replan} equal to the start time of the disruption, regardless of the state or location of the agents. At that time, two possibilities are given: agents can be performing 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, or ending of the current stage of the trip. This relates to the functional goal 4. In scenario ST, T_{replan} is actually coinciding with T_{info}, 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, T_{replan} in ST is time and space based.

In both SD and ST, there is the possibility that some agents are already on board on a disrupted public transport vehicle when they know about the disruption (shown in purple color in figure 5) through call announcements and a display. This case corresponds to the functional goal 3B. In such a case, all passengers onboard will receive the information that their trip cannot be performed as planned, when the vehicle actually becomes disrupted (T_{info}). The agents will need to disembark and replan; in such case, T_{replan} is also the same

Figure 5: Flowchart of the proposed methodology



as T_{info}.

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 the functional goal 5, and shown in yellow color in figure 5). In such a situation, there is no concept of T_{info}, but T_{replan} corresponds to the moment of being denied boarding. The within-day replanning determines an adjusted daily-plan from the time and location in which they are denied boarding. Finally, the daily-plans of the agents are first adjusted from T_{replan} until the next activity in their daily-plans that does not require adjustment. In fact, a delay from the first disrupted trip might propagate through the entire daily-plan. Moreover, a traveler might face multiple times replanning over a daily plan, especially in case of denied boarding. This relates to the functional goal (6).

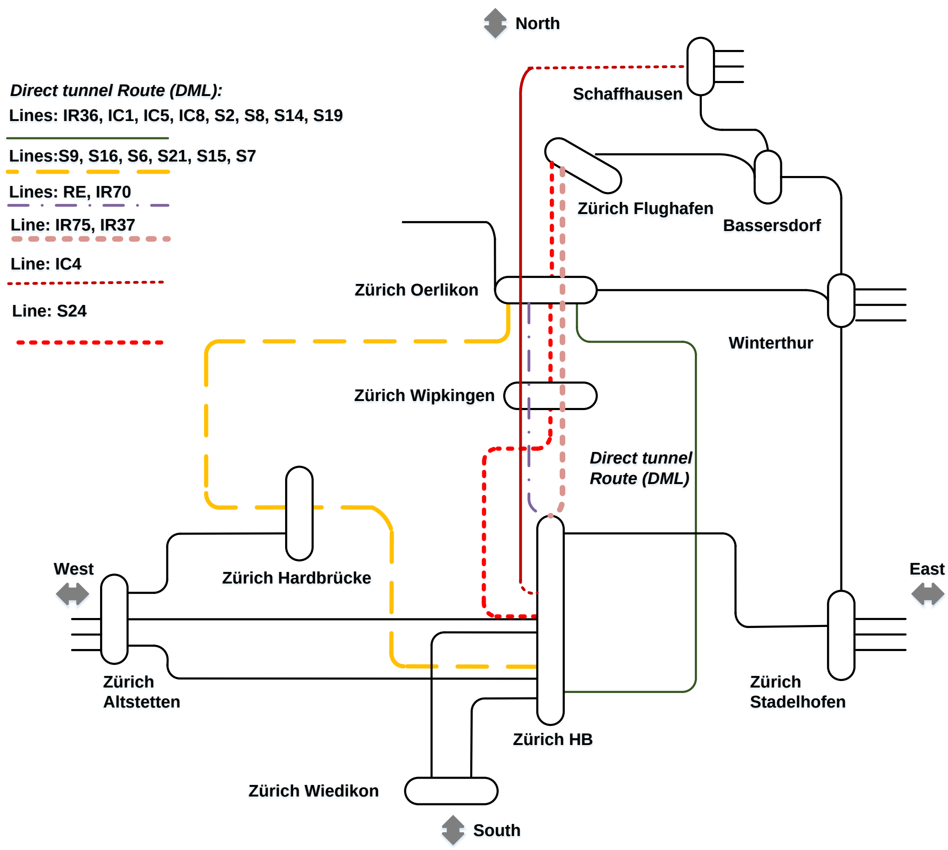
5 Case study

To test our methodology and evaluate the direct and indirect effects of a disruption on a large multimodal network, we chose on the entire transport demand in Zürich, and its public transportation system. However, the proposed methodology is not limited to any particular geographical situation, and can be applied universally. We represent the population of Zürich by means of agents, at 1 %-symbol sampling rate, that is, each agent represent 100 persons in real life; capacities of road links and vehicles are scaled accordingly. This results in 15'286 agents. We refer to a disruption affecting the core of the public transport network, namely affecting Zürich HB, which is the central rail station in Zürich, and Zürich Oerlikon, the second-largest nodal point. Between those two stations, three alternative rail infrastructure connections are running via Zürich Hardbrücke, via Zürich Wipkingen and via the Zürich cross-city link (DML) tunnel. Services at Zürich Hardbrücke station are operated by six train lines: S15, S9, S16, S6, S7, and S21. Services at Zürich Wipkingen station are also operated by six train lines: S24, RE, IC4, IR75, IR37, and IR70. The tunnel line (undisrupted) is used by eight train lines: S2, S8, S19, S14, IR36, IC8, IC5, and IC1. There are moreover a series of trams and buses, which with or without a transfer allow for a connection between those two major stations. A schematic view of the disrupted lines and stations is illustrated in Figure 6. The disruptions are confined to geographical and time dimensions. The dotted lines in Figure 6 represent the disrupted sections of the rail lines, while the solid lines are those sections of the rail lines, which are always available for trains to run. All other public transport, based on tram or buses or other vehicles, is not affected by the disruption, as well as all road transport. We assume that on a normal working day, a disruption occurs on both rail infrastructure connections between Zürich HB and Zürich Oerlikon via Zürich Hardbrücke and Zürich Wipkingen.

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 Time, which is from 16:00 to 19:00:

- For the lines via Zürich Hardbrücke and Zürich Wipkingen, all the train scheduled are canceled between Zürich HB and Zürich Oerlikon. For the line, IC4, since it does not have any stop between Zürich Oerlikon and Zürich Wipkingen, the cancellation is extended until/from Schaffhausen. The same is true for lines IR75 and IR37, being canceled until/from Zürich Flughafen.
- Between 16:00 and 19:00, the original train schedules beyond either Zürich HB or

Figure 6: Details of rail elements in Zürich scenario for the considered example



Zürich Oerlikon (apart for the exceptions just introduced for IC4, IR75 and IR37) are maintained.

- Before 16:00 and after 19:00, the original train schedules are not affected.
- Some terms used in the upcoming section are defined here:
- The Disruption Time is the time between disruption start (16:00), and disruption end (19:00).
- 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 6.
- A Disrupted Vehicle is a vehicle used by a service, which is not able to run due to the disruption.
- 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). In addition, for lines IC4, IR75, and IR37, which do not have any intermediate stop, the extended Disrupted Stations are Schaffhausen and Zürich Flughafen.

Referring to this disruption, we identify agents affected by the disruption as those running at the disrupted time, on a disrupted vehicle, between the disrupted stations, in the EOD scenario. In other words, the agents daily-plan under scenario EOD would use any Disrupted Lines (S15, S9, S16, S6, S7, S21, S24, RE, IC4, IR75, IR37, and IR70), during the Disruption Time, to travel between the Disrupted Stations (Zürich Hardbrücke, Zürich Wipkingen, Zürich HB, and Zürich Oerlikon - for IC4 Schaffhausen and finally Zürich Flughafen for lines IR75 and IR37), or travelling further, but requiring to pass over the disrupted lines. In the simulated test case, 140 agents (therefore corresponding to 1400 people in real life) cannot perform their usual trip. These agents are called "directly affected agents" and we analyze their behavior and utility in detail. We later study in sections 6.3 and 6.4 the indirect effects of the disruption on the "indirectly affected agents", who face denied boarding due to the replanned directly affected agents

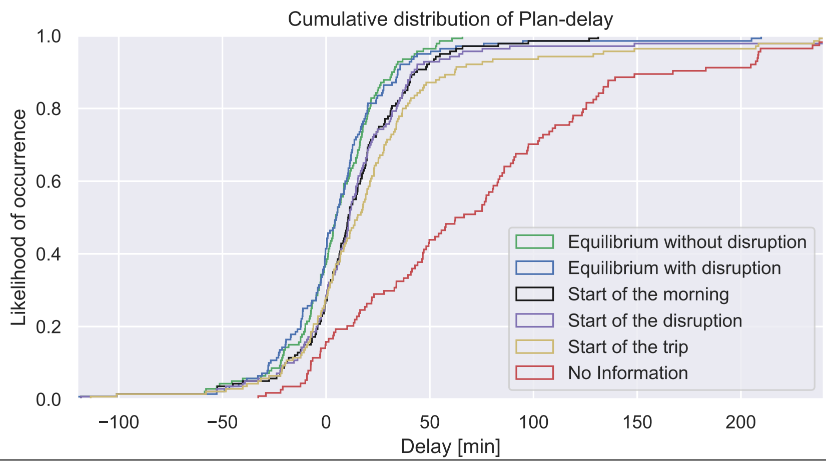
6 Results

6.1 Delay Analysis, directly affected agents

In this section, we quantify the effects of the different information strategies on arrival time of the directly affected agents only, to evaluate the role that information strategies have on mitigating the Plan-delay and Activity-delay of the agents directly affected by the disruption.

We start by considering the Plan-delay. This is the difference between the time that agents arrive at the location of their activities, and the time that agents wished to arrive as in input data, or Base Plan scenario. We compute a scenario-wide Plan-delay quantity by summing up, for each scenario, the Plan-delay for all directly affected agents, for all activities taking place after the disruption begins. In fact, on a normal day without disruption, agents may experience anyway a delay (schedule delay in transport economics), that they accept as minimal disutility, thereby arriving possibly slightly late at work or the activities of their choice. In other terms, the Plan-delay is the delay on a normal day, which will be increased by the delays caused by the disruption, when a disrupted scenarios is considered. The cumulative distribution of Plan-delay (i.e. delay compared to desired time in the Base Plan) under different scenarios are shown in Figure 7. X-Axis shows the delay, in minutes, Y-axis the cumulative probability, varying from 0 to 1; the

Figure 7: Cumulative distribution of Plan-delay for directly affected agents



scenarios are represented in the legend with specific colors; the same color scheme is used throughout the paper.

Figure 7 demonstrates how EOD scenario (green) corresponds to the least plan-delay (i.e., the one at the left-most side of the Figure), and a slightly worse solution (i.e. slightly larger delays, for all agents) is reported by EWD (blue). After these two (ideal) equilibrium scenarios, the rank of scenarios in terms of increasing delays is SM (black), SD (purple), with comparable values; further, ST (yellow), and NI (red), with the largest Plan-delay. These results are in agreement with our understanding.

The delays of the agents are due to the disrupted trips; and the propagation of delays towards later activities and trips. Moreover, some agents may experience denied boarding due to full capacity and, therefore, even longer waiting times. The statistics for the Plan-delay which happens after the disruption, i.e. for all the activities that have been done after the begin of the disruption at 16:00, is reported in table 1.

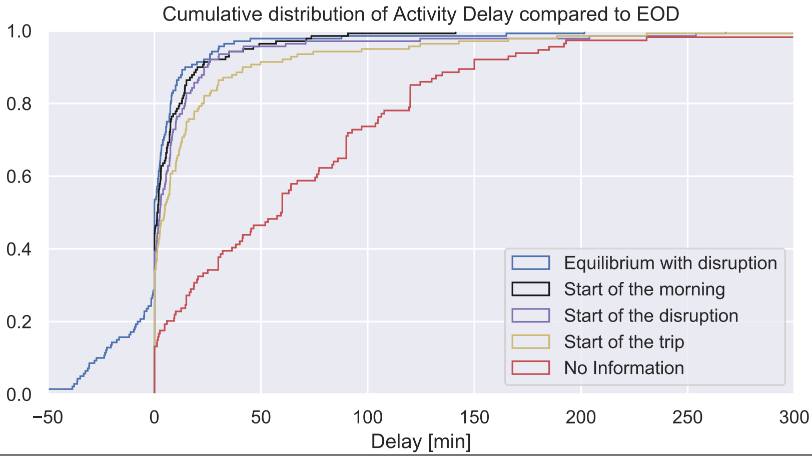
The detailed numerical results of Plan-delay are reported in Table 1, as scenarios (columns). In general, the lower, the better; but a very negative plan-delay corresponds to a negative schedule delay, which might be again resulting in disutility. All numbers are in minutes unless otherwise reported. The rows report the data as follows. Regarding the mean and its normalized value wrt to EOD, the rank of the scenarios follows the order identified already in the previous diagrams. The overall impact of the disruption can be already estimated by the 62% more delays experienced in the EWD. In other terms, even in

Table 1: Agents' Plan-delay in each scenario

	EOD	EWD	SM	SD	ST	NI
Mean	4.0	6.0	12.4	17.0	23.4	74.2
% of EOD	100	150	310	425	586	1858
Minimum	-118.2	-134.7	-118.2	-118.2	-113.5	-32.7
25 perc	-6.9	-9.5	-0.7	-0.8	-1.2	18.9
50 perc	4.7	5.0	10.7	11.3	15.1	64.4
75 perc	17.7	16.9	26.0	28.0	33.9	110.2
90 perc	31.9	34.5	42.7	41.3	62.0	161.6
Maximum	65.8	209.8	131.2	314.8	331.9	331.9
Agents	140	140	140	140	140	114

presence of perfect information and optimal response, the disruption results in some unavoidable delay. When no equilibrium is considered, but the disruption is still known well in advance, i.e. scenario SM, the delay is three times as in EOD, and twice as in EWD. 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. The best non-anticipatory scenario, i.e. SD, assumes all agents are able to adjust their daily plan as soon as the disruption starts, and is resulting in almost twice as large delays as the SM. The ST scenario has further 25% more delay. No information (NI) unsurprisingly results in by far the worse delay, almost 20 times more than EOD. The spread between the lower percentile and the higher percentile is relatively constant (24 to 28 minutes for the interquartile range is about for all approaches, apart from ST = 35 minutes, and NI, 90 minutes). In other terms, having information not only reduces delay, but reduces the amount by which different agents experience delay, reducing especially the large delays. This effect is also evident between SM and SD, which differ mostly on the very high percentile, i.e. the very delayed agents, while most other figures are in good agreement. In other terms, knowing about the disruption earlier helps the most those people who will suffer the largest delay. The minimum delay for NI is largely positive at 18 minutes, while all other replanning approaches can guarantee that at least somebody arrives early, due to some replanning. The maximum delay is very large for all non-anticipative scenarios, i.e. SD ST and NI, which hints at the fact that despite replanning, some agents are still experiencing a very large delay. In fact, some services canceled during the disruption have no alternative available in the multimodal public transport network of Zürich.

Figure 8: Cumulative distribution of Activity-delay (delay wrt EOD) for directly affected agents



We now investigate the Activity-delay. This 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. In general, the lower, the better; again a very negative Activity-delay corresponds to a negative schedule delay, which might be resulting in disutility. The cumulative distribution of Activity-delay under different scenarios is shown in Figure 8, and the detailed statistics about the Activity-delay in Figure 8 and Table 2. The layout and conventions are the same as the previous Figure and Table.

Table 2: Activity-delay (delay wrt EOD), in each scenario

	EWD	SM	SD	ST	NI
Mean	2.1	8.5	13.1	19.4	67.1
Minimum	-54.26	0	0	0	0
25 perc	-1.51	0.02	0.02	0.02	15
50 perc	0	1.5 2.59	4.75	59.7	
75 perc	6.11	7.6	10.09	15.3	104.5
90 perc	14.75	20.4	23.5	41.8	147.8
Maximum	201.65	141.2	267.8	321.3	321.3
Agents	140	140	140	140	114

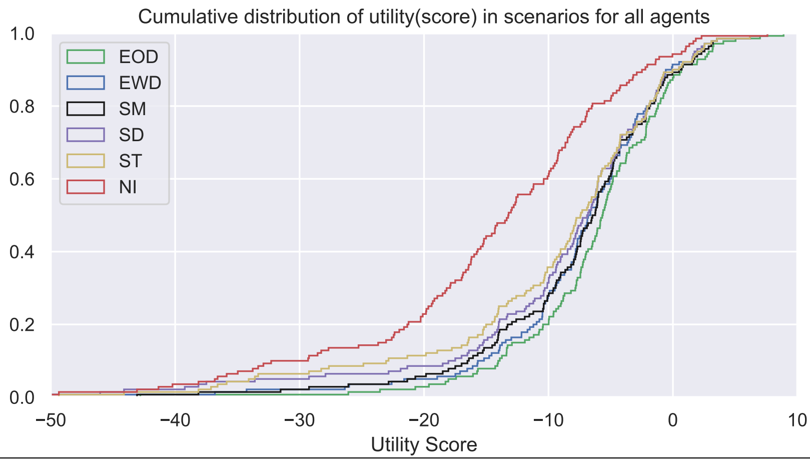
Figure 8 reports the Activity-delay wrt to the EOD (therefore, EOD is not shown, and would correspond to a 0 Activity-delay). Three main patterns are evident: EWD results in positive and negative delays at the same time, with a 50 percentile actually equal to the EOD. The NI results in large Activity-delay, ranging from 0 till well above 300 minutes. The other approaches exhibit limited difference, but a clear rank is evident, with SM performing better than SD performing better than ST. The gaps between those three approaches are all in the order of 5 minutes. It can be seen in Figure 8 that some agents experience a negative activity-delay in the EWD compared to EOD, corresponding to an earlier arrival. On the other hand, some other agents experience a positive Activity-delay. In fact, the iterative day-to-day approach seeks for a different equilibrium, where agents collectively change their plans, and as a result might have a different timing of activities and trips, and even changing transport mode. Overall, the net effect is still a delay, albeit a minor one, quantifiable in 2.5 minutes extra. From Table 2 it is also evident how EWD requires changing the plans to many agents, with a 90-percentile value of Activity-delay actually higher than SM and SD. In other terms, the larger the degrees of freedom that a population of agents has, to deal with a disruption, the larger the changes that the agents will experience, some in positive, some in negative. Figure 8 clearly highlights the large variability of EWD, but its low mean. All within-day replanning have a positive Activity-delay. The maximum delay is 321, which is more than 5 hours; this might be related again to possibly stranded passengers. We also remark how NI results in less agents considered in the figure, as 26 agents (corresponding to 18% of the 140 directly affected agent) cannot perform any activity after the disruption.

Overall, Table 2 shows that the Activity-delay has a similar rank and behavior as the Plan-delay, but different absolute values. Based on this, we will later focus the discussion of the indirectly affected agents on the Activity-delay only.

6.2 Score Analysis for directly affected agents

In this section, we discuss the results in terms of utility score, rather than delay. Similarly to the previous sections, we discuss the results in terms of a cumulative distribution plots, which highlights the heterogeneity of effects towards the affected agents, and numerical details in a table. Those are Figure 9 and Table 3 respectively. The same conventions as for the previous Figures and Tables apply. Contrary to delay (a lower delay is better), a higher score is better. Considering this, Figure 9 is mostly specular compared to Figures 7 and 8, with different concavity, and reversed horizontal positioning of the best/worst conditions.

Figure 9: Cumulative distribution of the utility score for the 140 directly affected agents



Overall, the rank (best to worst) of the scenarios follows mostly the previously identified dynamics, i.e. EOD better than EWD, SM, SD, ST and NI. The directly affected agents by definition have a user equilibrium daily plan where public transport is used (otherwise, they would not be disrupted). In case they cannot perform their desired trip as in the user equilibrium, they will experience a negative utility. In the specific case, they mostly resort in changing mode of transportation, which avoids the disruption, but results in less utility, given the used score function. Moreover, we remark that we report in Figure 9 only the directly affected agents; already from the previous two sections, it was evident how the EWD in fact, changes activities, routes, trips for many agents. In the specific case, the global mean score (i.e. of all 15286 agents, not just those 140 directly affected by the disruption) in EWD decreases by 0.02774 (0.8% decrease) from the EOD solution, this latter being evaluated at -3.25886. For the directly affected agents only, it decreases more, a 17% reduction (Table 3). In other terms, there are other agents, which, in the newly found user equilibrium with disruption, actually benefit from the corresponding reduction of utility that the directly affected agents incur. This heterogeneity of effects that a large-scale change of conditions brings was already discussed, for the smaller group of directly affected agents. Summarizing this effect, changing much in the daily-plan of the agents, a globally better solution can be found, but some agents might actually experience lower disutility than in other cases.

Looking at the within-day replanning scenarios, the gap between SM, SD and ST is rather limited to within 10% of the EOD; the minimum, 75 percentile and maximum are relatively equivalent. In other terms, the difference lies mostly in a lot of agents within the lower half of the score, which experience a further decrease in score, the later information is shared and replanning can be performed. The maximum score is anyway positive, i.e.

Table 3: Agents' Score, in each scenario

	EOD	EWD	SM	SD	ST	NI
Mean	-6.3	-7.4	-7.7	-9.0	-9.6	-14.7
% of EOD	100	117	122	142	152	233
Minimum	-42.8	-55.2	-43.1	-59.0	-49.3	-51.6
25 perc	-9.1	-10.3	-10.4	-11.6	-13.5	-19.5
50 perc	-5.7	-6.6	-6.4	-6.9	-7.4	-13.2
75 perc	-2.1	-3.1	-2.8	-3.0	-2.9	-7.4
90 perc	0.7	-0.5	0.5	0.0	0.0	-2.5
Maximum	8.9	7.6	7.6	7.6	7.6	7.6
Agents	140	140	140	140	140	140

some agent surprisingly improves utility in the wake of the disruption. Similar effects, affecting a negligibly small amount of agents, were reported also in (Leng and Corman 2020) and are to be imputed to outliers in the large data analyzed, and the approximations in the functioning of the agent-based simulation.

The gap between the SM and SD scenario, quantifiable in 8% relates to the benefit of knowing the disruption beforehand, and having a larger set of possible choices to choose for replanning. The slightly larger difference between SD and ST shows how a later information time decreases the utility even further. Both those effects are stronger for the lower percentiles of scores, i.e. those agents experiencing the highest disutility. In any case, the gap with NI is very large, delivering almost twice as large disutility as the second-worst. NI is also reporting a distinctively large spread of score between min and max, and also interquartile range, i.e. the stranded passenger who are not able to replan experience a very large disutility (which is a parallel to the delay discussed in the previous sections).

As a conclusion, in unexpected disruptions agents cannot react by shifting their activity to a moment earlier in time, and cannot drop activities to improve their score. Therefore, we see the value computed for the score largely equivalent to delays, for what concerns a discussion of the effects of information strategies towards network performance by means of within-day replanning. For this reason, we will focus only on Activity-delay in the next sections.

6.3 Indirectly affected agents

We so far investigated the agents who are not able to perform their trip as it was planned, because of a disrupted public transport vehicle, i.e. the directly affected agents. However, when considering the vehicle capacity, the disruption has an indirect effect on other users of the public transport network as well. This indirect effect is firstly quantified here, as variations (increase/ decrease) in the occupancy level on the other lines, due to a disruption happening somewhere in the network. Practically, this results in lines, which bypass the disruption, being more loaded, and therefore resulting more often in denied boarding to anybody willing to take them. Overall, the former phenomena will lead to delay for a broader geographical and time dimension, with more agents than the directly affected ones, actually experiencing a disutility related to the disruption (negatively indirectly affected agents, experiencing a positive delay).

It can also happen that the disruption results in less loads in specific lines, for instance those where people on the disrupted vehicles would normally transfer to; this results in less load on vehicles somewhere in the network, and possibly more utility for a restricted set of passengers (positively indirectly affected agents, experiencing a negative delay, i.e. an early arrival). This chapter investigates in detail and quantifies those two effects.

Figure 10 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 red color of the bubbles shows the negative, and the blue shows the positive indirectly affected agents. The bigger the size of the bubble represents a larger number of agents affected for that specific location. The two largest bubbles are the focal points at Zürich HB (middle, bottom half) and Zürich Oerlikon (middle, center).

As can be seen, the number of agents who are negatively indirectly affected (overall amount of red) is highest in SD scenario, and the second-highest in the SM scenarios, both larger than the NI scenario. This result comes from the fact that agents in NI scenario will have no within-day replanning, therefore not changing the occupancy level of the other parts the public transport network. Their adjustment will result in travelling later when the disruption finished, which is a large peak of people, but that would mean to move after 19.00, that it after peak hour, therefore resulting in less crowding experienced or caused. The two scenarios, SD and SM, have instead an explicit adjustment by the within-day replanning module. As a consequence, they are able to avoid the disrupted area,

Figure 10: Location and amount of agents negatively and positively indirectly affected by the disruption. Map size is about 15 km. (scenarios A: SM, B: ST, C: SD, D: NI)

but increase the occupancy level of the other public transport lines (not affected by the disruption). As those lines might be crowded, more agents will experience denied boarding and therefore be indirectly negatively affected by the disruption. 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 the last, compared to the other scenarios, they will resort less to use other lines of the network, therefore spreading less the negative indirect effects throughout the network. They also avoid to move all together when the disruption ends, i.e. what happens in NI scenario.

Thus, we see a tradeoff between reducing delays for the directly affected agents (SM, ST), and increasing spread of the delays in the network (more negatively indirectly affected agents), aiming for generalized small delays throughout the network. On the other hand, NI has the largest heterogeneity in effects. The directly affected agents suffer large delays, but not do not spread the disruption to other travelers, resulting in the solution with the highest heterogeneity of results for the agents. The best solution in those reported is SM, which nevertheless exploits information before the disruption takes place. Figure 10 also illustrates that in the NI scenario, the negatively and positively indirectly affected agents are localized at the disrupted places. In scenarios which include replanning, like SM, agents are affected in a broader geographical dimension, effectively making the disruption impact a much larger area.

Figure 11 shows the negatively and positively indirectly affected agents, based on the time at which their delay occurs. The same scenarios as in the previous Figure are reported, the bubble size refers again to the amount of agents affected, the color refers instead to a timeline after the disruption begins (respectively starting later than 16 and before 17, later than 17 and before 18, ...): earlier times are in darker color, later times in lighter colors. The Figures 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 NI scenario. The positively affected agents are present until 21.00 in SM, SD and ST scenarios, and until to 22.00 in the NI scenario. This is again consequence of their replanning, which happens only as a shift in time (they postpone their trip until the disruption is over), which keeps lighter loads in other parts of the public transport network for a longer time. In general, 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. This also hints at the complexity of the dynamics of the indirect effects, which have been quantified here.

The largest indirect effects of the disruption are well identified close to Oerlikon, in the first moments of disruption (16.00-18.00) which shows the vulnerability of this central station, for the considered disruption. The affected stations have the largest share of negative affected agents, with Zürich main station having no positively affected agent. This hints at the interconnection of the network and the availability of sufficient capacity in the vehicles departing.

We finally discuss the positive delay and negative activity-delay (earlier arrival) for the indirectly affected agents in each scenario. Figure 12 illustrates the data for negatively (left) and positively (right) indirectly affected agents, as a bar chart. The amount of agents affected is reported at the bottom of the plot.

Figure 11: Time and amount of agents negatively and positively indirectly affected agents by the disruptions, Map size is around 15 km. (Scenarios A: SM, B: ST, C: SD, D: NI)

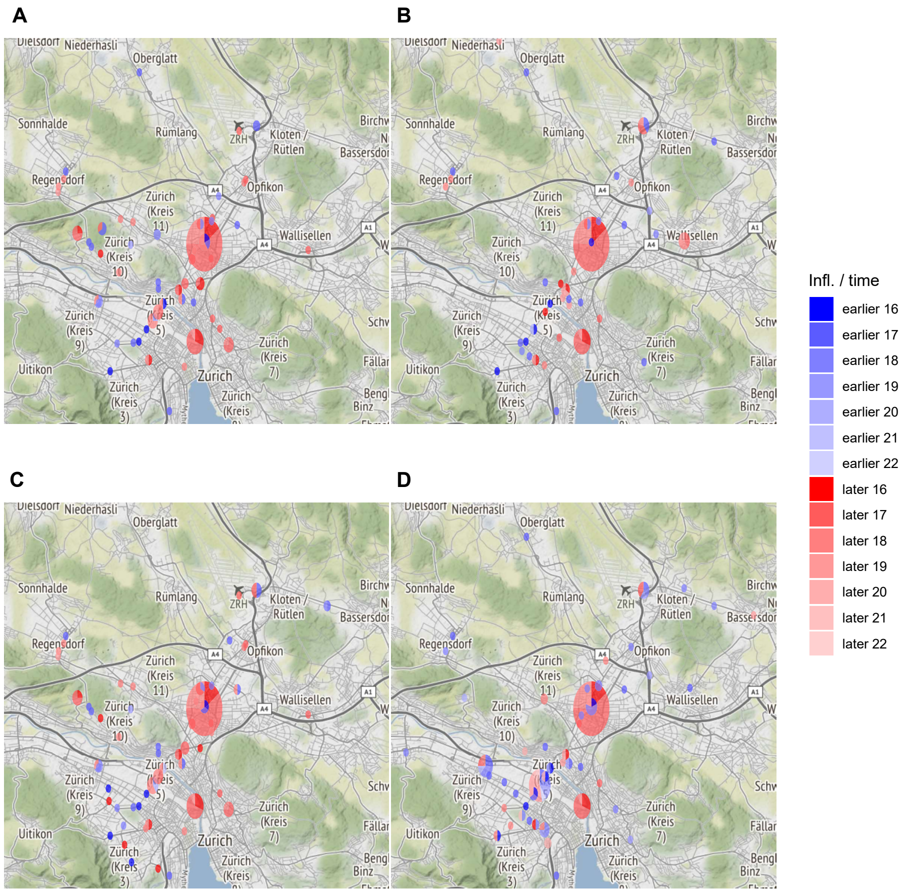
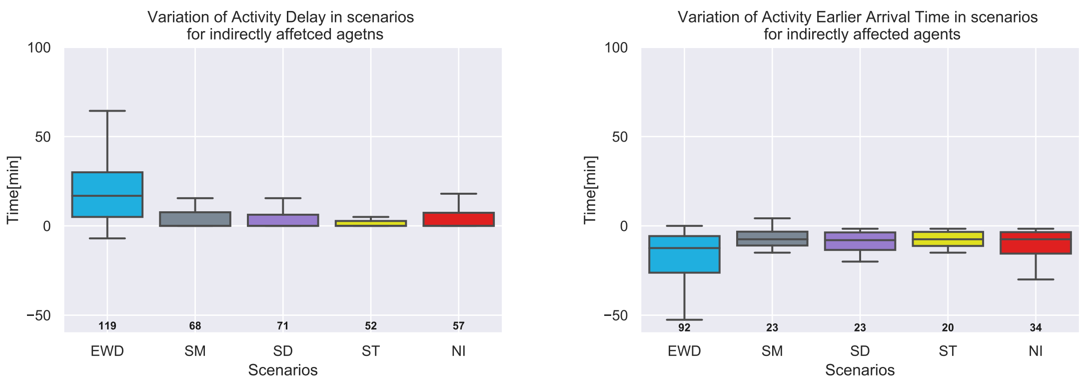


Figure 12: Activity-delay for activities after disruption time for negatively(left) and positively(right) indirectly affected agents



The EWD shows already a large variation with roughly the same amount of agents experiencing a negative effect (24 minutes on average) and positive effect (10 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 very small on average. ST has the smallest amount of negatively affected agents, as well as the 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 is to be traced to the equilibrium process and its approximation process. Almost all scenarios have higher absolute improvement for positive effects than negative effects, though the amount of positive affected agents is roughly half than those negatively affected. In absolute terms, the amount of agents indirectly affected is comparable with 20% of the directly affected agents.

Table 4 (respectively Table 5) presents a numerical overview of activity-delay, i.e. wrt to the EOD solution; the style is the same as for previous Tables. Please note that the amount of agents experiencing negative, i.e. delays (respectively, positive, i.e. early arrival) indirect effects is variable, with EWD having the highest. In terms of magnitude, the largest deviation is for the NI scenario, and the positive indirect effect. EWD again results the largest number of indirectly affected agents, and the largest magnitude for the negative, and a magnitude comparable to the largest, for the positive effects. The lowest amount comes to the ST, also less than SD.

6.4 Comparing the direct and indirect effects

We finally review together direct and indirect effects to further appreciate the heterogeneity of the different information strategies and scenarios. We expand the study to include all scenarios introduced; in fact in the EOD, EWD and NI there is no reaction to denied boarding; or no replanning at all. We thus compare directly EWD and NI to the EOD scenario. We moreover introduce a specific EOD+Replan denied boarding (EOD+RDB in short), which allows a direct fair comparison when within-day replanning is included

Table 4: Activity-delay for activities after disruption time, for negatively indirectly affected agents

	EWD	SM	SD	ST	NI
Mean	19.4	6.4	5.9	4.9	4.2
Minimum	-7	0	0	0	0
25 perc	5	0	0	0	0
50 perc	16.8	0	0	0	0
75 perc	30	7.6	6.2	2.8	7.3
90 perc	42.5	27.8	15.5	14.5	13.5
Maximum	84.6	67	67	52	30
Agents	119	68	71	52	57

Table 5: Earlier arrival time (negative Activity-delay) for activities after disruption time, for positively indirectly affected agents

	EWD	SM	SD	ST	NI
Mean	-16.3	-12.1	-13.5	-11	-14.6
Minimum	-94.5	-60	-60	-60	-120
25 perc	-26.2	-11	-13.5	-11.2	-15.5
50 perc	-12.4	-7.5	-8	-7.5	-7.5
75 perc	-5.7	-3.2	-3.7	-3.4	-3.5
90 perc	-0.7	-1.8	-2	-1.8	-2.1
Maximum	39.2	4.2	-1.6	-1.6	-1.6
Agents	92	23	23	20	34

(i.e. EOD+Replan denied boarding is compared to SM, SD, ST). Even in the ideal EOD situation, 635 agents are denied boarding due to full capacity of some vehicle. The user equilibrium solution includes this delay and discomfort, though agents are not able to avoid to take a crowded vehicle, or the effects of interaction of the agents is within the approximation of the final user equilibrium. In the EOD+RDB Scenario, the number of agents who are denied boarding due to the full capacity during an undisrupted day is reduced to 629 agents. In other terms about 1% of the agents (6 out of 635) is able to react to a denied boarding, taking other lines which happen to be uncrowded, and avoiding own disutility, but also avoiding insisting in boarding a crowded line. This hints how the capacity effects are present 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 6. 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. 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 indirect effects are almost one order of magnitude smaller in total, as result of a comparable magnitude of effect, but affecting a much smaller amount of agents. Instead the direct effects are much larger, almost four-fold. Those direct effects are actually experienced by the same amount of people, which therefore are much more delayed than in the EWD. SD is the lower bound in case of unexpected disruptions, and increases mostly only in terms of direct effects, while indirect effects are comparable to SM. ST further reports higher direct effects, and lower indirect effects, for a grand total delay which is roughly double than SM. Finally, NI has a tremendously high direct effect, and the smallest amount of indirect effects. EWD manages to reach a very small average delay, of less than 4 minutes when the absolute magnitude of effects is divided by the very large amount of agents affected (351 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, and the amount of agents affected decrease. Therefore, a solution changing the activity 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, in order to decrease the effect of the disruption.

7 Conclusion

In a public transport disruption, due to the dynamic nature of the public transport system, passenger flows and capacity limitations, disruptions effects are not confined to the disrupted area and time, but the consequences of the disruption are spreading in a broader geographical and time dimension. We consider different information dissemination strategies and the resulting trips and activities of passengers when facing a disruption, including equilibrium and non-equilibrium situations. We use the microscopic agent based simulation tool MATSim, for which we develop extensions to the within-day replanning module to include specifically the influence of vehicle capacity, and the replanning process

Table 6: Summary of direct and indirect effects

Quantification	EWD	SM	SD	ST	NI
Direct Effect (Activity-delay), avg minutes	2.1	8.51	13.08	19.36	67.11
number of agents affected	140	140	140	140	140
Agents minutes	294.15	1192.08	1831.71	2709.82	7650.39
Negative Indirect Effect (Activity-delay), avg minutes	19.45	6.38	5.94	4.86	4.22
number of agents affected	119	68	71	52	57
Agents minutes	2314.54	433.82	421.61	252.68	240.39
Positive Indirect Effect (Early Arrival), avg minutes	-16.3	-12.11	-13.52	-10.96	-14.58
number of agents affected	92	23	23	20	34
Agents minutes	-1499.94	-278.42	-310.96	-219.25	-495.63
Grand total delay, agents minutes	1108.75	1347.48	1942.36	2743.25	7395.15
Grand total, agents affected	351	231	234	212	231

as mediated by the information about the disruptions that the passengers might have available.

We quantify the direct (i.e. those people who cannot proceed their wished trips as the line is disrupted) and indirect effects (i.e. further cascade of crowding effects when people replan their trips to avoid the disrupted lines) of a disruption in a public transport network. We show that different information dissemination strategies have large impact on the direct effects, and even more on the indirect effects, in terms of their occurred delay and utility; indirect effects can further be negative (i.e. crowding, delay) or positive (less crowding, early arrival).

Our results demonstrate the large impact of information on passenger flow, and the impact they experience. When the information reaches the travelers at the latest moment (scenarios ST and NI), the most significant indirect impacts of the disruption are observed at the disrupted stations, in terms of number of directly affected agents and the delay they experience. Those scenarios have the least significant negative indirect impact of the disruption. When instead more information would be available, even in an ideal case that a disruption is known beforehand (scenarios SM and SD), the indirect effects are not anymore localized at the disrupted stations, but throughout the entire network. The earlier availability of information can significantly reduce the delay that directly affected agents experience, but causes larger amount of indirectly affected agents, who experience relatively small delays.

In other terms, by disseminating increasing information, disruptions effects gets milder, but larger in space, and more varied in positive and negative aspects. The scenarios with least information instead are very strongly affecting few passengers, with no perceivable impact for the rest of the network.

To the best of our knowledge, this is the first time that the direct, negative, and positive indirect effects of a public transport disruption have been quantified in a public transport disruption. The present study is valuable for further understanding of passenger flow evolution after public transport disruptions, and to understand the risks and opportunities for development measures improving system performance in planning, operations, and real-time management of public transport networks.

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 in exposure, or further in variation of effects (i.e. some lines face strong performance reduction, while other face a performance improvement). The design of a timetable and vehicle scheduling considering risk of disruptions may decrease the likelihood of disruption and exposure; and the online computation of different disposition timetables and their impacts (See (Corman *et al.*, 2016). 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, medium, moreover multiplied by the degree by which travelers include information in their decision process, and the delay with which they might react. We expect that travelers might have similar choices process, for instance forming clusters based on age, gender, job, etc., as well as affinity with the public transport network. It would be worthwhile to include those factors while replanning, for instance, assuming that old travelers may prefer to have a direct, but longer, trip, or will have more trouble in getting access to online route information and guidance typically available on mobile devices.

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