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To Wait or Not to Wait? Redirecting Passengers and Reallocating Capacities During Incidents in Public Transport Systems

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"If you get tired, learn to rest, not to quit." – Bansky

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Frederik Bachmann

Executive Summary

Humanity's greatest challenge is to adjust its way of life in a way that planet Earth stays habitable for us as well as for other living beings. Consequently, the emissions we produce need to be drastically reduced in various sectors of our daily lives. In the passenger transport sector, this can, besides avoiding trips, be accomplished by a change in our transport habits, for example, by a shift towards more environmentally friendly modes of transport such as public transport (PT). An improvement in the reliability of PT services raises its attractiveness and can motivate people to use it more often. Incidents (e.g. traffic accidents, technical failures, passenger falls, etc.) occur every day in PT operation and lower its reliability.

In literature, there are many investigations focussing on *supply-centric* incident management which refer to methods that are used for readjusting the PT supply following an incident to mitigate its negative effects such as passenger delays. Significantly less has been done in the area of *passenger-centric* incident management, which is understood here as methods that include public transport (PT) users in the reduction of their delays, for instance, by redirecting them through the provision of path advice.

This thesis introduces a novel contribution to this research area. In addition to an extensive literature review about incident management in PT systems, findings from visits to operations control centres, complement the knowledge gained through the literature. Moreover, a PT user survey concerning passengers' perception of incidents and incident management was conducted to better understand the passenger side during incidents.

Most importantly, the gathered knowledge and gained insight in the practice of incident management and the perception of PT users during incidents have been used to develop the model introduced here. This model redirects affected passengers onto available alternative paths during incidents considering their remaining capacities. This reduces passenger delays. Furthermore, the model includes the reallocation of capacities in the forms of buses during incidents to support passenger redirection with extra capacities on the suggested alternative paths. The model is tested in the Mandl network considering a PT bus system as well as an autonomous PT system and in a more complex real network of the city of Kassel, Germany.

The results show the great potential of this model to reduce the relative delay of affected passengers through capacity-aware redirection of passengers. The effectiveness of the model grows with an increase in the severity and duration of an incident as well as with the share of travellers who follow path advice. However, further testing and development are needed as limitations of the model have been identified and room for further research has been recognised.

On the whole, this work represents a new step towards implementing passenger redirection and capacity reallocation in practice and is a contribution to close the gap between research and practice in *passenger-centric* incident management in PT systems.

Kurzfassung

Die größte Herausforderung der Menschheit besteht darin, ihre Lebensweise so zu gestalten, dass der Planet Erde für uns und andere Lebewesen bewohnbar bleibt. Daher müssen unter anderem die von uns verursachten Emissionen in verschiedenen Bereichen unseres täglichen Lebens drastisch reduziert werden. Im Bereich des Personenverkehrs kann dies, neben der Vermeidung von Fahrten, durch eine Veränderung unserer Mobilitätsgewohnheiten erreicht werden. Zum Beispiel durch eine Verlagerung auf umweltfreundlichere Verkehrsmittel wie den öffentlichen Verkehr (ÖV). Eine Verbesserung der Zuverlässigkeit des ÖV erhöht dessen Attraktivität und kann Leute dazu motivieren diesen öfter zu nutzen. Störungen wie Verkehrsunfälle, technische Ausfälle und Fahrgaststürze treten täglich im ÖV-Betrieb auf und verringern dessen Zuverlässigkeit.

In der Literatur finden sich zahlreiche Untersuchungen, die sich mit dem *betriebszentrierten* Störungsmanagement befassen. Damit sind Methoden zur Anpassung des ÖV-Angebots an eine Störung gemeint, die deren negative Auswirkungen wie Verspätungen abmildern. Deutlich weniger geforscht wurde im Bereich des *fahrgastzentrierten* Störungsmanagements. Darunter werden Methoden verstanden, die betroffene Fahrgäste in die Reduzierung ihrer Verspätungen einbeziehen. Zum Beispiel durch deren Umleitung mit Hilfe von Routenempfehlungen.

Die vorliegende Arbeit leistet einen Beitrag zu diesem Forschungsgebiet. Neben einer umfassenden Literaturrecherche zum Thema Störungsmanagement im ÖV, ergänzen Erkenntnisse aus Besuchen in Leitzentralen die durch die Literatur gewonnenen Erkenntnisse. Darüber hinaus wurde eine Umfrage unter ÖV-Nutzern zur Wahrnehmung von Störungen und Störungsmanagement durchgeführt, um ein besseres Verständnis der Fahrgastseite zu erhalten.

Der Kernbeitrag dieser Arbeit ist ein Modell, in dessen Entwicklung das gesammelte Wissen und die gewonnenen Erkenntnisse geflossen sind. Das Modell leitet Fahrgäste während einer Störung auf Alternativrouten, unter Berücksichtigung deren Kapazitäten, um. Außerdem beinhaltet das Modell die Neuzuweisung von Kapazitäten, um die Fahrgastumleitung zu unterstützen. Das Modell wird im Mandl-Netz unter Berücksichtigung eines Bussystems sowie eines autonomen ÖV-Systems und in einem komplexeren realen Netz der Stadt Kassel getestet.

Die Ergebnisse zeigen das große Potenzial dieses Modells die relative Verspätung der betroffenen Fahrgäste durch kapazitätsberücksichtigende Umleitung der Fahrgäste zu reduzieren. Die Wirksamkeit des Modells nimmt mit der Schwere und Dauer einer Störung sowie mit dem Anteil der Fahrgäste, die den angebotenen Routenempfehlungen folgen, zu. Es sind jedoch weitere Tests und Entwicklungen erforderlich, da auch Grenzen des Modells identifiziert und Raum für weitere Forschungsansätze erkannt wurden.

Insgesamt stellt diese Arbeit einen neuen Schritt zur Einführung der Umleitung von Fahrgästen und der Neuzuweisung von Kapazitäten in die Praxis dar und ist ein Beitrag zum Schließen der Lücke zwischen Forschung und Praxis im Bereich des *fahrgastzentrierten* Störungsmanagements im ÖV.

Contents

Chapter 1

Introduction

The first chapter of this thesis introduces the reader to the topic of the investigation conducted, describes the motivation which has led to the goals and research questions of this work, as well as explains the applied methodical approach and structure of the thesis.

1.1 Motivation

The greatest challenge of our time is to adapt the human way of life to a sustainable way of living so that planet Earth remains habitable for our kind and for other living beings. Besides the exploitation of the limited resources of planet Earth [Meadows, 1972; Global Footprint Network, 2022], is the anthropogenic warming of the global temperature, called climate change, a key problem. Especially through the combustion of fossil fuels such as oil, gas, and coal, mankind artificially increases the concentration of greenhouse gases like carbon dioxide and others in the atmosphere, which boosts the greenhouse effect on the planet [Hofmann et al., 2006].

Over a century ago, scientists and society already started to discuss and warn about the influences of the combustion of fossil fuels on the climate [Arrhenius, 1896; Callendar, 1938; Revkin, 2016]. In the scientific world, there is a consensus of over 97% on the statement that humans cause global warming [Cook et al., 2013]. As climate change causes devastating consequences such as extreme weather events, dramatic loss of biodiversity, destruction of whole biotopes, as well as severe negative effects on our health, the Intergovernmental Panel on Climate Change (IPCC) recommends drastic changes in various sectors of our way of living to mitigate these consequences [McMichael, 2003; Ceballos et al., 2015; Hughes et al., 2017; IPCC, 2018].

Transportation is one of these sectors which play a significant role in the emission of greenhouse gases. Therefore, a change in our mobility behaviour is necessary to reduce the emissions in this sector [Waterson et al., 2003; Chapman, 2007; Europeean Environment Agency, 2022]. To achieve this goal a reduction of travel as well as a switch to means of transport which are more compatible with the limits of Earth and our budget for the emission of greenhouse gases is inevitable.

In passenger transport, more of people's trips, need to be conducted with more environmentally friendly means of transport. For short distances, active mobility such as walking and cycling are the most obvious choices. For longer distances, PT, supported by shared mobility services, is the most obvious alternative [Waterson et al., 2003; Chapman, 2007;

Schröder et al., 2022]. Schröder et al. [2022] point out that apart from the ecological costs, also the economic costs for society can be reduced by shifting from motorized private transport to PT and active mobility.

So-called push and pull strategies can support a change in the mobility behaviour of people. Push strategies refer to measures that lower the attractiveness of a transport system such as applying restrictions and reducing investments in the corresponding infrastructure and thus "pushing" travellers away from certain means of transport; pull strategies refer to measures which increase the attractiveness of a system by for instance lowering fares or improving infrastructure and thus "pulling" travellers towards a certain means of transport [Hrelja and Rye, 2022; Sommer et al., 2022]. Push strategies, for instance, restrictions on motorized private transport can trigger anger and frustration in the society as it contradicts with people's mobility habits [Buehler et al., 2017]. Pull strategies such as improving the attractiveness of PT systems, however, give people incentives to change their mobility habits. Among other options, it is therefore expedient to improve the attractiveness of the aforementioned means of passenger transport like PT as well as shared and active mobility such as cycling and walking.

1.2 Goals, Scope and Research Questions

This thesis focuses on urban mass PT, such as bus, tram, metro, and comparable services. The attractiveness of a PT system rely on several aspects such as its flexibility, fares, and reliability. A PT system's attractiveness can be raised by lower fares or improve its flexibility by raising the services' frequency and extend its network [Baum, 1973; Cats, Susilo et al., 2017; van Lierop et al., 2018; Mietzsch, 2019; Andor et al., 2021].

Another possibility is to improve its reliability. The term reliability can be interpreted in different ways, in the context of PT. On the one hand, there is the perspective of the PT operator who understands reliability as maintaining and operating the PT system as scheduled [Briem, 2023]. On the other hand, there is the perspective of the PT users on which this thesis focuses.

For travellers, reliability was stated as one of the most important characteristics of transport systems [Prashker, 1979; Outwater et al., 2011; Carrel, Halvorsen et al., 2013; Allen et al., 2019; Helfers et al., 2022]. From a PT users perspective there are various aspects to the reliability of a PT system. Allen et al. [2019] for example list access to transport, availability (time interval), speed, reliability of arrival time, and easiness of transfer. Prashker [1979] considers a higher level of detail and differs between the reliability of different parts of travel time (i.e. walking, waiting, in-vehicle time) which the author names under travel-time reliability. Furthermore, mechanical reliability referring to that a vehicle is mechanically fit to serve, performance reliability referring to a transport service performing as estimated, weather influence, and others are taken into account. Reliability can therefore also be understood in the context of a system being fit to serve as planned.

Carrel, Halvorsen et al. [2013] states that a clear definition in the context of passenger transport is yet missing in literature. In the following, it is focussed on the part of reliability that refers to reliable travel time and arrival time of PT users.

It is also mentioned by Carrel, Halvorsen et al. [2013] that some forms of unreliability such as delays due to congestion during peak hours might not be perceived as unreliable by daily commuters as they expect those during peak hours. For people who are not used to the dynamics in PT, also to be expected delays during peak hours are probably perceived as unreliable. However, if unreliability is caused by unplanned and unpredicted events such as incidents, it is perceived as such by both, the passengers as well as the operators [Carrel, Halvorsen et al., 2013; Bachmann, Briem et al., 2022; Briem, 2023].

Incidents are events such as traffic accidents, deployment of emergency forces, technical failures, falling passengers, etc. which disrupt the PT service. Further examples and explanations of incidents are given in Section 2.1.3. They occur daily in PT operations and lower its reliability and thus its attractiveness. Therefore, it is desirable to keep their negative effects on PT services, such as delays and cancellations, as low as possible.

The field of research which focuses on the dissolution of incidents and the mitigation of their negative effects is called incident management. It is the umbrella goal of the method introduced here to improve incident management in PT and thus to improve the reliability of PT systems. In more detail, to include the passengers affected by an incident in the incident management and the reduction of delays.

As Section 2.2.1 shows, a lot of research has been done in the area of incident management regarding the operator or supply side, respectively. This research finds answers to the question how the service can be temporally adjusted to the disturbances caused by an incident? Hence, this is referred to as *supply-centric* incident management in the following. Less has been done on the passenger side.

This leads to another goal of this thesis which is the understanding of the passengers' perspective during incidents. The general idea of the model presented in Chapter 4 is to redirect passengers affected by an incident by providing them with concrete path advice. This advice guides them through the PT network during incidents and reduces their overall delay. The area of research which includes affected passengers in incident management and the reduction of their delays by for example redirecting them is understood here as *passenger-centric* incident management (PCIM).

In addition, one hypothesis is that by a complementary reallocation of capacities, in the forms of PT vehicles, the positive effects of passenger redirection can be further improved. To better understand the effectiveness of passenger redirection and capacity reallocation during incidents in PT systems, this thesis aims to answer the following research questions:

1. To what extent does path advice lower the overall passenger delay during incidents?

2. Under which circumstances is the redirection of passengers reasonable?

3. What are factors that influence the effectiveness of passenger redirection?

4. Does capacity reallocation support passenger redirection?

The development of this thesis started as part of the project "Towards the Ultimate Public Transport System" conducted by the research company TUMCREATE Limited, in which an autonomous PT system, the Dynamic Autonomous Road Transit (DART) system, has been investigated [Rau, Tian et al., 2018; Rau, Jain et al., 2019; TUMCREATE, 2021]. Therefore, it is a subsidiary aim of the work presented here to understand incidents and incident management in the context of autonomous PT systems.

1.3 Overall Approach and Thesis Structure

To accomplish the aforementioned goals and to answer the listed research questions in the previous section the methodology presented here has been developed.

Figure 1.1 shows the structure of this thesis and the connections of its elements. The shades of grey indicate of the thematic depth of a particular element. After this introductory Chapter 1, Section 2.1 gives insight into relevant adjacent research terms and topics as background. Furthermore, Section 2.2.1 explains the state-of-the-art of *supply-centric* incident management through a corresponding literature review as well as findings through visits to the operations control centre (OCC) of several PT operators. This helps to better understand the supply side during incidents. The same section also describes the state-of-the-art in PCIM, which is the research area this thesis belongs to. As it is indicated by Figure 1.1, PCIM connects the supply side with the passenger side.

To better understand the passenger side during incidents, a PT user survey was conducted of which setup and results are presented in Chapter 3.

Based on the knowledge gathered through Chapters 2 and 3, a model for passenger redirection and capacity reallocation has been developed which is formulated in Chapter 4 and evaluated in Chapter 5.

Chapter 6 discusses the limitations of the model and compares it to other works in the field of PCIM.

Chapter 7 concludes the work and gives incentives for future research.

To avoid misunderstandings, the term path refers to the way of a PT user, whereas the term route is used in the context of vehicles. The terms traveller, passenger and PT user are understood as synonyms.

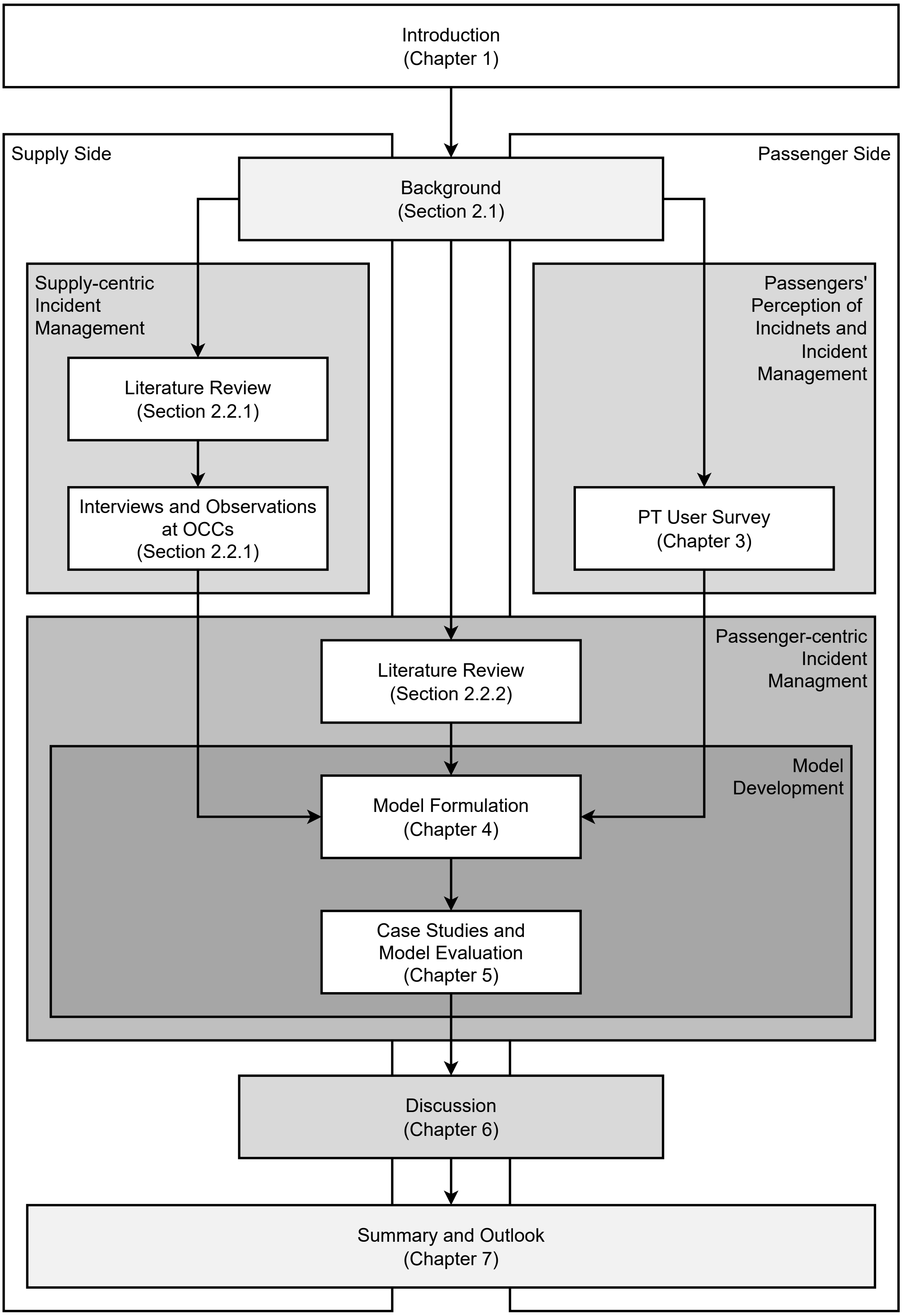


Figure 1.1: Thesis structure

Chapter 2

State of the Art Analysis

This chapter is meant to equip the readers with the necessary background knowledge to better understand the methodology introduced here and to put it into the context of already existing investigations.

2.1 Background

The following subsections provide the readers with a variety of terms and topics which are not directly tackled by this thesis but are connected to it and relevant for the understanding of the methodology presented here. It gives a short insight in the state of the art of these.

2.1.1 Passenger Demand Assignment

Passenger demand assignment (PDA) models have been developed to predict and analyse the distribution of passenger demand onto a PT network, meaning, to associate certain passenger flows with certain PT lines and vehicles. In this way, it is determined which PT lines and vehicles are used by how many passengers in a certain period. These models have mainly been used in PT planning processes, for example, to solve the PT network design and frequency setting problem, to provide the passenger demand of a city with an appropriate PT service [Ul Abedin et al., 2018]. Generally speaking, one has to distinguish between the following model aspects: frequency- (or headway-) and schedule- (or timetable-) based, deterministic and stochastic, referring to the path-choice model within PDA, dynamic or static, and congested or non-congested demand assignment models [Lam and Bell, 2007, pp. 93-198; Fu et al., 2012; Gentile and Nökel, 2016, pp. 287-484; Ul Abedin et al., 2018]. The contrast between frequency- and schedule-based models is described in Table 2.1 by Ul Abedin [2019].

Frequency- or headway-based models are faster in computing results whereas schedule- or timetable-based models need more data and computational effort. However, the latter provide a higher level of detail. Usually, time-dependent origin-destination (OD) matrices serve as demand input for PDA models. There are several sources from which predictions of the demand can be derived, namely: sample censuses, ticket sales, automatic vehicle location (AVL), automatic fare collection (AFC), smartphone data, or automatic passenger count (APC) [Bachir et al., 2019; Ge, Sarhani et al., 2021; Hussain et al., 2021; Mo, Koutsopoulos and Zhao, 2022].

The deterministic and stochastic characteristic of a PDA model refers to its path choice component. In any PDA model there is a path choice model which clarifies the passenger's decision about which path to take from the origin to the destination. In literature, the term path is also referred to as a strategy that describes a list of subsequent decisions which enables a passenger to get from an origin to a destination within a given PT network [Spiess and Florian, 1989]. The topic of path choice is further discussed in Section 2.1.2.

The adjectives dynamic and static describe the kind of input in terms of supply and demand data that is used for a PDA model. Especially macroscopic models work with a static demand and supply for the period of the simulation. Dynamic PDA models however take certain variations in supply and demand for a day or even a week or month into account [Gentile and Nökel, 2016, p. 312].

The characteristic mentioned last of PDA models refers to the question of whether the models are applied to a congested or uncongested network. Uncongested networks which do not take capacity constraints of PT services into account are simpler and need less data, whereas congested networks consider capacity constraints, are more complex, and computationally more expensive. Since it is a complex problem to consider "fail-to-board" or even "fail-to-sit" factors due to overcrowding, capacity constraints have not always been considered in research and practice [De Cea and Fernández, 1993; Schmöcker, Bell et al., 2008; Schmöcker, Fonzone et al., 2011; Fu et al., 2012; Briem, Buck, Ebhart et al., 2017].
However, in the last two decades, more and more PDA models for congested models have been developed. Fu et al. [2012] give a comprehensive overview of the literature about PDA models.

Assignment type	Advantages	Disadvantages
Headway-based	Ideal for the strategic planning Minimum data requirement Computationally efficient	Unable to identify peak load Not suitable for low frequency PT network Lacks detailed attributes of PT service
Schedule-based	Ideal for detailed spatio-temporal planning Suitable for low frequency PTnetwork Coordination of timetable possible	Requires extensive information Computationally expensive

Table 2.1: Headway and schedule-based assignment comparison [Ul Abedin, 2019]

2.1.2 Shortest Path Search and Path Choice

As mentioned in the previous section, path choice models are used in PDA models to predict the passengers' choices about which path they are likely to take among all their options to reach their destination. Their options and the corresponding travel times of these are examined by shortest path search algorithms. These algorithms analyse a network to calculate the shortest path, meaning the path with the lowest costs according to certain criteria in a network between an origin and a destination. It is thereby also referred to as the cheapest path. However, in most cases, the costs of time are used as criteria.

The first algorithms to solve the shortest pathfinding problem were published in the late 1950s by Bellman [1958] and Dijkstra [1959]. Most of the algorithms that have been developed since then can be considered as extensions or modifications of these two. For example, the A*-algorithm that builds upon the Dijkstra algorithm [Hart et al., 1968; Bast et al., 2016].

Another extension is the k-shortest paths search algorithm which does not look for just one shortest path between an origin and destination, but a certain number of shortest paths defined by the variable k. This is determined by certain criteria or just by a given deterministic value [Hershberger et al., 2007].
Casey et al. [2014] compare the performance of nine different shortest path search algorithms solving the dynamic multi-modal pathfinding problem. They describe that there are quite significant differences in finding the fastest paths in a road or a PT network due to the restrictions which come along with timetable dependencies in PT networks.

Furthermore, dynamic variations of originally static algorithms such as the Dijkstra or the A*-algorithm are explained. It is differentiated between static and dynamic path searches. As already mentioned in the previous section, this refers to whether the inputs for the link travel times are defined statically or dynamically, meaning time-dependent. All these algorithms have the purpose to find the fastest or the fastest and additionally subsequent fastest paths from a certain origin to a certain destination. A comprehensive overview of path search algorithms and the underlying approaches for route planning is given by Bast et al. [2016].

Whether a path is more or less convenient for a traveller is calculated by taking certain factors such as the travel time or crowding into account. A distinction is to be made between the actual travel time of a path and the perceived travel time. The perceived travel time considers the differences in perceiving waiting, walking, and in-vehicle time or transfers, whereas the actual travel time represents the actually needed time to travel a certain path [Cats, Koutsopoulos et al., 2011; Kim et al., 2015].

Equation 2.1 shows a utility function representing the perceived travel time by Cats, Koutsopoulos et al. [2011]. Each part of a travel time (i.e. waiting, walking, and in-vehicle time) is multiplied by a coefficient β which represents the differences in the perception of the different parts. For instance, waiting for a certain period is perceived as longer compared to riding for the same amount of time. Furthermore, the number of transfers is multiplied with a penalty time, because transfers are inconvenient for travellers.

Ceder and Jiang [2019] introduce a path search procedure that takes into account personal preferences of individual travellers over a variety of path characteristics to offer travellers the most satisfactory path via a smartphone application (also known as app).

$$U_i = \beta_{wait} \cdot t^i_{wait} + \beta_{ivt} \cdot t^i_{ivt} + \beta_{walk} \cdot t^i_{walk} + \beta_{trans} \cdot trans_i + \eta_i \tag{2.1}$$

Where:

U_i = Utility of path i,
$t^i_{component}$ = time needed for path component (waiting, walking, in-vehicle) of path i,
$\beta_{component}$ = corresponding coefficient of path component,
$trans_i$ = number of transfers on path i,
η_i = error term of path i.

The goal of path choice models is to reflect the passengers' decisions on which path to take as realistically as possible. Therefore, for such models, the perceived travel time is more relevant. Generally, travel time is a prerequisite for path choice models. Once a set of attractive paths or hyper-paths, as it is referred to by Nguyen and Pallottino [1988], is determined, the set can be assessed according to the paths' features or even the traveller's preferences. Then, it can be decided on a path within the given set.

Moreover, it is to be differentiated between deterministic and stochastic path choice models. A deterministic path choice model, on the one hand, is simpler in a way as it assumes certain rules after which it is decided which path passengers take according to their origin, destination, available attractive lines, and the next approaching PT vehicle. It determines one particular path for each passenger or respective passenger group. A stochastic path choice model, on the other hand, assigns certain probabilities to the different factors which influence the path choice of passengers, meaning the solution is not one particular path but several paths with certain probabilities for being chosen. Therefore, the latter is more realistic but at the same time more complex which is why in practice deterministic path choice models are still in use [Gentile and Nökel, 2016, p. 311].

Y. Liu et al. [2010] present a review on path choice models for PT users. Besides the choice of the path, first, the transport mode among a traveller's options is chosen [Sohn and Yun, 2009]. Rahimi Siegrist, Büchel et al. [2022], for example, show that passenger information (PI) and measures such as increasing the capacity of roads or PT lines can influence the mode choice during an incident. However, as this thesis focuses on PT systems, mode choice is not further discussed here.

2.1.3 Incidents in Public Transport

As pointed out in Chapter 1, this thesis belongs to the research area of incident management. Incident management starts with incidents occurring daily in PT systems. In literature, there are different definitions and understandings of various terms such as delay, incident, disruption, disturbance, reliability problems and so on. Nevertheless, they are all in the same premise of understanding [Vuchic, 1969; Carrel, 2009; Zhu and Goverde, 2019a; Briem, Buck, Magdolen et al., 2020]. Carey [1999] for instance differentiates between exogenous and knock-on delays. Exogenous delays are caused by failure of equipment such as vehicles or infrastructure, lateness of crew, passenger boarding and alighting, etc. Knock-on delays are understood as delays which are caused by exogenous delays but can be attributed to the planning process and timetable. These are delays that could be prevented by changing the headway of the PT service for example. Abkowitz et al. [1978] distinguish in environmental and inherent reliability problems in PT. Environmental problems are problems such as traffic conditions, traffic signals, crew and vehicle availability, and deviations in passenger demand. Inherent problems include the distribution of transfer times, boarding and alighting times, travel times, and waiting times, so basically, problems that are perceived by the passengers.

In the thesis presented here the term incident is understood as any event which disturbs or even disrupts the PT services. Disturbances are understood as the consequences of incidents. Typical disturbances are delays, cancellations, or any other deviation of the planned PT timetable. Severe disturbances, such as complete service cancellations over several hours or delays of more than one hour are also referred to as disruptions.

It is further distinguished between external and internal incidents. The origin of external incidents lies outside the PT system, typical examples are traffic accidents and congestion, deployments of emergency forces, and passenger-related incidents such as falling passengers and vandalism of passengers or other people, whereas internal incidents have their origin within the PT system, such as technical failures, PT vehicle breakdowns, and PT driver-related issues.

Disturbances are subdivided into primary and secondary ones. Primary disturbances are direct consequences of an incident, whereas secondary disturbances can be a result of primary disturbances. A famous example of a secondary disturbance, which is thoroughly investigated in literature is bus bunching [Vuchic, 1969; Strathman et al., 2001; Gershenson and Pineda, 2009; Weinsziehr et al., 2023]. Due to an initial incident, a bus is delayed (primary disturbance). The delay results in passengers who actually want to take the following bus, but are already at the stop when the delayed bus arrives, boarding the delayed bus. Hence, a constantly rising number of passengers get on the delayed bus, which prolongs its dwelling time due to more people boarding and alighting, which increases the bus's delay even further. At the same time, fewer travellers board the following bus, which reduces its dwelling time, consequently, it keeps catching up with the delayed bus and causes bunching (secondary disturbance) [Berrebi et al., 2018]. Table 2.2 gives an overview of incident examples, categorised by the related subject and type. Detailed descriptions of further incident examples can be found in Annexe A.

Additional Causes of Incidents in Autonomous PT Systems: Autonomous mobility in PT is a constantly growing topic in research and practice and several projects with theoretical investigations and practical field tests have already been carried out [BVG and Charité, 2017; Rau, Jain et al., 2019; Volvo AB, 2019; S. Wang and Zhao, 2019; Hamburger Hochbahn AG, 2021; Pigeon et al., 2021; Poinsignon et al., 2022] As autonomous vehicles are operated differently, they also lead to changes in incident management in PT. For such autonomous PT services, the listed incidents in Table 2.2 are applicable as well. The only exception is the PT driver-related incidents since autonomous vehicles are driverless. However, the deployment of autonomous vehicles raises three additional categories of incidents [Taeihagh and Lim, 2019]. These new categories of incidents shown in Table 2.3 also have the potential to cause disturbances and lower the reliability of PT systems. However, the remainder of this thesis focuses on incident management as it is today.

Category	Type	Examples
PT operations-related	Internal	Missing (replacement) driver, missing PT vehicle, OCC is understaffed, etc.
Infrastructure-related	Internal	Signal disruption, track switch failure, railway barrier malfunction, etc.
PT vehicle-related	Internal	Flat tyre, engine failure, charging issues, door malfunction, etc.
PT driver-related	Internal	Driving wrong route, health issues, late for work, etc.
Traffic-related	External	Illegal parking, congestion, accident blocking tracks or roads, etc.
Emergency-related	External	Ambulance, police, or fire department deployments blocking stops, tracks or roads, passenger needs medical attention, etc.
Passenger-related	External	Falling passenger, high passenger demand, passengers blocking doors, overcrowding, etc.

Table 2.2: Incident categories in PT

Category	Type	Examples
System maturation-related	Internal	Difficulties to adjust to rarely occurring incidents and driving manoeuvres, etc. [S. Wang and Zhao, 2019]
Cyber security-related	External	Hacking attacks on autonomous vehicles or corresponding infrastructure, etc. [Sheehan et al., 2019]
Society-related	External	Acceptance and proper interaction with autonomous vehicles, etc. [Salonen, 2018], [Pigeon et al., 2021; Yuen et al., 2022]

Table 2.3: Incident categories in autonomous PT services

2.1.4 Passengers' Reactions to Incidents

Incidents, such as the ones mentioned in the previous section, cause PT service cancellations and delays which lead to passenger delays or even trip cancellations. This section gives a short insight into the common reactions of PT users to incidents.

It is to be differentiated between sudden, unplanned incidents such as the ones described in the previous section and planned incidents which are known to the PT users in advance, such as construction sites and maintenance work. In the latter case, passengers have more time to change their trip plans in accordance with the present incident situation. The focus of this thesis lies on the first kind of suddenly occurring, unplanned incidents.

Table 2.4 by Lin, Shalaby et al. [2016] shows typical reactions of PT users categorized by the nature of the decision, namely: intermediate action, which is taken pre-trip or en-route, as a response to suddenly occurring incidents; pre-planned intentions, which can be short-term or long-term, as a reaction to planned incidents, and gradual adaptions according to changes in the PT service, either short- or long-term.

Common reactions to sudden incidents are waiting for the dissolution of the incident, changing the departure time of the trip, and changing the chosen path within the PT network, which can also go along with a shift in the PT mode, a shift of the transport mode towards a private car, a taxi, cycling or walking for example, and cancellation of the trip.
As pointed out by E. Rahimi et al. [2020], many factors influence the reaction to incidents of passengers, namely: location and duration of the incident, weather, the remaining distance to the destination, car ownership, availability of information about the incident, alternatives in the PT network, as well as other modes of transport. In addition, the waiting tolerance of PT users during incidents is influenced by many factors, which have been summarised by E. Rahimi et al. [2019]. Arrival time flexibility, the purpose of the trip, distance, experience with ride-hailing and bike-sharing services, availability of alternative paths through the PT network, the density of the walking links, as well as socio-demographics are named as such factors.

Lin, Srikukenthiran et al. [2018] present the results of a combined revealed and stated preference survey. Its results show that the remaining distance of travellers to their destination strongly affects the likelihood of travellers deciding on walking the distance instead of waiting for an alternative ride on PT facilities. Furthermore, the authors compare the modal split of travellers with and without PI, showing the available alternative options in the PT system during the incident. A significant increase in the share of people using an alternative path through the PT network is observed. PI is thereby an important factor when it comes to passengers' reactions to incidents.

The importance of adequate PI is also emphasized by Passenger Focus [2011]. Rail riders have been asked about their information preferences during incidents. An estimation of the delay, the reason for the incident, and alternative paths through the PT network have been stated as most important.

Adelé et al. [2019] show that there is a relation between passengers' attitude towards PI and their likelihood of changing the chosen path during incidents. Another result is that the longer the duration of the incident, the fewer passengers wait and the more choose an alternative path. Further, Bai and Kattan [2014] show that PI in combination with other factors such as weather, car ownership, and others, influence the reaction of passengers to service disturbances such as delays.

Moreover, Wilke [2023] presents a model to predict the reaction of passengers to suggestions for alternative connections in long-distance railway services during disruption. The author differentiates between internal and external factors which influence the willingness to follow given suggestions. Internal factors are related to the passenger such as age, travel habits, etc. and external factors are referring to factors concerning the circumstances of the incident as well as properties of the used PT service. The results show that a seat guarantee on the proposed connection, as well as the possibility of continuing the journey in first class, positively influences the willingness to take the proposed connection, especially in case of a service cancellation. In situations in which an alternative connection is suggested to prevent overcrowding, the influencing factors are less successful. These are factors that are hard or not at all transferable to urban PT services which do not provide for seat reservations or different classes. Nevertheless, another finding is that monetary incentives such as vouchers for drinks or a fare reduction influence the willingness to follow connection suggestions positively. The latter in particular could also be applicable in urban PT services. Apart from that, a survey of railway service customers reveals that about 57% would follow connection suggestions without an incentive in the situation of the service cancellation.

The topic of passenger reactions to incidents is further discussed in Chapter 3, which presents the results of a PT user survey tailored to this thesis.

Intermediate action	**Pre-planned intention**	**Gradual adaption**
Pre-trip and en-route	**Short-term and long-term**	**Short-term and long-term**
Wait until service restored (no change)	No change (long-term)	No change
Departure time change only (pre-trip)	Path change only	Path change only
Path change only	Transit mode shift	Transit mode shift
Transit mode shift	Mode shift	Mode shift
Mode shift	Destination change	Destination change
Trip cancellation	Trip cancellation	Trip cancellation

Table 2.4: Most common alternatives at different stages [of a passenger's trip] [Lin, Shalaby et al., 2016]

2.1.5 Passenger Information

The previous section already implies the importance of PI, especially during incidents. Furthermore, as pointed out by the research questions stated in Section 1.2, one of the goals of the methodology presented in this thesis is to include passengers affected by an incident actively in the mitigation of the delays caused by an incident. Consequently, it is necessary to communicate with PT users in general and especially in the event of an incident. PI is the connection between PT operators and PT users. Its potential and benefits are presented in this section.

PI describes the kind of information PT users are provided with to plan their trips in a PT system. Typical aspects are the fare of a PT service and its timetable. Based on this information, users can plan their trips as well as compare the service with other modes of transport, e.g. taxi, private car, or cycling. Today, there are many information channels available that are used to inform travellers about the PT service: Speaker announcements, dynamic PI displays at stops and in PT vehicles, the operators' representation on websites or social media channels, as well as online trip planners on websites or as part of smartphone apps of operators or third parties (e.g. GoogleMaps, Oeffi or CityMapper) [Brakewood and K. Watkins, 2019; Bachmann, Briem et al., 2022; Bachmann, Tsakarestos et al., 2023].

The direction of development of PI is implied by Chow et al. [2016]. The authors introduce the investigation of online PT information connected with the user's smartphone and wearable device (i.e. smartwatch). By comparing the timetable information with the global positioning system (GPS) information of the user and the remaining distance to the stop, feedback can be given to the user if an adjustment of the walking speed is necessary to catch the desired PT service. Trip planners on websites and as part of smartphone apps are connected via an application programming interface (API), such as the general transit feed specification (GTFS), to enable them to provide the timetable of a PT system [Mobility Data, 2022]. With these information technologies, it is also possible to provide customers with real-time information, for example about the actual arrival times of PT vehicles, in which also delays of vehicles due to incidents or other reasons can be considered.

Dziekan and Kottenhoff [2007] show that dynamic PI displays at stops, providing PT users with real-time departures, have a positive effect on the travellers' perception of waiting time, their certainty and trust in the service, as well as their general satisfaction with the PT service. Even stronger positive effects are shown by Ferris et al. [2010], who introduce a cross-channel PI system, including a smartphone app, a website, a phone service, and a short message service (SMS). This system called OneBusAway provides the users with real-time arrival information as well as locations of stops and further information. K. E. Watkins et al. [2011] also use OneBusAway and investigate the waiting times of passengers. The actual and the perceived waiting time was reduced through mobile real-time PI.

Through a simulation study, Cats, Koutsopoulos et al. [2011] reveal that real-time PI has the potential to reduce travel times and cause shifts in the travellers' path choice. Furthermore, Drabicki et al. [2023] complements a discrete path choice model with the findings through a PT user survey concerning the willingness of travellers to wait for the next PT service to avoid in-vehicle crowding, when provided with real-time crowding information.

Moreover, Chan and Schofer [2014] and Pender et al. [2014] investigate the potential of social media during disruption in PT systems and emphasize the importance of real-time PI to passengers in general. A comprehensive review of investigations about PI, especially real-time PI, is given by Brakewood and K. Watkins [2019]. The authors summarize and compare the existing literature about PI as well as the corresponding findings. The main benefits of real-time PI are reduction of waiting time (perceived and actual) and total travel time, increase in usage of and satisfaction about PT, as well as the perceived security of PT users.

In the following, PI refers to real-time passenger information in PT. Bachmann, Tsakarestos et al. [2023] bring the topic of PI into context with incident management. A summary of investigations about the effects of capacity-aware passenger redirection during incidents is given by the authors. As this is the research area of this thesis it is comprehensively discussed in Section 2.2.2.

2.2 Incident Management in Public Transport

As the term already gives away, incident management describes the management of incidents as well as the disturbances they cause. In practice, dispatchers in OCCs are the backbone of incident management. They monitor the PT service and take disposition measures to mitigate the negative effects of incidents on the PT system and return the PT service to normal operations. In the following, different aspects and perspectives of incident management will be examined. The topic of incident management is divided into two parts: *supply-centric* incident management that focuses on disposition measures to adjust the PT service to an incident situation, and PCIM that focuses on the PT users' perspective during incidents and their involvement in the reduction of passenger delays. PCIM is understood here as an enhancement or extension of *supply-centric* incident management.

2.2.1 Supply-centric Incident Management

Many disposition measures in incident management have been thoroughly investigated, this section will provide for both an insight in studies which have been done about *supply-centric* disposition measures as well as an insight in the state of practice.

Literature Review

Supply-centric measures focus on the supply side of incident management, meaning that the focus lies on the measures taken by dispatchers to rearrange the PT supply in accordance with an incident.

Eberlein [1995] categorises these measures into three groups, namely: station control, inter-station control, and other strategies. For a more general expression, it is referred to stops rather than stations in the following.

Stop control strategies, include all measures which take place at a stop or temporarily alter the stops served by a PT line. Holding and stop(s) skipping measures such as expressing and deadheading are typical measures of this category.

Inter stop controls refer to strategies such as speed control and traffic signal prioritisation, these measures influence the course of PT vehicles while they are between two stops.

All other measures fall under the category of other strategies. These are for instance dispatching additional vehicles or extending and splitting trains or platoons of PT vehicles. All of the other strategies are related to a change in the capacity of the PT service and could therefore be also titled capacity-related strategies.

The list below shows an overview of *supply-centric* disposition measures with a short description, and corresponding studies, organised by the mentioned categories. References which appear under more than one measure investigate the differences or the combination of the respective measures.

Stop control strategies

Holding

A PT vehicle's dwelling time is extended to increase the headway to the preceding vehicle and/or reduce the headway to the following vehicle. This is done to readjust the vehicle's run in accordance with a PT schedule or to the desired headway.

Studies: [Eberlein, 1995; Eberlein, Wilson et al., 1999; Eberlein, Wilson et al., 2001; Cats, Larijani, Koutsopoulos et al., 2011; Daganzo and Pilachowski, 2011; Cats, Larijani, Ólafsdóttir et al., 2012; Delgado et al., 2012; Sáez et al., 2012; Ceder, Hadas et al., 2013; Nesheli and Ceder, 2014; Berrebi et al., 2018; Rodriguez et al., 2023]

Stop(s) skipping (Expressing, deadheading)

A delayed PT vehicle skips one or several stops to reduce its delay. Expressing describes the skipping of stops along the planned route, while deadheading means that all passengers alight the vehicle at the next stop and it moves directly to the terminal to start the next run on schedule or at least with less delay.

Studies: [Eberlein, 1995; Eberlein, Wilson et al., 1999; Eberlein, Wilson et al., 2001; Sáez et al., 2012; Ceder, Hadas et al., 2013; Nesheli and Ceder, 2014; Rodriguez et al., 2023]

Rerouting PT vehicles

This measure is often used when the planned route of a PT line is affected by any kind of blockage, for example, due to a traffic accident. A temporarily altered route is established. Due to the rerouting, some of the stops of the affected line might be temporarily not served.

Studies: [Mandl, 1980; Cats, Koppenol et al., 2017; Friedrich et al., 2018; Yap et al., 2018]

Short-/Long-turning, line-splitting

At the terminal of a route, PT vehicles turn around to serve the opposite direction of a route after a short break, which is called layover time. Short-turning describes the disposition measure through which the turning around is done before reaching the terminal of a route, for example, to avoid an incident at the end of the route or supporting the opposite direction earlier than planned. If this is done on both sides of an unserved section of a PT line, for example, due to an incident, it is called line-splitting. Long-turning is rarely used. It extends a route beyond its planned end and the turning around at the end of a route is done later. This is used to support another PT line.

Studies: [Ceder, 1989; Tirachini et al., 2011; Canca et al., 2016; Gkiotsalitis, Z. Wu et al., 2019]

Inter stop control strategies

Speed control

PT drivers who are off schedule are told to speed up or slow down to readjust their position in accordance with the schedule. This is solely done within legal boundaries.
Studies: [Daganzo and Pilachowski, 2011; T. Liu et al., 2014]

Traffic light prioritisation

PT vehicles in mixed traffic are preferred at signalised intersections to reduce their delay due to waiting at red lights. With the change in the level of prioritisation, this can also be used to speed up or slow down a PT vehicle. This measure is mainly a matter of planning, however, it is also referred to incident management in literature.
Studies: [Chang et al., 2003; Lee et al., 2005]

Other / Capacity related strategies

Dispatch standby buses

Some PT operators reserve buses to be deployed spontaneously when needed. These buses are positioned at strategically reasonable locations. Whenever a PT vehicle breaks down or a PT line faces unusual high and overwhelming demand, a standby bus can replace a troubled PT vehicle or support an over-demanded PT line.
Studies: [Cats and Jenelius, 2015; Petit et al., 2018; Morales et al., 2019]

Dispatch on-demand services

Similar to the previous measure of dispatching standby buses, this measure describes the dispatching of on-demand services such as taxis to replace broken down PT vehicles or support an over-demanded PT line with extra capacity.
Studies: [Cebecauer et al., 2021]

Rail replacement / bus-bridging service

Breakdowns and failures in railway services can have very severe consequences. Furthermore, it takes often a lot of time to fix the problem which leaves the PT users without service for a long time. If a rail-bound PT line needs to be split or replaced completely, the unserved section is temporarily bridged by a rail replacement bus service.
Studies: [H. Hu et al., 2016; Bojic et al., 2021; Itani and Shalaby, 2021; Luo and Xu, 2021; J. Wang et al., 2021]

Train- / Platoon-splitting and -extending

In PT modes with a modular setup, for example, tram or metro trains, it is thinkable that one PT line with dispensable capacity helps out another over-demanded one, by reallocating some vehicle modules such as train carriages or half of the train in cases of two or more coupled trains, or dispatch corresponding extra vehicles. In the future, this might be also possible with platoons of autonomous road-bound bus modules such as the DART system [Rau, Tian et al., 2018].
Studies: [Schmöcker, Cooper et al., 2005; Bachmann, Rau et al., 2021]

As the description above clearly shows, most *supply-centric* disposition measures in PT incident management are well investigated. For a more comprehensive and detailed overview of investigations about *supply-centric* incident management measures, it is referred to Ceder [2016, pp. 309–332], Nesheli [2016] and Gkiotsalitis and Cats [2021] and Ge, Voss et al. [2022].

State of Practice – Findings Through Visits to Operations Control Centres

The previous section enumerates *supply-centric* disposition measures and lists several corresponding studies. However, significantly fewer studies have focused on the state of practice in incident management. In practice, incident management in PT systems is done by dispatchers in OCCs. They are the main actors of incident management in PT systems, monitoring the PT service with the help of an intermodal transport control system (ITCS) and taking disposition measures as soon as deviations from the schedule occur. Pangilinan et al. [2008] investigate such an ITCS and describe it thoroughly. With the help of AVL of buses through the GPS and in rail-bound services through signalling, it is possible to monitor PT vehicles' location in real-time and compare it to the schedule. In this way, the dispatchers notice in real-time if a PT vehicle is off schedule [Sáez et al., 2012].

Carrel, Mishalani et al. [2010] describe the processes and challenges in the OCC of a metro line. The authors conclude that staff management is a crucial factor in incident management. Missing staff and unavailability of replacement staff have the potential to worsen every kind of incident.

Briem, Buck, Magdolen et al. [2020] have interviewed dispatchers of the OCC in Karlsruhe, Germany, to understand their perspective on incident management. The authors categorise the dispatchers' answers into three categories, namely: influences and limitations, described dispatching procedures, and other topics besides incident management. They conclude that passengers themselves and staff management restrictions, such as the legal driving time of drivers, are the most predominant influences and limitations on dispatching decisions. Moreover, they point out that rerouting PT vehicles is the most preferred disposition measure to mitigate an incident's negative impact on the PT service. This is often followed by short- and long-turning measures to return the PT service to its schedule. Furthermore, the authors provide insight into the motivation of dispatchers by asking them why they chose their jobs.

Briem [2023] comprehensively analyses vehicle data of an ITCS to identify deviations from the PT schedule and compares it with actually taken disposition measures. The author notes that not for every incident, disposition measures are taken and proposes an assessment model for PT schedules to verify their scope for disposition measures.

Bachmann, Briem et al. [2022] present the finding through visits to six OCCs in Germany and Singapore, they interviewed OCC directors and trainers and observed dispatchers during their work. Whereas the findings through interviews cater for a comprehensive overview of the processes and procedures in an OCC, the observations of dispatchers during their work add valuable and detailed findings about the dynamics in OCCs taking place while dispatchers handle incidents. This is especially true for communication between the involved parties, such as PT drivers, dispatchers, emergency forces (i.e. police, ambulance, fire department), PT users, and towing services. This work was an important first piece of the puzzle to this thesis,

as it helps to understand the operators' view on incidents.
As mentioned before, dispatchers play the main role in PT incident management, by monitoring the service and take disposition measures whenever a deviation from the timetable occurs. To do so, they talk to the drivers via radio and to emergency forces and ground staff (i.e. transport wardens, mechanics) via phone to manage incidents adequately. In most cases, the information about an incident is provided by the PT drivers who send a call signal to the OCC in accordance with the present situation, once they encountered an incident.

Figure 2.1 shows the step-by-step procedure taking place in an OCC when an incident occurs. In most cases, it is a PT driver who encounters the incident first, as the drivers are out in the field and directly affected by such (Step 1). Right away, the driver notifies the dispatchers in the OCC about the encountered incident (Step 2). There are four different call signals to initialize a call corresponding to the present situation: assault, accident, missing replacement, or wish-to-talk call. The priority of these calls decreases from the first to the last mentioned. As per the call signal, the dispatcher follows certain procedures to handle the situation (Step 3). Flow charts and explanations of these procedures are given in detail by Bachmann, Briem et al. [2022].

In Step 3, two things happen simultaneously, the dispatchers instruct the drivers of the disturbed PT line and calls the emergency forces, if necessary. In OCCs the staff work closely together and support each other when an incident occurs in order to be able to handle this stressful event. If the situation requires the deployment of a transport warden, one is dispatched in Step 4. A transport warden is a field dispatcher. In Step 5 the emergency forces and the transport warden arrive on site. The transport warden talks to the emergency forces and coordinates the dissolution of the incident on site. Moreover, some situations, such as an assault on the driver or an accident can be quite burdening for PT drivers, hence, the transport warden is also on-site to help the driver in any way necessary. Once a transport warden got a clear picture of the situation, the OCC is provided with more detailed information about the present situation. In this way, the dispatchers can readjust their taken measures according to the additional information, if needed, and give the drivers updated instructions in Step 7. At this point, all decisions needed to resolve the incident have been made. Therefore, in Step 8, the dispatchers monitor the incident situation and let the subsequent PT drivers inform them about the development of the situation. Once the situation is cleared in Step 9, the dispatchers revoke all given instructions.

Even though there have been many investigations in incident management as pointed out in the previous section, the authors identified a gap between research and practice. Many findings of scientific studies have not yet been implemented in practice. This is one of the goals of the here described work by Bachmann, Briem et al. [2022], to let practice benefit more from research. Another goal is to identify potentials for improvement. As pointed out before, the most important tasks of dispatchers are monitoring the service and handling incidents by communicating with the other involved parties. This is mostly done verbally via radio and phone. Already today PT vehicles are equipped with AVL to enable the dispatchers to monitor their delay. However, when a troubled PT vehicle needs assistance from emergency forces, because it is involved in an accident, for example, its location has to be forwarded verbally via the dispatcher to the emergency forces and the ground staff. All information is going via the dispatchers who are thereby a bottleneck in the incident management system. Although dispatchers do an outstanding job to keep a certain quality of service and resolve incidents as quickly as possible, especially during peak hours, when traffic and passenger demand are high, it can easily come to overwhelming situations. When dispatchers are overwhelmed, disposition measures are stalled and thereby incidents' dissolutions as well. This caters for additional delays for PT services and consequently their users.

Therefore, it is desirable to reduce this bottleneck in the system and establish more direct and automated communication between PT vehicles and emergency forces, by automatically transmitting the troubled PT vehicle's GPS location to the emergency forces, for example. Another possibility is to automatically match the location of a broken down PT vehicle with the location of the operator's mobile mechanics and transport wardens. The closest ground staff get a request on their mobile device with the location and situation of the troubled vehicle. Then, they have several seconds to answer the request, otherwise, it is forwarded to the second closest personnel and so on. This kind of procedure is already used in ride-hailing services such as Uber or Lyft to match customers with drivers [Özkan and Ward, 2020; Uber Technologies Inc., 2022].

In addition, misunderstandings, especially through language barriers are an issue in the communication between drivers and dispatchers. The better the communication, the better the incident management. Due to the lack of drivers, PT operators continuously more often hire drivers from neighbouring countries. In many cases, this comes along with language barriers which could be solved by language courses for the drivers and/or dispatchers. However, that would be rather demanding. Another thinkable solution would be translations. Both, the dispatchers and the drivers are already equipped with computers or board computers. Today's translation programmes are capable of translating spoken words into written words in real-time. Such translations could be displayed on the monitors to avoid further misunderstandings between dispatchers and drivers. It goes without saying that in the case of the driver's monitor, this is only done when the vehicle is standing still. Otherwise, a verbal output by the computer is also technically feasible.

With autonomous vehicles emerging, a higher level of automation in OCCs is generally desirable. To install the infrastructure for direct communication not only between the involved people but also between people and machines as well as between machines to speed up communication, reduce misunderstandings and support dispatchers. In this way, dispatchers can focus on their most important job, to decide on adequate disposition measures to dissolve an incident and return the PT service to normal operations as quickly as possible. This particular investigation by Bachmann, Briem et al. [2022] also helps to understand how the PCIM method presented here could be implemented in practice. This is discussed in Section 6.3. Furthermore, it helped with the development of the aforementioned work by Briem [2023].

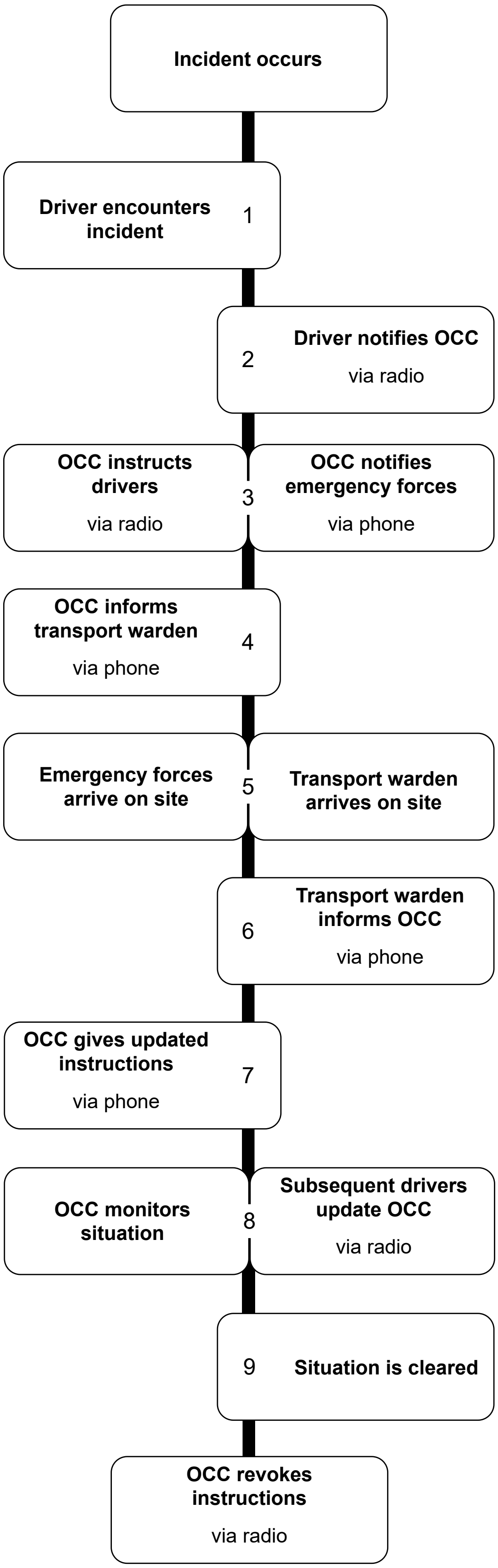


Figure 2.1: Incident management procedure of an OCC [Bachmann, Briem et al., 2022]

2.2.2 Passenger-centric Incident Management

Even though the studies in Section 2.2.1 focus on *supply-centric* measures, most of them are *passenger-oriented* in a way that they try to adjust the PT service to a present incident situation to reduce passenger delays. There is also a large variety of works in literature concerning *passenger-oriented* disruption management in railway operations. These works focus mainly on the rescheduling of trains and cancellation decisions during severe incidents in regional and long-distance railway services. One goal is to also provide dispatchers with decision support [Rückert et al., 2017; Veelenturf et al., 2017; Long et al., 2021].

This chapter introduces investigations that are not only *passenger-oriented* but *passenger-centric*. This means they do not merely reduce passenger waiting and travel times during incident situations but they also include the passengers as part of incident management and the delay reduction. This is done by providing them with adequate PI about the incident or even available alternative paths and services, on which basis they can re-plan their disturbed trip. Thereby, this section introduces the literature of the research area this thesis is associated with, *passenger-centric* incident management (PCIM). The orientation for this section is based on Bachmann, Tsakarestos et al. [2023], the authors summarise, compare, and discuss the to-date conducted investigations about capacity-aware passenger redirection (CAPR). As in the mentioned reference, this section is subdivided into academic investigations and approaches in practice.

Another research area about passenger redirection is to be found in air traffic. In case of a service disruption, airline customers are redirected onto other scheduled flights to ensure that they reach their destination with a minimum of delay [Sinclair et al., 2014; Y. Hu et al., 2015; Hassan et al., 2021]. However, there are many differences between the natures of passenger air transport and land PT when it comes to operations and incident management. In air transportation, each passenger is known by name, origin and destination, and seat number. Furthermore, the headway between certain connections, the number of airports, and the vessels are very different than in land PT especially in urban PT in which the headways are very small, the passengers are not known, and the vessels are smaller and there is a bigger variety among them (i.e. buses, trams, metros, etc.). Therefore, the research area of passenger redirection in air transportation is not further considered here.

The reviewed work is very diverse in their assumptions, considerations, and approaches. Therefore, several criteria of comparison have been derived from the literature review, which are used in the Tables 2.5 and 2.6:
Firstly, the focus and goal of each work is presented. Even though most of them aim to reduce passenger delays or inconvenience, respectively, the focus of the works differentiates.

Secondly, as CAPR is a crucial aspect of PCIM, the consideration of capacity constraints is another important criterion of comparison, since secondary disturbances through overcrowding are to be avoided.

Thirdly, the meaning of PI has already been explained in Section 2.1.5. Since it is one of the core ideas of PCIM to involve passengers actively in the reduction of their delays, communicating with them is vital. Three different aspects of PI have been included, namely:

its content, which refers to the information which is given to travellers; its schemes, explaining the used timings and location of the PI, and its channels, clarifying which PI channels have been considered in the corresponding work.

Fourthly, as passengers are the main focus of PCIM, criteria of comparison about their representation and handling in the presented approaches are included. Furthermore, used compliance rates, which describe the share of affected travellers, who would follow path advice, if given during an incident, and, if applicable, how the effect of PI during incidents on a path choice model is considered.

Fifthly, the resources that have been used to conduct the corresponding investigation, such as used tools and algorithms, as well as if an optimisation is taken into account, are criteria of comparison.

Sixthly, the conducted case studies are compared. Here, the criteria of comparison are the used networks, the characteristics of the considered incidents (i.e. duration, location), the demand input, and the transportation modes that have been taken into account.

Lastly, the considered *supply-centric* disposition measures as well as if and how the integration of the corresponding PCIM method into an OCC are used as criteria for comparison.

For describing some of the criteria of the presented works the following three terms are used in the Tables 2.5 and 2.6: *considered*, which expresses that the corresponding feature is considered in the developed method of the corresponding reference; *mentioned* means that the corresponding feature is mentioned but not considered and lastly *not mentioned* for which the corresponding feature is neither mentioned in the publication nor considered in the corresponding PCIM method.

Academic Investigations

Table 2.5 by Bachmann, Tsakarestos et al. [2023] presents and compares twelve relevant academic contributions to the research field of PCIM, which are introduced in the following.

Literature Review: Cats and Jenelius [2014] investigate the betweenness centrality and vulnerability of PT networks. To do so, a stochastic and dynamic notion of a PT system has been developed. Their case study includes five different incident scenarios in the PT network of Stockholm, Sweden. The incident takes place in the metro part of the network. In each scenario, four different PI schemes have been tested, namely: no PI, PI at stops, clustered PI at transfer hubs, and network-wide PI. The PI broadcast contains the updated arrival times of PT services in accordance with the changes through the incident. This PI has then a corresponding influence on the path choices of the simulated agents and thus onto the passenger assignment in the simulation. The scenarios with PI are then compared with the scenario without PI. The results show the positive influence of PI on passenger delays. In all but one cases, the passenger delay has been reduced. The phenomenon that the delay increased through PI in this one case is explained by overcrowding effects on the alternative paths. These could not provide sufficient remaining capacity for the additional demand of passengers transferring onto these because of the incident. A danger of such effects is specifically present when the disrupted PT service has a significantly higher capacity than the services of the alternative paths. For example, passengers transferring from a disrupted metro line onto bus lines. The authors conclude that such secondary incidents could be avoided by employing effective PI schemes as well as proactive fleet management. Moreover, they point out that the importance of a link in a PT network also depends on the available real-time PI and not only on the betweenness centrality.

van der Hurk et al. [2018] present an optimisation model to reduce passenger delays and operators' costs by providing travellers, affected by an incident, with concrete path advice and rescheduling trains. The developed model builds upon Kroon et al. [2015]. Severe disruptions of several hours at different locations are simulated in the Dutch railway network. Passengers who require path advice are clustered into indivisible groups in accordance with their OD relation. Furthermore, capacity constraints are considered for the path advice to avoid secondary incidents as previously mentioned.

Moreover, a compliance rate is introduced to account for passengers who receive path advice but do not follow it. Especially travellers who know the PT network well, such as commuters, might decide to redirect themselves rather than follow path advice given by the operator. Several compliance rates have been tested by the authors, deterministic values between 0% and 100% compliance as well as logarithmic calculated compliance rates. The logarithmic values take the difference in travel time between the fastest and the suggested alternative path into account. If the difference is larger than ten minutes, the willingness to follow path advice decreases rapidly.

It is concluded that rescheduling rolling stock and providing path advice can significantly reduce the passenger overall delay and operational costs. A further finding is that the location of the incident plays a crucial role. The closer to the centre of the PT network the incident location is, the more severe the negative effects of the incident, however, also the more effective is path advice, as more alternative paths are available. Interestingly, the best results are to be seen in scenarios with less than complete compliance. Additionally, the better the prediction of the demand assignment, the better the effects of the rescheduling model, as capacity bottlenecks appear more rarely.

Passenger redirection during severe disruption in a long-distance railway network is investigated by Müller-Hannemann et al. [2019] in cooperation with the German railway operator German rail [Translated from German: Deutsche Bahn] (DB). Through a multi-commodity flow model with an event-activity network, optimal alternative paths are found. This work also considers capacity constraints and even introduces a soft (number of seats) and hard (total number of allowed passengers) constraint. Furthermore, the authors take a penalty for crowding into account which increases rapidly once the soft constraint is exceeded. This work also handles the passengers as indivisible groups, corresponding to their ODs, which is justified by the fact that it is impossible to know who is travelling with whom.

The idea of the authors is that their PCIM method can support dispatchers in their decisions in delay management [Dollevoet et al., 2012] while considering the passengers' perspective and providing real-time PI. Several different approaches are tested, namely: nocap, in which the passengers are redirected without consideration of the remaining capacity; greedy, which redirects passengers by groups, meaning that already assigned groups influence the redirection options for the groups to be redirected and two approaches using Pareto fronts are performed [Knowles and Corne, 1999]. The results of the study show that the developed PCIM method reduces passenger delays and lowers the number of passengers without an alternative path. The authors further test their approach with an increase in demand by 20% and show that the capacity-aware redirection of passengers becomes more important with an increase in demand. Furthermore, it is pointed out that searching for available alternative paths is the computationally most expensive part of their method.

Another piece of research in the field of PCIM is contributed by Zhu and Goverde [2019a]. With the help of an event-activity network, passengers, who are affected by train delays and cancellations, are dynamically reassigned. The disruption timetable which reflects the service offered during the disruption is considered. By comparing the passengers' paths with the disruption timetable, affected passengers can be identified. Re-planning decisions based on the disruption timetable are done for each traveller individually. If the updated arrival time of a certain passenger exceeds a set threshold, the passenger is assumed to leave the PT system.

In the simulated scenarios, the incident duration and location do not differ (one hour of full section blockage) but the location and content of the given PI. It is given nowhere and at stations and/or on trains. Its content includes the operating services and in some scenarios also the level of train congestion. Furthermore, different thresholds at what point in time the PI interventions are triggered are tested. The scenarios are tested in the Dutch railway network.

Findings include that the publication of the given PI reduces passenger delays. The more locations the information is broadcast, the greater the drop in delays. The higher the acceptance of delays, the fewer people leave the system. The information about the level of occupancy of trains helps to lower the delays further. Moreover, the incident is more severe for people who are already on the trip, compared to the ones starting their trip after the occurrence of the incident, as they have more options to re-plan.

The works by Zhu and Goverde [2019a] and by Zhu and Goverde [2019b] – the latter is about a timetable rescheduling model – are combined and further developed by Zhu and Goverde [2020] to a *passenger-oriented* timetable rescheduling model in which the dynamic reassignment of passengers during disruption is considered by the timetable rescheduling model to improve the overall situation even further than the two models do separately. For each disruption, several rescheduling timetables can be found, and each of these is combined with a corresponding dynamic reassignment of passengers to find the best solution. The results show a significant drop in passenger delays. In Table 2.5, Zhu and Goverde [2019a] and Zhu and Goverde [2020] share a column as the latter builds upon the first work and the authors are the same. As Zhu and Goverde [2019a] focuses more on PCIM than Zhu and Goverde [2020] it is more relevant to the following discussions.

Moreover, the four publications by Leng and Corman [2020], Leng, Liao et al. [2020], M. Rahimi et al. [2021] and Rahimi Siegrist and Corman [2021] share the same column in Table 2.5 and are referred to as *Corman group*, named after the common last author.

Leng and Corman [2020] focus on the effects of different information schemes during incident situations. Three different schemes are tested, namely: no information, in which affected passengers notice the disruption of the PT services when they reach the corresponding stop to take the disrupted service; timely information which refers to the dissemination of PI at the time of the incident's occurrence and advanced information which covers cases in which the incident is already known in advance to the passengers such as planned construction sites.

The authors use the agent-based tool Multi-Agent Transport Simulation (MATSim) [Horni et al., 2016], to model disruption scenarios in the railway network of Zurich, Switzerland. A within-day planning procedure is implemented to equip agents with the option to adjust their daily plans during the day, for example, re-plan their trips in accordance with an incident. An agent's day plan exists of several activities and trips. Their results show that the advanced information scheme caters for almost no delays, whereas the timely information scheme reduces the delays less but still by a significant amount compared to the no information scheme.

Leng, Liao et al. [2020] present an extension to the previously introduced paper. The authors conclude that by combining disposition measures with PI passenger delays can be further reduced. The authors investigate the mutual influence of PI availability with disposition measures such as rescheduling rolling stock. A mixed integer programming optimisation model is developed and implemented in the framework, which is introduced by Leng and Corman [2020]. It is used to find the optimal disposition measures in combination with the three aforementioned PI schemes.

Additional findings are gained by M. Rahimi et al. [2021], by combining PI with measures such as increasing frequency or increasing the capacity of PT vehicles on lines which are relevant to the passengers who are re-planning their day due to the incident.

In addition, Rahimi Siegrist and Corman [2021] used the same framework as the other works of the *Corman group* to cast light on the direct and indirect effects of the three PI schemes during the service disruption. Furthermore, the authors introduce two more information schemes: one at which the passengers receive the PI at the beginning of their next trip and a special form of advanced information in which the passengers are also aware of the decisions of other travellers.

As an overall conclusion of the works of the *Corman group*, it can be summarised that PI about an occurred disruption helps to significantly reduce passenger delays. Furthermore, the earlier the passengers are informed, the stronger its positive effect. Additional delay reductions can be gained by combining the information schemes with disposition measures such as rescheduling rolling stock or increasing the capacity or frequency on the relevant alternative paths. Another finding by Leng, Liao et al. [2020] is that partially cancelled railway services have a much better effect on passenger delays than fully cancelled services. Furthermore, M. Rahimi et al. [2021] found out that picking specific PT lines for an increase in capacity is most effective, among their tested disposition measures. Moreover, Rahimi Siegrist and Corman [2021] point out that the negative effects of an incident spread through a network and affect passengers who are not directly disturbed by an incident, as well.

Further research in the field of PCIM is done by Bachmann, Rau et al. [2021] and Bachmann, Dandl et al. [2023]. The two publications show earlier stages of the PCIM method which is also presented in this thesis and are summarised in the same column in Table 2.5.

The method by Bachmann, Rau et al. [2021] redirects affected passengers during incidents by assuming that these passengers are provided with concrete path advice. Here, the redirection duration is introduced which states for how long it is reasonable to redirect passengers during an incident. This, of course, is only beneficial as long as the alternative path caters for an earlier arrival at the destination than the original path of a passenger. Travellers are grouped in accordance with the stop at which they are redirected, which is referred to as the redirection point and their destination.

A numerical case study has been conducted in a simple artificial network with assumed demand. Three different incident scenarios are tested: 1) disrupted PT services are rerouted, 2) additionally, passengers are redirected, and 3) in addition, dipensable capacities are reallocated. The scenarios have been conducted in a PT bus system as well as in the DART system [Rau, Tian et al., 2018], which is an autonomous PT system with a modular setup. This is further described in Section 5.2.3. Through the modular setup, it is more suited for capacity reallocation than buses as a platoon of modules can be split and parts of its capacity can be dispatched while maintaining the service's headway on the original line. In contrast, a bus cannot split and its reallocation means a reduced level of service on its original line.

This is also confirmed by the results of Bachmann, Rau et al. [2021]. The redirection of passengers already significantly reduces the delay whereas the additional reallocation of capacities lowers them further. The DART system caters for better results than the bus system in this matter.

The conceptional framework of Bachmann, Rau et al. [2021] is picked up and developed further by Bachmann, Dandl et al. [2023] and implemented in Python [Python Software Foundation, 2022] to conduct a simulation study. It is then combined with the simulation tool Simulation of Urban MObility (SUMO) [Lopez et al., 2018] to conduct a more sophisticated simulation study as the previously introduced work.

The tested scenarios take place in the Mandl network [Mandl, 1979] with a PT network design by Ul Abedin [2019]. Two different incident durations (30 and 60 minutes) and two different disposition measures are tested, namely: rerouting, in which the PT services are rerouted, and line-splitting, in which the disrupted PT lines serve in loops on both sides of the incident location in the network (Section 2.2.1). Passengers are provided with path advice which is computed by a heuristic and by an optimisation approach. The results are then compared with each other. As van der Hurk et al. [2018], the authors also consider different compliance rates to take passengers who do not follow the path advice into account. Values of 57%, 100%, and logarithmic calculated values are used for the passengers' compliance. A PT user survey by the German Federal Ministry of Transportation and digital Infrastructure [Translated from German: Bundesministerium für Vekehr und digitale Infrastruktur] (BMVI) revealed that 57% of the participants would be willing to follow an operator's path advice [BMVI, 2019]. The logarithmic compliance rates are adopted from van der Hurk et al. [2018].

Bachmann, Dandl et al. [2023] conclude that path advice has the potential to significantly reduce passenger delays during incidents. Further findings are that the optimisation approach achieves better results than the heuristic and that their method is more effective in the combination with rerouting PT lines than line-splitting. Moreover, their results reveal that the incident duration has a considerable influence on delay reduction. The longer the incident the lower the positive effect of their PCIM method.

One case in which logarithmic calculated compliance rates are used shows an increase in delay. The authors explain this by overcrowding effects such as also stated by CATS and JENELIUS [2014]. It could also show that the logarithmic function might not be suitable to reflect a complex situation of an affected passenger who has to decide on taking path advice or not. As described in Section 2.1.4, many factors influence passengers' reactions to incidents and to connection suggestions. In addition, BACHMANN, RAU et al. [2021] derive from their results that the additional reallocating of capacities during incidents can support passenger redirection and further reduce delays.

Lastly, the work by MO, KOUTSOPOULOS, SHEN et al. [2023] is introduced in this section. They mathematically formulate passenger flow distribution to run several scenarios in an event-based public transit simulator. PT users with the same OD relation receive the same path advice. A historical incident case in the metro network of Chicago, United States of America (USA), is used. Like most of the aforementioned studies, this work also considers capacity constraints. In addition, uncertain passenger demands are considered to take PT users into account who leave the system due to the incident.

The result of the path advice optimisation is compared to three benchmark scenarios. In the first, the passenger flows are distributed evenly, it is therefore referred to as uniform path share. In the second, paths' capacities are considered during the assignment process, which is therefore named capacity-based path shares, and the last is called status-quo path share as this case reflects the actual decisions of the passengers on the day of the incident, which are inferred from smart card data. All results show an improvement in the passengers' situation through the given path advice.

Comparison: All these presented works have in common that their focus lies rather on the passenger than on the supply side. By informing the passengers either about the incident and the changes to the PT service or by giving them concrete path advice, they are directly involved in the passenger delay reduction. Table 2.5 reveals that the goal of decreasing passenger delay during incidents is approached and accomplished in various ways by the investigations.

The focus of CATS and JENELIUS [2014] lies on the influence of PI on a PT system's vulnerability; VAN DER HURK et al. [2018] focus on path advice and capacity adjustment; MÜLLER-HANNEMANN et al. [2019] concentrate on the algorithmic and computational implementation of path advice; ZHU and GOVERDE [2019a] bring the reassignment of passengers into focus; LENG and CORMAN [2020] concentrate on passenger behaviour during incidents; LENG, LIAO et al. [2020] and M. RAHIMI et al. [2021] focus on the mutual influence between *supply-centric* measures and PI availability. RAHIMI SIEGRIST and CORMAN [2021] centre their work on the positive and negative indirect effects of incidents; BACHMANN, DANDL et al. [2023] focus on path advice whereas BACHMANN, RAU et al. [2021] additionally focus on capacity readjustment. The focus of the work by MO, KOUTSOPOULOS, SHEN et al. [2023] lies on the distribution of passenger flows. Therefore, although the studies presented have the same objective, namely to reduce passenger delays during incidents, they are focused on different issues.

One of the crucial aspects which need to be examined in PCIM is the remaining capacity on alternative paths, to avoid secondary disturbances [Cats and Jenelius, 2014; Bachmann, Tsakarestos et al., 2023]. Hence, it is not surprising that each of the introduced academic investigations in PCIM considers the PT supply's capacity. However, as suggested by Cats and Jenelius [2014], it needs effective PI schemes and proactive fleet management to avoid such negative effects. Effective PI schemes could be interpreted here as concrete path advice, redirecting passengers onto paths with sufficient remaining capacity. Therefore, it is also interesting to compare the various considerations of the works introduced here in this matter. PI is subdivided into its content, schemes, and channels:

1) PI content: Cats and Jenelius [2014], Zhu and Goverde [2019a] and Zhu and Goverde [2020] inform the passengers about expected arrival times during the incident, and the latter two also inform about train occupancies. The same is true for the *Corman group*[1] who instead of mentioning estimated arrival times mention the estimated duration of the incident as well as the affected PT lines to the travellers. Müller-Hannemann et al. [2019] do not inform about occupancy in general but suggest connections with low occupancy, furthermore, the authors assume that the passengers inform themselves and choose their path selfishly. van der Hurk et al. [2018], Bachmann, Rau et al. [2021], Bachmann, Dandl et al. [2023] and Mo, Koutsopoulos, Shen et al. [2023] give concrete path advice to affected passengers.

2) PI schemes: Müller-Hannemann et al. [2019], Bachmann, Rau et al. [2021], Bachmann, Dandl et al. [2023] and Mo, Koutsopoulos, Shen et al. [2023] do not mention any schemes; Zhu and Goverde [2019a] and Zhu and Goverde [2020] disseminate PI at stops and/or on trains; Cats and Jenelius [2014] test four different PI schemes, namely: no information, information at stops only, clustered information at transfer hubs, and network-wide information; the *Corman group*[1] simulates five PI schemes that differ in the time of dissemination: no information, timely information (at the start of the incident), advanced information (before the incident), "equilibrium with disruption" which is a special case of the advanced information and at the start of the trip. van der Hurk et al. [2018] assume perfect information availability.

3) PI channels: as mentioned in Section 2.1.5, there are a variety of available communication channels in PT systems between the PT operator and the PT users. Cats and Jenelius [2014], van der Hurk et al. [2018], Müller-Hannemann et al. [2019] and Zhu and Goverde [2019a] do not clarify the PI channels they take into account; Bachmann, Rau et al. [2021] and Bachmann, Dandl et al. [2023] mention the use of all available channels, whereas the *Cormann group*[1] assumes appropriate available channels. Mo, Koutsopoulos, Shen et al. [2023] consider smartphones, websites, and PI displays at stops. To conclude the works' considerations on PI, all of them consider PI as an important part of PCIM. However, some of them clearly identify PI channels to be used and also clarify when the information is to be given, whereas other works simply mention the necessity of information dissemination.

To take the reaction of passengers on the given PI into account, the travellers are dealt with in two different ways in the approaches presented. Cats and Jenelius [2014] and Zhu

[1] Leng and Corman [2020], Leng, Liao et al. [2020], M. Rahimi et al. [2021] and Rahimi Siegrist and Corman [2021]

and GOVERDE [2019a] and the *Corman group*[1] handle the passengers individually, whereas the rest considers indivisible passenger groups. Even though it is easier to find sufficient room in the system for individuals, MÜLLER-HANNEMANN et al. [2019] argue that it is impossible to know who travels with whom. Furthermore, BACHMANN, DANDL et al. [2023] emphasize the availability of collective PI channels (i.e. speakers and dynamic PI displays) through which it is impossible to inform PT users individually. According to the PT user survey presented in Chapter 3 the collective PI channels are preferred by PT users during incidents. In addition, BACHMANN, TSAKARESTOS et al. [2023], who formulate requirements for an ideal PCIM method, point out that it could lead to confusion and mistrust if people travelling together would receive different path advice and that PI needs to be consistent across all channels along the whole journey. In summary, most works handle the passengers as indivisible groups, as it is who of the affected travels together and some PI channels do not provide for the possibility of informing PT users individually.

In any case, just because PI or even path advice is given, it does not necessarily mean that people follow given suggestions. Most of the academic investigations consider such behaviour. In the case of CATS and JENELIUS [2014] and the *Corman group*[1], this matter is handled by a path choice model (Section 2.1.2) which is influenced by the used PI scheme. In ZHU and GOVERDE [2019a], the path choice depends on the set maximum for the accepted delay. VAN DER HURK et al. [2018] and BACHMANN, DANDL et al. [2023] consider different rates of compliance. Deterministic values as well as a logarithmic function to calculate compliance rates are used. BACHMANN, RAU et al. [2021] and MO, KOUTSOPOULOS, SHEN et al. [2023] assume complete compliance and MÜLLER-HANNEMANN et al. [2019] do not mention such considerations. Mainly there are two approaches concerning the consideration of travellers' reaction to given PI. Studies which take path advice into account, consider different compliance rates or simply full compliance, whereas studies which provide affected passengers with the arrival times of services and crowding information use path choice models.

To implement the approaches introduced here, different tools and algorithms have been used in the studies. CATS and JENELIUS [2014] use the simulation tool BusMezzo [CATS, 2022]; VAN DER HURK et al. [2018] mention the developed algorithm advice and rolling stock rescheduling problem with uncertainty (ARSRU); MÜLLER-HANNEMANN et al. [2019] use the round-based public transit optimized router (RAPTOR) [DELLING et al., 2015] to find alternative paths and the Gurobi Optimizer [GUROBI OPTIMIZATION LLC, 2022] to solve their optimisation problem; ZHU and GOVERDE [2019a] and ZHU and GOVERDE [2020] mention the event-activity network as well as the adapted fix and optimise (AFaO) algorithm they developed; the *Corman group*[1] uses the simulation tool MATSim [HORNI et al., 2016] to conduct their case studies; BACHMANN, RAU et al. [2021] present a numerical investigation whereas BACHMANN, DANDL et al. [2023] use SUMO and the Gurobi Optimizer [LOPEZ et al., 2018; GUROBI OPTIMIZATION LLC, 2022], both mention the developed PCIM method. MO, KOUTSOPOULOS, SHEN et al. [2023] mention a event-based public PT simulator. All of the works use different tools to implement the developed methods. The only

[1] LENG and CORMAN [2020], LENG, LIAO et al. [2020], M. RAHIMI et al. [2021] and RAHIMI SIEGRIST and CORMAN [2021]

tool which is named more than once is the Gurobi Optimizer for solving optimisation problems.

In most works optimisation plays a role. Cats and Jenelius [2014] and Bachmann, Rau et al. [2021] just mention the possibility of optimising in the outlook; van der Hurk et al. [2018], Müller-Hannemann et al. [2019] and Bachmann, Dandl et al. [2023] and the *Corman group*[1] minimise the passenger delay; Zhu and Goverde [2019a] and Zhu and Goverde [2020] aim on optimising the passenger-operator balance, and Mo, Koutsopoulos, Shen et al. [2023] optimise the passenger flow distribution.

Besides the used tools and optimisation goals, the presented investigations also differ in the inputs and assumptions considered in their case studies. van der Hurk et al. [2018], Zhu and Goverde [2019a] and Zhu and Goverde [2020] use a part of the Dutch railway network; The *Corman group*[1] use the PT network of Zurich, Switzerland; Cats and Jenelius [2014] test their approach in the PT network of Stockholm, Sweden; Müller-Hannemann et al. [2019] use a part of the German long-distance railway network; Bachmann, Rau et al. [2021] do not conduct a simulative but numerical investigation and use a simple artificial network to do so; Bachmann, Dandl et al. [2023] apply a PT network design by Ul Abedin [2019] of the Mandl network [Mandl, 1979]. The metro network of Chicago, USA, is utilised by Mo, Koutsopoulos, Shen et al. [2023]. Concluding, all works use different environments for their case studies, besides the exception of the Dutch railway network which is used by van der Hurk et al. [2018], Zhu and Goverde [2019a] and Zhu and Goverde [2020]. Nevertheless, the rest of the input considered by them differs.

Furthermore, the publications vary in the assumed duration of the incident it ranges from half an hour in Bachmann, Rau et al. [2021], Cats and Jenelius [2014], Zhu and Goverde [2019a] and Zhu and Goverde [2020] to four hours in van der Hurk et al. [2018].
Moreover, the demand input is assumed by Zhu and Goverde [2019a], Zhu and Goverde [2020] and Bachmann, Rau et al. [2021], whereas the rest considers historical travel data.

The relative gained reduction in passenger delays of the presented academic investigations, shows a wide range with most results showing a positive effect of PCIM on the passenger delay reduction. Cats and Jenelius [2014] accomplish a relative reduction of passenger delays of up to 4%, whereas one case shows an increase of 2.5% which is explained by overcrowding effects. The results of the case study by van der Hurk et al. [2018] show a relative passenger delay reduction of up to 30% while reducing the number of affected passengers by 20%. Nevertheless, in one case the relative delay is increased by 2%. Müller-Hannemann et al. [2019] present results between 10.5% and 11.5% of relative delay reduction. The outcome of the work by Zhu and Goverde [2019a] ranges between 13.8% and 46.7% of relative delay reduction. It is further derived by Zhu and Goverde [2020] that passenger delays can be further reduced due to adjusting the rolling stock rescheduling scheme to the outcome of their dynamic passenger assignment model. The *Corman group*[1] shows significant improve-

[1] Leng and Corman [2020], Leng, Liao et al. [2020], M. Rahimi et al. [2021] and Rahimi Siegrist and Corman [2021]

ments in the passengers' situation with relative delay reductions between 93.2% and 99.8%. The PCIM method by Bachmann, Rau et al. [2021] achieves a relative delay reduction by 63.3% given path advice. This is further improved by the reallocation of capacity to 73.2% in a bus system and to 73.8% in an autonomous PT system. The highest accomplished reduction of passenger delays by Bachmann, Dandl et al. [2023] is at 96.0%, however, in one case the delay increases by 15%. This is explained by overcrowded bus stops as well as that the used logarithmic function by van der Hurk et al. [2018] has not been fully adjusted to their passenger redirection approach. Furthermore, as elaborated on in Section 2.1.4, there are many factors influencing travellers' reactions to incidents as well as their willingness to follow path advice. Hence, the logarithmic function by van der Hurk et al. [2018] which merely considers the aspect of the travel time difference between the suggested path and the fastest alternative path does probably not live up to the complexity of passengers' willingness to comply to path advice. Mo, Koutsopoulos, Shen et al. [2023] accomplish a relative delay reduction for the affected passengers of up to 20.6%. Nonetheless, also in this work, there is a case in which the delay increases by 6.4%. This is explained through the rationality with which passengers choose their path during normal PT operations. In summary, also the results of the various academic investigations introduced here concerning the relative delay reduction of affected passengers show a wide range of outcomes between an increase in delay of 15% and a reduction of up to 99.8%. However, as implied in this section there is a large variety among the approaches, input and environments introduced here through which it is inadequate and inappropriate to directly compare the results of the presented investigations. Nevertheless, the outcomes clearly indicated the potential of PCIM methods in general.

Another aspect of the academic investigations is the consideration of different kinds of PT modes. van der Hurk et al. [2018], Müller-Hannemann et al. [2019], Zhu and Goverde [2019a], Zhu and Goverde [2020] and Mo, Koutsopoulos, Shen et al. [2023] solely consider trains or metro, whereas Cats and Jenelius [2014] and the *Corman group*[1] take several PT modes into account, however, in the last mentioned works the incident also occurs in the rail-bound part of the network. Bachmann, Rau et al. [2021] and Bachmann, Dandl et al. [2023] focus on bus operations.

As elaborated on in Section 2.2.1, *supply-centric* disposition measures are well investigated and part of the daily business of OCCs. In addition to the incident which disrupts the PT service, these disposition measures also cause alterations to the PT service, and thus the available alternative paths for the PT users. Therefore, it is not surprising that all investigations consider disposition timetables that reflect not only the service changes through the incident but also the taken disposition measures. While doing so, some works focus on specific measures. In the paper by Cats and Jenelius [2014] it is holding; van der Hurk et al. [2018] and Zhu and Goverde [2020] and the *Corman group*[1] mention rescheduling, while Zhu and Goverde [2020] also use short-turning and flexible stopping and the *Corman group*[1] focus on rerouting and increase in capacity. Rerouting is also named by Bachmann, Rau et al. [2021] and Bachmann, Dandl et al. [2023], as well as line-splitting. In summary,

[1] Leng and Corman [2020], Leng, Liao et al. [2020], M. Rahimi et al. [2021] and Rahimi Siegrist and Corman [2021]

all academic investigation seem to share the understanding that it is necessary to consider *supply-centric* disposition measures taken when developing PCIM methods. Consequentially, all of them consider corresponding disposition timetables, whereas some of them even integrate such measures as part of their approach.

Even though disposition timetables, which are a result of the dispatchers' decisions, are taken into account, the OCC is mentioned, at most. The same goes for an integration of PCIM into OCCs as suggested by BACHMANN, TSAKARESTOS et al. [2023]. The MÜLLER-HANNEMANN et al. [2019], ZHU and GOVERDE [2019a] and ZHU and GOVERDE [2020] and the *Corman group*[1] do not mention it. This is one of the major differences in comparison to the approaches in practice, which are introduced in the next section.

[1]LENG and CORMAN [2020], LENG, LIAO et al. [2020], M. RAHIMI et al. [2021] and RAHIMI SIEGRIST and CORMAN [2021]

Table 2.5: Overview of academic investigations [Bachmann, Tsakarestos et al., 2023]

Reference	Cats and Jenelius [2014]	van der Hurk et al. [2018]	Müller-Hannemann et al. [2019]	Zhu and Goverde [2019; 2020]	*Corman group*[1]	Bachmann et al. [2021; 2023]	Mo, Koutsopoulos, Shen et al. [2023]
Focus	Passenger information	Path advice, capacity adjustment	Computational implementation of path advice	Passenger reassignment	Passenger behaviour	Path advice, capacity adjustment	Passenger flow distribution
Main goal	Analysis of PT system vulnerability	Reduction of passenger delay	Reduction of passenger delay	Reduction of passenger delay	Reduction of passenger delay	Reduction of passenger delay	Reduction of passenger delay
PT system's capacity	Considered	Considered, adjusted	Considered	Considered, adjusted	Considered	Considered, adjusted	Considered
PI content	Expected arrival times	Path advice, capacity shortages	Self-informing passengers assumed	Expected arrival times, train occupancies	Affected lines, disruption duration, vehicle capacities	Path advice	Path advice
PI schemes	At stops, clustered, network wide	Perfect information is assumed	Not mentioned	At stations and/or on trains	Timely, advanced information	Not mentioned	Not mentioned
PI channels	Mentioned	Not considered	Mentioned	Mentioned	Assuming appropriate channels	On all available channels	Mobile phones, websites, displays at stops
							Continues

Table 2.5: Overview of academic investigations [Bachmann, Tsakarestos et al., 2023] (continued)

Reference	**Cats and Jenelius [2014]**	**van der Hurk et al. [2018]**	**Müller-Hannemann et al. [2019]**	**Zhu and Goverde [2019; 2020]**	***Corman group*[1]**	**Bachmann et al. [2021; 2023]**	**Mo, Koutsopoulos, Shen et al. [2023]**
Passenger handling	Individually	Indivisible passenger groups	Indivisible passenger groups	Individually / indivisible passenger groups	Individually	Indivisible passenger groups	Indivisible passenger groups
Compliance rate / path choice	Path choice dependent on PI scheme	Deterministic, logarithmic compliance assumed	Not mentioned	Path choice dependent on accepted delay	Path choice dependent on PI scheme	Deterministic, logarithmic [van der Hurk et al., 2018] compliance assumed	Full compliance assumed
Used tools / algorithms	BusMezzo	ARSRU	RAPTOR, Gurobi	Event-activity network, AFaO	MATSim	SUMO, Gurobi / PCIM method	Event-based PT simulator
Optimisation	Mentioned	Minimise passenger delay	Minimise passenger delay	Passenger-operator balance	Minimise passenger delay	Mentioned, minimise passenger delay	Passenger flow distribution
Case study	Stockholm PT network	Part of the Dutch railway network	Part of the German railway network	Part of the Dutch railway network	Zurich PT network	Simple artificial, Mandl network	Metro network of Chicago
Incident	0.5 hours, five different disrupted lines	3 – 4 hours, unsure period, link closure	Train cancellations based on historical data	1 – 2 hours, link closure	3 hours, link closure	0.5, 1 hour(s), link closure	1 hour, line suspension
							Continues

Table 2.5: Overview of academic investigations [Bachmann, Tsakarestos et al., 2023] (continued)

Reference	**Cats and Jenelius [2014]**	**van der Hurk et al. [2018]**	**Müller-Hannemann et al. [2019]**	**Zhu and Goverde [2019; 2020]**	***Corman group*[1]**	**Bachmann et al. [2021; 2023]**	**Mo, Koutsopoulos, Shen et al. [2023]**
Demand input data	Historical travel data	Historical travel data	Historical travel data	Assumed demand	Historical travel data	Assumed demand / [Mandl, 1979]	Historical travel data
Modes of transport	Urban PT modes	Railway	Railway	Railway	Urban PT modes	Buses	Metro
Disposition measures	Disposition timetable, holding	Disposition timetable, rescheduling	Disposition timetable	Disposition timetable, short turning, flexible stopping, rescheduling	Disposition timetable, rescheduling, rerouting, capacity increases	Disposition timetable, rerouting, line-splitting	Disposition timetable
Integration in OCC	Mentioned	Mentioned	Not mentioned	Not mentioned	Not mentioned	Mentioned	Mentioned

[1] Leng and Corman [2020], Leng, Liao et al. [2020], M. Rahimi et al. [2021] and Rahimi Siegrist and Corman [2021]

Approaches in Practice

In addition to the previously discussed academic investigations, approaches in practice are reviewed as well. In contrast to the academic investigations, which focus on ideal and optimised solutions to reduce passengers' delay in simulation environments, the focus of the approaches in practice lies on the feasibility of PCIM methods.

Literature Review: It is common practice in well-developed PT systems to provide passengers with the type and location of incidents. However, information about suggested alternative paths is rarely to be found in practice, especially in terms of capacity-aware passenger redirection. The dissemination of alternative paths, if applicable, is done in different ways in practice. Either in forms of collective information via dynamic PI displays at stops and in vehicles or through speaker announcements and staff. If path advice is given, it is usually based on pre-planned alternative paths for recurring disruptions and vulnerable parts of the network.

In the United Kingdom (UK) such pre-planned, static alternative paths are published by the National Rail of UK on their website [National Rail (UK), 2023]. The necessity of providing PT users not only with the information about an incident but also with alternative paths is also expressed by the customer information strategy of the Transport for London (TfL). The provision is realised through staff at stations that receive real-time information on the PT system's status via social media such as Twitter. The crowding at stations is also calculated based on electronic ticket data and provided in real-time [TfL, 2016; TfL, 2017]. In addition, the real-time PI is made available for third parties via an open source data platform [TfL, 2023].

Nevertheless, some agencies do not publish any or very little information about their customer information strategies. Transport for New South Wales (TfNSW) for instance, mention in their incident management framework that informing the PT user is important and that it is the responsibility of the communications coordinators to ensure that corresponding PI is given [TfNSW, 2023].

Approaches that go beyond the aforementioned state of practice are mostly part of smartphone apps and referred to as Mobility-as-a-Service (MaaS). One example is the French smartphone app "monRER A" by the the autonomous administration of the Paris transport services [Translated from French: Régie Autonome des Transports Parisiens] (RATP). With this app, user can monitor their trip and receive information about delays and alternative paths in accordance with their origin and destination, in case an incident occurs. An alternative path is taken into account as such by the app when it fulfils the criterion of reducing the user's travel time [RATP, 2023].

A customisable MaaS app is offered by the German company Mobimeo GmbH. One relatively famous example of this app is the DB track agent [Translated from German: DB Streckenagent] from the German railway operator DB. This app tracks the journey of its user and suggests alternative paths in case of disruption. Micro mobility services such as bike and e-scooter sharing are also included [Mobimeo, 2023].

Comparable to the previous approach is the service provided by the Montréal transport company [Translated from French: Soviété de Transport de Montréal] (STM). Twitter notifications are used to provide PT users with information about an incident such as location and an estimation of its duration. In addition, a short redirection with alternative metro lines is sent with a suggestion to search for an alternative path by bus via the STM app [INIT, 2023; STM, 2023].

These examples give an adequate representation of the state of practice of PCIM in well-developed PT systems. Even though path advice is provided in some cases, it is done without the consideration of capacity constraints, which can lead to secondary disturbances [Cats and Jenelius, 2014; Bachmann, Tsakarestos et al., 2023]. Nevertheless, approaches in practice are introduced below that take capacity constraints into account when redirecting passengers.

In Germany, a project about the targeted redirection of passengers was conducted over several phases and years. A pre-phase, financed by the German Federal Ministry of Transport, Building, and Housing [Translated from German: Bundesministerium für Vekehr, Bauen und Wohnen] (BMVBW), had the main goal to define passenger redirection plans in case of often reoccurring incidents, using the experience of every day OCC practice [BMVBW, 2001]. Two standardised interfaces were used which have been developed by the association of German transport companies [Translated from German: Verband Deutscher Verkehrsunternehmen] (VDV), the VDV453 which links ITCS of different operators, and the API VDV454, which connects ITCS with online PT trip planners [VDV, 2001, pp. 164–165; VDV, 2018a; VDV, 2018b]. The latter enables travellers to look for paths through the PT network based on real-time data. BMVBW [2001] suggests that PCIM need to be integrated in the system architecture of an OCC.

Building upon this pre-phase, in the first phase of the project, which has been financed by the German Federal Ministry of Transport, Building, and Urban Development [Translated from German: Bundesministerium für Vekehr, Bauen und Stadtentwicklung] (BMVBS), the theoretical framework for the redirection of passenger flows has been developed and adopted to concrete procedures and calculations [BMVBS, 2009]. One result is the identification of three distinct passenger groups, divided by their geographical relation towards the incident site, which need different treatment during an incident:

(a) passengers who are already in the system and in the close vicinity of the incident without any alternative paths, who are in need of the deployment of additional PT vehicles;

(b) travellers who are also already in the system and on their way towards the incident, however, who have still the possibility of altering their journey in accordance with the incident situation, who are in need of corresponding PI at stops and in PT vehicles to avoid the incident and unnecessary delays;

(c) PT users who have not started their trip yet and have thereby the possibility of re-planning their journey through the PT network and also to post-pone their trip, if possible, and are, therefore, in need of corresponding internet-based PI via PT operators' websites and online trip planners.

This concept was tested in an offline trial run, using the PT trip planner called electronic timetable information [Translated from German: Elektronische Fahrplan Auskunft] (EFA). The output of EFA is path advice for the passenger groups (b) and (c) considering qualitatively the capacities of the PT lines, meaning that PT lines with similar capacities as the disrupted lines are considered for the path advice. The concept and its results were discussed by a panel of German operators, who concluded that passenger redirection during incidents is generally reasonable. The suitability of existing operation software was explored and further research gaps were identified. Moreover, shortcomings of existing interfaces have been found [BMVBS, 2009].

BMVBS [2011] used these findings in the second phase of the project to develop two corresponding prototypes for the cities of Berlin and Stuttgart in Germany to verify the potential of this PCIM system. Offline data from the respective OCCs was used as inputs. One finding was that the number of possible alternative paths needs to be reduced to keep the passenger redirection applicable for both, the passengers and the dispatchers in the OCCs. Another major outcome was the awareness of the crucial role of the capacities and the passenger volume of the PT system for the redirection process. Due to the lack of APC systems or comparable sources (Section 2.1.1) in the PT systems of Berlin and Stuttgart, realistic online data was not available. Furthermore, it is concluded that the minimum incident duration for a collective passenger redirection is 30 minutes, considering the processing times of the OCC in such situations as well as the extension of travel times due to the longer alternative paths.

The consortium of PT operators of this project phase has agreed on the statement that for an incident duration of less than 30 minutes, the simple information about the existence of an incident would be sufficient for PT users to re-plan their trips. Since this consortium was not accompanied by an academic institution, details about the developed prototype, the conducted tests, and the results have not been published. The main conclusion has been that further refinement of interfaces is necessary and that one of the biggest challenges is the prediction of passenger demand. The most important achievement of phase two was the development of the two prototypes mentioned before.

Based on these, online tests were conducted in the third and last phase of the German passenger redirection project which was financed by the BMVI. The aforementioned lack of real-time demand data was taken into account during this project phase by limiting the number of potential paths even further. Furthermore, the targeted groups for redirection were reduced to group (a), which is at the incident site, and part of group (b) which is already in the close vicinity of the incident. This was mainly since at the time of the project phase, PT trip planner apps on smartphones were widely used. This lead to a simplification of the original idea of wide-area redirections to individualised PI.

Nevertheless, this phase has catered for a communication standard for incident occurrences from OCCs to operators' trip planner apps. Moreover, a field test with the further developed prototype from phase two were carried out in the operation area of the transport association Berlin/Brandenburg [Translated from German: Verkehrsverbund Berlin/Brandenburg] (VBB), Germany. To ensure consistency between the individual and collective information channels, the PI was transmitted to the mobile trip planner Hanover consulting timetable information system [Translated from German: Hannover Consulting Fahrplan Auskunftssystem] (HAFAS) as well.

Because real-time disposition timetables, reflecting the altered PT supply during the incident was not available during the field trial, path calculations were done based on static timetables which led to some miscalculations. Apart from that, the system performed well from the operators' perspective. However, the suggestion of not ideal alternative paths from the passengers' point of view, especially of experienced PT users led to the realisation that transparency about the incident and its consequences is the key of gaining higher compliance rates during the redirection process.

The results of a customer trial reveal that about 57% of the customers are willing to follow path advice by the operator. This is the same share of survey participants which would follow connection suggestions in case of a disruption in long-distance railway services according to Wilke [2023]. Further main conclusions are that a collective redirection is technically feasible and reasonable, however, to be successful such a PCIM system depends on real-time data on the demand of the residual capacity of the available paths and the disposition timetable [BMVI, 2019].

A passenger redirection project from Japan is presented by Tsuchiya et al. [2006]. A prototype for the Japanese railway network is introduced that provides passengers at stations with a map of alternative paths during an incident to help them find a suitable path. For the prototype's input, a database with historical incidents and their durations was built to estimate an incident duration which is considered in the path advice. The system calculates the travel time of all possible paths for each station to each destination station, taking into account the estimated incident duration as well as a recovery time, which reflects the time from the dissolution of the incident's source to the return to normal operations.

Furthermore, the prototype is capable of considering more than one incident. PT users who want to receive path advice in correspondence to their travel plan can use an online app. Tsuchiya et al. [2006] demonstrate that in a less dense network such as a long-distance railway network, pragmatic solutions to the passenger redirection problem are feasible. It is indicated that an operational prototype has been developed which is yet to be tested in the field.

A more individualised approach comes from Italy by Bruglieri et al. [2015]. The authors developed a prototype algorithm as an extension for PT trip planners to allow their users to look for paths during an incident. The algorithm considers the closure of lines and stations as incident scenarios and was integrated into the PT trip planner of Milan, Italy.

Residual capacity in the PT system has not been considered and incident information is assumed to be provided by the OCC. Since this work focuses on the redirection of individuals and not on the system's optimal redirection of the collective of affected passengers it is not considered in the following summary and comparison of the approaches in practice introduced here.

Comparison: Table 2.6 which is also adopted from Bachmann, Tsakarestos et al. [2023] shows the main characteristics of these publications. Even though the focus of all approaches in practice mainly lies on the feasibility of PCIM methods, they still have distinctions in their approaches, goals, additional foci, and conducted field trials or case studies, respectively.

In addition to the general aforementioned focus, the approaches in practice have a common main goal which is determining feasible path advice [BMVBW, 2001; Tsuchiya et al., 2006; BMVBS, 2009; BMVBS, 2011; BMVI, 2019].

Furthermore, the work by BMVBS [2009] focuses on the development of procedure concepts for a PCIM in an OCC. Another focal point for BMVBS [2011] is the development of a prototype as well as a lab test. In addition, BMVI [2019] focuses on technical aspects and a customer trial with the prototype developed by BMVBS [2009]. Tsuchiya et al. [2006] also focus on the development of a prototype. The approaches in practice have the common goal of validating the feasibility of an implementation of PCIM in practice. In addition, some of them developed corresponding prototypes in the process.

As the academic investigations, all approaches in practice also consider the capacity of the supply. However, most of them do so in a qualitatively manner.

As mentioned in Section 2.1.5, PI plays a crucial role in PCIM. In all approaches in practice, its content is path advice, BMVBS [2011] and BMVI [2019] also broadcast the location and kind of incident. As mentioned in Section 2.1.5, knowing the reason for an incident increases the understanding of PT users, which is also pointed out by BMVI [2019].

Regarding PI schemes, BMVBS [2009] considers informing clustered passenger groups, which is adopted by BMVBS [2011] and BMVI [2019]. Tsuchiya et al. [2006] present PI at all stations. BMVBW [2001] merely mentions PI schemes in general as well as PI channels, the latter is also true for BMVBS [2011]. BMVBS [2009] considers speakers, displays, and PT trip planners as possible channels; BMVI [2019] smartphones and PT trip planners and Tsuchiya et al. [2006] smartphones and displays. As in the academic investigations, also in the approaches in practice, the role of PI in PCIM is stressed. However, here, the focus lies more on the considered PI channels than on the information schemes as it is the case in the academic investigations. Furthermore, the content is path advice in all works, which is not the case for the academic investigations.

All works handle the affected passengers as a collective and none of them considers a compliance rate. However, BMVI [2019] determined a possible compliance rate of 57% through a customer trial.

Since no simulations have been conducted, the used tools are rather of practical nature, such as PT trip planners [BMVBS, 2009], own prototypes [Tsuchiya et al., 2006; BMVBS, 2011], OCC infrastructure [BMVI, 2019], or a database with preselected scenarios [Tsuchiya et al., 2006]. BMVBW [2001] presents purely conceptional work. As investigations in practice have mostly also economic intentions, publishing findings are often not intended or has a side role, at most. Therefore, it is harder to find publications, which is one of the reasons that most of the mentioned approaches in practice are from Germany because these are the works, to which the author has access. However, even in such reports, developed algorithms are not described. This might be one of the explanations for the still-existing gap between research and practice which is further discussed in the next section. BMVBS [2011] and BMVI

[2019] did also not share their algorithms, the others did not even mention any.

None of the approaches in practice mentions any kind of optimisation. Nevertheless, all of them conducted some kind of field trial. BMVBW [2001] solely focuses on the visualisation of path advice. BMVBS [2009] presents calculated examples, whereas Tsuchiya et al. [2006] conducted an offline prototype test. BMVBS [2011] tested multiple scenarios in two German cities, Berlin and Stuttgart, and BMVI [2019] did a field trial in real operation in Berlin/Brandenburg, Germany.

The approaches in practice merely mention PI channels and OCC infrastructure as used tools. Algorithms and prototypes are mentioned at most, which is partly due to the fact that commercial interests are involved in these works and that it is less common to make findings publicly available in practice. Nonetheless, some of them conducted field trials.

When it comes to considered incidents, the practical works show also different considerations. BMVBW [2001] defines incident classes. BMVBS [2009] considers an incident duration of 30 minutes and various scenarios of disrupted PT services. Tsuchiya et al. [2006] and BMVBS [2011] solely mention incidents but do not specify any features. BMVI [2019] takes historical information of 31 incidents into account. However, all approaches in practice solely mention the necessity of a demand input but do not specify it.

The four publications about the German project consider various urban PT modes [BMVBW, 2001; BMVBS, 2009; BMVBS, 2011; BMVI, 2019], whereas Tsuchiya et al. [2006] apply their developed prototype in the railway system of Japan.

BMVI [2019] is the only practical study that does not consider *supply-centric* disposition measures. Since the main focus of these works has been the feasibility in practice, all of them considered the integration in an OCC, the heart of incident management in PT systems [Carrel, Mishalani et al., 2010; Briem, Buck, Magdolen et al., 2020; Bachmann, Briem et al., 2022]. BMVBW [2001] considers it in the system's architecture, BMVBS [2009] go a step further and developed a concept for the PCIM to be an integrated part of the OCC. Based on that, BMVBS [2011] presents the prototypes as part of the OCC and BMVI [2019] links them to the OCC's existing system architecture via standardised interfaces.

Table 2.6: Overview of approaches in practice [Bachmann, Tsakarestos et al., 2023]

Reference	**BMVBW [2001]**	**BMVBS [2009]**	**BMVBS [2011]**	**BMVI [2019]**	**Tsuchiya et al. [2006]**
Focus	Feasibility	Concept for procedures in an OCC	Prototype development and lab test	Customer trial of the prototypes from BMVBS [2009], technical aspects	Prototype development
Main goal	Feasible path suggestions	Feasible path suggestions	Feasible path suggestions	Feasible path suggestions	Feasible path suggestions
PT system's capacity	Considered	Considered	Qualitatively considered	Qualitatively considered	Qualitatively considered
PI content	Path advice	Path advice	Path advice, location, and kind of the incident	Path advice, location, and kind of the incident	Path advice
PI schemes	Mentioned	Informing clustered groups of passengers	Based on the concept of BMVBS [2009]	Based on the concept of BMVBS [2009]	PI presented at all stations
PI channels	Mentioned	Speakers, displays and PT trip planners	Mentioned	Mobile phones, PT trip planners	Displays and mobile phones
Passenger handling	Passenger collective	Passenger collective	Passenger collective	Passenger collective	Passenger collective
Compliance rate / Path choice	Not mentioned	Not mentioned	Not mentioned	Evaluated compliance rate via questionnaire	Not mentioned
					Continues

Table 2.6: Overview of approaches in practice [Bachmann, Tsakarestos et al., 2023] (continued)

Reference	**BMVBW [2001]**	**BMVBS [2009]**	**BMVBS [2011]**	**BMVI [2019]**	**Tsuchiya et al. [2006]**
Used tools / Algorithms	Purely conceptual work	PT trip planner / Pseudocodes	Own prototypes / Algorithms not disclosed	OCC infrastructure / Algorithms not disclosed	Own prototype using a database with pre-selected scenarios
Optimisation	Not mentioned	Not mentioned	Not mentioned	Not mentioned	Not mentioned
Case study	Exemplary visualisation	Calculated examples	Multiple scenarios in Berlin and Stuttgart	Test in real operation in Berlin	Offline prototype test
Incident	Definition of incident classes	0.5 hours, different service disruptions	Mentioned, not specified	31 historical incidents	Mentioned, not specified
Demand input data	Mentioned	Mentioned	Mentioned	Mentioned	Mentioned
Modes of transport	Urban PT modes	Urban PT modes	Urban PT modes	Urban PT modes	Railway
Disposition measures	Considered	Considered	Considered	Not considered	Considered
Integration in OCC	Considered in system architecture	Concept planned as an integral part of an OCC	Prototypes planned as an integral part of an OCC	Prototypes linked to the OCC via standardised interfaces	Considered

2.3 Summary and Research Gaps

The sheer diversity of incidents and their characteristics undoubtedly implies that the management of incidents is very complex, as has also been pointed out in this chapter. Most investigations about incident management focused on *supply-centric* disposition measures, describing the readjustment of PT supply to a present incident situation and its return to operations as scheduled.

Typical measures are holding, stop-skipping, rescheduling, rerouting, short-turning, line-splitting, and various measures to provide for additional capacity. Less has been done in the field of PCIM. Furthermore, most of the scientific literature presented here focuses on rail-bound transport either by merely considering railway services or in case of investigations taking several PT modes into account, the incident takes place in the railway part of the respective network. The only papers about capacity-aware passenger redirection or PCIM, respectively, which are focussing on bus operations are by Bachmann, Rau et al. [2021] and Bachmann, Dandl et al. [2023] which describe earlier stages of the methodology presented here. Due to this reason, even though this thesis considers multi-modal urban PT systems, there is an emphasis on bus operations.

Furthermore, the academic investigations show a weak connection to practice meaning that aspects which need to be considered for an implementation of PCIM in practice are ignored, such as the infrastructure of OCCs, as also pointed out by Bachmann, Tsakarestos et al. [2023]. However, the approaches in practice introduced here, show a weak connection to the state of the art in research, meaning that the developed solutions do not live up to possibilities which have already been explored in research, such as optimisation of path advice algorithms.

Therefore, to contribute to the closure of the gap between research and practice, OCCs were visited [Bachmann, Briem et al., 2022], and a PT user survey was conducted. The survey results are presented in the next chapter. Those help to understand the two sides which need to be connected during incidents through PCIM, the PT users and PT operators or the passenger and supply side, respectively. This shapes the methodology presented in this thesis as indicated in Figure 1.1.

Moreover, the findings of the OCC visits and the PT user survey has supported the development of the model presented in Chapter 4. This model is a novel contribution to the research field of PCIM.

This literature review clearly points out the potential of PCIM in PT for its users and operators due to the reduction of delays and pressure on the PT system in terms of demand on alternative paths and accelerated recovery from incidents. Further important findings are:

- factors which influence the reaction of passengers to incidents,
- the necessity of considering passengers not following path advice (compliance),
- available PI channels in a PT system,
- retrievable data concerning the PT supply,
- and available information about an incident as well as disposition measures taken by OCC staff.

Chapter 3

Passenger Perceptions of Incidents and Incident Management

One of the most important aspects of the method presented here is moving the passengers' view during incidents into focus (Chapter 1). Therefore, it is crucial to understand what actually happens to passengers during incidents, how they perceive them, how they feel about incidents, and how such inconvenient situations can be improved for them. A basis for this understanding has been laid out in Section 2.1.4. To complement this basis and to improve the understanding of the passengers' perception of incidents and incident management a PT user survey was conducted. Its setup and results are presented in the following.

3.1 Passenger Survey Setup

This web-based PT user survey was conducted in Berlin, Germany and Singapore. Both cities are very big, with a population of 3.7 and 5.6 million inhabitants, respectively. In both cities a large and complex PT network is in operation. In Berlin, the registered cars to inhabitants ratio is 33.3% (in 2020) and in Singapore, 11.5% (in 2020), which indicates the importance of the PT system in both cities [Singapore Department of Statistics, 2022; Statistics Office Berlin-Brandenburg, 2022]. The level of PT service is comparable as well as the available resources and objectives of the PT systems.

Table 3.1 gives some information about the survey. In Berlin, the survey took place at the end of 2020, ran for 55 days, and the answers of 658 participants were analysed. The survey platform was provided by the Berlin transport company [Translated from German: Berliner Verkehrsbetriebe] (BVG) which is the main PT provider in Berlin. BVG also promoted the survey on their website [BVG, 2023] and on the BVG app. In Singapore, the survey ran at the beginning of the year 2021 for 43 days. The answers of 189 participants were analysed. The survey was advertised via the websites of the PT operator Tower Transit and the research company TUMCREATE, as well as via the Facebook profile of the German Embassy in Singapore, a Facebook group of PT users and a Telegram group for surveys conducted in Singapore [Tower Transit, 2020; TUMCREATE, 2021; Durov, 2023; Meta, 2023].

Unfortunately, there is an obvious gap between the number of participants in the two cities. This is despite the fact that more efforts have been made in Singapore to reach more people, as previously mentioned. For the survey in Singapore a confidence level of about 80% is achieved with a margin of error of 5%, whereas for the survey in Berlin a confidence level of 99% is achieved with a margin of error of 5% [Herz et al., 1992; Momentive, 2023].

Therefore, a higher level of confidence would have been desirable for the survey in Singapore. Nevertheless, the results still give an insight in PT users' perception of incidents and incident management. Additionally, the results of the two cities are somewhat comparable as shown in the next section.

City	Start date	End date	Number of days	Number of participants
Berlin	28.10.2020	21.12.2020	55	658
Singapore	04.01.2021	15.02.2021	43	189

Table 3.1: Information about the PT user survey

The survey contains a revealed preference part that casts light on incidents which the participants experienced themselves, as well as on the background of the participants. A stated preference part is about incident situations in an autonomous PT system.

Through the questions about the experienced incident, the participants have been asked details about the incident they encountered, how the PT operator and they reacted to the incident, how they received information and which, and about their preferences regarding PI during incidents. Furthermore, they also were asked how they felt about this event. One important question in this section was about their willingness to follow a path suggestion, given by the operator during an incident. In the stated preference part, the participants were asked to imagine that their experienced incident would happen in an autonomous PT vehicle. Again, they were asked how they felt about this incident in the new imagined environment and what information they would like to perceive and how. Since there is no PT driver in autonomous vehicles to turn to, incident situations might be more stressful for passengers.

The survey part about the background of the participants contained questions to put the given answers in perspective of the participants' age, profession, education, transport habits, etc.

3.2 Survey Results

The presentation of the results is structured as follows. First, the sample description is presented to get an overview of the background of the participants and to better understand the given answers. Second, the answers concerning the incidents which the participants experienced are presented. Third, their preferences in PI provision during incidents are introduced. The results presented last show answers to questions regarding the perceived emotions of the PT users during the experienced incident as well as their attitude towards the question how they feel about an incident taken place in an autonomous PT system.

Pie charts show the results of single choice questions, bar charts the results of multiple choice questions, and columns charts the results of scaling questions. Thereby, the type of the corresponding question is indicated by the kind of chart. The survey comprised more than 50 questions of which only those which are most relevant to the topic of this thesis are presented.

3.2.1 Sample Description

The target group of this survey were PT users who knew the respective PT network reasonably well and experienced at least one incident in it. Therefore, the questionnaire started with two screening questions about whether the participant had ever experienced an incident in PT and if they lived in the respective city and for how long. Participants who had never experienced an incident in PT or did not reside in the respective city were excluded. The rest of the participants have almost completely lived at least for two years in the respective city (96.2% in Berlin and 98.4% in Singapore, Figure B.1). This is also important, as participants were asked to answer the questions *without* the consideration of the COVID-19 pandemic, which hit the global society at the beginning of 2020 [Wolrd Health Organization, 2021].

Furthermore, as the target group were PT users, they were asked about their primary means of transport as well as the frequency with which PT has been used.

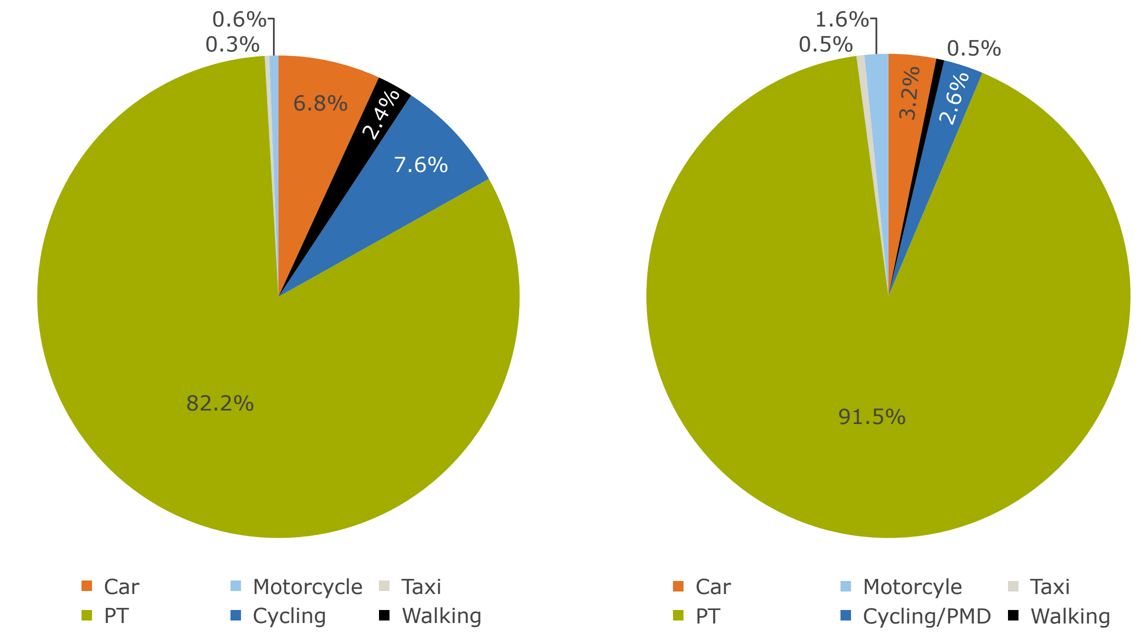
Please note that "N" below each chart expresses the number of participants who answered the respective question. As can be seen from Figure 3.1, for most participants PT was by far the most important means of transport. Compared to the previously mentioned car to inhabitants ratios, also for the participants of the survey in Berlin, the car plays a bigger role (6.8%) than for the participants in Singapore (3.2%). Section 2.1.4 also discusses the influence of car ownership, not only on the travellers' reactions to incidents, but also on mode choice in general. In Berlin, "Cycling" was named by 7.6% of the participants, and 2.6% by the participants in Singapore. In the questionnaire of Singapore, "personal mobile device (PMD)" was added to the category of "Cycling", which is the umbrella term for e-scooters and comparable devices. Walking and riding motorcycles or taxis play a minor role for the participants of both cities.

To understand the participants' transport habits even better, Figure 3.2 presents the participants' usage frequency of PT. Again, the answer options differ slightly between the two cities, in the questionnaire for Berlin an "(Almost)" was added to the answers "Daily" and "Never" as well as the answer option "Don't remember". The second answer option in Singapore was "Most days", whereas in Berlin it was "Several times [a week]", meaning the same. Most participants use PT daily, with 68.5% in Berlin and 52.9% in Singapore. Most of the rest use PT either "Several times [a week]"/"Most days" with 19.9% in Berlin and 39.7% in Singapore or once a week with 6.4% in Berlin and 5.3% in Singapore. The remaining answers appear in an insignificant number with only 1.5% in Berlin and 0.5% in Singapore stating that they never use PT.

Looking at the three presented questions, it can be assumed that the target group of PT users who had an understanding of the respective PT network is well represented by the sample.

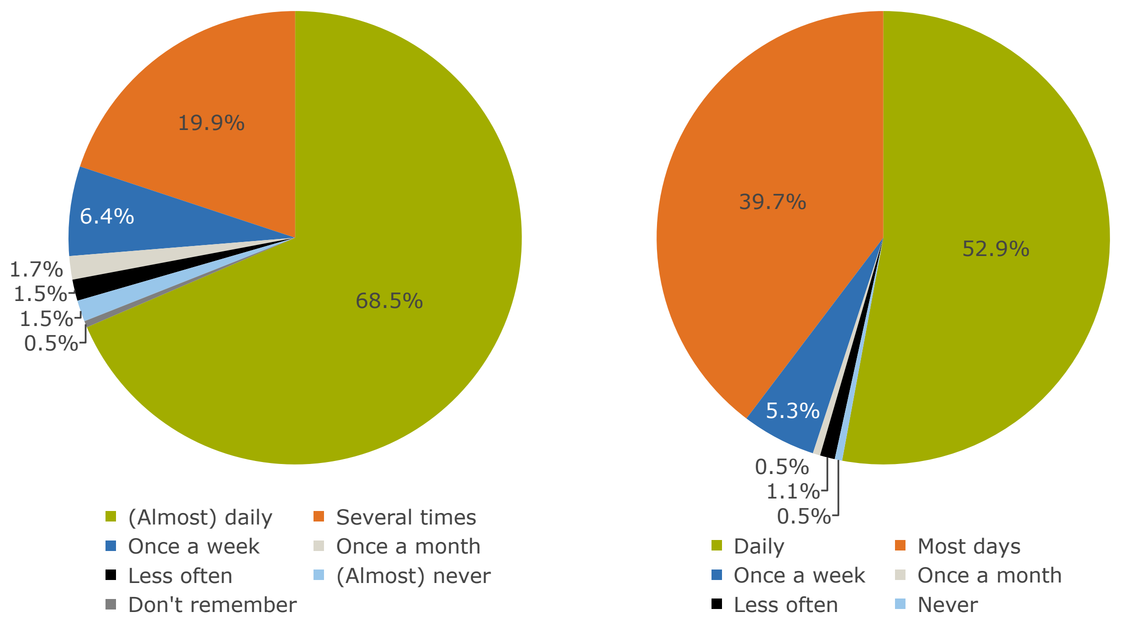
Within this group of people, the goal was to have a good distribution of participants in matters of age, gender, education level, and labour status. In this way, different demographic groups within the respective societies are represented fairly evenly.

In Berlin, the under-20-year-olds (5.5%) and the 70+ olds (4.0%) are rather underrepresented, whereas the rest is fairly distributed with shares of 11.9% for 60 to 69 year-olds to 25.2% for 30 to 39 year-olds. Nevertheless, the age distribution is comparable to the results from the census of 2011 [Statistics Office Berlin-Brandenburg, 2022]. However,



(a) Berlin (N=658) (b) Singapore (N=189)

Figure 3.1: In the last 2 years, before the COVID-19 pandemic, which has been your primary means of transport?



(a) Berlin (N=658) (b) Singapore (N=189)

Figure 3.2: In the last 2 years, BEFORE the COVID-19 pandemic, how often do you take PT?

the age distribution in the census refers to all inhabitants. A shift in the age distribution among PT users might be possible as especially young and old people rely on PT as some of them are not allowed or not capable of driving a car or bicycle. In Singapore, the 20 to 29 year-olds are strongly overrepresented with 55.6% resulting in a comparative underrepresentation of the rest. Especially the age groups of 50 to 59 year-olds (2.1%), 60 to 69 year-olds (0.5%), and 70+ year-olds (0.5%) are strongly underrepresented, which needs to be kept in mind when interpreting the results of the survey. The remaining 40 to 49 year-olds (8.6%), under 20 year-olds (13.4%) and 30 to 39 year-olds (19.3%) are fairly represented compared to Singapore's census of 2010 [Singapore Department of Statistics, 2022]. Please note that in Singapore two participants have been excluded from the results of this question as they answered this question with a four-digit number. It is therefore assumed that they did not wish to reveal their actual age (Figure B.2).

Regarding the gender of the participants, we have a slight shift towards male with 58.2% of male, 40.7% of female and 1.7% of diverse in Berlin and 58.7% of male, 40.1% of female and 0.5% of other in Singapore (Figure B.3). However, in the censuses of both cities, there is a slight switch towards females with 48.6% of males and 51.4% of females in Berlin and 49.3% of males and 50.7% of females in Singapore [Singapore Department of Statistics, 2022; Statistics Office Berlin-Brandenburg, 2022]. Both censuses do not consider other gender identifications.

The last two distributions to describe the survey sample are about the highest accomplished education and current labour status of the sample. In Berlin, about 30% finished school but did not yet complete vocational training or gain a job degree of any kind. Over 40% have obtained an academic degree, which shows a bias towards the higher educated part of the society, compared to the census. In Singapore, compared to the census, there is also an obvious bias towards the higher educated part of the society, with almost half having a high school or job degree, which is summarised in this questionnaire, and more than 40% having an academic degree, which fits well to the bias age distribution (Figure B.2).

Concerning the labour status, there is a bias towards the working part of the society in Berlin with over 70% working either full-time (56.5%), part-time (11.6%) or self-employed (5.6%) compared to 48.9% in the census. In Singapore, according to the census, 67.6% of the population is working, whereas among the survey participants about half are working. There is a clear bias towards students with 38.6%, which again fits well with the bias regarding the age in the sample from Singapore (Annexe B.1).

Therefore, it can be concluded that the samples of both cities have a slight bias towards males and the samples' education level is higher than the education level of the respective society. Regarding the age, the sample of Berlin is somewhat fitting, whereas the Singaporean sample is too young with a focus on the age of 20 to 29 years. The Berlin sample has a bias towards the working part of the society and the Singaporean sample towards students. These biases need to be kept in mind, when interpreting the following survey results [Singapore Department of Statistics, 2022; Statistics Office Berlin-Brandenburg, 2022].

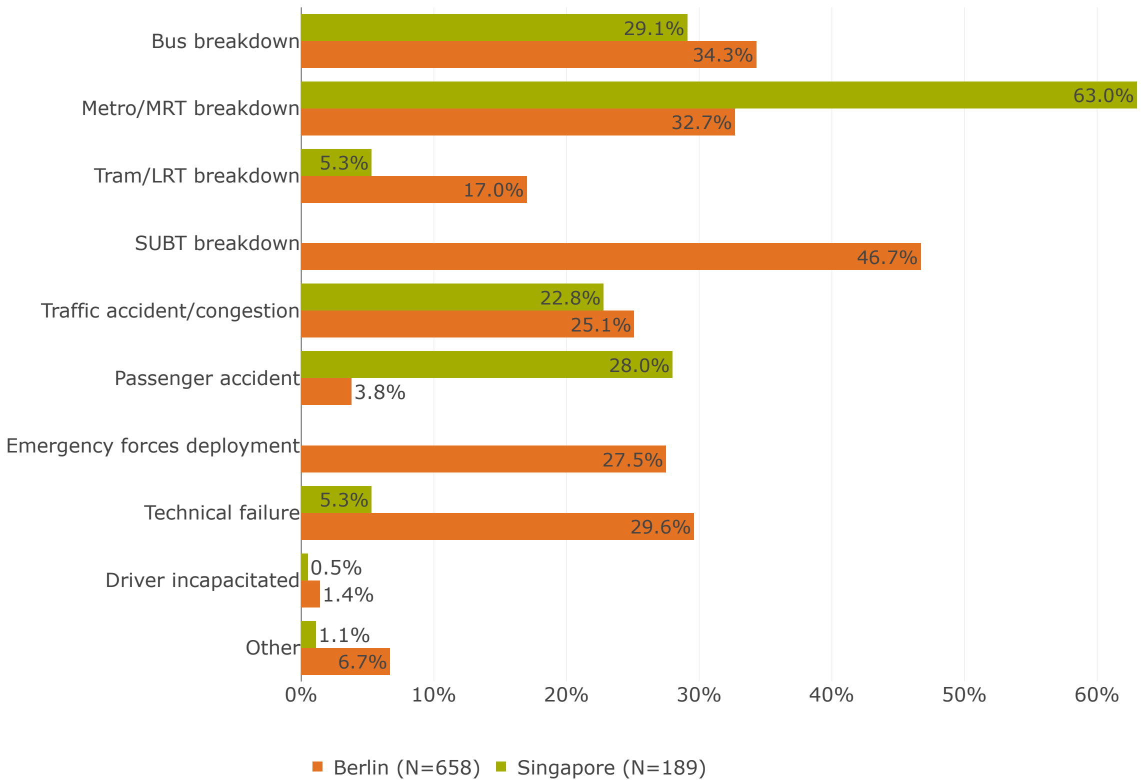


Figure 3.3: Which of the following happened during the incident?

3.2.2 Experienced Incidents

This section includes questions which focus on the incidents experienced by the participants. First, the question about what happened is shown in Figure 3.3. In addition to understanding what kind of incident the participants encountered, this question was also meant to help the participants refresh their memory about the incident. As Figure 3.3 shows, most of the incidents involved the breakdown of a PT vehicle, especially rail-bound vehicles. It is to be mentioned that a few days before the survey was launched in Singapore a mass rapid transit (MRT) breakdown occurred in the PT system, which on the one hand might be an explanation for this imbalance in terms of different kinds of experienced incidents, on the other hand, it also raised the number of people who recently experienced an incident in PT. However, also in Berlin, most participants experienced a breakdown in a railway service, the suburban train (SUBT). Please note that the questions given to participants in Berlin are slightly different to the ones given in Singapore. In Berlin, traffic congestion, ambulance deployment, and traffic accidents are standing-alone answers, whereas in Singapore the latter two were given as examples for traffic congestion. This question helps to understand the given answers to the following questions.

The next question is about at what stage of their journey the participants were when they noticed the incident. This gives an idea about the available information and about which information channels passengers were likely to had access to, such as speaker announcements

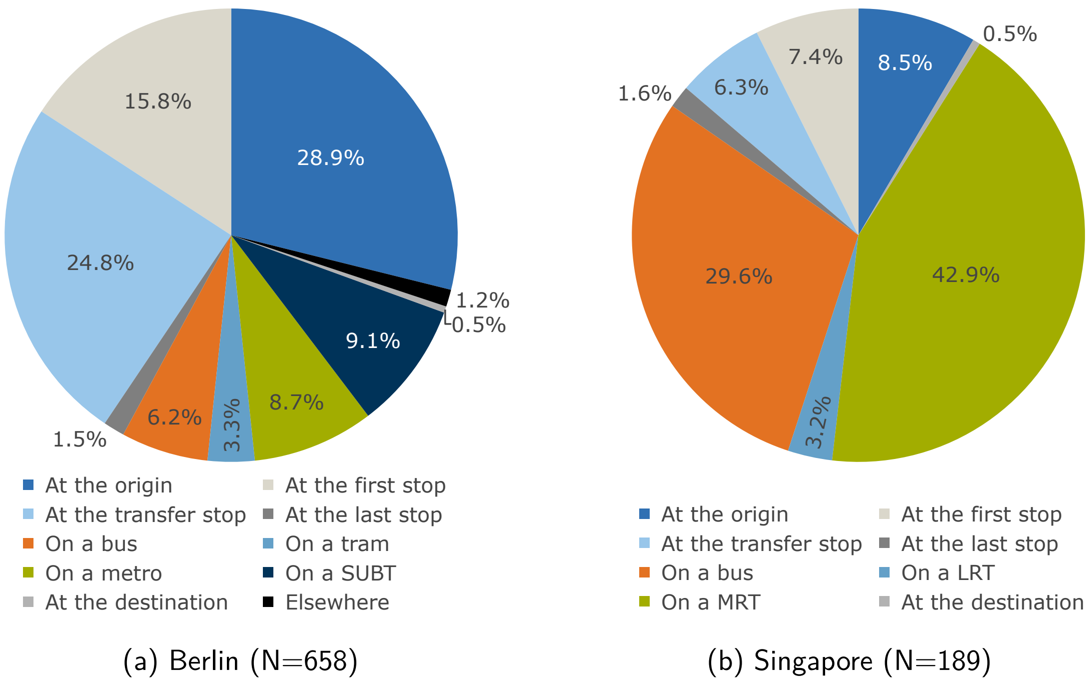


Figure 3.4: Which stage of your trip were you at when you found out about the incident?

or PI displays at stops (Figure 3.4, Section 2.1.5). As one can see, the differences between Berlin and Singapore are quite big here, whereas in Berlin most people noticed the incident while standing at the stop or being at the origin, in Singapore, most people were in a PT vehicle, on a MRT or a light rail transit (LRT). The location of PT users at the point of time at which they notice an incident can influence the way they are informed about it. In both cities most of the participants, 32.5% in Berlin and 31.7% in Singapore, have been informed by the respective PT operator (Figure B.8).

In the results from Singapore, it is noticeable that a lot of people noticed the incident due to the affected travel speed of the respective PT vehicle (22.8%). Furthermore, the most given answer which fell under the category "Other" were "the vehicle stopped unexpectedly or broke down" with 6% of all given answers. This can be explained by the kind of incident most participants experienced which involved some kind of PT vehicle breakdown. The third most given answer is that "the MRT did not arrive or depart" (14.3%). Passengers on board a breaking down vehicle usually notice the incident very quickly through the unexpected slowing down or stopping of the PT vehicle, whereas PT users at a station often realise it through the non-arriving vehicle. This fits well with the answers in Figure 3.4 about the place where people found out about the incident since most survey participants from Singapore were on a PT vehicle when they noticed the incident. In Berlin, apart from the most frequent answer which is also "informed by the operator", the second, third, and fourth most frequent answers are about not arriving or departing PT vehicles (46.0% in total). This again fits well with the results shown in Figure 3.4, since most people in Berlin noticed the incident while being at a stop. Please note that there are different rail-bound PT modes available in Berlin and Singapore, therefore, the answers differ, as you can see in the legends below the charts. Whereas there are Tram, SUBT and metro in Berlin, there are MRT and LRT in Singapore (Annexe B.2).

As mentioned before, the location of the participants also influences the availability of information channels. At stops and on PT vehicles there can be PI displays and speakers for announcements. Moreover, at stops, one will also find station personnel or ticket inspectors, and on board you are more likely to find a driver. Additionally, at the origin or destination people most likely gain information over smartphone apps or websites. The participants were asked if they got information from the operator and if yes, through which channel and what kind of information they were provided with (Figures 3.5 and B.9).

Multiple choices were possible for these questions. As about 30% of all participants in both cities received official information (Figure B.8), "N" is smaller in these questions. Among the people who answered the question, speaker announcements are the primary information channel in both cities. Whereas in Berlin, only the PI displays at stops and in PT vehicles represents another important channel, in Singapore, also the operators' staff and social media play an important role. The three most chosen channels, speakers, displays, and operators' staff, are all to be found at stops as well as on PT vehicles. Passengers were not only asked which channel was used to inform them, but also what information they were provided with.

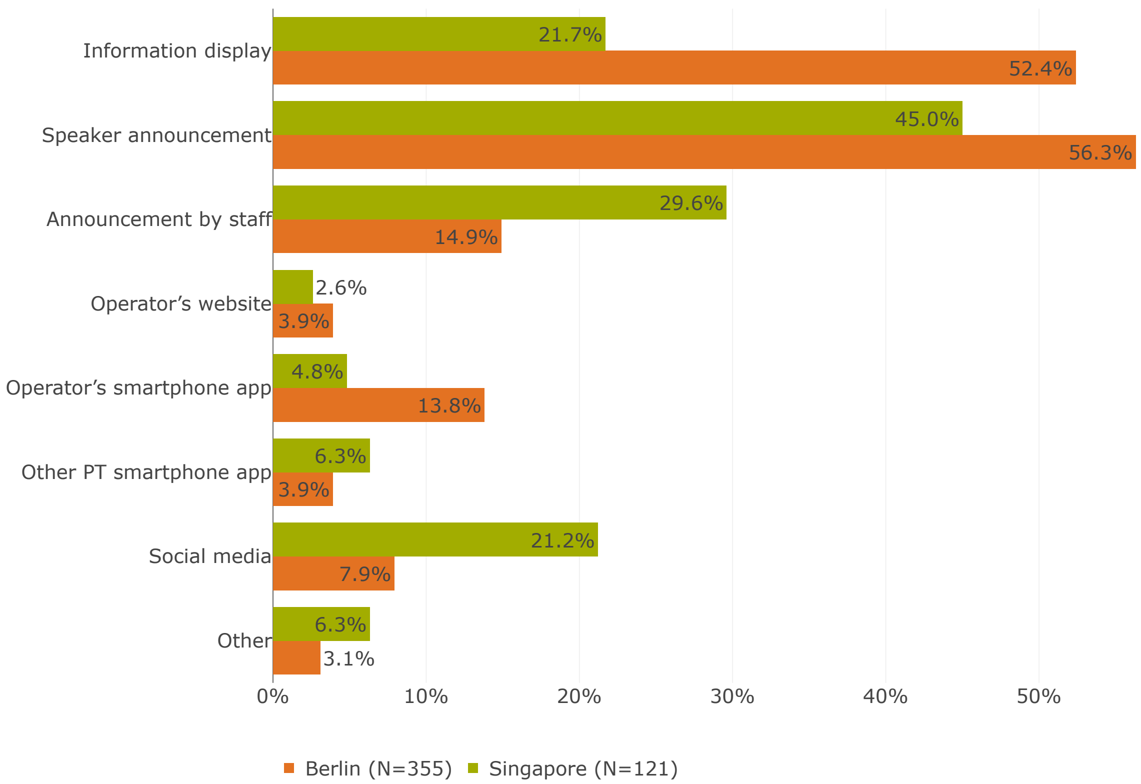


Figure 3.5: Which of these channels did you obtain official information from?

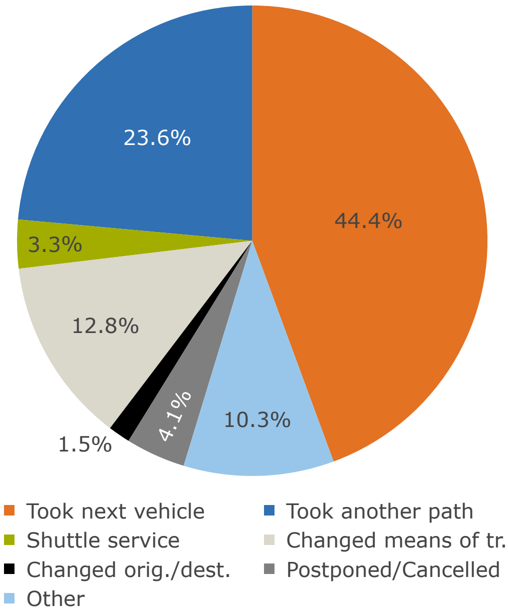
In both cities, the cause of the incident, affected PT services, and possible delays were often transmitted information with 69.6% in Berlin and 32.3% in Singapore (Figure B.9). One difference between the two cities in the context of these kinds of information is that the information about affected PT services and possible delays was more often given in Berlin with 27.9% and 42.8%, respectively, than it was given in Singapore with 23.3% and 33.9%, respectively. However, more information was provided in Singapore regarding the delay duration (26.5% in Singapore and 15.2% in Berlin) and advice about switching to another means of transport or PT line (27.5% in Singapore and 21.2% in Berlin). In Singapore, at least 9% got an advice for another PT line, but, how to go from there was not given (Annexe B.2).

The last question of the section about experienced incidents is about the reaction of the participants to the incident. It becomes obvious that the number one reaction to incidents in both cities was to wait for the next vehicle on the desired PT line. This is possible if the incident merely affects the PT vehicle but not the stop or the whole line as it would be the case for a blocked railway track for example (Section 2.1.3).

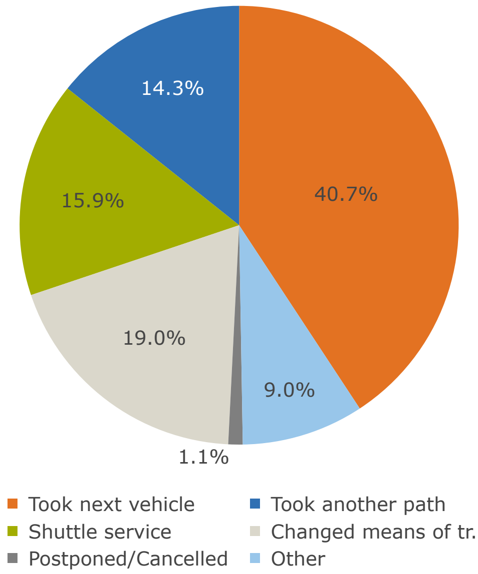
Please note that the participants in Berlin had one more answer option than the participants in Singapore in the question shown in Figure 3.6. It is also to be mentioned that the majority of the participants of Singapore, whose answers fall under "Other" (7.4%) pointed out that they were stuck in the PT vehicle and therefore did not have an option other than waiting in the PT vehicle. As Figure 3.3 indicates, most participants experienced some kind of vehicle breakdown. Relatively many people also chose to take another, unaffected path, in Berlin, it is the second strongest answer to this question. People who know the PT system well or are even experienced in reacting to incidents are usually doing well in finding an alternative path quickly. Also, a lot of people switched to other means of transport such as private cars, taxis, cycling, or walking. Especially severe incidents with long delays motivate people to find another possibility of getting to their destination if they are in a hurry, which was true for most of the participants.

For 78.3% or respectively 58.5% of the participants in Singapore and Berlin, the trip was not postponable according to the question about the urgency of the trip. Section 2.1.4 points out that there are many factors which influence passengers' reactions to incidents, car ownership and the purpose of the trip are for example two of them. Another answer option was about switching to shuttle services, such as rail replacement services. However, these are only established by the dispatchers if the incident is very severe and takes a lot of time to be dissolved (Section 2.2). As aforementioned, shortly before the survey was launched in Singapore, a MRT breakdown occurred and a shuttle service was probably established, which explains the comparably high number of people who switched to a shuttle service in Singapore.

For more information about the incidents, experienced by the survey participants it is referred to Annexe B.2. These charts presented show that incidents are very diverse in their kind and severity as well as their impact on and perception of PT users and the possible reactions to them.



(a) Berlin (N=658)



(b) Singapore (N=189)

Figure 3.6: How did you react to the incident?

3.2.3 Passengers' Preferences

The previous section presents how survey participants received information and what its content was. However, this does not necessarily mean that this has been their preferred information channel during incidents. As incidents are usually unexpected and confusing events, people might want to be informed differently. Therefore, the participants were asked about their preferred communication channel during incidents and which information they would like to receive in such situations (Figures 3.7 and 3.8).

The participants could tick up to two options. In this way, it was ensured that the participants did not tick all answers which helped to reveal actual preferences. In both cities, the speaker announcements and dynamic PI displays at stations and in vehicles play the most important role, however, in Berlin, the PI displays are the most preferred information channel with 67.3% and speaker announcements as second most preferred information channel with 45.3%. In Singapore, it is the other way round, speaker announcements are the most preferred channel with 63.0% and PI displays with 44.4% as the second most preferred channel. Also, the PT staff, such as PT drivers or station personnel, play an important role in both cities when it comes to PI dissemination. In Singapore, it is the third most chosen channel with 34.9% and in Berlin with 18.8% the fourth most. Whereas in Berlin the third most preferred information channel is the PT operators app (26.3%), this information channel plays only a minor role in Singapore (7.9%). This can be explained by the different ride fare systems in Berlin and Singapore. Singapore's PT system uses smart cards and credit cards and the fare is calculated for each trip individually by distance travelled [Ministry of Transport, Government of Singapore, 2022]. In Berlin, there is a zone system and the fare depends on the number of zones passed on a trip. Moreover, it is necessary to purchase a ticket in Berlin,

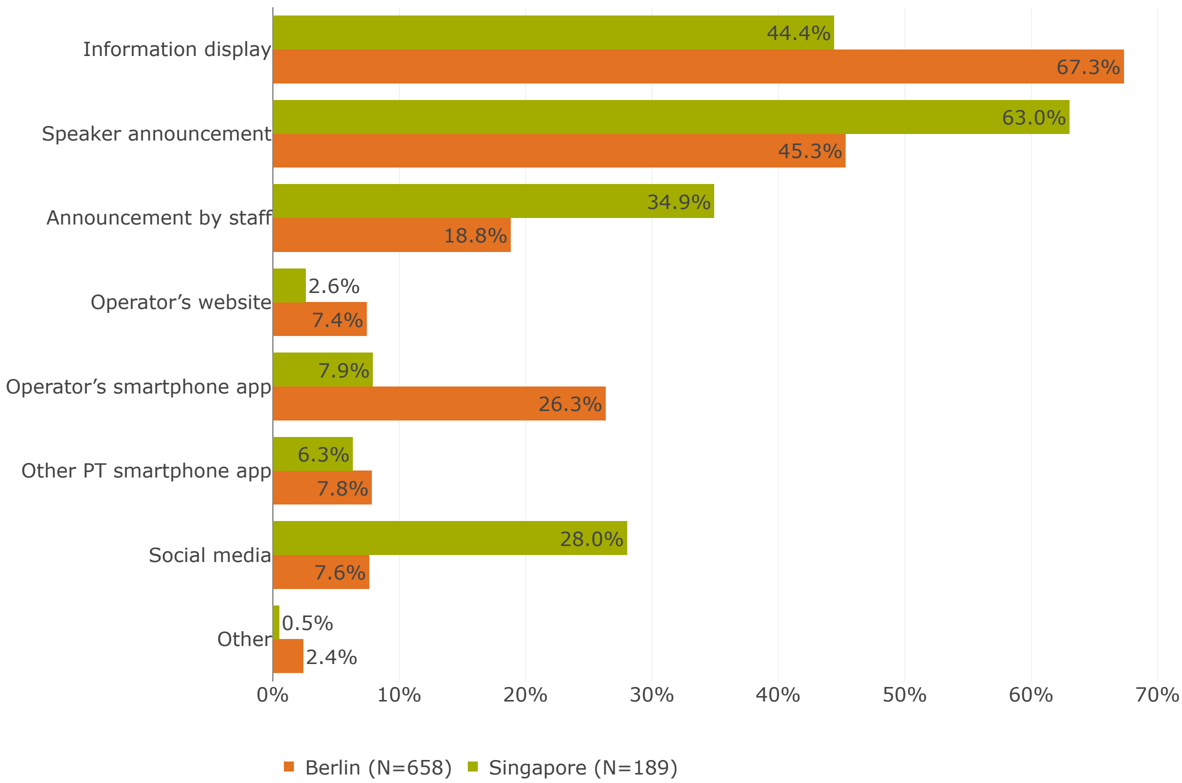


Figure 3.7: What are your preferred communication channels during incidents?

which can be also done via the BVG app [State of Berlin, 2022]. Therefore, the app has more functions than PT operators' apps in Singapore, which serve mainly the purpose to inform.

A significant difference between the cities appears also in the usage of social media (e.g. Facebook, Twitter, Telegram, etc.). Whereas in Berlin only 7.6% of the participants chose this answer, in Singapore it was 28.0%. This is partly explainable by the fact that in Singapore, the survey was also published in a Facebook group and a Telegram channel, whilst the Berlin survey was solely shared on BVG's website and smartphone app. PT users who noticed the survey on a certain information channel were likely familiar with this channel and probably preferred it for incident information as well. Furthermore, the location where the participants were, when the incident occurred, might also influence the answers as it had probably also an influence on the question about through which channel they received information (Figure 3.5). However, since the establishment of the smartphone with all its functions and capabilities, social media, websites and PT apps can easily be used from anywhere.

Another topic regarding the preferences of information during incidents is the content of the information the passengers receive. In order to be able to react properly to an incident, travellers need adequate information [Bachmann, Tsakarestos et al., 2023]. As it is shown in Figure 3.6 the three most often used reactions to an incident were: waiting for the next PT vehicle of the same line, using another line or a shuttle service, or switching to another means

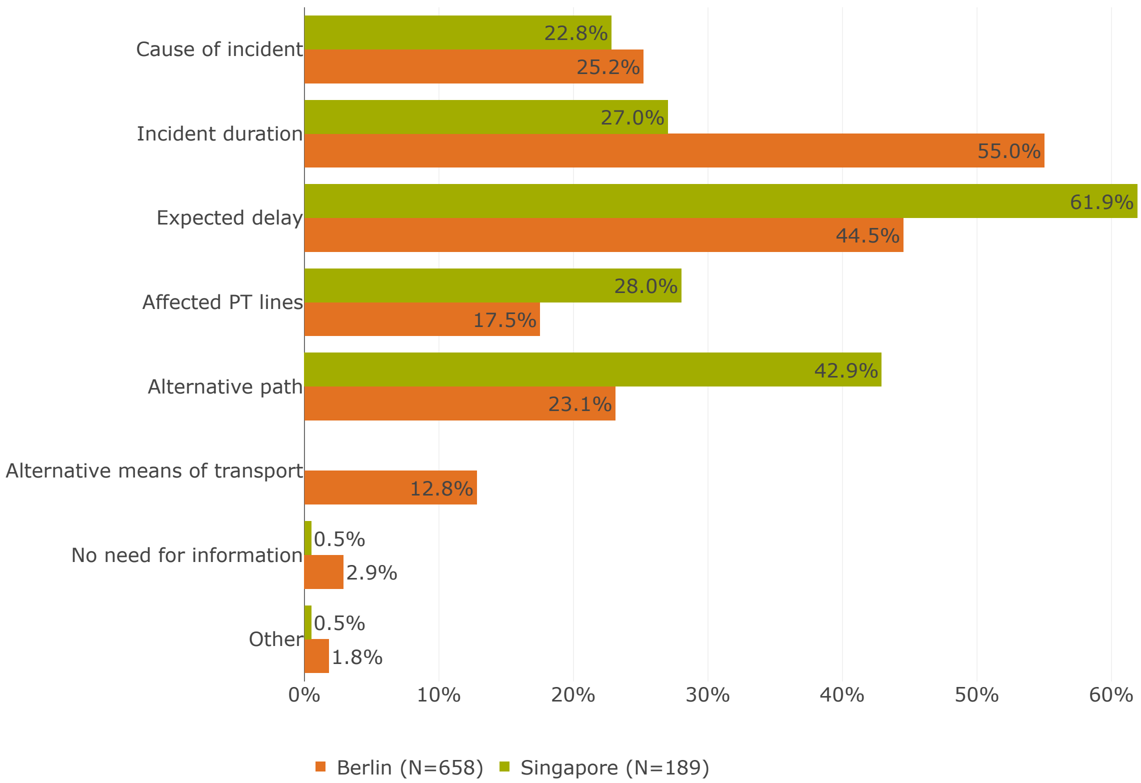
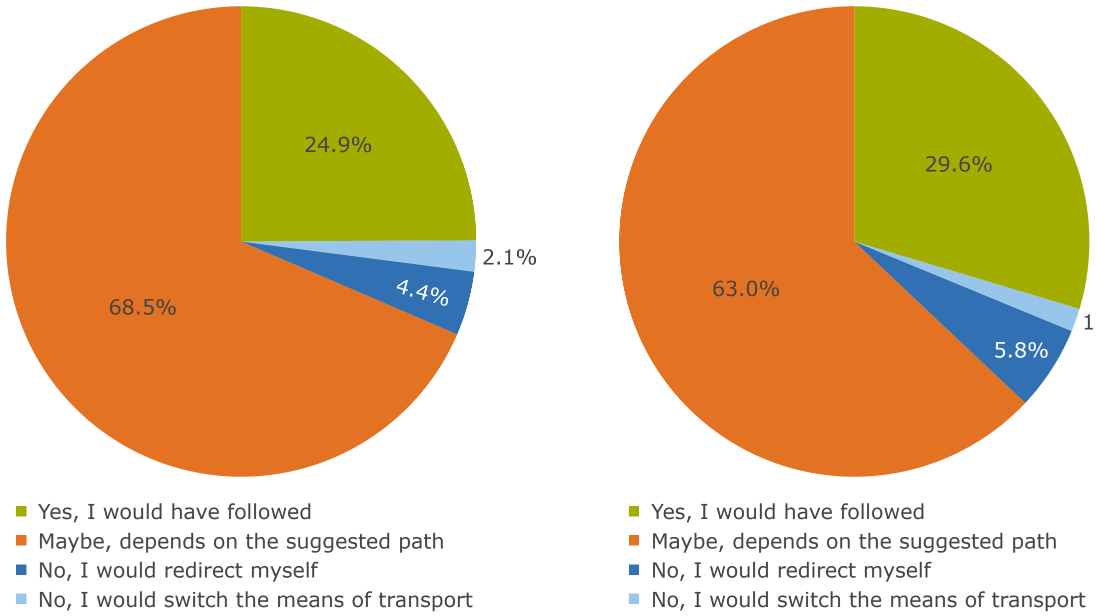


Figure 3.8: What would have been the most important information for you during this incident?

of transport. To choose the most convenient option, travellers need certain information such as the to-be-expected delays. In Figure 3.8, it is presented that only very few people ticked the answer option about not needing any information in incident situations (Berlin: 2.9%; Singapore: 0.5%). In Berlin, the to-be-expected duration of the incident and the expected delays due to the incident is the most important information for the survey participants with 55.0% or 44.5%, respectively. In Singapore, the preference of the to-be-expected delays is clear with 61.9%, followed by an alternative path within the mass PT network. Mass PT network includes all means of PT which transport most of the passenger demand (e.g. bus, MRT, metro, etc.), but do not include modes that transport individual persons and small groups, such as taxis, which are also part of PT. In Berlin, people were more interested in the cause of the incident (25.2%), than alternative paths (23.1%), followed by affected PT lines (17.5%), and suggestions for alternative means of transport (12.8%). Please note that the last-mentioned answer was not an option in the survey conducted in Singapore. There, the affected PT lines are almost as interesting to the participants (28.0%) as the duration of the incident (27.0%). The cause of the incident plays the smallest role in Singapore, with 22.8%. The rather small but existing differences between Berlin and Singapore in this question could be explained by the information the participants were used to. This would mean that in Berlin the cause of an incident was more often communicated than in Singapore, for example. In Singapore, also more people answered that they would like a path suggestion, almost 20.0% more than in Berlin. This might show that PT users in Berlin were more used to finding their alternative path, which also fits with their desire for information about the expected delay and incident duration. Part of the 20% might also come through the additional answer option in Berlin about suggestions for alternative means of transport.



(a) Berlin (N=658)

(b) Singapore (N=189)

Figure 3.9: If the operator provides you with an alternative path within the PT network, would you take it?

Since path advice is a core aspect of the method presented in Chapter 4, participants were asked if they would follow a path suggested by the PT operator and what are the most important characteristics of an alternative path. As to be seen in Figure 3.9, the results of Singapore and Berlin are very comparable concerning alternative paths. A quarter in Berlin to almost a third in Singapore answered that they *would* follow a path suggested by the operator. However, in both cities, over 60%, in Berlin almost 70%, stated that they *may* follow a suggestion, depending on the suggested alternative path. Only 7.4% in Singapore and 6.5% in Berlin *would not* follow a path suggestion, either because they would find an alternative path themselves or leave the PT system to switch to another means of transport.

Also, when it comes to the most important characteristics of an alternative path, the answers of the participants of the two different cities are comparable (Figure B.10). In both cities, the fastest path is the preferred path with 36.6% in Berlin and 48.7% in Singapore, followed by the path with the most reliable travel time with 17.5% in both cities. The third most common answer in Berlin was about the path with the same destination stop with 17.2% (9.0% in Singapore). In Singapore, the third most common answer is the one with the highest chance of not being crowded and thus also the one with the highest chance of being seated with 10.6% (2.9% in Berlin). The path with the fewest transfers played only a role in Berlin with

15.2% (3.2% in Singapore). In both cities, amenities and shops basically played no role with 0.5% in Berlin and 0.0% in Singapore. The fact that less walking and fewer transfers play a minor role in Singapore can be explained by the distribution of age among the participants in Singapore, which is a bias towards young people who are generally less averse to walking than older generations (Figure B.2).

3.2.4 Perceived Emotions

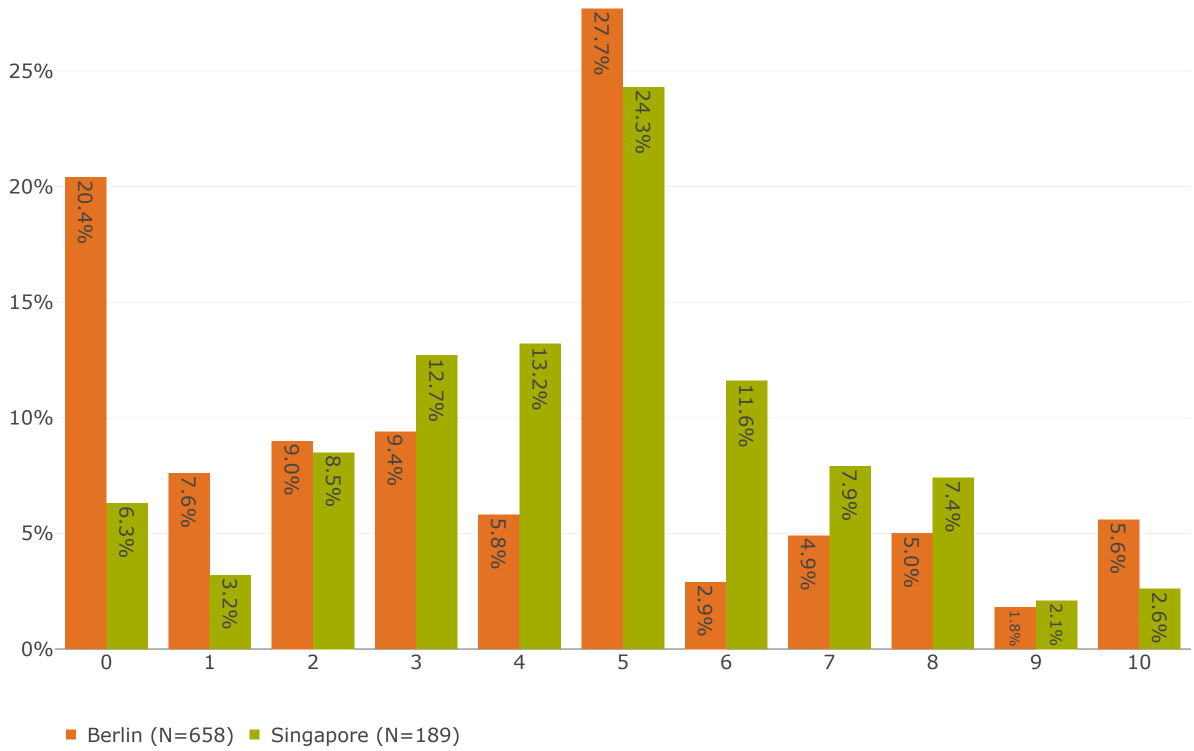


Figure 3.10: How confident are you that an autonomous, i.e. driverless, vehicle (e.g. an autonomous bus) will handle a similar incident well? (0 Not at all confident, 5 Neutral, 10 Extremely confident)

This thesis was part of the research project "Towards the Ultimate Public Transport System" which investigated the aforementioned DART system, an autonomous PT system [Rau, Tian et al., 2018; TUMCREATE, 2021]. Therefore, in this section, the presented questions were asked about two different scenarios. The first scenario was about the incident the participants experienced. For the second scenario, the participants were asked to imagine that a similar incident takes place in an autonomous PT system.

The first question in this section aimed at gaining a better understanding of the differences between the responses to the two scenarios above. Therefore, participants were asked how confident they were about an autonomous vehicle handling an incident well, which is similar to the one they experienced (Figure 3.10). Depending on the kind of incident a participant experienced, the PT vehicle itself played a stronger or weaker role in the situation. Therefore, it can be assumed that according to the kind of incident, people also expected an autonomous vehicle to handle a certain situation well or not.

In addition, PT vehicles are not yet well established in today's traffic. At the time of the survey, only two experiments were conducted in the two cities. In Berlin, there was an autonomous shuttle operating on the campus of the Charité hospital and in Singapore there was an autonomous bus, serving a PT line on the campus of the Nanyang Technological University (NTU) [BVG and Charité, 2017; Volvo AB, 2019] (Section 2.1.3). Therefore, experiences with autonomous vehicles and especially with autonomous vehicles were rather limited, if existent at all. This explains the high share of neutral answers. In general, the answers are somewhat balanced with a tendency towards less confident, which is particularly strong in Berlin, due to more than 20% of the people who answered with "not at all confident". As mentioned before, PT operators helped to broadcast the survey. In Singapore, the survey was advertised on the website of the PT operator Tower Transit, as well as, in a Facebook group of PT users, a Telegram channel for surveys conducted in Singapore and on websites of TUMCREATE, and the Facebook profile of the German embassy in Singapore. In Berlin, the survey was solely published on BVG's website and smartphone app. Websites of PT operators are not only visited by PT users but most likely also by PT drivers, who naturally have a dismissive attitude towards autonomous PT systems, as they are reducing the number of available driver jobs. Therefore, there might be a bias in these answers for some of the participants in Berlin.

The next two figures support the statement in the last paragraph, of people not being too sure about autonomous vehicles yet. Figure 3.11 shows the participants' answers to the question about their perceived level of pleasantness when thinking about the risk that a similar incident might occur. In both cities, the most given answer is "5 Neutral" and the rest strongly leans towards different levels of unpleasant. However, whereas in Berlin 32.1% answered with "5 Neutral" and 18.8% with "0 Unpleasant", in Singapore it's 21.7% for "5 Neutral" and 10.1% for "0 Unpleasant". In Singapore, more people used the answer options between "10 Pleasant" and "5 Neutral" than the participants from Berlin.

In general, people from Singapore seem also a bit more optimistic towards their next incident experience in PT than people from Berlin, as the answer options between 6 and 9, which are the different levels of pleasant are higher than in Berlin. Nevertheless, "10 Pleasant" was given by 2.4% in Berlin and merely by 0.5% in Singapore. How come some people have a pleasant feeling when thinking about the risk of experiencing an incident in PT again, which is usually or even mostly an unpleasant event? Two possible explanations might be that the incident did not disrupt the participants' travel plans as expected or that the PT operator reacted very well to the incident and resolved it rather quickly.

Figure 3.12 shows the same question however, the participants were asked to imagine that they experience the incident while being in an autonomous PT vehicle: "Can you indicate how unpleasant or pleasant you feel now, at this moment, when you think about the risk of a similar incident occurring with an autonomous, i.e. driverless, vehicle?". Compared to the emotions towards the actually experienced incident, the participants reacted a lot more neut-

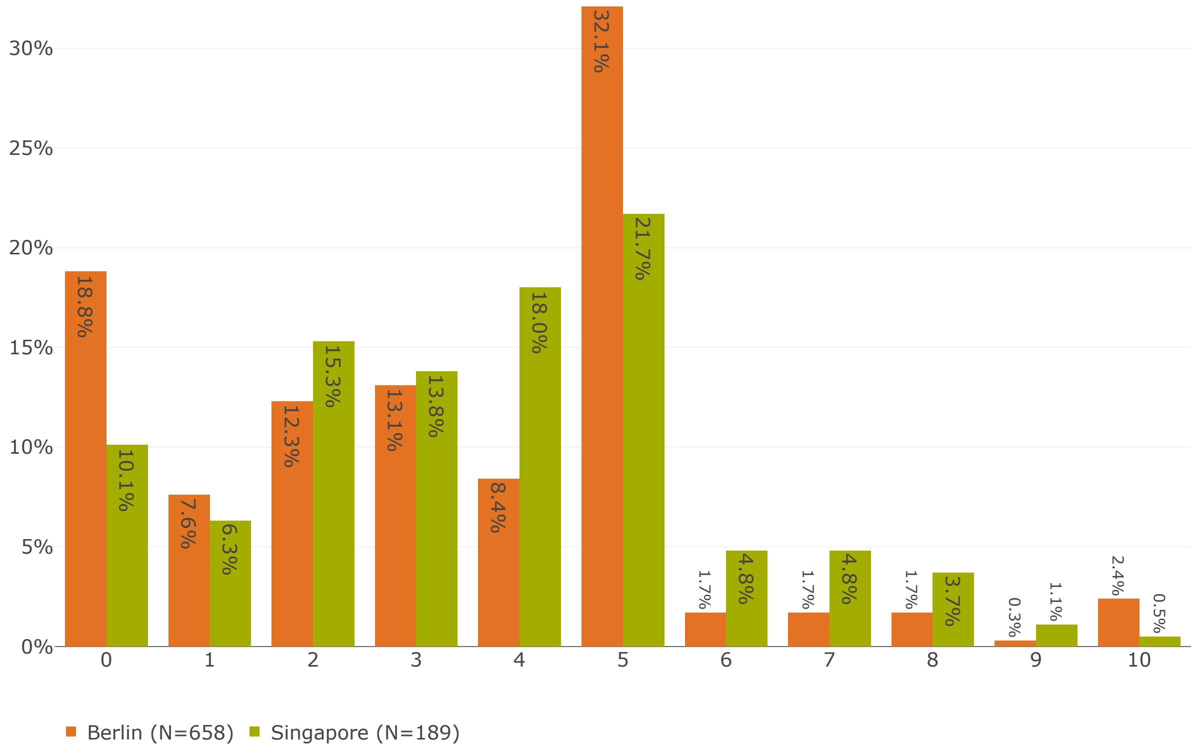


Figure 3.11: Can you indicate how unpleasant or pleasant you feel now, at this moment, when you think about the risk of a similar incident occurring again? (0 Unpleasant, 5 Neutral, 10 Pleasant)

rally, with 47.3% in Berlin and 33.3% in Singapore, when it came to imagining the incident in an autonomous PT system. This is understandable as it is a stated preference question and as mentioned before the experiences with autonomous PT vehicles were rare if existed at all. More interestingly, the number of people who felt unpleasant towards the risk of experiencing an incident in an autonomous PT vehicle dropped in both cities compared to the experienced incident. In Berlin, there is a more significant drop than in Singapore. In general, participants seem to expect autonomous vehicles to handle the same situation better than the experienced incident has been handled.

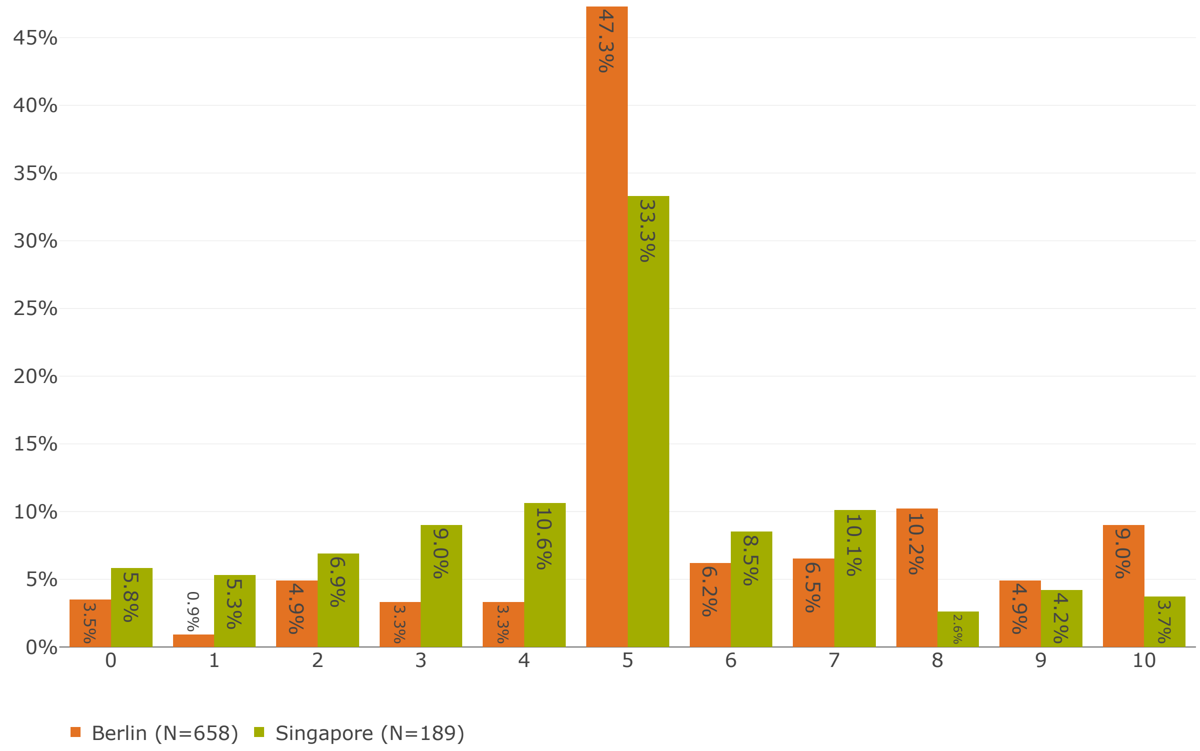


Figure 3.12: Can you indicate how unpleasant or pleasant you feel now, at this moment, when you think about the risk of a similar incident occurring with an autonomous, i.e. driverless, vehicle? (0 Unpleasant, 5 Neutral, 10 Pleasant)

In the previous section, we saw that 24.9% to 29.6% of the people *would* follow path suggestions by the PT operator if given during an incident and 63.0% to 68.5% *may* follow it (Figure 3.9). In Figures 3.13 and 3.14, it is shown how willing people are to follow path instructions during incidents on a scale between "0 Not at all willing" and "10 Extremely willing". Moreover, the same question is presented for the scenario in an autonomous PT system, to see if this influenced their willingness to follow such instructions.

Even though "5 Neutral" is the most given answer in Berlin, with 24.5%, the majority lies between 7 and 10 with 10 as the second most given answer with 18.7%. In Singapore, it looks very similar, with most answers lying between 7 and 10, however, here, the two answers given most often are 7 with 20.6% and 8 with 18.5%. "5 Neutral" is significantly less represented (16.9%) than in Berlin, nevertheless, so is 10 (10.6%). The answers from 0 to 4 are considerably less represented in both cities. This fits very well with the answers given in Figure 3.9 and also shows that most of the people who answered with "maybe" tend differently strongly towards "yes".

When comparing the answers for the experienced incident with the one given for the scenario with an autonomous PT vehicle, it becomes obvious that the number of positive answers (6 to 10) declines strongly towards neutral, which increases by 5.9% in Berlin and by 9.6% in Singapore. Especially in Berlin, the negative answers (0 to 4) show a clear increase with "0

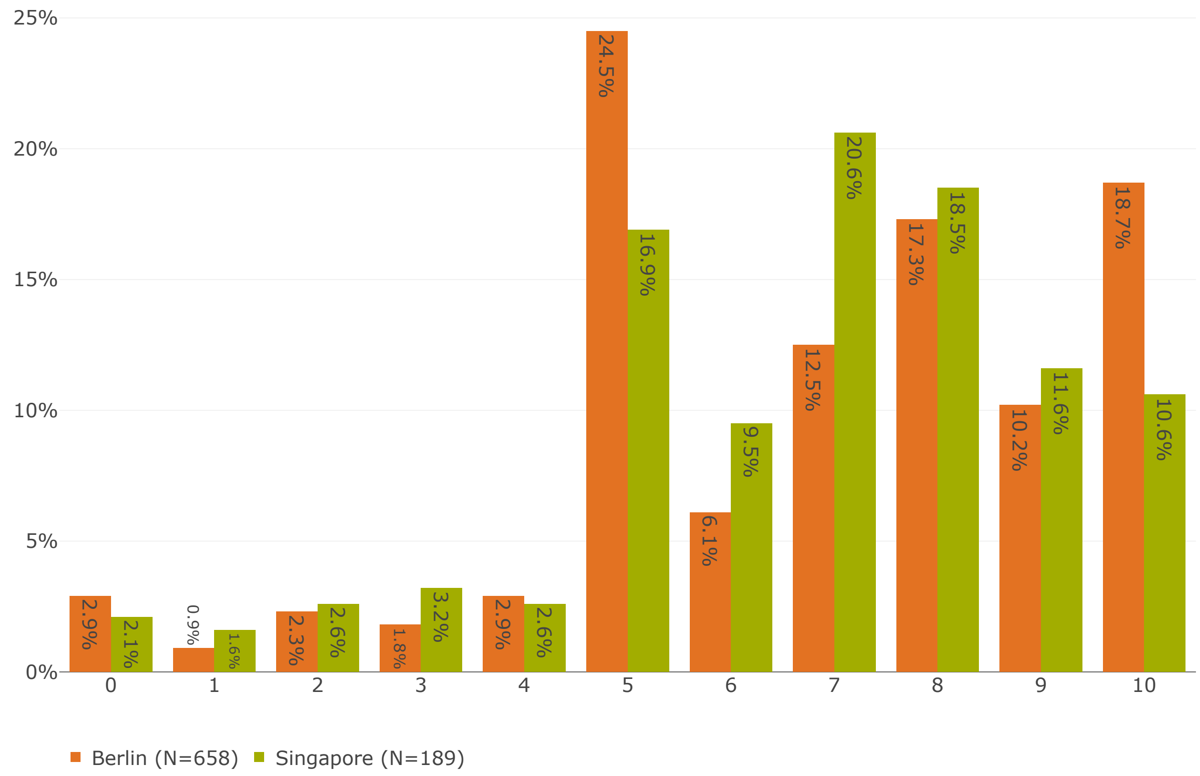


Figure 3.13: During such incidents, how willing are you to follow path instructions from the transport operator? (0 Not at all willing, 5 Neutral, 10 Extremely willing)

Not at all willing" growing by 7.4%. In Singapore, next to 5, 4 shows the most significant increase with 8.5%.

Hence, the participants from Singapore were more optimistic towards autonomous PT vehicles than the participants from Berlin, when it came to following given path suggestions. This can be explained by the fact that also in the question if participants would follow path suggestions, more people from Singapore answered "yes" than people from Berlin (Figure 3.9). The answers given in Figures 3.9, 3.13, and 3.14 are of particular interest for the PCIM method presented here, as providing travellers affected by an incident with path advice is a crucial part of it, as explained in Chapter 4.

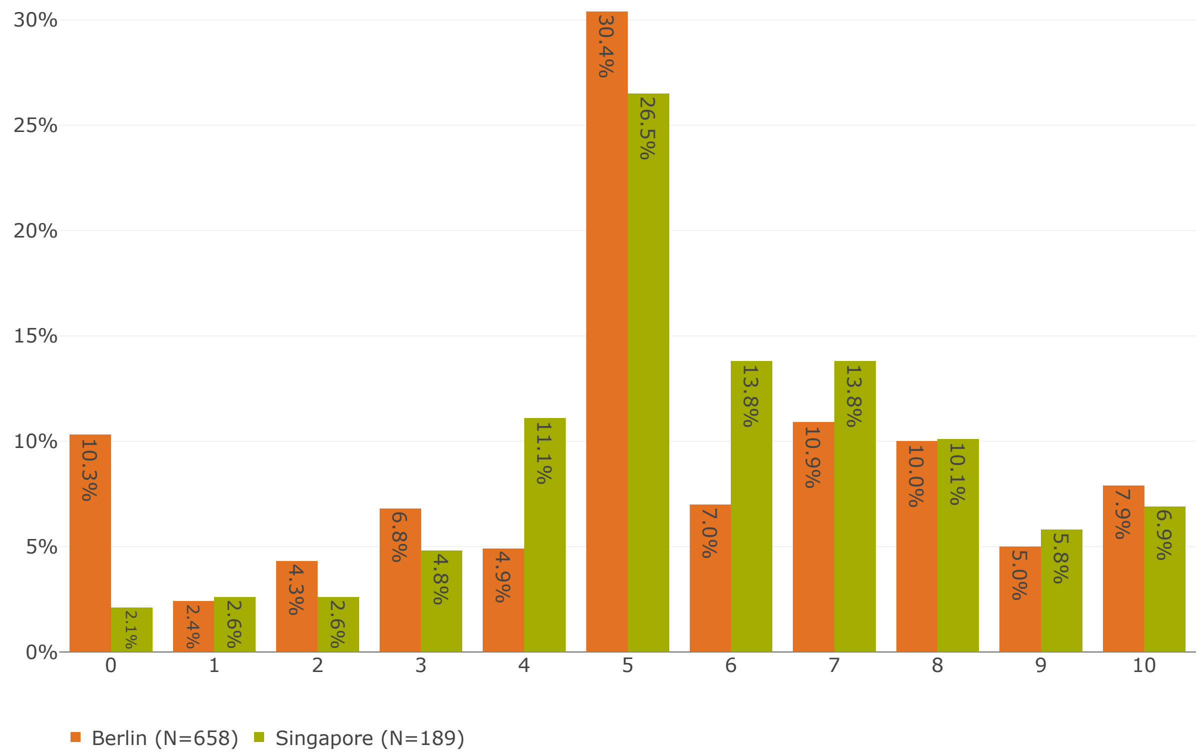


Figure 3.14: During such incidents, how willing are you to follow path instructions from the autonomous, i.e. driverless, vehicle? (0 Not at all willing, 5 Neutral, 10 Extremely willing)

3.2.5 Correlations

Figure 3.15 shows the correlation matrices of some of the questions which have been asked in the PT user survey. Such matrices can give an idea about relations between the answers given in the asked questions. In such colour-formatted correlation matrices, as they are used here, the colour indicates whether a correlation is positive (blue) or negative (red). If two answers – A and B – have a positive correlation (blue), it means that if answer A is ticked, it is likely that answer B is ticked as well. In case of a negative correlation (red), if answer A is ticked, it is likely that answer B is not ticked.

Another important aspect is the strength of the correlation between two answers, indicated by the intensity of the colour of a field. The more intense a field's colour, the stronger the correlation, as it is also indicated by the scales next to the matrices. The weaker a correlation between two answers, the more fades the colour. Hence, white fields indicate no correlation between the respective answers. Logically, each answer has a positive correlation of 1.0 with itself, which is why the fields in the diagonal of the matrix from the top left to the bottom right are filled with an intense blue colour [Friendly, 2002].

In Figure 3.15, "Willingness" refers to the participants' willingness to follow path instructions in a today's PT system (Figure 3.13). The next six or respectively seven answers refer to the trip stage of the participants, at the origin, at the first stop, at a transfer stop, at the last stop, on a PT vehicle, at the destination, or elsewhere (Figure 3.4). Please note that the last answer option was only given in the questionnaire for Berlin.

The following five answers refer to the channels, the participants usually use to find their path through the PT network, which are referred to as path search channel (PSC) (Figure B.6). The participants could choose between the options of using an app (of an operator or third party), the operator's website, network maps displayed at stations and on PT vehicles, asking PT staff, family and friends or other travellers, or another channel.
The next seven answers refer to the participants' preferred PI channel during incidents, which is named incident channel (IC) here (Figure 3.7). The given options were PI displays at stops or on vehicles, speakers, through PT staff, via an app (of an operator or third party), through an operator's website, via social media, or another channel.

The last column and row refer to the participants' age. The values of the willingness and age is normalised, meaning their range goes from 0 to 1 instead of their actual values with corresponding values in between to make them better comparable to the other answers which values are either 0 or 1, depending on whether a participant ticked (1) the respective answer or not (0) [Rothe et al., 1996]. Please note that for Berlin the participants chose among the age groups shown in Figure B.2, whereas in Singapore, the participants put in their exact age in years. Through the normalisation those two are also comparable, while the steps from 0 to 1 are finer in Singapore. As all questions had more than one option, the correlation is mostly not very strong. The more options the less obvious can be the correlation. The fact that vice versa is mostly not given for question with multiple answer options might be an explanation for why the correlation gets less obvious. Nevertheless, the correlation matrices in Figure 3.15 still give an idea about the correlation between some of the answers.

Looking at the results from Berlin, among the PSC, there is an indication that participants, who find their path through the PT network via an app, also prefer to receive incident information via an app, the blue colour in the corresponding field is relatively intense. This is an understandable correlation, if someone is familiar with a certain information channel, chances are high that this person also turns to that channel when it comes to incidents. This might also be the explanation for the positive correlation between PSC- and IC-other in the matrix for Singapore. Furthermore, their is an evidently negative correlation between PSC-app and age in Berlin, as the corresponding field shows a relatively intense red colour. This means that the older participants are the more likely it is that they did not tick PSC- or IC-app, whereas the correlation is stronger for PSC, also due to the fewer answer options. A stronger affinity of younger generations towards technology such as smartphones and apps is a reasonable assumption here. In Singapore, a noticeable negative correlation regarding the age is to be seen in the relation to PSC-map, while there is a positive relation towards IC-other. As there is a bias towards people between 20 and 29 years in the data from Singapore (Section 3.2.1), this correlation needs to be interpreted with caution. It might mean that younger people rather use maps to find their paths and that elderly rather prefer other channels than the listed during incidents, for example asking another traveller.

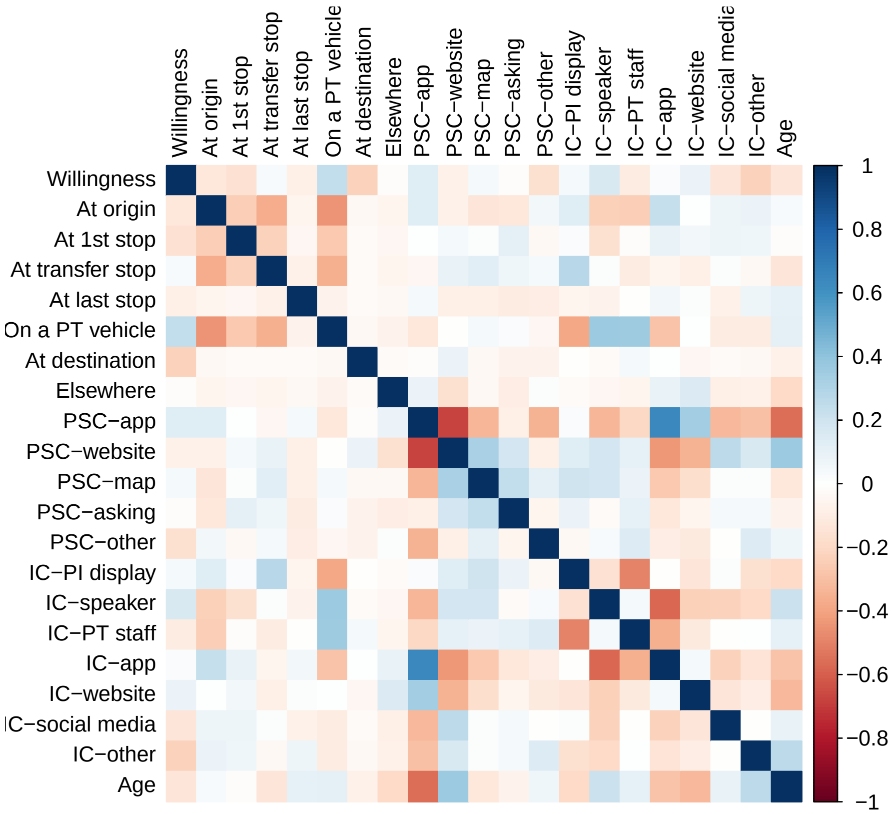
Regarding the stage of the trip when encountering the incident, in Berlin, there is a weak correlation (colour with low intensity) between people who were at a transfer stop, when they experienced the stated incident and have a preference towards PI displays when it comes to incident information. If a stop is equipped with such a display, it probably also provides waiting people with incident information. The people who ticked both answers regarding their location and IC probably received information through the displays and might have already built some trust in this channel. A comparable correlation seems to exist between participants who encountered the stated incident while they were on a PT vehicle and IC-speaker and IC-staff, whereas there is a negative correlation of comparable intensity towards IC-PI display and with a smaller intensity towards apps. A possible explanation is that in contrast to the people at stops, many passengers, who experienced an incident while being on a PT vehicle received incident information through speaker announcements and PT staff, most likely the driver, and therefore had built some trust in these channels. As only two options could be given for this question, fewer people ticked PI display. In Singapore, there is a relatively strong correlation between the trip stage "Vehicle" and the other stages which is probably due to the fact that many participants in Singapore have been on a vehicle (75.7%) while noticing the incident (Figure 3.4).

Concerning the willingness to follow path instructions, there are no strong correlations. One noticeable correlation in Berlin is that people who have been on a vehicle when encountering the incident are more likely to follow path instructions. This might be related to the two IC channels which show a positive correlation with the location PT vehicle, staff and speaker announcements. This probably indicates that passengers rather trust path suggestions when PI is provided by one of these channels. It is also perceivable that people who were at their destination are less willing. This is understandable, once a passenger reaches the destination, there is no need for any information regarding the trip, unless the next trip starts shortly after.

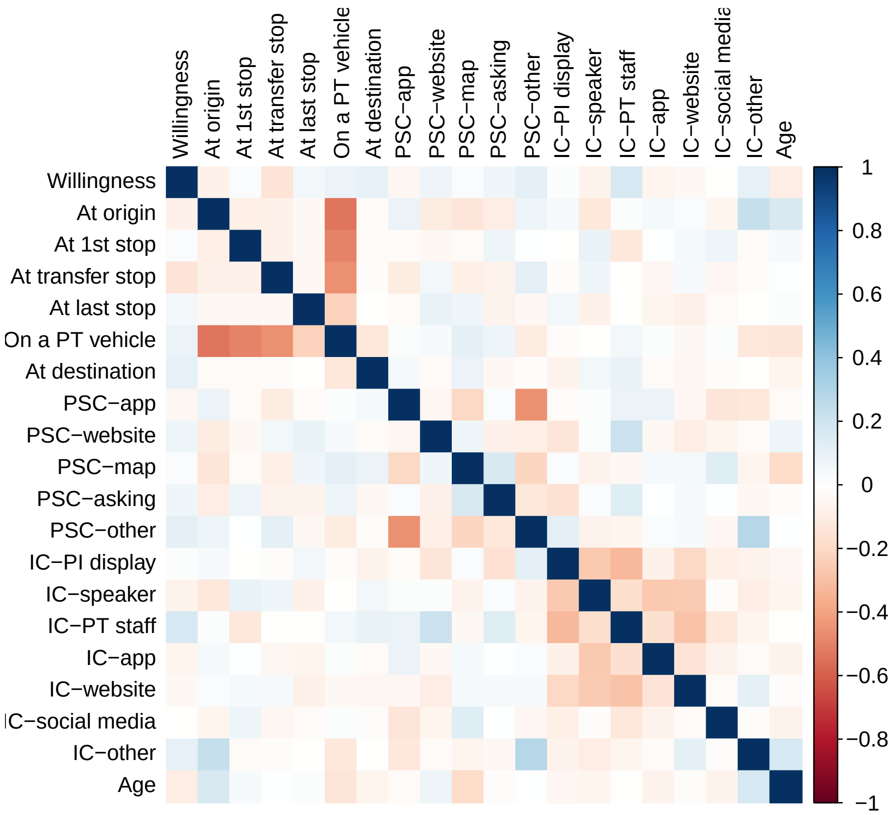
Other noticeable correlations are mainly among different answers of the same question. In Singapore, there is a detectable negative correlation between the participants' willingness to follow path instructions and the trip stage "transfer stop". This is somewhat unfavourable, because a transfer stop is a practical location for path suggestions due to the multiple options of PT lines. This is especially true for transfer hubs with a large variety of lines. Moreover, as in Berlin, there is a positive correlation with IC-PT staff which might be an indication of people trusting path instructions more when given by staff.

Among the other questions, correlations are even weaker and therefore are not presented here. This correlation analysis shows that there are no strong correlations found here, especially regarding the preferences towards specific IC and the willingness to follow path instructions, which are relevant for the model presented in Chapter 4. Furthermore, the correlations to be found in the results from Berlin differ from the ones from Singapore. However, in both cities some relations between the age and certain PI channels as well as trip stages and PI channels are pointed out here. These indicate comparable patterns, even though Berlin and Singapore are two very different cities in terms of geographic location, climate, culture, and population density.

The correlation matrices also show that the group of people who is willing to be redirected is very heterogeneous, which indicates that path advice should be receivable by all groups of society via all available PI channels as it is also suggested by Wilke [2023]. As already pointed out in Section 2.1.4, there are many factors influencing a passenger's reaction to an incident and to follow a given suggestion for alternative connections.



(a) Berlin (N=658)



(b) Singapore (N=189)

Figure 3.15: Correlation matrices

Chapter 4

Model Formulation

REdirecting Passengers and reAllocating Capacities Knowingly (REPACK) is the name of the algorithmic PCIM method which solves the problems and achieves the goals mentioned in the introduction (Chapter 1). Two earlier versions of the PCIM method presented here have been published by BACHMANN, RAU et al. [2021] and BACHMANN, DANDL et al. [2023]. Therefore, this chapter contains overlapping elements with the mentioned publications since the general idea and the conceptual framework have not changed significantly in the course of its development. Nonetheless, compared to the two previous versions, many aspects have been refined and completely new elements have been integrated. Corresponding comments can be found in the following sections.

4.1 Real Life Story

This section explains the general idea behind REPACK, which is to redirect passengers by giving them concrete path advice and simultaneously reallocating capacities during incidents, as its name already indicates. Figure 4.1 provides a simple toy network (STN) to explain the method. It has been adopted from UL ABEDIN [2019], modified, and already used by BACHMANN, RAU et al. [2021]. It includes seven nodes with stops and four PT lines. The numbers next to the links are the link travel times in minutes and the colour of a link refers to the line which operates on it. In this PT system, all lines are served by buses. The black curved link represents an adjacent parallel street which is not used during normal operations, meaning when no incident occurred.

Imagine you are travelling through the STN. Your origin is Node 3 and your destination is Node 6. You choose to take the fastest path, which means taking the red line to your destination node. While you are still at Node 3, an incident suddenly occurs between Nodes 4 and 5. This completely blocks the PT services between those two nodes for a certain duration. The dispatchers in the OCC react to the incident by rerouting the red and yellow lines along adjacent parallel streets, which is represented by the black curved link in Figure 4.1. This causes an increase in travel time of 14 minutes. Through dynamic PI displays at your stop and the PT app on your smartphone, you receive the information that your original trip is disrupted by this incident for 30 minutes and the corresponding delay is provided. If you know the PT network well, you can quickly conclude that your fastest alternative path is to take the cyan line until Node 4 and then transfer to the rerouted red or yellow line to finally reach your destination without much delay. However, this is probably what most travellers who are in the

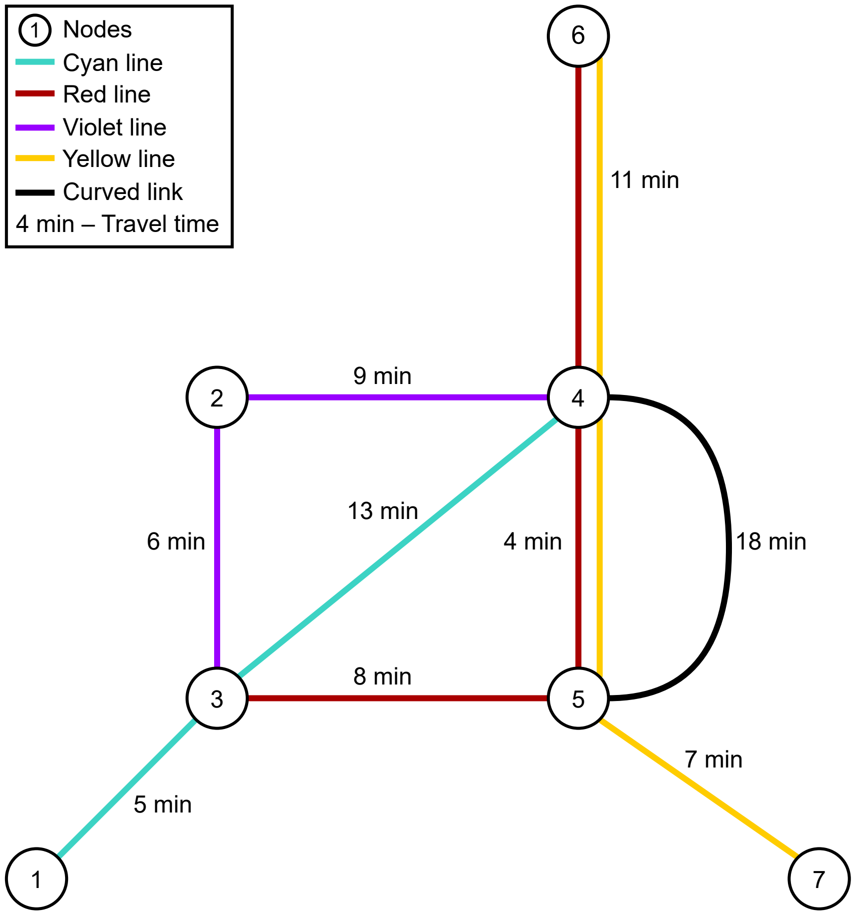


Figure 4.1: Simple Toy Network (STN) [Bachmann, Rau et al., 2021]

same situation as you would conclude. As pointed out by Cats and Jenelius [2014] and in Section 2.2.2, PI about incidents can also lead to secondary incidents due to overcrowding effects, leading to additional delays. This is especially true if the disrupted PT mode has a higher capacity than the modes of the fastest alternative path. Therefore, one central point of REPACK is to provide incident-affected travellers with concrete path advice to avoid too many passengers transferring to the same alternative path, hence to avoid overcrowding on alternative paths.

Assume that the cyan line would be overloaded by the additional demand if all affected passengers who come from Node 1 or 3 and want to go to Node 4 or 6 would choose the cyan line during the incident. In this case, it would be useful to split them in accordance with the available remaining capacities of the cyan and violet lines. However, if the path advice comes from collective information channels such as dynamic PI displays or speaker announcements, it is impossible to give path advice to individuals. It is only possible to give the same path advice to all passengers travelling in the same direction. Furthermore, imagine that you are not travelling alone, but with your favourite travel companion. If the two of you would receive different path advice, for example through a PT app on your smartphones, it could lead to confusion and dissatisfaction among the informed passengers like you and your travel companion. Hence, it is reasonable to group the affected passengers in correspondence to the node at which they are receiving path advice and their destination. Let us assume that the passenger group coming from Node 1 is the group which is supposed to stay on the cyan line until Node 4 as they are already on this line. Consequently, you, standing with your travel companion at Node 3, receive the information to take the violet line and then change at Node 4 onto the red or yellow line to reach your destination at Node 6. At this point you probably ask yourself, why not take the faster cyan line? Therefore, it might be helpful for you and the other PT users affected by the incident to be informed about the reason for this redirection, which in this case, is the capacity shortages on the cyan line. The better the affected passengers understand the situation, the more willing they will be to follow given instructions (Section 2.1.5). As the results from the PT user survey presented in Chapter 3 show, the cause of the incident is relevant to the affected passengers. Furthermore, the survey revealed that collective PI channels such as speaker announcements and dynamic PI displays play the most important roles during incidents from the passengers' point of view (Figure 3.7).

Imagine you and your travel companion follow the suggestion and take the violet line. In this case, you reach your destination later than planned, however, you reach it without any additional delays caused by waiting for the incident to be resolved or denial of boarding due to overcrowding. If not enough travellers were to follow the suggestion, or even if you were not to follow it but instead were to take the cyan line, you might experience further delays because of the exceeding of the cyan line's remaining capacity. Exceeding capacities leads to delayed departure due to prolonged boarding and alighting times as well as boarding denial and additional waiting time for subsequent PT vehicles. If you take the advised path but too many of the other affected passengers do not follow the path advice, they might cause delays on the red line and you could face additional delays at Node 4. However, due to the additional availability of the yellow line, the delays are probably much less than the delays the passengers on the cyan line have to face. In any case, a sufficient number of affected passengers must follow the path advice, to avoid secondary disturbances. Furthermore, imagine the passenger redirection is additionally supported by buses which have been withdrawn from low demand PT lines and reallocated to the cyan line to avoid the exceedance of its capacity. In this way, it might even be possible to redirect all affected passengers via the cyan line, including you and your travel companion, which would further reduce passenger delays.

This example gives reason to assume that path advice can reduce passenger delays and that reallocation of capacities decreases them even further. This is shown by Bachmann, Rau et al. [2021] in a numerical example. REPACK redirects affected passengers during incidents on alternative paths with sufficient remaining capacity and reallocates capacities to support the passenger redirection while avoiding severe delays on the PT lines from which the capacities are withdrawn.

4.2 Problem Statement

In the previous section, a picture was painted showing how a PCIM method, and specifically REPACK, could be perceived by passengers in practice. This section describes the theory behind this picture, stating the theoretical problem which is to be solved by REPACK. The problem to be solved is that there is an incident that causes passenger delays. It is therefore this method's main goal to reduce the delays of affected passengers as much as possible. One important assumption is that the incident's location, the disrupted PT services, as well as an estimation of the incident's duration can be provided by the OCC staff. Through interviews of OCC directors and trainers and observations of dispatchers in OCCs during their work, it has been concluded that dispatchers have quite a good intuition about the duration of an incident [Briem, Buck, Magdolen et al., 2020; Bachmann, Briem et al., 2022]. Furthermore, in Section 2.2.1 it has been elaborated upon how dispatchers take disposition measures to resolve the incident and reduce its negative effects on the PT system. The timetable which depicts the changes in the service during the incident and thus also the corresponding disturbances and the disposition measures taken (e.g. rerouting or splitting PT lines) is called a disposition timetable. When an incident occurs in a PT network, it usually does not affect the whole network, but rather specific PT lines and thus not all PT users $u \in U$ in the network, with u being one user and U being the set of all PT users. Hence, the following kinds of passengers can be distinguished:

- Affected PT users $U_a \subset U$, are the passengers whose trips are directly affected by the incident since they planned to take one of the disrupted PT lines. The focus of the presented methodology lies on them, U_a being the set of all affected users.
- Indirectly affected PT users $U_{ida} \subset U$. These travellers take PT lines which are not disrupted by the incident, but which are however under increased pressure due to the additional demand of the $u \in U_a$ transferring on to these PT lines. Additional demand can lead to secondary incidents due to overcrowding effects (Section 2.2.2), U_{ida} being the set of all indirectly affected users.
- Unaffected PT users $U_{una} \subset U$ are the passengers who are not at all affected by the incident because their trip takes place long before or after the incident when there are no consequences of the incident, or because they take PT lines which are neither disrupted nor occupied by transferred affected passengers, U_{una} being the set of all unaffected users.

Even though the PT network is disturbed by an incident which causes delays for the PT users, it is assumed that no one leaves the PT system. Another goal is therefore to provide the passengers with path advice in such a way that everybody is accommodated in the PT system and an adjusted equilibrium state is reached. Furthermore, it is assumed that an OD matrix, as an estimation of the passenger demand, is available. As elaborated by Gkiotsalitis and Cats [2021], there are various sources of information about the demand which can be used to derive a corresponding OD matrix either based on historical data or even in real-time, based on how well a PT system is equipped in this matter. Typical sources for demand data are automatic passenger counts and fare collection, ticket sales, and sample census data (Section 2.1.1). Although it is assumed that no traveller leaves the PT system, it would be unreasonable to assume full compliance. As one can see in Figure 3.9 (Chapter 3), some passengers would rather find a path on their own or keep their original trip plans. To consider these passengers within REPACK, two factors are taken into account. First, a self-redirection rate which expresses the share of passengers who prefer to redirect themselves is considered.

Second, a compliance rate is taken into account, as mentioned in the previous section. The self-redirection rate is one of the various aspects which is not part of the earlier versions of the method described here, presented by Bachmann, Rau et al. [2021] and Bachmann, Dandl et al. [2023]. The compliance rate refers to the share of passengers who do follow the given path advice. The rest, the passengers who do not redirect themselves or follow the given path advice, are assumed to stay on their original path.

It goes without saying that for passengers to be able to follow given path advice, they need to receive it. For this purpose, several PI channels are available in PT systems, as described in Section 2.1.5. However, depending on the PT system, only some of these channels might be available to the travellers. Furthermore, in Figure 3.7 (Chapter 3), the survey participants stated different preferences regarding the PI channel through which they would want to receive information about the incident and its consequences. Hence, an information rate is used to consider passengers who do not receive path advice and to be able to take different cases of availability of PI channels into account.

Another restriction to the solution to this problem is that it is reasonable to not redirect passengers individually but to group them. First, it is not known who is travelling with whom, and giving a group of people who are travelling together different path advice can lead to confusion. Second, in general, if people get redirected at the same stop and have a common destination, especially on the collective PI channels (e.g. speakers, displays) the information should be consistent, otherwise, it might lead to confusion and distrust in such a PCIM method (Section 2.1.5). As stated in the literature review in Section 2.2.2, passengers are usually handled as indivisible groups in PCIM methods.

Here, the affected passengers are grouped into OD pairs $od \in OD_a$, in accordance with their origin of redirection o and destination d, od being one OD pair, ODa being the set of all affected OD pairs, subset of the set of all OD pairs OD ($OD_a \subset OD$). An origin of redirection is the stop from which onward the passengers need an alternative path through the PT network. For travellers who did not start their trip before the beginning of the incident, this stop is the same as the starting stop of their original trip. For passengers who are already on their way, it is the next stop of their current trip.

When passengers are redirected, it should also be ensured that secondary incidents through overcrowding are avoided. Therefore, the remaining capacity on the alternative paths needs to be taken into account. Consequently, another assumption is that corresponding information about the PT system's capacity and occupancy is accessible.

The solution to the stated problem should thereby be that path advice given by the operator should be disseminated to all affected passengers in a manner such that: 1) travellers with the same origin of redirection and destination receive the same path advice, 2) the path advice is to be broadcast consistently across all PI channels, and 3) the given path advice considers the remaining capacity of the alternative paths. If an approach solves this problem accordingly, it fulfils the requirements for CAPR as stated by Bachmann, Tsakarestos et al. [2023].

The bullet list below summarises the mentioned assumptions:

- dispatchers in OCCs can estimate the incident duration,
- nobody leaves the PT system,
- the passenger demand on the PT system is given as an OD matrix,
- the capacity and occupancy of the PT vehicles is known.

To reach the main goal of minimising the overall delay of $U_a \subset U$, which is expressed mathematically in Equation 4.1, REPACK has been developed. The delay is hereby defined by the difference between the originally planned arrival time of a passenger to their actual arrival time at the respective destination.

$$\min \sum_{u \in U_a} \Delta tt_u \tag{4.1}$$

Where:

$u \in U_a$ = PT user in set of all affected PT users,
Δtt_u = delay of PT user $u \in U_a$.

The procedure of the PCIM method REPACK consists of four algorithmic processes that are presented in Figure 4.2. In the following flow charts, in this chapter, eclipses refer to the terminals (i.e. its start and end), rectangles represent processing steps, diamonds indicate decisions at what processes split, and parallelograms refer to information or data.

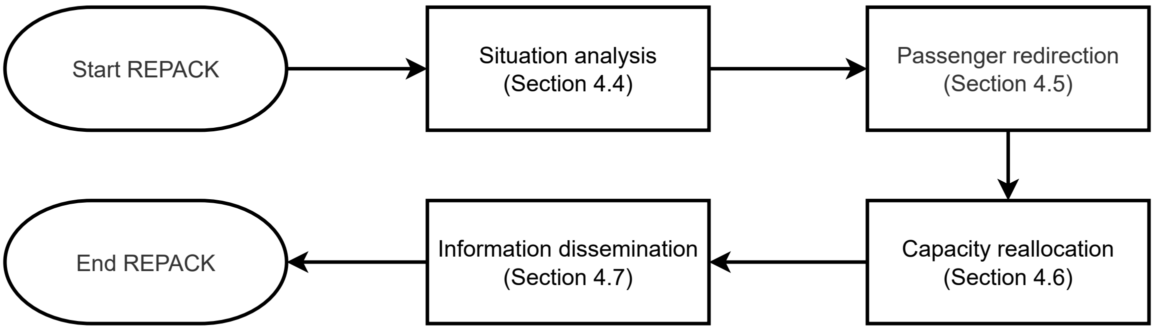


Figure 4.2: Procedure of REPACK

The first process – situation analysis presented in Section 4.4 – retrieves the needed information about the incident, the PT supply and the passengers' trips. The second process – passenger redirection presented in Section 4.5 – exploits the gathered information to redirect the passengers affected by the incident in the PT network. Note that during the second process, the remaining capacity on the alternative paths and thus all $u \in U_{ida}$ who occupy part of the capacity on the alternative paths are considered. Additionally, the third process – capacity reallocation presented in Section 4.6 – checks the PT system for dispensable capacities which could be reallocated to support the passenger redirection. Once a redirection strategy is set, the last process – information dissemination presented in Section 4.7 – then disseminates corresponding path advice across all available PI channels and informs the PT drivers about the reallocation of their vehicles. Before diving into the first process of the REPACK procedure, the next section describes how the PT network, including the timetable and especially the aforementioned disposition timetable reflecting the PT service during the incident, is represented during the procedure.

4.3 Network Graph

To search the PT system for available paths as well as check their travel times and remaining capacity, the PT supply needs to be represented properly. As in BACHMANN, DANDL et al. [2023], this is done with a directed network graph $G = (N, L)$ with nodes N and links L. Figure 4.3 shows a part of the PT network presented in Figure 5.2 in Section 5.2.2 as represented in the graph introduced here. Stop areas (e.g. s1) consist of two types of nodes: 1) stop nodes $N_P \subset N$ which reflect the physical PT stops and 2) line nodes $N_L \subset N$ which represent the PT lines serving a particular stop node. A line node is connected to its corresponding stop node via a link (dashed lines), which is for transferring between lines as well as getting off and on the PT vehicles. Each stop area includes at least two stop nodes, reflecting the PT stops for operations in opposite directions, such as two stops across a street. Walking links (dashed arrows) connect the different stop nodes (e.g. s1_1, s1_2) of a stop area. Larger transport hubs with several stops, such as stop area s2 in Figure 4.3 can have even more than two stop nodes. If a stop node is served by more than one PT line, it is connected to a corresponding number of line nodes. These represent the PT lines which service the corresponding stop node. The colour of a line node indicates the colour of the PT line in Figure 5.2 (Chapter 5). The PT links (arrows) connect the line node of a particular PT line with the line node of the same PT line of the next stop, reflecting the line route. The PT vehicles serving a line node are stored as attributes at each node with there departure time and remaining capacity in the graph.

When an incident occurs, it is not the regular timetable which needs to be represented by G, but the disposition timetable, which takes the incident itself into account as well as the disposition measures taken by the OCC (see Section 2.2.1). It thereby represents the PT supply in line with the condition of the PT system during the incident. The incident can then be expressed by its start (t_i^s) and end time (t_i^e) as well as by the links it disrupts $L_i \subset L$. From these links, the disrupted PT lines and affected PT vehicles can be derived as well. Since the capacity of the system is a crucial aspect in PCIM, it must also be represented in G in order to be able to check the available paths found for their remaining capacity. As mentioned in the previous section, it is assumed that the capacity and occupancy of all PT vehicles are known. Therefore, the remaining link capacity c_l of $l \in L$ can be calculated by summing up the remaining free places on all PT vehicles crossing l. A path $p \in P$ is defined as a specific order of $l \in L$, P being the set of all paths. The remaining path capacity c_p is thereby defined by the smallest c_l among all links which are part of p ($L_p \subset L$).

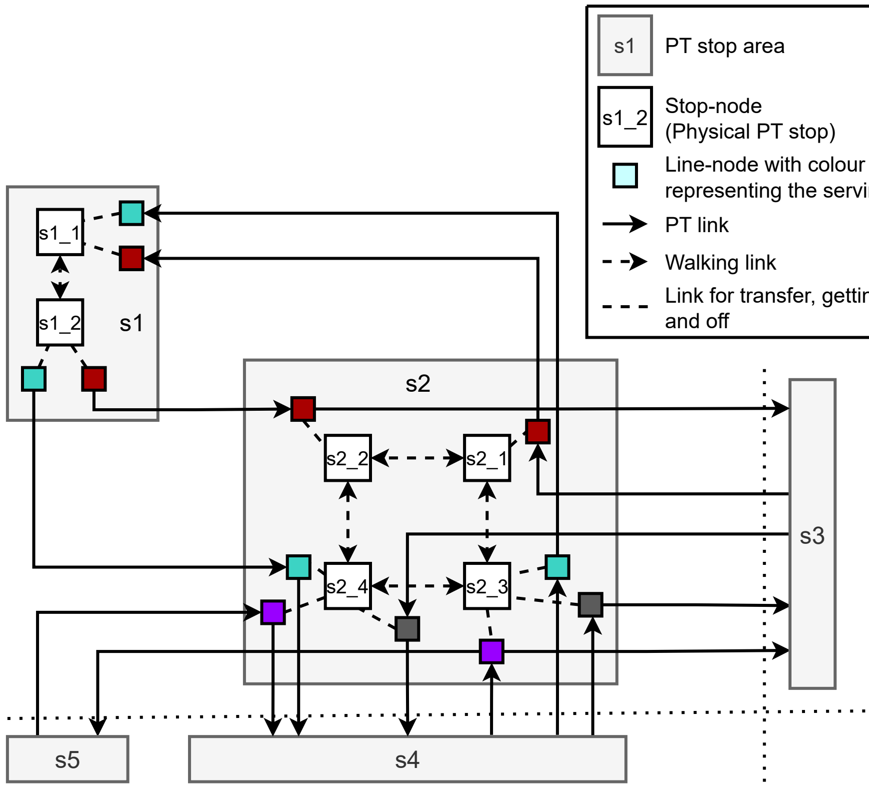


Figure 4.3: Example for the used representation of the PT supply [Bachmann, Dandl et al., 2023]

4.4 Situation Analysis

This process is the first in the procedure of REPACK and is shown in Figure 4.4. After the incident occurred, Step 1 is to gather the incident data. Important incident data is its location and with that the disrupted PT lines as well as an estimation of its duration. Even though each incident has its own characteristics and its duration is hard to predict, through interviews with OCC directors and trainers, as well as through observations of dispatchers during their work, it is known that especially experienced dispatchers have quite a good intuition about the duration of an incident [Briem, Buck, Magdolen et al., 2020; Bachmann, Briem et al., 2022] (Section 2.2.1).

Next (Step 2), the travel data is retrieved which includes the supply side, meaning the planned PT schedule as well as the passenger side i.e., information about the passengers' trips. If this method is implemented in practice, it is conceivable that the timetable can be retrieved via an interface such as GTFS or together with the incident information from an ITCS via an interface such as the VDV454 (Sections 2.1.5 and 2.2.2). Depending on how well a PT system is equipped, the passenger trip information can be catered for through the PT operators' model of the PT network and corresponding estimates of the passenger demand on the day the incident occurred. For example, it is imaginable that day categories (e.g. weekdays, holidays, special event days) are formed which show typical passenger demands. In accordance with the day of the incident a category is picked to predict the passenger demand.

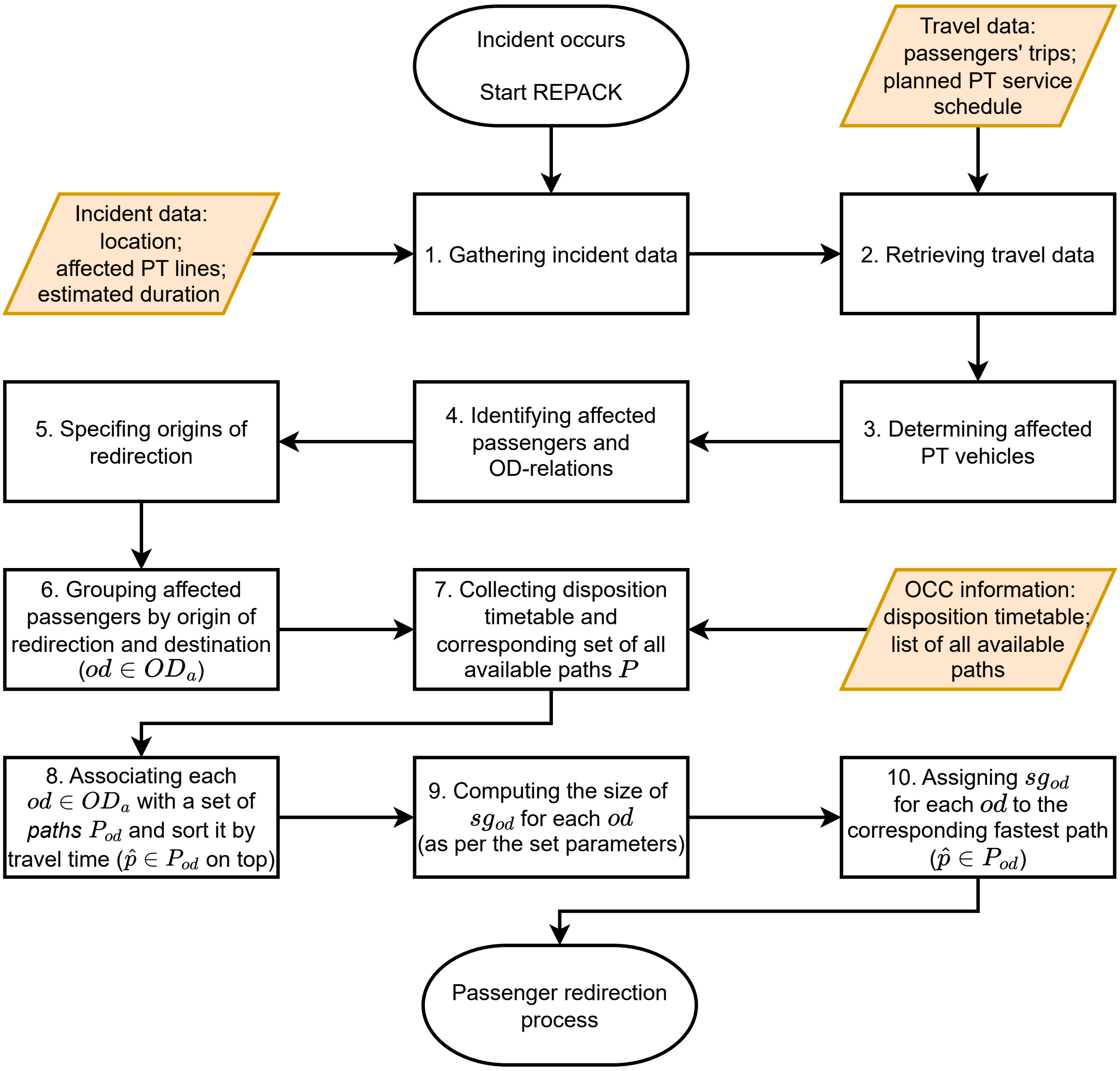


Figure 4.4: Situation analysis process

In PT systems with APC or AFC, it might also be possible that real-time demand data is available (Section 2.1.1).

Based on the timetable and the incident information, it can then be determined in Step 3 which PT vehicles would be affected by the incident. If this information is merged with the passenger trip data, the affected passengers and their OD relations can be identified (Step 4). In Step 5 the origins of affected passengers' redirections are specified. An origin of redirection describes the stop from which passengers need to be redirected. For affected travellers whose trip has not started at the time the incident occurs (t_i^s), the origin stop of their trip is the same as the origin stop of their redirection, whereas for affected travellers who already started their trip it is the next stop they are passing or the stop at which they are transferring at the time the incident occurs. Through this step and based on the previously received passenger trip data, it is known from which stop to which stop in the network the affected passengers need alternatives to their original path.

As pointed out in Section 4.1, it is reasonable to group the affected travellers according to the origin of their redirection and their destination (Step 6). OD is the set of all OD pairs in the network. $OD_a \subset OD$ is the set of all od which are affected by the incident. This grouping method avoids passengers travelling together receiving different path advice as suggested by Müller-Hannemann et al. [2019]. Moreover, it helps to prevent confusion among the affected travellers, especially when the path advice is disseminated via collective PI channels such as speaker announcements and dynamic PI displays at stops and in PT vehicles, which are the preferred channels of travellers during incidents as shown in Figure 3.7. Before coming to the redirection process, the actual PT service being operated during the incident needs to be examined. For this purpose, the disposition timetable, which includes the disposition measures (Section 2.2.1) taken by the dispatchers in the OCC, is collected (Step 7). Additionally, the corresponding available paths in this altered PT network are fetched.

The collection of available paths in accordance with the incident and the disposition measures taken is a process that could be preprocessed in practice. It is conceivable that a corresponding database could be built in which the available paths are saved and associated with different possible incident situations, which would speed up Step 7. A filtering process could then further adjust such a comprehensive list of available paths to the detailed characteristics of the present situation. This filter can be part of Step 7 or 8, in which each $od \in OD_a$ is associated with a set of potential alternative paths for od ($P_{od} \subset P$) which connect the respective od's origin of redirection with its destination.

Here, a set of all available simple paths is found using the method by Sryheni [2022]. The characteristic "simple" refers to the absence of loops in a path. The algorithm validates every opportunity to go from one vector or node to another within the corresponding graph ($G = (N, L)$), representing the disposition timetable as described in Section 4.3. By saving the already visited nodes while going through the network, it is ensured that each node which is part of a path is only visited once. However, this method might be too inefficient for larger networks with a high number of nodes, as the number of possible connections grows by a factor of $|n|!$ with $|n|$ being the number of nodes. In such cases, a k-shortest path algorithm as described in Section 2.1.2 is probably more appropriate.

This set of paths is sorted by the estimated travel time of paths, from the fastest to the slowest alternative path. The actual instead of the perceived travel time (Section 2.1.2) is used here, as it is assumed that in special situations such as incidents, people are more willing to take a more inconvenient path, if necessary, in the form of crowded PT services or a longer perceived travel time, in order to reach their respective destination with a minimum of delay [Carrel, Halvorsen et al., 2013]. The fastest alternative path of a set of paths is depicted as $\hat{p} \in P_{od}$ in the following. It is also the path which is assumed to be taken by passengers who rather redirect themselves in an incident situation than follow the operator's path advice (Step 9). As known from the survey results in Figure 3.9 (Section 3.2.3), some passengers prefer to redirect themselves, meaning choosing an alternative path on their own. Commuters, for example, who know the PT network well, probably prefer to take the fastest alternative path. Therefore, the methodology presented here considers a self-redirected share of affected passengers for each $od \in OD_a$. The self-redirection rate ξ is multiplied by the number of passengers associated with an od. Afterwards, a random sample of the corresponding size is taken to build the respective group of self-redirected passengers, which is referred to as

sg_{od}. This is done for each $od \in OD_a$ before all sg_{od} are then assigned to their corresponding $\hat{p} \in P_{od}$ in Step 10. These two steps differ significantly from the earlier versions of this method which do not consider the passengers who redirect themselves [Bachmann, Rau et al., 2021; Bachmann, Dandl et al., 2023].

Ultimately, this process analysed a present incident situation. That is, all $p \in P_{od}$ of each $od \in OD_a$ are identified and the sg_{od} are assigned, so, the redirection process can begin.

4.5 Passenger Redirection

In the following, two approaches are presented to solve the passenger redirection problem. Therefore, at the 11th step in Figure 4.5, the algorithm splits into two approaches. The blue area contains the rule-based heuristic approach and the red area contains the optimisation approach.

4.5.1 Heuristic Approach

To reduce passenger delay, it makes sense to redirect passengers only as long as it is faster than to wait for the incident to be resolved and stay on the original path $0 \in P_{od}$. For this purpose, Equation 4.2 is formulated to calculate the redirection duration T^p_{od}, which expresses the period during which path advice is disseminated to a certain $od \in OD_a$ on a certain path $p \in P_{od}$. It has been adopted from Bachmann, Dandl et al. [2023] and slightly modified. A time constant t_{con} which is used by Bachmann, Dandl et al. [2023] to consider delays due to missed PT vehicles and interference with other passengers has been replaced by the product of the longest headway $\breve{h}_p$ among the PT lines which are part of path p and the factor ψ, by which $\breve{h}_p$ is multiplied. Through $\breve{h}_p$, differences in the headway among the various PT lines which are part of path p are taken into account. Therefore, product of $\breve{h}_p$ and factor ψ can be used to adjust Equation 4.2 to a certain PT system to achieve better results. Besides the consideration of missed PT vehicles and interference with other passengers, this product can also used to prolong the redirection duration if a negative value is set for ψ. If for example an incident is severe and caters for a recovery time, describing the period between the dissolution of the incident and the end of delays induced by the incident (Section 2.2.2), it might be reasonable to extent the redirection duration. This is further discussed in Section 5.2.1. Once T^p_{od} elapses, the point of time is reached at which it makes more sense for the passengers of od to wait for the remaining time until the dissolution of the incident and stick with $0 \in P_{od}$.

$$T^p_{od} = (t^e_i - t^s_i) + (tt^{od}_0 - tt_p) - \breve{h}_p \cdot \psi \tag{4.2}$$

Where:

tt_p = travel time needed for path p,
tt^{od}_0 = travel time needed for the original path 0 of an od,
t^e_i = end time of the incident,
t^s_i = start time of the incident,
$\breve{h}_p$ = longest headway among the PT lines which serve a section of p,
ψ = calibration parameter to adjust T^p_{od}.

Based on T_{od}^{p}, the redirection demand of od on a particular path p can be examined. It expresses how many people are redirected if OD pair od is assigned to path p. After the passengers of sg_{od} are deducted from all passengers associated with an $od \in OD_a$, the rest is divided into a redirection group rg_{od}^{p} and a waiting group wg_{od}^{p}. The redirection group rg_{od}^{p} contains the passengers who are actually redirected whereas the waiting group wg_{od}^{p} refers to the passengers who are waiting for the dissolution of the incident and staying on $0 \in P_{od}$. The decision of who belongs to which group is done based on T_{od}^{p}.

For each passenger of an od who is not in sg_{od}, it is therefore checked if the respective arrival time at the origin of redirection (t_{arr}^{o}) lies before the end of the corresponding T_{od}^{p}, measured from the start time of the incident (t_i^s), as shown in Equation 4.3. If so, the redirection is reasonable for them and they are assigned to rg_{od}^{p}; if not, they are assigned to wg_{od}^{p}. Since the redirection of passengers is only reasonable as long as it reduces their delay: the smaller tt_p, the longer T_{od}^{p} and therefore the more passengers in group rg_{od}^{p}.

$$t_{arr}^{o} < t_i^s + T_{od}^{p} \tag{4.3}$$

Where:

t_{arr}^{o} = arrival time at the origin of redirection,
t_i^s = start time of the incident,
T_{od}^{p} = redirection duration of passengers associated with od for path p.

However, passengers who receive path advice do not necessarily comply with it. As shown in Figure 3.9, a few people would redirect themselves, some people *would* follow the path advice, and most just *might* follow path advice. The people who redirect themselves are already taken care of through group sg_{od}, however, some people might also not follow path advice because they would prefer to stick with $0 \in P_{od}$. To consider these travellers, a compliance rate η is taken into account. This rate corresponds to the size of the share of affected and compliant passengers. In addition, the information rate ζ, which expresses the share of affected passengers who actually receive the path advice, might also reduce the number of people who would follow it. Depending on which information channels are available to the passengers, the information rate can be less than 100%. Furthermore, in accordance with Figure 3.7, the most important information channels are the collective ones (i.e. speakers, dynamic PI displays at stops). Since the space at displays is limited and very long announcements are confusing, it is not possible to inform all rg_{od}^{p} via the collective channels. Therefore, for these channels, the information rate is smaller. The rest $(1 - \eta \cdot \zeta)$ is additionally associated with wg_{od}^{p}.

The heuristic approach (blue area in Figure 4.5) builds on the idea that the larger rg_{od}^{p}, the larger the reduction of passenger delays once a fitting path $p \in P_{od}$ is found. Therefore, the heuristic approach starts with the $od \in OD_a$ with the largest rg_{od}^{p} for its fastest path ($\hat{p} \in P_{od}$). The smaller tt_p is, the longer is T_{od}^{p} and the larger is rg_{od}^{p}. To bring $OD_a \subset OD$ in corresponding order, in Step H12 of the heuristic approach, T_{od}^{p} is calculated for $\hat{p} \in P_{od}$ for each $od \in OD_a$, which enables the examination of the sizes of $rg_{od}^{\hat{p}}$ and $wg_{od}^{\hat{p}}$ for each $od \in OD_a$ on their respective $\hat{p} \in P_{od}$ (Step H13). In Step H14 of the heuristic approach, $OD_a \subset OD$ can then be sorted accordingly by the size of $rg_{od}^{\hat{p}}$.

Then, for each OD pair $od \in OD_a$ taken in Step H15, the corresponding set of available paths ($P_{od} \subset P$) is checked in Step H16. P_{od} is sorted by the paths' travel time (tt_p, Step 8 in Figure 4.4), with the fastest path $\hat{p} \in P_{od}$ on top. As long as no fitting path $p \in P_{od}$ is found, the next p is inspected. In Step H17, T^p_{od} of the currently examined p is calculated to then examine in Step H18 the corresponding size of rg^p_{od} and wg^p_{od} as per the set parameters (i.e. η, ζ, ξ, ψ). Through the size of rg^p_{od}, it is known how much room is needed if OD pair od is assigned to path p. To avoid secondary incidents on path p due to overcrowding, as mentioned before [CATS and JENELIUS, 2014], the remaining capacity of path p (c_p) is examined in Step H19.

In the heuristic approach, this is done segment-wise. A path p is divided into path segments ($ps \in PS_p$) in accordance with the PT lines which are serving on path p. Due to the segment-wise calculation of c_p, the travel time of rg^p_{od} along path p can be considered. When passengers travel along a path, they occupy space on the corresponding PT lines for the corresponding path segment $ps \in PS_p$. For each path segment they need a certain travel time. Correspondingly, on the subsequent path segments they occupy space later. Therefore, for a redirection group rg^p_{od}, it is reasonable to check the remaining capacity of a segment of path p in the period where this segment would actually be occupied by rg^p_{od}. At this point, it can be checked whether the current path p possesses sufficient remaining capacity for the size of rg^p_{od} and if the additional passenger demand can consequently be accommodated (Step H20). If it does, in Step H22a, the passengers in rg^p_{od} are redirected onto path p, whereas the passengers in wg^p_{od} are informed to stay on $0 \in P_{od}$. The path to which rg^p_{od} is redirected is referred to as the assigned path $\tilde{p} \in P_{od}$. To consider these groups in the next steps, the remaining capacities of the paths are updated accordingly in the PT network graph (Figure 4.3).

If Step H20 is answered with "NO", it is checked if there are still paths $p \in P_{od}$ left in Step H21. If there are, the process returns to Step H16 and picks the next path $p \in P_{od}$ and repeats Steps H17 to H20. If not, rg^p_{od} and wg^p_{od} are assigned to $0 \in P_{od}$ in Step H22b and it is checked in Step H23 if all $od \in OD_a$ have been processed. If not, the process goes back to Step H15, takes the next $od \in OD_a$ and repeats Steps H16 to H23. This step-by-step assignment of passenger groups is comparable to the greedy approach presented by MÜLLER-HANNEMANN et al. [2019], however, it works with a random order of passenger groups. If the question in Step H23 can be answered with "YES", the heuristic approach of the passenger redirection process reaches its end and leads to the next process of REPACK, which is the capacity reallocation process. However, before explaining this process, the optimisation approach of the passenger redirection is described in the following section.

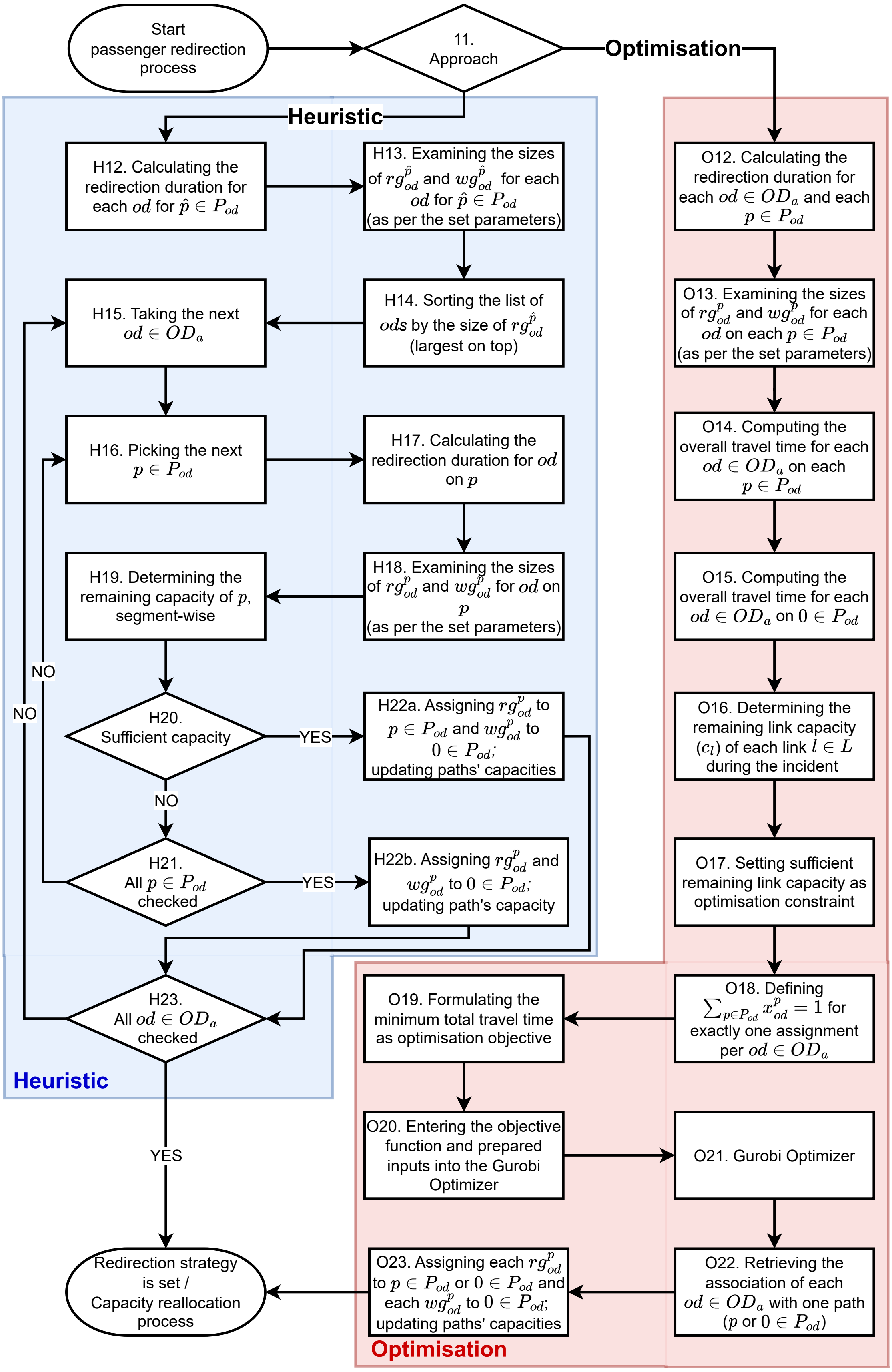


Figure 4.5: Passenger redirection process

4.5.2 Optimisation Approach

In addition to the previously explained heuristic approach, the passenger redirection is also formulated as an optimisation problem. Instead of handling $OD_a \subset OD$ in a specific order (largest to smallest $rg_{od}^{\hat{p}}$) as the heuristic approach does, the goal of the optimisation approach is to find the ideal match between the available paths $p \in P_{od}$ and the $od \in OD_a$ to be redirected to minimise the overall delay of all $u \in U_a$ (Equation 4.1). To do so, in Step 12 of the optimisation approach, T_{od}^p (Equation 4.2) is calculated for each OD pair $od \in OD_a$ and each path $p \in P_{od}$. Based on this, the sizes of rg_{od}^p and wg_{od}^p can be examined for each OD pair $od \in OD_a$ and each path $p \in P_{od}$ in Step O13, as per the set parameters (i.e. η, ζ, ξ, ψ), by checking whether passengers arrive at their respective origin of redirection, before T_{od}^p is elapsed (Equation 4.3). Note that for this step, the self-redirected group sg_{od} is subtracted from all PT users associated with $od \in OD_a$ ($u \in U_{od}$), before the remaining passengers of $U_{od} \subset U$ are added to the redirection or waiting group (rg_{od}^p and wg_{od}^p).

At this point of the optimisation approach, the number of passengers in rg_{od}^p and wg_{od}^p is known for each OD pair $od \in OD_a$ and each path $p \in P_{od}$. Thereby, the corresponding total travel time TT_{od}^p for each OD pair $od \in OD_a$ on each path $p \in P_{od}$ can be computed in Step O14 (Equation 4.4). Note that this is also done for the respective original paths $0 \in P_{od}$ to include the cases in which no alternative path could be found (Step O15).

$$TT_{od}^p = |rg_{od}^p| \cdot tt_p + \left(|wg_{od}^p| \cdot tt_0^{od} + \sum_{u \in wg_{od}^p} t_u^i \right) \tag{4.4}$$

Where:

TT_{od}^p = total travel time of OD pair od, if assigned to path p,
tt_p = travel time needed for path p,
tt_0^{od} = travel time needed for the original path 0 of OD pair od,
t_u^i = waiting time of PT user $u \in U_{od}$ until the end of the incident (t_i^e).

The total travel time of OD pair od on path p (TT_{od}^p) expresses the incurred loss of time of an OD pair $od \in OD_a$ if it is assigned to a specific path $p \in P_{od}$. Thus, the overall incurred loss of time can be calculated for a specific solution to the passenger redirection problem which is used by a optimisation solver to find the ideal match between available paths and all rg_{od}^p.

As already emphasised in the explanation of the heuristic approach, the consideration of the remaining capacity on the alternative paths is a crucial point in the PCIM method presented to avoid secondary incidents through overcrowding effects. Therefore, in Step O16, the remaining capacity c_l of each link $l \in L$ is determined by checking the remaining capacity of each PT vehicle crossing a link l in a specific period. Here, the period of the incident from t_i^s to t_i^e is used. Moreover, staying within the available remaining capacity is set as an optimisation constraint in Step O17 (Equation 4.7).

The path-link matrix is represented by $M \in 0, 1^{P_{od} x L}$, in which the element m_{pl} is 1 for every link $l \in L$ that is part of path p ($l \in L_p$). Like the heuristic approach, the optimisation approach thereby also considers all indirectly affected PT users $U_{ida} \subset U$ who are assigned to their respective path and thereby occupying parts of the PT network's capacity. The constraint (Equation 4.6) ensures that each redirection group rg_{od}^p is solely assigned to one specific path

$p \in P_{od}$ through x^p_{od} (Step O18). Equation 4.5 shows the mathematical formulation of the optimisation problem to which the objective of minimising the overall delay of all affected passengers is set in Step O19.

$$\min_{x^p_{od}} \sum_{od \in OD_a} \sum_{p \in P_{od}} x^p_{od} \cdot \Delta tt^p_{od} \tag{4.5}$$

subject to:

$$\sum_{od \in OD_a} \sum_{p \in P_{od}} x^p_{od} \cdot |rg^p_{od}| \cdot m_{pl} \leq c_l \qquad \forall \quad l \in L \tag{4.6}$$

$$\sum_{p \in P_{od}} x^p_{od} = 1 \qquad \forall \quad od \in OD_a \tag{4.7}$$

Where:

m_{pl}	= binary element of $M \in 0, 1^{P_{od}xL}$ which is 1 if link $l \in L_p$,
$M \in 0, 1^{P_{od}xL}$	= path-link matrix,
c_l	= remaining link capacity of $l \in L$,
x^p_{od}	= binary decision variable which is 1 if od is assigned to p.

In Step O20, the optimisation function (Equation 4.5) as well as the prepared inputs are then entered in the Gurobi Optimizer. This is a solver of mathematical optimisation problems such as the one presented here. For further information about Gurobi, it is referred to Gurobi Optimization LLC [2022]. This optimiser solves the optimisation problem formulated in Equation 4.5 and hence, finds the ideal match between each OD pair $od \in OD_a$ and a specific path $p \in P_{od}$ so its objective of minimising the overall travel time of $OD_a \subset OD$ is fulfilled (Step O21). In Step O22, this association of each OD pair $od \in OD_a$ with a path $p \in P_{od}$ is retrieved and can afterwards be used in Step O23 to assign all rg^p_{od} and wg^p_{od} accordingly. At this step, the optimisation approach is at its end and also leads to the capacity reallocation process, as the heuristic approach does.

4.6 Capacity Reallocation

As pointed out in Section 2.2.1, it is becoming increasingly difficult for operators to find enough drivers operating the vehicles to conduct the PT service as planned [Bachmann, Briem et al., 2022]. Hence, chances that operators can afford to keep standby vehicles and drivers available are very low, if existent at all. Therefore, if additional capacity is needed, it is often taken from other lines which are less in demand. Keeping this in mind, the introduced process examines if buses can be withdrawn from some of the PT lines with lower demand to be reallocated to the PT lines which are needed to support the passenger redirection. In the following, the first type of PT lines is called support PT lines ($PL_{sup} \subset PL$), and the latter type is called insufficient PT lines ($PL_{ins} \subset PL$). Both types are subsets of all PT lines PL. In the previously described process of the passenger redirection, an OD pair $od \in OD_a$ could not be assigned to its fastest alternative path $\hat{p} \in P_{od}$ if this path did not possess sufficient remaining capacity to accommodate its corresponding redirection group rg^p_{od}. It is therefore the aim of this process to reallocate dispensable buses to the insufficient lines which are required to assign an OD pair $od \in OD_a$ to a faster alternative path ($tt_p < tt^{od}_{\tilde{p}}$), to improve the redirection strategy for the corresponding OD pair od if possible. If it is, the delays of the corresponding OD pair and thus the total delay of the affected passengers can be further reduced compared to the redirection strategy which has been found during the passenger redirection process.

Figure 4.6 shows the step-by-step procedure of the capacity reallocation process. First, in Step 24, the buses are identified that are actually operating during the incident. Since rail-bound services, such as tram and metro trains, are very restricted regarding their routing possibilities due to the boundaries of railway infrastructure, only buses are considered. Buses operate on the denser street network; therefore, they are more flexible than rail-bound vehicles and it is more likely for them to be able to support another line. When a bus is withdrawn from its originally scheduled line, it causes additional delays on that line. In order to keep these delays low and avoid that the reallocation of capacities causes more delays than it reduces, it is checked for each considered bus if the following bus can accommodate the additional demand on the original line of the considered bus (Step 25). In this case, the corresponding travellers would additionally wait for the period of the corresponding line's headway, at most. Therefore, the support lines from which the buses are withdrawn should ideally have a relatively small headway, depending on the PT system and situation.

In Step 26, based on the number of buses that can be withdrawn from the support lines ($PL_{sup} \subset PL$), the dispensable capacity is computed. Especially during the peak demand of a day, it is possible that no bus can be spared because all buses B are needed at their original assignment. Hence, in Step 27 it is checked if dispensable capacity is actually available. If not, the redirection strategy set in the passenger redirection process remains unchanged, the capacity reallocation process ends and the subsequent information dissemination process starts. If there are dispensable capacities, the process continues with Step 28.

In this step, the travel times between different line routes are retrieved. These can either be preprocessed based on historical data or, if the PT system is adequately equipped, real-time travel times can be used. Thereby, it can be determined in this step how long each available bus would need from the beginning of its originally scheduled line route to the beginning of any other line route they might be reallocated to. At this point in the procedure, it can be examined which of the affected OD pairs $od \in OD_a$ can be redirected onto a faster alternative path $p \in P_{od}$. This process is built heuristically, based on the same ideas as the heuristic redirection approach introduced in the previous section. Thereby, the list of affected OD pairs $OD_a \subset OD$ is sorted by the size of the redirection group $rg^{\hat{p}}_{od}$ in association with the fastest alternative path $\hat{p} \in P_{od}$. The idea is, the faster the path on which an affected OD pair $od \in OD_a$ is assigned to ($\tilde{p} \in P_{od}$), the longer the corresponding redirection duration T^p_{od}, the larger rg^p_{od}, and hence, the bigger the reduction of the overall delay (Step 29). In the next step, Step 30, it is then checked whether the currently investigated $od \in OD_a$ is already assigned to its corresponding fastest path or not ($\tilde{p} \in P_{od} = \hat{p} \in P_{od}$). If yes, the situation for this od cannot be improved and the next OD pair $od \in OD_a$ is taken. If not, in Step 30b one alternative path $p \in P_{od}$ after another is taken to check whether od can be redirected onto a faster alternative path than it is currently redirected onto, starting with the fastest path $\hat{p} \in P_{od}$.

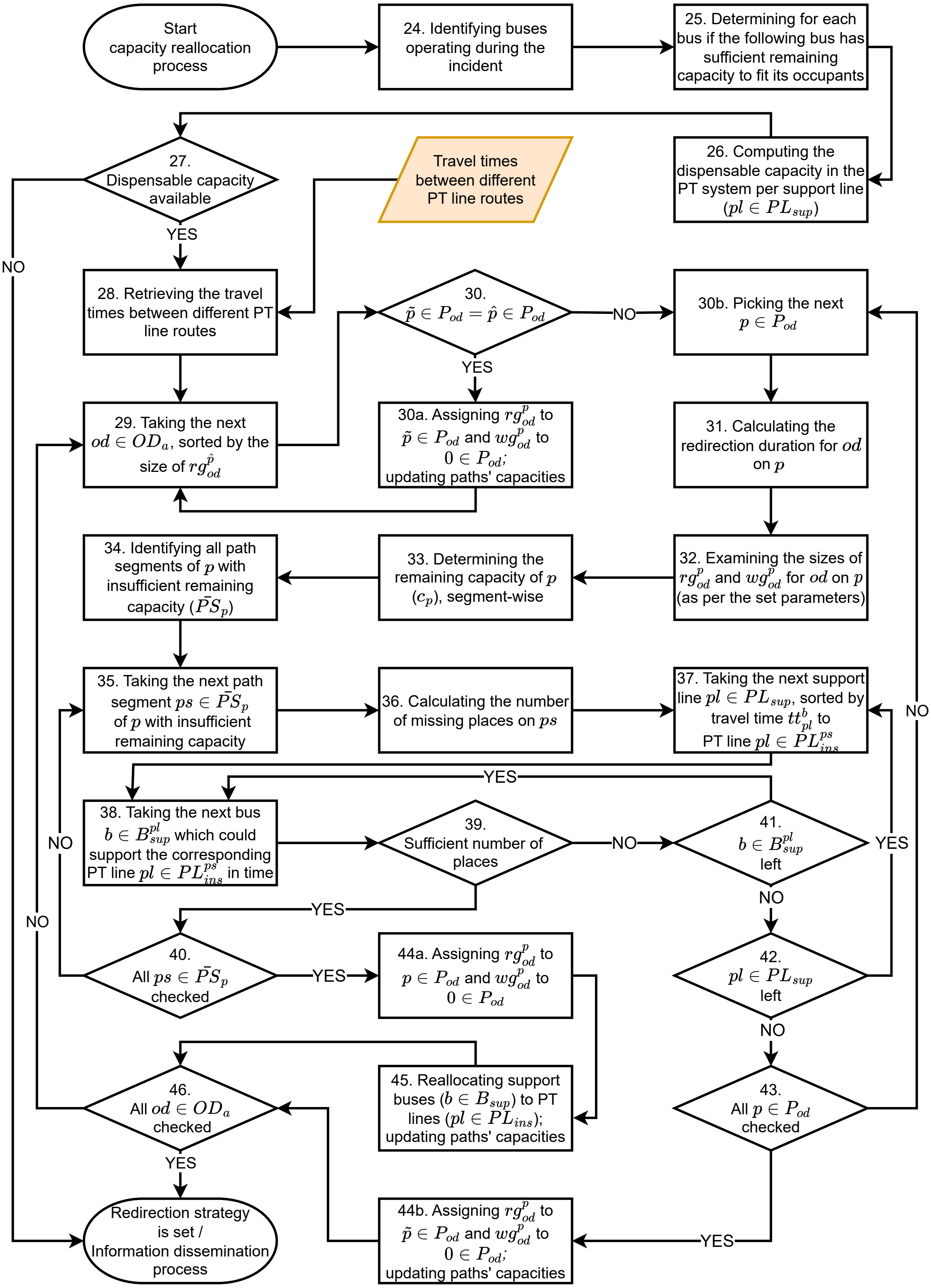


Figure 4.6: Capacity reallocation process

The following steps are the same as in the heuristic approach in Section 4.5.1. Therefore, in Step 31, the redirection duration is calculated for the currently investigated path $p \in P_{od}$ to afterwards examine the sizes of the corresponding redirection and waiting groups (rg^p_{od} and wg^p_{od}). Since the capacity reallocation process in the overall procedure (Figure 4.2) is performed after the redirection process, the self-redirected group sg_{od} of each OD pair od is already considered in this examination of group sizes.

In the following, the remaining capacity of path p (c_p) is determined (Step 33). As in the heuristic redirection process, this is done segment-wise. A path is divided into path segments ($ps \in PS_p$) in accordance with the PT lines which are serving path p, PS_p being the set of all path segments of path p. In this way, the remaining capacity of each segment of p can be determined for the period for which rg^p_{od} would actually occupy a certain path segment $ps \in PS_p$. In case the OD pair od has not been redirected onto path p during the passenger redirection approach, path p has not sufficient remaining capacity. In Step 34, it then can be identified which path segments provide insufficient remaining capacity ($ps \in \bar{PS}_p$), $\bar{PS}$ being the set of path segments with insufficient capacity, and hence which PT lines would need additional buses so that redirection group rg^p_{od} of OD pair od can be redirected onto path $p \in P_{od}$.

By reallocating buses, the number of free places of certain insufficient path segments $ps \in \bar{PS}_p$ and thus their remaining capacity can be increased. Furthermore, it can be determined from when to when a path segment would be occupied by the passengers of rg^p_{od}. Each rg^p_{od} has a certain travel period during which the group is travelling along its path p through the PT network, starting with the departure of its earliest member and ending with the arrival of its latest member. This travel period can be divided in correspondence to the path segments. Then, starting at Step 35, each insufficient path segment $ps \in \bar{PS}_p$ is investigated regarding the travel period of rg^p_{od} on this particular ps as well as its number of missing free places to fit rg^p_{od}. This number of places is calculated in Step 36. The next PT line is then taken from the set of support lines $PL_{sup} \subset PL$ to which previously identified potential supporting buses (Step 25) are associated with. The set of support lines $PL_{sup} \subset PL$ is sorted by the travel time a bus $b \in B$ takes to get from the start of its original line route at the support line to the start of the line route of the insufficient PT line of $ps \in \bar{PS}_p$ (tt^b_{pl}). In this way, the process first checks the buses which are fastest at the insufficient line $pl \in PL^{ps}_{ins}$, PL^{ps}_{ins} being the set of PT lines with insufficient capacity, associated with path segment ps. The faster the buses $b \in B_{sup}$ are reallocated, the more buses can support the insufficient line during the incident.

Furthermore, PT drivers are legally obliged to observe driving times. Therefore, the drivers' duty roster is planned accordingly and it is reasonable that through the capacity reallocation the drivers do not exceed their driving times. This also shows how complex the process of capacity reallocation can get. Here, legally prescribed driving times and duty rosters are not considered. Then, in Step 38, the next bus of the currently examined supporting PT line $b \in B_{sup}$ is checked to see whether it would arrive at the path segment $ps \in \bar{PS}_p$ in time or not. Here, "in time" means that bus b would arrive at the corresponding start of the insufficient line's route early enough to arrive at the start of the corresponding path segment $ps \in \bar{PS}_p$ within the period in which this segment would actually be occupied by the redirection group rg^p_{od} of the currently investigated OD pair od. Equation 4.8 expresses the period in which a bus needs to arrive at the corresponding path segment $ps \in \bar{PS}_p$ of path $p \in P_{od}$ to be considered as a supporting bus.

$$t^p_{s,ps} <= t^b_{dep} + tt^b_{pl} + tt^b_{ps} < t^p_{e,ps} \tag{4.8}$$

Where:

$t^p_{s,ps}$ = start time of passenger redirection at path segment $ps \in \bar{PS}_p$ of path $p \in P_{od}$,
$t^p_{e,ps}$ = end time of passenger redirection at path segment $ps \in \bar{PS}_p$ of path $p \in P_{od}$,
t^b_{dep} = original departure time of bus $b \in B_{sup}$ at $PL_{sup} \subset PL$,
tt^b_{pl} = travel time of bus $b \in B$ from its original line route to the route of line $pl \in PL^{ps}_{ins}$,
tt^b_{ps} = travel time of bus $b \in B$ on line $pl \in PL^{ps}_{ins}$ to the start of path segment $ps \in \bar{PS}_p$.

In Step 39, it is then checked if the number of missing places, calculated in Step 36 can already be compensated by the supporting buses $b \in B_{sup}$ found so far. If yes, it is checked whether all insufficient path segments $ps \in \bar{PS}_p$ have been checked. If not, the next segment $ps \in \bar{PS}_p$ is taken in Step 35 and the previously described steps are repeated. If all insufficient path segments $ps \in \bar{PS}_p$ have been checked in Step 44a, the redirection group rg^p_{od} is assigned to the corresponding path $p \in P_{od}$, and the waiting group wg^p_{od} is assigned to the original path of the OD pair $0 \in P_{od}$. Afterwards, the found support buses $b \in B_{sup}$ are reallocated to the corresponding insufficient PT lines to ensure that path p has sufficient remaining capacity to fit the redirection group rg^p_{od} (Step 45). Additionally, the corresponding paths' capacities are updated in the network graph G.

As the last step in this capacity reallocation process, it is ensured that all affected OD pairs $od \in OD_a$ have been checked (Step 46). If not, the next OD pair od is examined starting at Step 29; if so, the process ends and the following information dissemination process begins.

If in Step 39 the number of additional places is insufficient, the process continues from there further to Step 41, determining the availability of additional supporting buses at the currently examined support line $PL_{sup} \subset PL$. If it does, it goes to Step 38 and verifies the sufficiency of the added places through the found supporting buses $b \in B^{pl}_{sup}$. If there is still not enough room, the process examines if there is a support line $pl \in PL_{sup}$ left for the insufficient path segment $ps \in \bar{PS}_p$ (Step 42). If there is at least one line available, the process takes the next support line in Step 37 and continues accordingly. If not, the process determines whether there are alternative paths $p \in P_{od}$ left in Step 43. Note that Step 43 is only executed until the process reaches the path to which the OD pair od has been assigned during the redirection process ($\tilde{p} \in P_{od}$). Otherwise the corresponding rg^p_{od} stays on the assigned path $\tilde{p} \in P_{od}$ because all remaining paths $p \in P_{od}$ have a longer travel time, as the set of paths is sorted by travel time. Taking a path p listed below the assigned path $\tilde{p} \in P_{od}$ would thereby worsen the situation for the passengers of OD pair od. If there is a corresponding path $p \in P_{od}$ left, the process investigates the next path p, starting from Step 30b. If not, the redirection group rg^p_{od} is again assigned to $\tilde{p} \in P_{od}$ and the waiting group wg^p_{od} to the original path $0 \in P_{od}$. This can be the same path, in the case that no faster alternative path with sufficient remaining capacity has been found (Step 44b).

Again, in Step 46, it is ensured that all affected OD pair $od \in OD_a$ have been checked, if not, the next OD pair od is taken and the process continuos at Step 29; if so, the capacity reallocation process ends and the next process about the dissemination of information is started. A new redirection strategy is set.

4.7 Information Dissemination

The last process of the REPACK algorithm is about the dissemination of the computed redirection strategy. This includes the PI as well as the information which is needed by the PT staff.

Therefore, in Step 47, it is checked whether capacity has been reallocated in the previous process. If so, the corresponding drivers of the supporting buses ($b \in B_{sup}$) are informed about their altered assignment (Step 48). In case no support bus $b \in B_{sup}$ could be found, this step is consequently skipped.

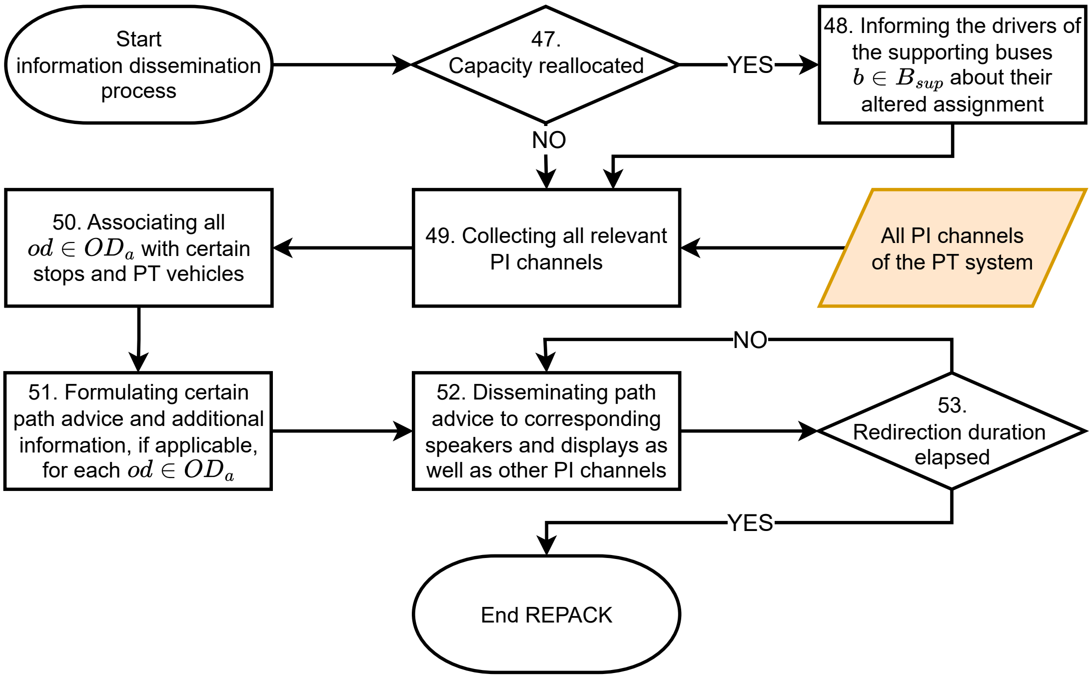


Figure 4.7: Information dissemination process

The following steps are about informing the affected passengers in accordance with the set redirection strategy. To do so, the relevant information channels need to be collected from all available PI channels the PT system has (Step 49). Especially for collective information channels such as speakers and dynamic PI displays at stops and in PT vehicles it is necessary to identify the relevant ones. Afterwards, each affected OD pair $od \in OD_a$ needs to be associated with a certain set of PI channels. To avoid confusion each OD pair od should receive the same path advice across all channels. Furthermore, it is not appropriate but rather confusing if path advice is disseminated at stops the corresponding rg^p_{od} are not passing and in vehicles which they are not riding. As different OD pairs od have different origins of redirection and some of them also use different PT lines along their distinct assigned paths $\tilde{p} \in P_{od}$, each OD pair $od \in OD_a$ needs to be associated with certain stops and vehicles its members are using to ensure that the corresponding speakers and PI displays disseminate right path advice (Step 50).

In Step 51 path advice and, if applicable, additional information (e.g. kind of incident, special comments regarding the redirection) is formulated for each OD pair $od \in OD_a$, which is then disseminated in Step 52 across all previously collected and associated PI channels. For PI channels such as PT trip planners on operators' websites and PT smartphone apps the given path advice can be picked in accordance with the entered origin and destination of the PT users.

Then, in Step 53, it is checked whether the corresponding redirection duration T^{p}_{od}, calculated during the passenger redirection and capacity reallocation process, elapsed. If not, the information dissemination continues, otherwise, REPACK ends. At this point it is more convenient for all passengers of each OD pair $od \in OD_a$ to wait for the dissolution of the incident which ideally does not take much longer. Then the PT service returns to its scheduled operation and all passengers can take their usual paths from their respective origin to their respective destination.

Chapter 5

Case Studies and Model Evaluation

In the following, a simulation study is presented, showing the results of various scenarios and cases in which the previously introduced model REPACK is tested in PT systems. This study assesses the effectiveness of REPACK in terms of reducing passenger delays in incident situations.

5.1 Model Implementation

Among the publicly available tools the open-source software SUMO has been preferred to others for several reasons: SUMO is a microscopic traffic simulator that is under continuous development at the German Aerospace Center [Translated from German: Deutsches Zentrum für Luft- und Raumfahrt] (DLR) [Lopez et al., 2018; DLR, 2022]. Before finally the decision has been made on SUMO, several other simulation environments were considered. At first, the commercial software PTV Visum by PTV Planning Transportation Traffic [Translated from German: Planen Transport und Verkehr GmbH] (PTV) was considered, a macroscopic traffic simulator which has been rejected here as it does not offer the level of detail needed to deal with the processes of REPACK. Through the literature described in Section 2.2.2, the attention turned to the publicly available mesoscopic simulation tool BusMezzo that is under development at the Smart Public Transport Lab at the Delft University of Technology [Cats, 2022]. This tool's functions are very suitable for the processes of REPACK and it has already been used for investigations on incident management and PI in PT systems [Cats, Larijani, Koutsopoulos et al., 2011; Cats, Koutsopoulos et al., 2011]. Unfortunately, the available documentation is limited [Cats, 2022]. The publicly available simulation software SUMO is well documented and provides helpful functions, such as feeding passenger routes as input to a simulation run, which is an important characteristic to simulate certain reactions of passengers to given path advice [DLR, 2022]. In addition, it comes along with helpful Python scripts to process simulation outputs and prepare simulation inputs. Therefore, the decision was made to use SUMO as a simulation environment.

The REPACK algorithm itself has been implemented in the object-oriented programming language Python which is employed by a large user community and provides for a variety of helpful packages [Python Software Foundation, 2022]. Several Python scripts have been written to implement REPACK as described in Chapter 4.

Figure 5.1 shows the step-by-step procedure of each simulation study conducted. In Step 1, a scenario without any incident is simulated to synthetically generate the "historical" travel data.

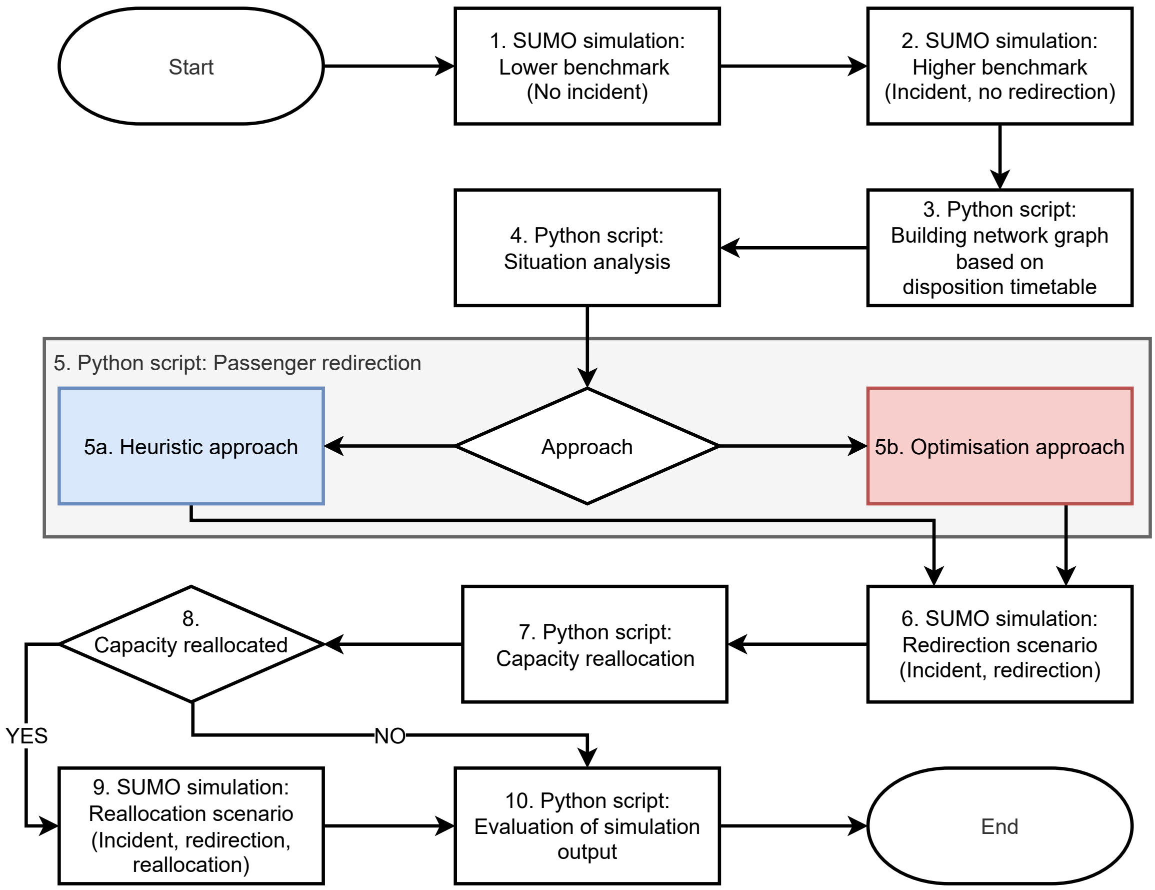


Figure 5.1: Simulation study procedure

The simulation output contains, among other things, the taken paths and associated travel times of the passengers, as well as the travel times and occupancies of the PT vehicles. The results of this scenario show the travel times under normal undisturbed conditions. Therefore, this serves as the lower benchmark scenario and is used to calculate passenger delays in the scenarios with an incident. The closer the results of REPACK are to the lower benchmark scenario, the better (Equation 4.1).

In Step 2, a scenario with an incident is conducted, however, without executing REPACK. Nevertheless, *supply-centric* disposition measures (e.g. PT line-splitting, PT line-rerouting), as described in Section 2.2.1, are performed. This serves as higher benchmark scenario. Therefore, for every scenario in which an incident occurs, a disposition timetable is defined which reflects the condition of the PT service as it is provided during the incident. This timetable includes the reduction of the service quality due to the incident as well as the changes to the service through the considered disposition measures.

Based on this timetable, a network graph, as explained in Section 4.3, is built. It is implemented using the Python package NetworkX [Hagberg et al., 2022]. This graph is used to conduct path searches and to check the available remaining capacities of paths identified (Step 3).

Step 4 refers to the first process of REPACK, "Situation Analysis" (Section 4.4). As its name indicates, this process analyses the present incident situation. The necessary incident information, such as its duration and location as well as disrupted PT services, is assumed. As mentioned in Section 4.4, in real use cases, this kind of information can be provided by the dispatchers in OCCs or even directly through an ITCS [Bachmann, Briem et al., 2022]. In this process, the affected passengers are identified and associated with OD pairs in accordance with their origin of redirection and destination. Furthermore, a set of available paths in the PT network is assigned to each of these OD pairs. Another output of this process is the assignment of the passengers who redirect themselves, meaning finding and taking an alternative path on their own. It is assumed that these passengers take the fastest path, as this path characteristic has been stated as the most important one by the participants of the PT user survey presented in Chapter 3 (Figure B.10).

The next process, "Passenger Redirection" (Section 4.5) finds suitable alternative paths for each OD pair. Since two approaches have been developed to solve the passenger redirection problem - heuristic and optimised redirection - the process branches out in Step 5 depending on the decision of which approach to use in a specific case study. The decision which approach is taken is done manually, nevertheless, the results presented below also indicate in which case, which approach should be preferred. As a result of this process each of the previously identified affected OD pairs $od \in OD_a$ is assigned to a specific alternative path $\tilde{p} \in P_{od}$ for the period of the redirection duration T^p_{od} or is assigned to the respective original path $0 \in P_{od}$ if no alternative path holding sufficient remaining capacity can be found (Section 4.5).

To be able to evaluate the results of the passenger redirection process, in Step 6, a simulation run is performed in which the incident occurs, the *supply-centric* disposition measures are taken, and the passengers are redirected in accordance with the outcome of the passenger redirection process. This is followed by the process "Capacity Reallocation" (Step 7). In this step, the process described in Section 4.6 checks whether dispensable capacities are available in the network and if their reallocation can support the passenger redirection. Its outcome is the reallocation of the corresponding buses from their original PT line to a line with insufficient capacity at which they are needed to assist the passenger redirection. Since there is the possibility that no sufficient dispensable capacities are available or that none of the dispensable buses would reach the insufficient PT lines in time, it is checked in Step 8 if in Step 7 buses are reallocated. If not, the procedure continues directly with the last step to evaluate the simulation results. If buses are reallocated, a simulation run is conducted in which the incident occurs, the *supply-centric* disposition measures are taken and the passenger redirection, supported by the capacity reallocation, is done.

In SUMO, the reallocation of buses is realised through SUMO's API, called traffic contol interface (TraCI) [DLR, 2022]. Whenever one of the reallocated buses enters the network, TraCI is used to change the line, route, and stops of the corresponding bus in accordance with its reallocation.

As the last step, the results of all simulation runs of the case study are evaluated. By subtracting the individual travel times of each passenger in the lower benchmark scenario from each of the other scenarios (no redirection, heuristic or optimised passenger redirection, and capacity reallocation), the respective delays as well as other indicators can be calculated to evaluate the performance of REPACK and its components (Step 10).

To evaluate REPACK, the relative delay of passengers compared to the lower benchmark scenario without an incident is used as key performance indicator. In addition, the total delay, the delay distribution, and the delay per time interval are used as indicators, to better understand the characteristics of the delay. The delay of a passenger includes the different parts of travel time, in-vehicle, waiting, and walking time. As waiting time is the part which is perceived as most inconvenient (Section 2.1.2), it is also investigated. Lastly, crowding at stops and in-vehicles is a known side effect of incidents (Section 2.2.2). Therefore, it is examined if REPACK has an influence on the traveller crowding at stops and the occupancy of PT vehicles.

The process "Information Dissemination" (Section 4.7) is not part of the case study procedure described here, as it explains mainly steps that are relevant for the implementation of REPACK in practice, such as broadcasting path advice via the available PI channels (Section 2.1.5) and informing the corresponding PT drivers about the capacity reallocation. The implementation of REPACK into practice is further discussed in Section 6.3.

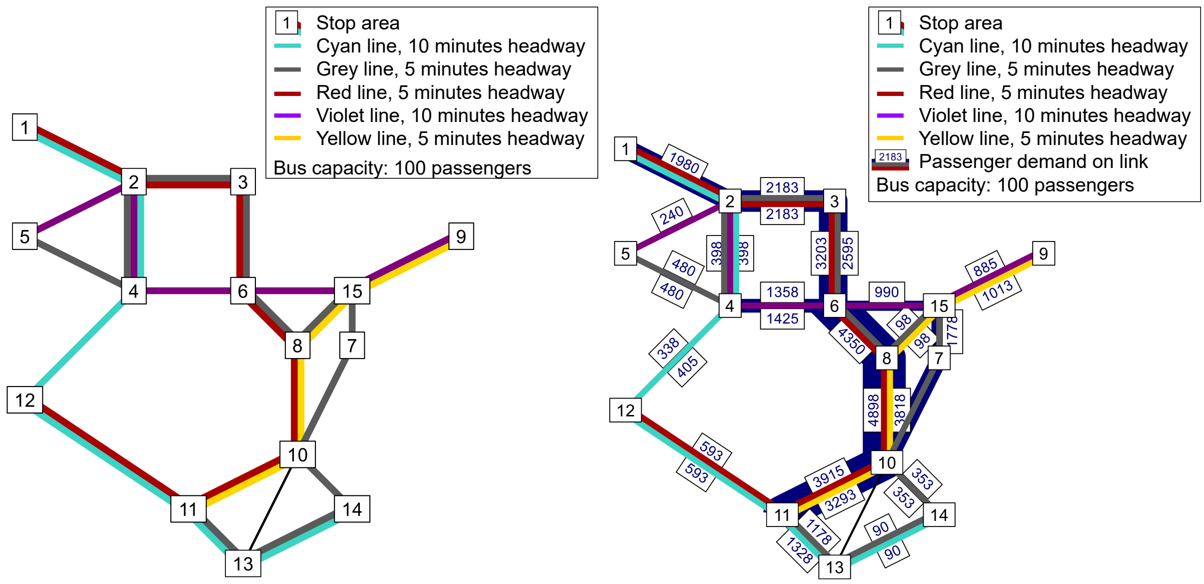
5.2 Implementation in the Mandl Network

As first environment to test the performance of REPACK, the Mandl network is used (Figure 5.2). It has been published by Mandl [1979] with link travel times and an OD demand matrix. The original network and demand matrix can be found in Annexe C. The network contains of 15 nodes and 21 links with link travel times from two to ten minutes. An important advantage of using such a benchmark network is the publicly available information on the travel times and demand, so future works in the field of PCIM can also use it and the results are comparable to the results of this work due to the same inputs. Due to the same reason it has been used by several investigations examining the PT network design and frequency setting problem, some of which are presented and compared by Ul Abedin et al. [2018]. Here, a PT network design by Ul Abedin [2019] is used as an environment for the following case studies.

Criteria for the choice of this PT network setup for the Mandl benchmark network have been that ideally all links of the network are covered by at least one PT line to have a relatively complex PT network for such a comparatively small road network. As REPACK relies on the availability of alternative paths in the network a minimum complexity is necessary to be able to demonstrate REPACK's functionality.

Furthermore, the link between Nodes 8 and 10 has been chosen as the incident location as it is centrally located in the network. As shown in Figure 5.2b, the centrality of the link caters for a relatively high number of affected passengers. Furthermore, it ensures the aforementioned availability of alternative paths, which would have not been given if the incident would occur between Nodes 1 and 2, for example. Since in the presented PT network design of the Mandl network, two lines are operating on this link and are therefore disrupted by the assumed incident, the consequences are correspondingly severe. These are features that are necessary to demonstrate the effectiveness of REPACK, since the more central the incident, the more PT users are affected and the more users can be potentially redirected.

Besides, the line route course, the timetable is an important input to represent the PT service in the simulation. For the sake of simplicity, the timetable has been modified from its



(a) Mandl PT network

(b) Mandl PT network with PT user demand

Figure 5.2: Mandl PT network [Ul Abedin, 2019]

original setting by Ul Abedin [2019]. First, all lines are served by buses with a capacity of 100 passengers. Second, there are only two headway settings, five minutes for the red, grey, and yellow lines and ten minutes for the cyan and violet lines.

Another important input is demand. There are different kinds of demand, namely: pedestrian, bicyclist, car, truck, and other motorized individual traffic demand, as well as PT user demand. Here, only PT user demand is considered. PT user demand is derived from the original OD matrix by Mandl [1979] (Annexe C). However, it has been modified to better suit the testing of REPACK. First, it is assumed that the whole demand, represented by the aforementioned matrix, is PT user demand as it also has been by the aforementioned investigations about PT network design [Ul Abedin et al., 2018]. Second, the OD relations which are affected by the assumed incident are increased to also increase the severity of the consequences of the assumed incident as more passengers are affected by it and need an alternative path. This has been done to ensure the visibility of REPACK's effect on the passenger delays. Which relations have been changed and to which extent is shown in Annexe C. Third, the overall demand has been increased to adjust it to the simplification of the service and the corresponding increased service frequency which also leads to an increased severity of the incident's disturbances and helps to investigate the effect of REPACK. Bachmann, Dandl et al. [2023] use double the original demand over a period of four hours. Their results show severe delays also for unaffected passengers who the authors explain through crowding at the bus stops. In order to avoid this effect or at least weaken it, here, the OD matrix is multiplied by 1.5 instead of 2.0. As in the aforementioned publication, the demand is spread over four hours. The OD matrix used here is shown in Table C.1 in Annexe C. Based on this matrix, the origins, destinations, and initial paths for the passenger demand are determined. For this, the dynamic user assignment tool "duarouter", which is part of SUMO, has been used [DLR, 2022]. This tool uses the Dijkstra algorithm (Section 2.1.2) to assign a particular path to each passenger, including specific PT lines to take by a certain passenger.

To consider the common line problem that describes situations in which more than one line could be used for a connection, here, the passengers' paths are checked for such situations and the list of available lines are complemented accordingly for each connection of each passenger [KURAUCHI et al., 2003]. In addition to the initial paths, this is also done during later steps in REPACK, when passengers are redirected onto alternative paths.

To minimise the possibility that the results of the case studies merely occur coincidentally, five different random seeds[1] are considered. These, for example, also cater for a variety of departure times for each passenger, which changes the simulation procedure for each seed. Moreover, they have also been used to create the initial path assignments for the lower benchmark scenario without an incident from the same OD matrix (Table C.1). These initial path assignments have been used for the lower as well as the higher benchmark scenarios. Ideally, the results of the cases in which REPACK is executed show lower overall passenger delays than the cases without. The closer the results are to the lower benchmark, the better.

Concerning the relative delays of affected passengers, the results show a maximum variance of 7.1%. With a margin of error of 2.5%, a confidence interval of at least 95%, depending on the considered case, can be achieved. Therefore, the number of seeds seems to be sufficient to ensure the legitimacy of the results [FGSV, 2006].

5.2.1 Scenarios and Cases

Incident Features and Disposition Measures

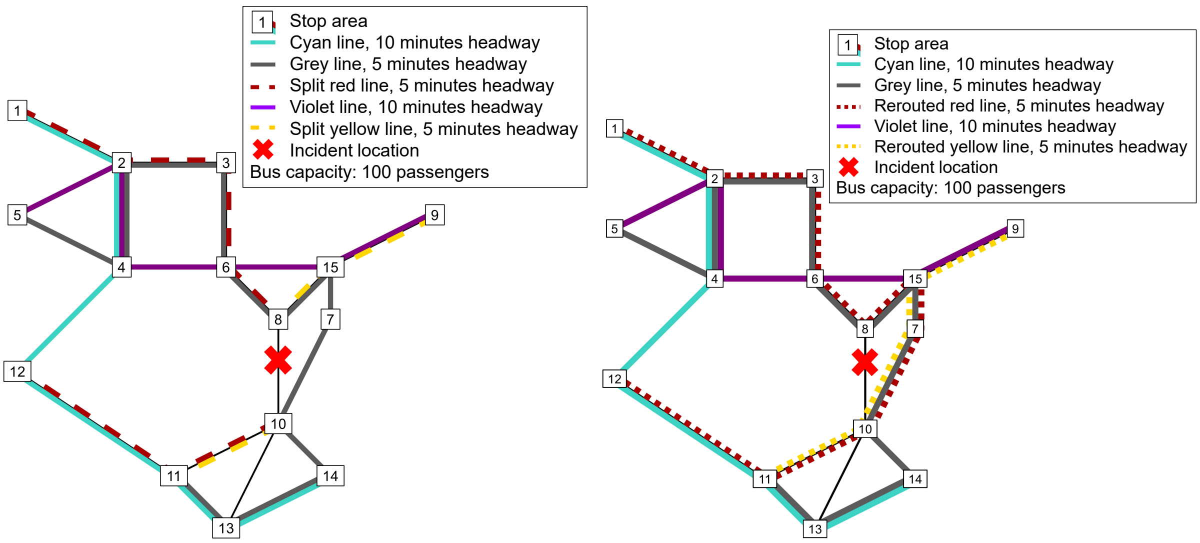
For all scenarios and cases in the Mandl network, the incident is located between Nodes 8 and 10. Furthermore, three different incident durations are tested, namely: 30, 60, and 90 minutes. For each incident duration and random seed, in addition to the lower benchmark scenario, two different scenarios with several different tested cases have been conducted. A scenario is defined by the disposition measure that is taken as a *supply-centric* response to the incident. This measure impacts the PT supply during the incident and shapes the disposition timetable.

In the first scenario, the applied measure is PT line-splitting (LS). It divides the disrupted line into two parts, one on each side of the incident's location. On both sides, the PT service is short-turned and the two line parts operate in loops on both sides of the incident. For the case study presented here, this means that the upper part of the red line operates between Nodes 1 and 8 and the lower part of it between Nodes 10 and 12. The upper part of the yellow line operates between Nodes 8 and 9, and the lower part between Nodes 10 and 11 (Figure 5.3a).

In the second scenario, the applied measure is PT line-rerouting (LR). In this scenario, the disrupted PT lines are rerouted via alternative routes (Section 2.2.1). For the cases conducted in Scenario LR, the red line is rerouted between Nodes 8 and 10 via Nodes 7 and 15, not

[1] Namely: 281218, 210619, 230619, 271019, and 120320

stopping at the latter two nodes. The yellow line is rerouted via Node 7, not stopping at this node. Furthermore, for the yellow line, the stop at Node 8 is cancelled during the period in which the rerouting is in progress (Figure 5.3b). The two scenarios represent the higher benchmark scenarios for the respective cases. The disposition measures are conducted for the whole period of the incident duration.



(a) Scenario LS

(b) Scenario LR

Figure 5.3: Mandl PT network with disposition measures

Parameters

Besides the scenario-specific disposition measures, the REPACK model described in Chapter 4 includes several parameters which need to be set. The parametrisation for the case study is shortly described in the following.

Self-redirection Rate ξ: The self-redirection rate ξ expresses the share of affected passengers who prefer to find an alternative path on their own instead of following given path advice. It is assumed that these people would choose the fastest alternative path irrespective of the PT system's state. In accordance with the survey results presented in Section 3.2.3, about 5% of the asked participants would rather redirect themselves than follow given path advice (Figure 3.9). As pointed out in Section 2.1.4, the reaction of passengers to incidents is influenced by a large variety of factors and therefore difficult to predict. Hence, it is reasonable to assume that this is also true for the passengers' willingness to follow given path advice. There are many factors that may influence the decision, be it the distance to the destination, car or bike ownership, weather, and many more. Therefore, to better understand the effect of people redirecting themselves on the performance of REPACK, a wider range of values for ξ have been tested: 0%, 10%, and 30%. Since 30% is already 25% more than the share of people who stated in the presented PT user survey that they would redirect themselves, higher values have not been considered.

Compliance Rate η and Information Rate ζ: The number of affected passengers of each affected OD pair $od \in OD_a$ is multiplied by the compliance rate η to calculate the number of people who would follow the path advice. Additionally, this number is multiplied by the information rate ζ, which is the share of passengers who receive the path advice. As shown in Section 3.2.3, most of the participants of the survey preferred to be informed via a collective PI channel (i.e. speaker announcement, dynamic PI displays) during incidents (Figure 3.7). Depending on how well equipped a PT system is in terms of the distribution of dynamic PI displays and speakers at stops and in PT vehicles, passengers may or may not receive path advice. Since the number of affected passengers of each OD pair $od \in OD_a$ is multiplied by both η and ζ, it is reasonable to set them as one parameter for the case studies to avoid redundancies. For example, the results would be the same for a case in which η is 50% and ζ is 70%, compared to a case in which η is 70% and ζ is 50%.

According to the results from the survey in Section 3.2.3, about one-quarter of the participants *will* follow given path advice, whereas about 60% *might* follow it. This implies a wide range of possible outcomes. As previously mentioned, it is likely that a lot of factors (e.g. weather, bike or car ownership, etc.) influence a passenger's reaction to an incident as well as the passenger's willingness to follow given path advice (Section 2.1.4). Therefore, it is difficult to predict how many people would actually follow path advice in a given incident situation. Furthermore, the reachability of passengers via collective PI channels can vary also depending on the location of the incident and of the passengers in the network. Whereas larger transfer hubs are often well-equipped with PI channels, this might not be the fact for small bus stops at the outskirts of a PT network. If no collective PI channels are available, the passengers rely on information via websites, social media, and PT smartphone apps. It is therefore reasonable to also test a wide range for the product of the compliance and information rates ($\eta \cdot \zeta$). Here, 0%, 35%, 70%, and 100% are tested. Furthermore, a special case is tested in which only a certain number of OD pairs is completely reachable and has thereby an information rate of 100%, whereas it is lower for the remaining OD pairs.

Once the number of passengers receiving the path advice and the number of those following it are calculated, a random sample of the corresponding size is taken of each OD pair $od \in OD_a$. As described in Section 4.5, it is then checked for these passengers whether they arrive at their respective origin of redirection on time before the redirection duration T^p_{od} elapsed or not (Equation 4.2). If they do, they are assigned to the redirection group rg^p_{od}, which is redirected onto the assigned alternative path $\tilde{p} \in P_{od}$. If not, they are assigned to the waiting group wg^p_{od} which stays on the original path $0 \in P_{od}$.

These are different cases compared to the test cases presented by Bachmann, Dandl et al. [2023], in which an information rate of 100% and compliance rates of 100%, 57%, and a logarithmic calculated compliance rate are considered. The 57% is the share for people who will follow given path advice, according to the results of a PT user trial by BMVI [2019]. The logarithmic compliance rate is introduced by van der Hurk et al. [2018] and takes the travel time difference between the assigned alternative path ($\tilde{p} \in P_{od}$) and the fastest alternative path ($\hat{p} \in P_{od}$) into account. If the travel time of the assigned path $\tilde{p} \in P_{od}$ is more than ten minutes longer than the travel time of the fastest alternative path $\hat{p} \in P_{od}$, the compliance rate drops rapidly. However, as pointed out in Section 2.1.4, various factors can influence the passengers' willingness to follow given path advice. Therefore, the mentioned difference in the paths' travel times is probably just one of several factors which also need to be considered in such an equation. Furthermore, WILKE [2023] points out that there are also influencing factors such as vouchers for free drinks and reduction in fare which could motivate people to follow a given connection suggestion. Consequently, a wide range of values for the compliance rate is tested here to cover a variety of different outcomes.

Factor ψ: In BACHMANN, DANDL et al. [2023], the last part of the equation to calculate the redirection duration T^p_{od} is a subtraction of five minutes. This is done to avoid missed buses leading to a disadvantage for redirected passengers. Five minutes has been chosen, as all lines of the case study conducted by BACHMANN, DANDL et al. [2023] have a headway of five minutes.

In more complex PT systems there is a variety of headways. Therefore, as explained in Section 4.5.1, the subtraction of a time constant in Equation 4.2 to calculate T^p_{od} is replaced by a product of two parameters. The first factor of the above product is the headway of the PT line that has the longest headway among the lines serving a given path p ($\breve{h}_p$), and the second factor, which is deterministically defined, is the factor ψ. This change caters for the consideration of different headways. As mentioned in Section 4.5, the product of factor ψ and $\breve{h}_p$, however, can also be used to extend the redirection duration in case of a recovery time, when a negative value is used for ψ. Through a rough screening of possible values for ψ, the following values have been chosen for testing: 1, 0, -1, -2, -3.

Most of the values are negative, leading to the redirection duration T^p_{od} being extended by the product of ψ and $\breve{h}_p$. However, the rough screening revealed that in some cases an extension of the redirection leads to better results concerning the average delays of all U and the affected passengers $U_a \subset U$. As explained, this indicates a recovery time.

The recovery time describes the period between the end of the incident and the point of time at which no more incident-related delays occur, for example, due to crowding at stops or in PT vehicles. Equation 4.2, however, only considers the incident duration, but not the recovery time, as it is very difficult to predict it, as pointed out by TSUCHIYA et al. [2006]. The authors suggest a linear function to predict the development of the recovery time, which is strongly related to timetable rescheduling in railway operations. In an urban PT system, many factors can influence the course of the recovery time: the demand, the occupancy of the PT services after the end of the incident, and traffic conditions, for example. Therefore, here, the adjustment towards the recovery time is done through $\psi \cdot \breve{h}_p$.

Minimum Redirection Duration Lastly, the minimum redirection duration is mentioned here. The minimum redirection duration is the threshold which needs to be met by the calculated redirection duration to trigger the passenger redirection for an affected OD pair $od \in OD_a$. If the calculated redirection duration is shorter than 5 minutes, the corresponding redirection group rg^p_{od} is not redirected. Shorter redirection durations would probably not be appropriate and would lead to confusion in practice, as PT users also need time to adapt to an incident situation.

5.2.2 Results of the Case Study in the Mandl Network

With two disposition measures – Scenarios LS and LR – three incident durations (t_i), three self-redirection rates (ξ), four values for the compliance and information rates product ($\eta \cdot \zeta$), and five values for factor ψ, in total, 360 study cases have been conducted. The relative delay of the affected passengers of all these cases is presented in Annexe C. In this section, some of these results are shown and discussed in detail.

To give a first brief insight into the results of the conducted case study, Tables 5.1 and 5.2 present the best outcome, in terms of lowest relative overall delay of the affected passengers in percent of each conducted case in Scenarios LS and LR with a self-redirection rate of $\xi = 0\%$. The lower the overall passenger delays are, the better. Moreover, of the four approaches used – heuristic redirection (HR), optimised redirection (OR), capacity reallocation in combination with heuristic redirection (CR+HR), and capacity reallocation in combination with optimised redirection (CR+OR) – the one that achieved the best outcome is named. If more than one approach achieved the best result, all of them are listed. The smallest relative delay for each incident duration t_i and ψ is presented in bold print. Further result tables are to be found in Annexe C.

ψ	t_i	$\eta \cdot \zeta$			
		0%	35%	70%	100%
1	30 minutes	HR, OR: 100.2	OR: 71.5	OR: 49.9	**CR+OR: 36.3**
	60 minutes	HR, OR: 100.0	OR: 63.3	HR: 34.7	**OR: 17.9**
	90 minutes	HR, OR: 100.1	OR: 61.1	OR: 30.8	**OR: 12.4**
0	30 minutes	HR, OR: 100.2	OR: 66.8	OR: 42.4	**CR+HR: 29.5**
	60 minutes	HR, OR: 100.0	HR, OR: 61.7	HR: 32.2	**OR: 15.3**
	90 minutes	HR, OR: 100.1	OR: 59.7	HR, OR: 29.1	**OR: 10.7**
-1	30 minutes	HR, OR: 100.2	OR: 64.9	HR: 39.0	**OR: 27.7**
	60 minutes	HR, OR: 100.0	OR: 59.8	HR: 30.8	**OR: 14.6**
	90 minutes	HR, OR: 100.1	HR, OR: 59.0	HR: 28.1	**OR: 10.1**
-2	30 minutes	HR, OR: 100.2	HR: 64.2	HR: 37.8	**OR: 28.6**
	60 minutes	HR, OR: 100.0	HR: 59.0	HR: 30.2	**OR: 14.4**
	90 minutes	HR, OR: 100.1	OR: 58.5	HR, OR: 27.8	**OR: 10.0**
-3	30 minutes	HR, OR: 100.2	HR: 63.7	HR: 37.1	**OR: 29.5**
	60 minutes	HR, OR: 100.0	OR: 58.2	HR: 29.9	**OR: 14.6**
	90 minutes	HR, OR: 100.1	OR: 58.1	HR: 27.5	**OR: 10.1**

Table 5.1: Lowest relative delays of each case for $U_a \subset U$ with $\xi = 0\%$ in Scenario LS
(HR: Heuristic Redirection; OR: Optimised Redirection;
CR+HR: Capacity Reallocation with Heuristic Redirection;
CR+OR: Capacity Reallocation with Optimised Redirection)

Generally, it can be observed that the longer an incident lasts, the more the delay is reduced through REPACK. This can be explained by the fact that the longer an incident lasts, the greater the delays. Since more passengers are affected by it, and because waiting for its dissolution takes correspondingly longer as well. Furthermore, it probably worsens the crowding at stops, which prolongs the recovery time after the dissolution of the incident.

The characteristics of ψ seem to be complex. It is a factor by which the headway of the PT line with the longest headway ($\breve{h}_p$), serving path p, is multiplied to subtract the product from the redirection duration (Equation 4.2). In this way the calculation of the redirection duration is adjusted to the service's longest headway of a path p and gives the opportunity to consider the recovery time (Section 5.2.1).

The best result of 10.0% among the outcomes of the cases with a self-redirection rate of 0% has been accomplished by the optimised redirection (OR) and a ψ of -2 for an incident duration $t_i = 90$ minutes. It should be noted that similar results of 10.1% are to be found for the same cases with values for $\psi = -1$ and -3, again, accomplished by Approach OR.

As mentioned before, the recovery time after the dissolution of an incident is very hard to estimate, as factors such as demand and capacity availability influence how quickly a PT system recovers from an incident. These two factors again depend on the time of day — if it's during on-peak hours, off-peak hours, or at the beginning or end of a peak — as well as on staff management in terms of availability of staff (Section 2.2).

As different PT lines operate with different headways, the longest headways on the found alternative paths also play a role. In this simulation study only two headways are considered: 5 minutes for the grey, red, and yellow lines and 10 minutes for the cyan and violet lines (Figure 5.2). In more complex, real-life PT systems, there are wider ranges of headways, which makes factor ψ a more important model element with a high influence on the redirection duration and outcome. Multiplying a deterministic value with the longest headway might therefore be too simple an approach, leaving room for further research.

In general, across all conducted cases, Scenario LR gives results with a less effective delay reduction (Table 5.2) compared to the results of Scenario LS. Here, the best result is a delay reduction of 39.5%, compared to the best result in Scenario LS of 90.0%. This is only accomplished with $\eta \cdot \zeta = 100\%$. With $\eta \cdot \zeta = 35\%$ the delay reduction ranges from 6.5% to 15.5% depending on the incident duration. An obvious explanation is that rerouted PT lines, which still serve most or even all of their stops mean a less severe disruption of the PT service than line-splitting. The delay is not dependent on the incident duration, but on the additional travel time through the altered route of the corresponding buses. This delay is significantly smaller than having to wait for the dissolution of an incident before being able to continue a trip on the planned PT line, as is the case for the passengers in Scenario LS. Therefore, the gap between the two levels of severity of the incident's disturbances of the two scenarios grows with the increase in the incident duration t_i.

The travel time on the red line, for example, increases by about 3.5 minutes. This is also an explanation for the insignificant effect of changing the value of ψ in this scenario. For most of the affected passengers staying on the rerouted line might still be the best alternative. This raises the question of the reasonableness of passenger redirection in such cases. However, as the results of some of the cases show, it still can lead to significant delay reductions under certain circumstances.

Interestingly, in Table 5.2 all of the results in the case of $\eta \cdot \zeta = 100\%$ are 100.0% compared to the no-redirection case. Again, this can be explained by the lower severity of Scenario LR

ψ	t_i	$\eta \cdot \zeta$			
		0%	35%	70%	100%
1	30 minutes	HR, OR: 100.0	HR: 93.5	OR: 86.9	**HR: 80.8**
	60 minutes	HR, OR: 100.0	OR: 89.3	HR: 78.4	**HR: 70.1**
	90 minutes	HR, OR: 100.0	HR: 85.5	HR: 71.4	**HR: 60.8**
0	30 minutes	HR, OR: 100.0	HR: 93.1	HR: 85.7	**CR+HR: 78.0**
	60 minutes	HR, OR: 100.0	OR: 89.1	OR: 78.0	**HR: 69.5**
	90 minutes	HR, OR: 100.0	HR: 84.5	OR: 71.6	**HR: 60.5**
-1	30 minutes	HR, OR: 100.0	HR: 93.4	HR: 86.1	**CR+HR: 77.9**
	60 minutes	HR, OR: 100.0	OR: 88.9	HR: 77.9	**HR: 69.4**
	90 minutes	HR, OR: 100.0	OR: 84.5	HR: 71.6	**HR: 60.5**
-2	30 minutes	HR, OR: 100.0	HR: 93.4	HR: 86.1	**CR+HR: 77.9**
	60 minutes	HR, OR: 100.0	OR: 88.9	HR: 77.9	**HR: 69.4**
	90 minutes	HR, OR: 100.0	OR: 84.5	HR: 71.6	**HR: 60.5**
-3	30 minutes	HR, OR: 100.0	HR: 93.4	HR: 86.1	**CR+HR: 77.9**
	60 minutes	HR, OR: 100.0	OR: 88.9	HR: 77.9	**HR: 69.4**
	90 minutes	HR, OR: 100.0	OR: 84.5	HR: 71.6	**HR: 60.5**

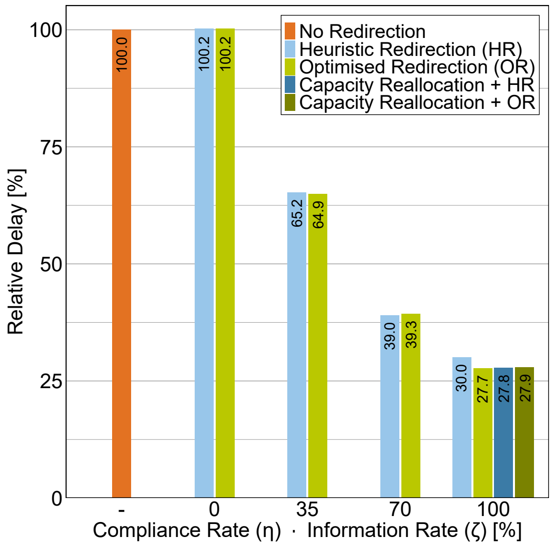
Table 5.2: Lowest relative delays of each case for $U_a \subset U$ with $\xi = 0\%$ in Scenario LR (HR: Heuristic Redirection; OR: Optimised Redirection; CR+HR: Capacity Reallocation with Heuristic Redirection; CR+OR: Capacity Reallocation with Optimised Redirection)

through which less travellers are queuing at the stops at Nodes 8 and 10, as the red and yellow lines still serve their stops. Due to this fact, there is less interaction among the travellers, generally less disturbances and thus less room for different outcomes in basically the same situation compared to the no-redirection case.

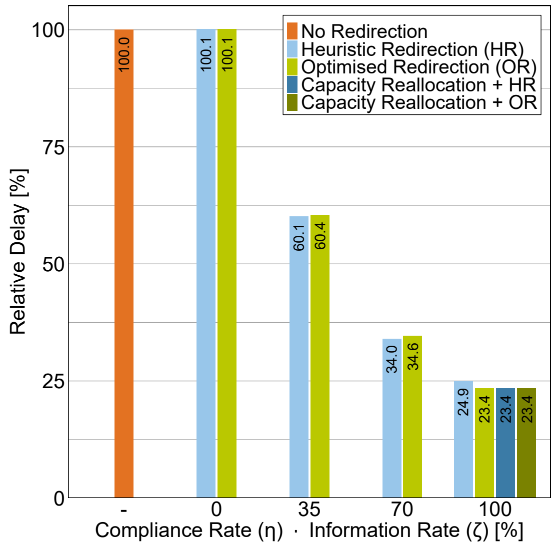
As can be derived from Tables 5.1 and 5.2, the more severe the disturbances of an incident on a PT system, the higher the likelihood for longer recovery times and thus the better the results with a negative value for factor ψ. Therefore, for further analysis and discussion on the effect of the different approaches and the impact on their performance by various products of compliance and information rates, self-redirection rates, and incident durations, in the following, for the more disruptive Scenario LS the results with $\psi = -1$ and for Scenario LR the results with $\psi = 0$ are used. In this way the calculation of the passenger redirection is slightly adjusted to the disruptiveness of a scenario and the likelihood for a perceptible recovery time.

Relative and Total Delay

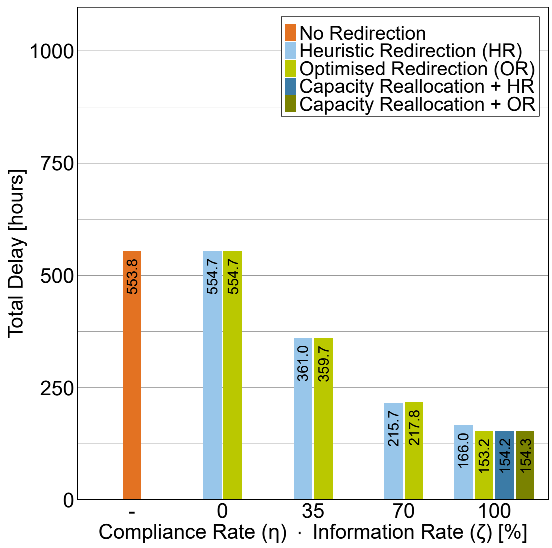
Figures 5.4a to 5.4d present the results of the simulation cases with an incident duration t_i of 30 minutes and a self-redirection rate ξ of 0% in Scenario LS. The upper two diagrams show the relative delay and the bottom the total delay, with the case of "No Redirection" as the higher benchmark case. The two diagrams on the left present the results for the affected PT users $U_a \subset U$ whereas those on the right side show the results for all PT users U.



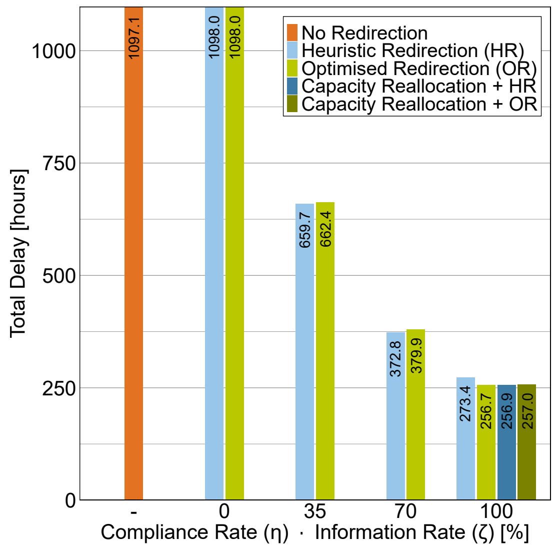
(a) Relative delay of $U_a \subset U$



(b) Relative delay of U



(c) Total delay of $U_a \subset U$



(d) Total delay of U

Figure 5.4: Overall relative and total delays of $U_a \subset U$ and U with $t_i = 30$ minutes and $\xi = 0\%$ in Scenario LS ($\psi = -1$)

In Figure 5.4a, which shows the relative delays of the affected passengers, it is immediately noticeable that the delay continuously falls with an increase in the compliance and information rates product ($\eta \cdot \zeta$). As the self-redirection rate ξ is 0%, here, the cases with a product of compliance and information rates of 0% show also a relative delay of about 100%, as no passengers have been redirected and the outcome of the simulation is, therefore, the same as in the case with no redirection. In addition, the approaches including the capacity reallocation are merely present in the case with $\eta \cdot \zeta = 100\%$. Reasons for this are described in the following.

Kindly note that the capacity reallocation has not been executed for some of the conducted cases and seeds. The capacity reallocation process is only done if the criteria for its execution have been met. These are the availability of dispensable capacity and that there is insufficient capacity on the fastest alternative path or alternative paths that are at least faster than the assigned one $\tilde{p} \in P_{od}$ (Section 4.6). The results of the approaches including capacity reallocation are therefore only considered in the evaluation process if the capacity reallocation process has been executed for all five random seeds of a case. Due to the different seeds, the travellers' departure times vary which can sometimes lead to the occupation of a vehicle that would be dispensable with the departure times caused by another seed, and the same applies to the need for capacity reallocation. Therefore, for the cases of $\eta \cdot \zeta < 100\%$, it might be the case that sufficient remaining capacity is available on the alternative paths.

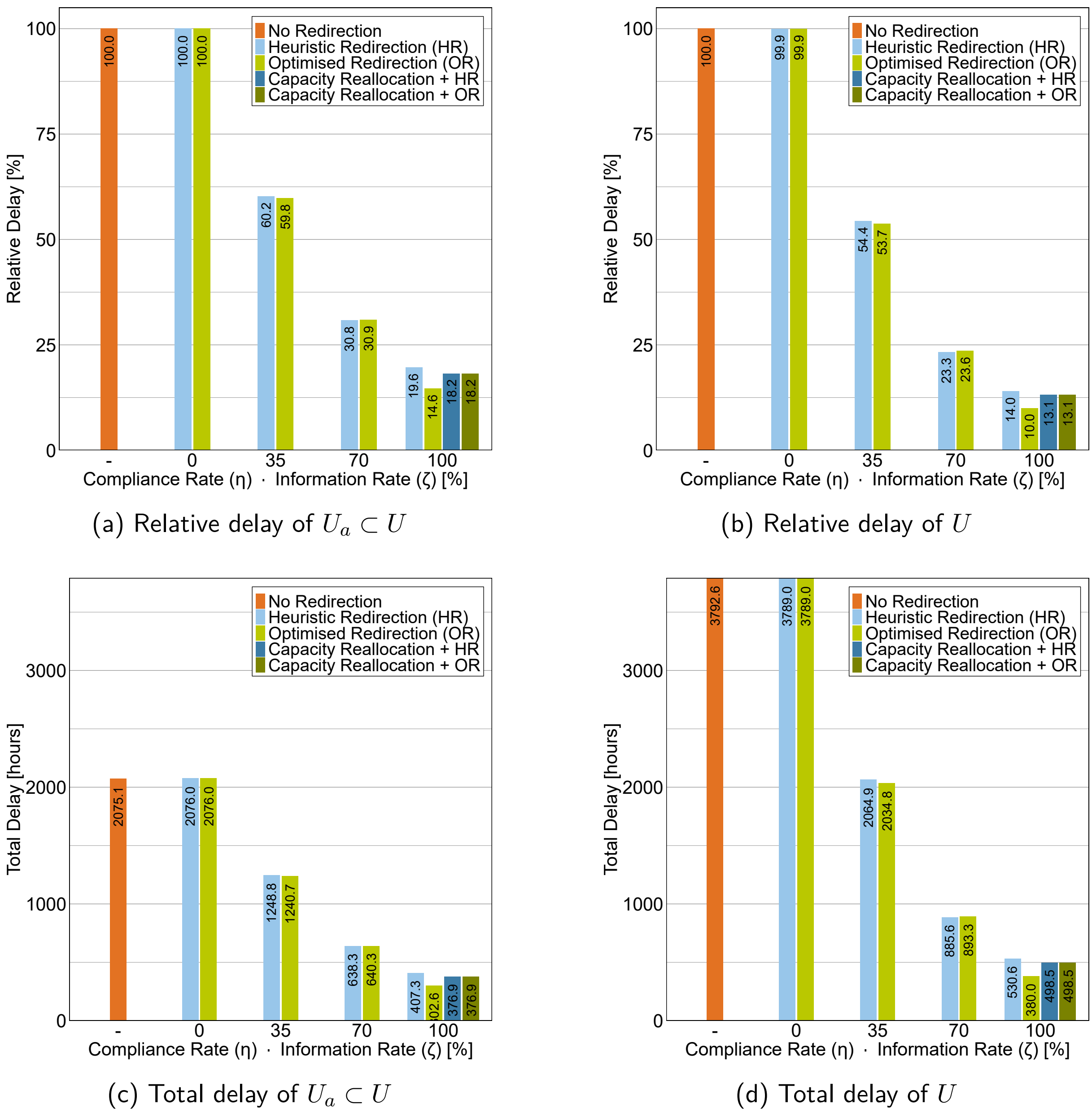
If this is the case, it might also be an answer to the question why the optimised redirection performs slightly worse than or equal to the heuristic besides the case with $\eta \cdot \zeta = 100\%$, in which it performs better than the heuristic. The validation of sufficient capacity on the alternative paths is done differently in the two approaches. Whereas in the optimised redirection approach, the capacity on all alternative paths is calculated for a fixed period which is equal to the incident duration, in the heuristic redirection approach, the remaining capacity is determined segment-wise (Section 4.5). The segment-wise determination of the capacity considers the travel time of a redirection group rg_{od}^{p} along an alternative path $p \in P_{od}$. It is therefore more precise in calculating the remaining capacity and might assign more redirection groups on faster paths, as long as there is sufficient remaining capacity on the respective fastest alternative paths. It can also lead to the assignment of fewer passengers to avoid overcrowding effects. This advantage of the heuristic over the optimised redirection seems to last until the fastest paths do not possess sufficient remaining capacity anymore, as seems to be the case with $\eta \cdot \zeta = 100\%$. Here, the optimised redirection performs better than the heuristic. An explanation for this is that the optimisation does not assign the redirection group of each affected OD pair $od \in OD_a$ step by step, going from the biggest to the smallest redirection group $rg_{od}^{\hat{p}}$, as is done in the heuristic, but all redirection groups are assigned in a way that the overall delay is minimised.

The two approaches including the capacity reallocation – CR+HR and CR+OR – perform similarly to the optimised redirection (OR). The fact that the capacity reallocation does not improve the outcome of the redirection approaches can be explained by the disadvantages which come along with it. Even though the relevant paths for passenger redirection are supported by extra capacity and additional runs, the reallocation of buses reduces the levels of service on the lines they have been withdrawn from. This quality reduction is due to the lower capacity as well as the longer headway. Furthermore, when capacities are reallocated, REPACK checks if the line from which the buses are withdrawn still possesses sufficient capacity for its demand. Additionally, it is validated that the reallocated bus arrives at the line with insufficient capacity in time, meaning before the corresponding redirection duration T_{od}^{p} elapses. However, it does not check how many passengers actually profit from a reallocated bus and it does not check the temporal offset to the regularly scheduled buses of the supported line. If a reallocated bus arrives shortly before or after a regularly scheduled bus at a stop of the line which is supported by it, there might be no passengers left at the stop to be picked up by the second vehicle. The capacity reallocation would be in vain in such a case and might even aggravate the situation as it reduces the service quality on the original line of a reallocated bus. At the same time it does not improve the service at the line with insufficient capacity which can also lead to more people being redirected than the corresponding alternative path can take as the additional capacity does not arrive at the alternative path when it is needed by the redirected passengers.

Considering all passengers (Figure 5.4b) the relative delays are smaller than the ones only taking affected passengers into account (Figure 5.4a). This is logical, as the number of the affected passengers of about 1,100 passengers, depending on the random seed value used (Section 5.2.1), is smaller than that of all 25,486 passengers. The delays of the affected passengers, however, are more severe. Other passengers who do not use the disrupted PT lines, but are affected by the crowding at the stops and in vehicles, are referred to as indirectly affected passengers ($U_{ida} \subset U$), whose delays also play a role in the consideration of the delay of all passengers (U). The relation between the outcomes of the relative delays is comparable between U and $U_a \subset U$. Looking at the total delays in Figures 5.4c and 5.4d, it becomes immediately evident that the delays of the indirectly affected passengers are not to be underestimated, with about half of the delays being associated with them. Besides, the indirectly affected passengers $U_{ida} \subset U$ who are affected through crowding, passengers who travel after the dissolution of the incident on the previously disrupted PT lines are especially likely to face delays as the system has not yet returned to its normal state, as affected passengers queue at stops. This raises the question of the definition of the affected passengers. So far it is limited to the passengers who would travel on the disrupted link during the incident. This definition might need to be redesigned, as it also needs to consider passengers of the same OD relations travelling after the dissolution of the incident on the previously disrupted links. Furthermore, it again stresses the necessity to investigate the recovery time of the PT system.

Figure 5.5 shows the outcome of the same cases but with an incident duration t_i of 60 minutes. The results show a comparable picture to that in the cases with $t_i = 30$ minutes. Nevertheless, two observations are easy to make. First, the overall relative delay is smaller than in the cases with a shorter incident duration. As a longer incident duration also causes an increase in the number of affected passengers, consequently the overall delay also rises, through which the effect of REPACK grows as well. Second, the capacity reallocation is again executed only in the case with a product of compliance and information rates of 100%. However, it performs noticeably worse than the optimised redirection, which reaches the best outcome in this example with an overall relative delay of 10.0% for all passengers U and 14.6% for the affected passengers $U_a \subset U$.

When dispensable buses are reallocated, the service quality on the PT line from which they have been withdrawn is reduced in terms of extending the service headway. This leads to longer waiting times at the first stop and transfer stops of travellers. Therefore, the capacity reallocation might be continuously more disruptive with an increasing incident duration. Moreover, it might be reasonable to limit the number of reallocated buses that have been withdrawn from the same line to limit the negative effects of capacity reallocation. Comparing the total number of delays of all and affected passengers, it can also be seen here that the delays of affected passengers – about 2,270 people – account for more than half of the delays of all passengers – 25,486 people. Hence, the relation between the affected $U_a \subset U$ and



(a) Relative delay of $U_a \subset U$

(b) Relative delay of U

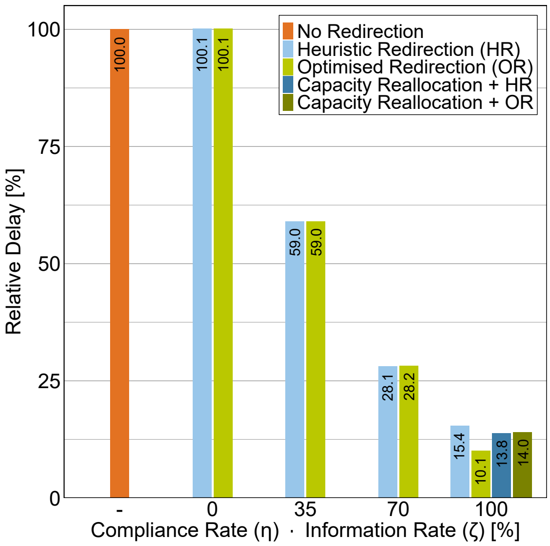
(c) Total delay of $U_a \subset U$

(d) Total delay of U

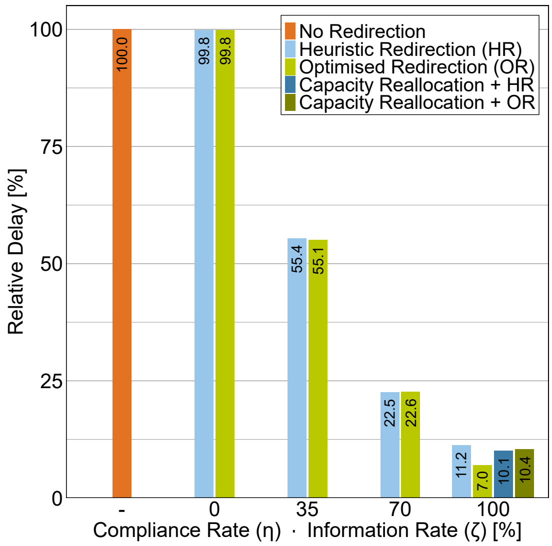
Figure 5.5: Overall relative and total delays of $U_a \subset U$ and U with $t_i = 60$ minutes and $\xi = 0\%$ in Scenario LS ($\psi = -1$)

indirectly affected passengers $U_{ida} \subset U$ seems to change with an increase in t_i. This indicates that the delays of the indirectly affected travellers $U_{ida} \subset U$ rise slower with an increase in the incident duration than do the delays of the affected passengers. Nonetheless, in all cases with $\eta \cdot \zeta > 0\%$, all approaches reduce the passenger delay significantly compared to the higher benchmark case with no redirection.

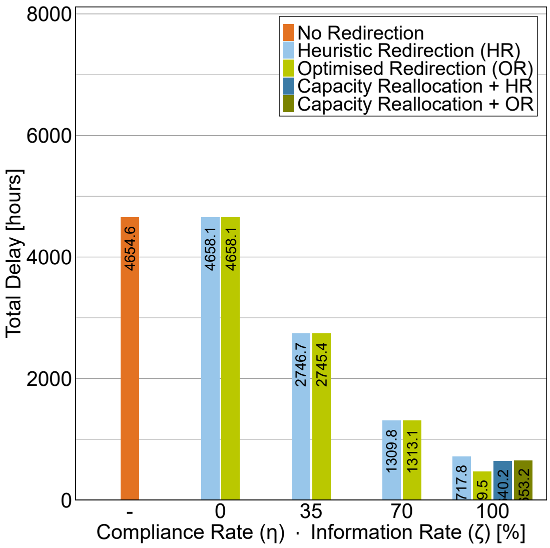
In Figure 5.6, the results with an incident duration of 90 minutes are presented. The trend implied by the differences between the previous two figures, namely that the relative delay



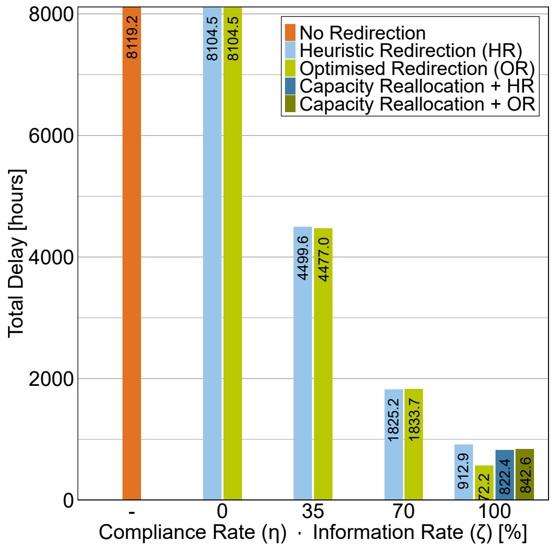
(a) Relative delay of $U_a \subset U$



(b) Relative delay of U



(c) Total delay of $U_a \subset U$



(d) Total delay of U

Figure 5.6: Overall relative and total delays of $U_a \subset U$ and U with $t_i = 90$ minutes and $\xi = 0\%$ in Scenario LS ($\psi = -1$)

further decreases with increasing incident duration, continues, with the optimisation approach performing best, with 7.0% for U and 10.1% for $U_a \subset U$, again, with a product of compliance and information rates of 100%. As before, this can be explained by the increasing total delay due to the longer incident duration through which the effectiveness of REPACK seems to further rise as well. The more people are affected – here, about 3,410 people – the more can be redirected, and the bigger the positive effect of passenger redirection. Another trend that continues is the relation between the total delay of all and the affected passengers. With an incident duration of 90 minutes the total delay of the affected passengers is about 57% of the total delay of all passengers whereas for $t_i = 30$ minutes they are 50% and for $t_i = 60$ minutes they are 55%. So, with a growing incident duration the influence of the delays of the indirectly affected passengers $U_{ida} \subset U$ seems to shrink. The fact that this effect is stronger between an incident duration of 30 and 60 minutes than between 60 and 90 minutes might be an indication that this effect does not grow linearly but weakens with an increase in the incident duration.

The relation between the two capacity reallocation approaches and the heuristic and optimised redirection is also nearly the same as in these cases with $t_i = 60$ minutes. Hence, the previously described disadvantage of the capacity reallocation of reducing the service quality on the PT lines from which the dispensable vehicles are withdrawn does not further worsen with a longer incident duration. Nonetheless, it raises the question of how this effect further develops with incident durations longer than 90 minutes. The ratio between the demand on the support line, from which the buses are withdrawn, and the demand on the line with insufficient capacity, to which the buses have been dispatched, is probably also a factor that influences the success of the capacity reallocation. Furthermore, so is the headway of the support line. The longer the headway of the support line, the longer the additional waiting time of the travellers on the support line, induced by the capacity reallocation. Moreover, as previously mentioned, another explanation for the performance of the reallocation approaches is the timing of the reallocated buses.

The following Figures 5.7a to 5.7f present the relative delay of the affected passengers $U_a \subset U$ with a self-redirection rate ξ of 10% on the left side and a rate of 30% on the right side with an increasing incident duration from 30 to 90 minutes from the top to the bottom of this set of figures. Since in these cases passengers are considered who redirect themselves and do not follow given path advice or who simply wait for the dissolution of the incident, even in the case with $\eta \cdot \zeta = 0\%$, the relative delay is lower than in the case with no redirection due to the reduced delays of the self-redirected travellers. Logically, the relative delay is lower with a higher value for ξ.

In cases with $t_i = 30$ minutes the approaches with a capacity reallocation – CR+HR and CR+OR – are not executed, at least not with all five random seeds used (Section 5.2.1). This might be due to the following reasons: Firstly, an increase of ξ and t_i does also increase the number of self-redirected passengers who occupy places on the fastest alternative paths as these are the paths they are assumed to take. With $t_i = 30$ minutes this effect seems to be too low to activate the capacity reallocation. Secondly, as the passengers who redirect themselves are chosen by chance, a situation might occur in which there are no fitting dispensable buses as in the cases with $\xi = 0\%$. This is due to self-redirected travellers occupy them. With an increase in the incident duration, the chance for dispensable capacities grows, as do the period during which they are looked for and the period during which they need to reach the PT line with insufficient capacity. Therefore, the longer the incident duration, the more severe the delays it causes, however, the higher the chance for dispensable capacity (Section 4.6). Hence, for the longer incident durations of 60 and 90 minutes, the capacity reallocation is executed. In the case of $\xi = 30\%$, CR+HR performs best with a relative delay for the affected passengers of 18.7% with $t_i = 60$ minutes. Interestingly, in this case only

CR+HR, but not CR+OR is executed. This might be due to the differences between the two redirection approaches through which the passengers are differently redirected, which seems to cater for no fitting dispensable capacities in the case of the optimised redirection.

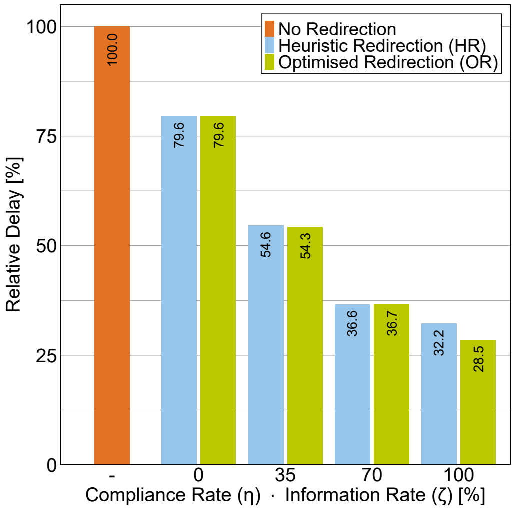
In the cases with $t_i = 90$ minutes CR+HR and CR+OR perform best, reducing the relative delay of the affected passengers by 84.2%. In these cases of $\xi = 30\%$, the advantages of CR+HR and CR+OR beat their previously discussed disadvantages. This leads to the capacity reallocation approaches performing best. Furthermore, it is also possible that some of the self-redirected passengers profit from the reallocated capacity as it is dispatched to faster alternative paths, ideally to the respective fastest alternative paths of the affected OD pairs $od \in OD_a$. The capacity reallocation increases not only the capacity on the line it is dispatched to, but also raises the frequency due to the extra vehicles. This reduces the waiting time for some of the redirected passengers and might also lower the waiting time for some of the self-redirected passengers. Nevertheless, the fact that the overall passenger delay reduction is smaller in the cases with a higher self-redirection rate implies that the overall redistribution of passengers is not ideal.

Generally speaking, the results with a self-redirection rate of higher than 0% show that even with people redirecting themselves, for example experienced commuters, REPACK still reduces the overall delay significantly. According to the previously presented results of the PT user survey, a self-redirection rate between 0% and 10% can be expected (Section 3.2.3).

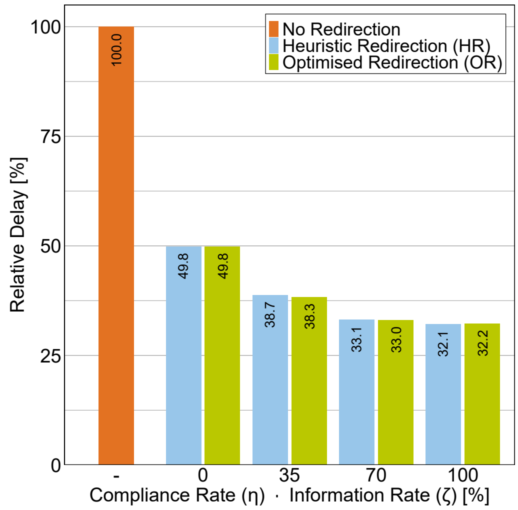
In addition to the previously shown results for the products of compliance and information rates of 0%, 35%, 70%, and 100%, in the following, results with finer steps for $\eta \cdot \zeta$ are presented for an incident duration of 60 minutes. This is done to investigate possible key values for these parameters for REPACK to be reasonable or to perform well. For example, to identify a necessary minimum value for the product of compliance and information rates.

Figure 5.8 shows the relative delay in 10% steps of $\eta \cdot \zeta$ of the affected passengers ($U_a \subset U$) on the left side and all passengers (U) on the right side. The results underline the reasonability of REPACK, as already with $\eta \cdot \zeta = 10\%$, there is a reduction of the passenger delay of about 10%. The reduction of the delay develops mainly linearly with respect to the increase in the product of the compliance and information rates ($\eta \cdot \zeta$). The approaches with capacity reallocation are only executed at $\eta \cdot \zeta = 100\%$; however, the optimised redirection performs best in this case, with a relative delay of 14.6% for the affected and 10.0% for all passengers.

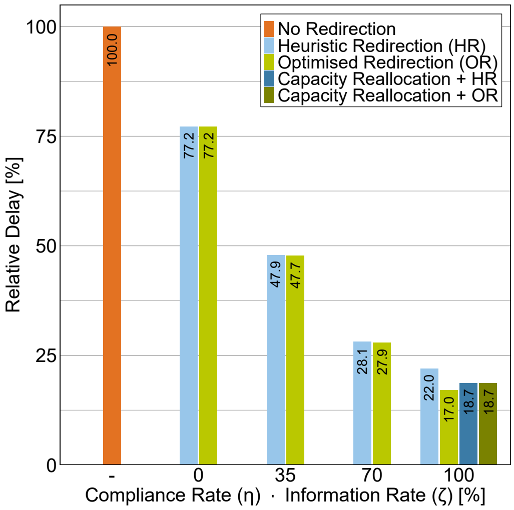
A product of compliance and information rates of 80% seems to be the tipping point where the advantages of the optimised redirection outweigh the advantages of the heuristic redirection. With a smaller product of compliance and information rates the heuristic performs better in most cases, whereas with a value of over 80%, the optimisation performs better. The to be expected product of the compliance and information rates can thereby be an indicator for the decision on which of the two passenger redirection approaches to be used.



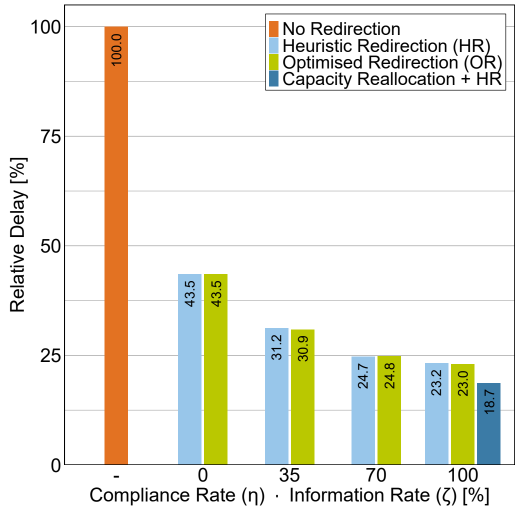
(a) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 10\%$



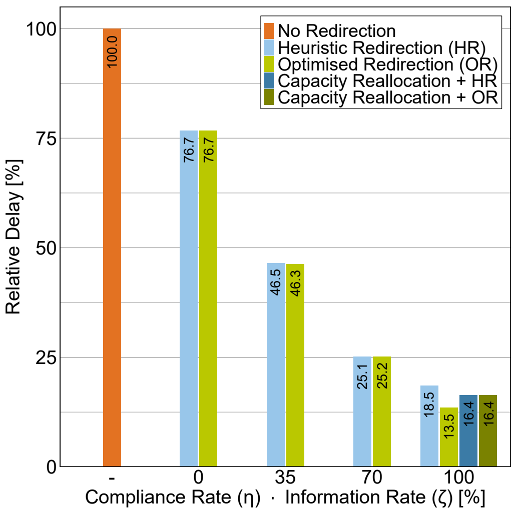
(b) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 30\%$



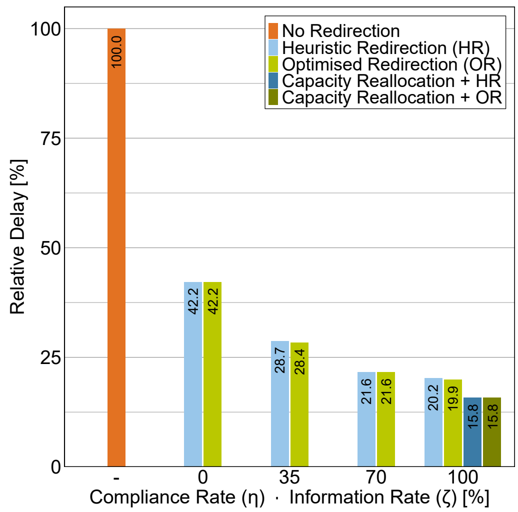
(c) $U_a \subset U$; $t_i = 60$ minutes; $\xi = 10\%$



(d) $U_a \subset U$; $t_i = 60$ minutes; $\xi = 30\%$

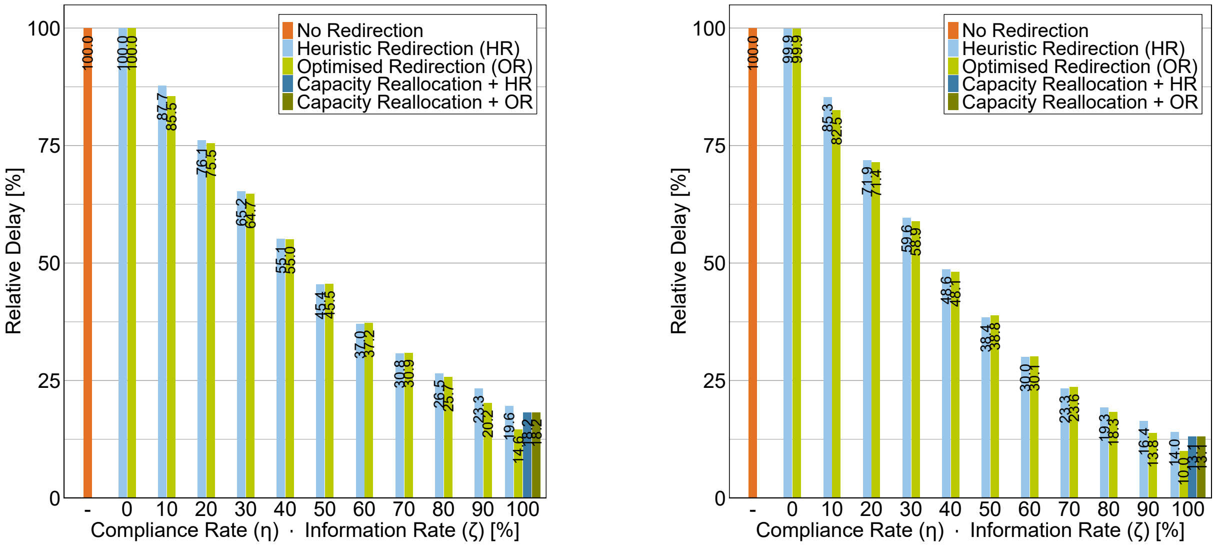


(e) $U_a \subset U$; $t_i = 90 minutes$; $\xi = 10\%$



(f) $U_a \subset U$; $t_i = 90$ minutes; $\xi = 30\%$

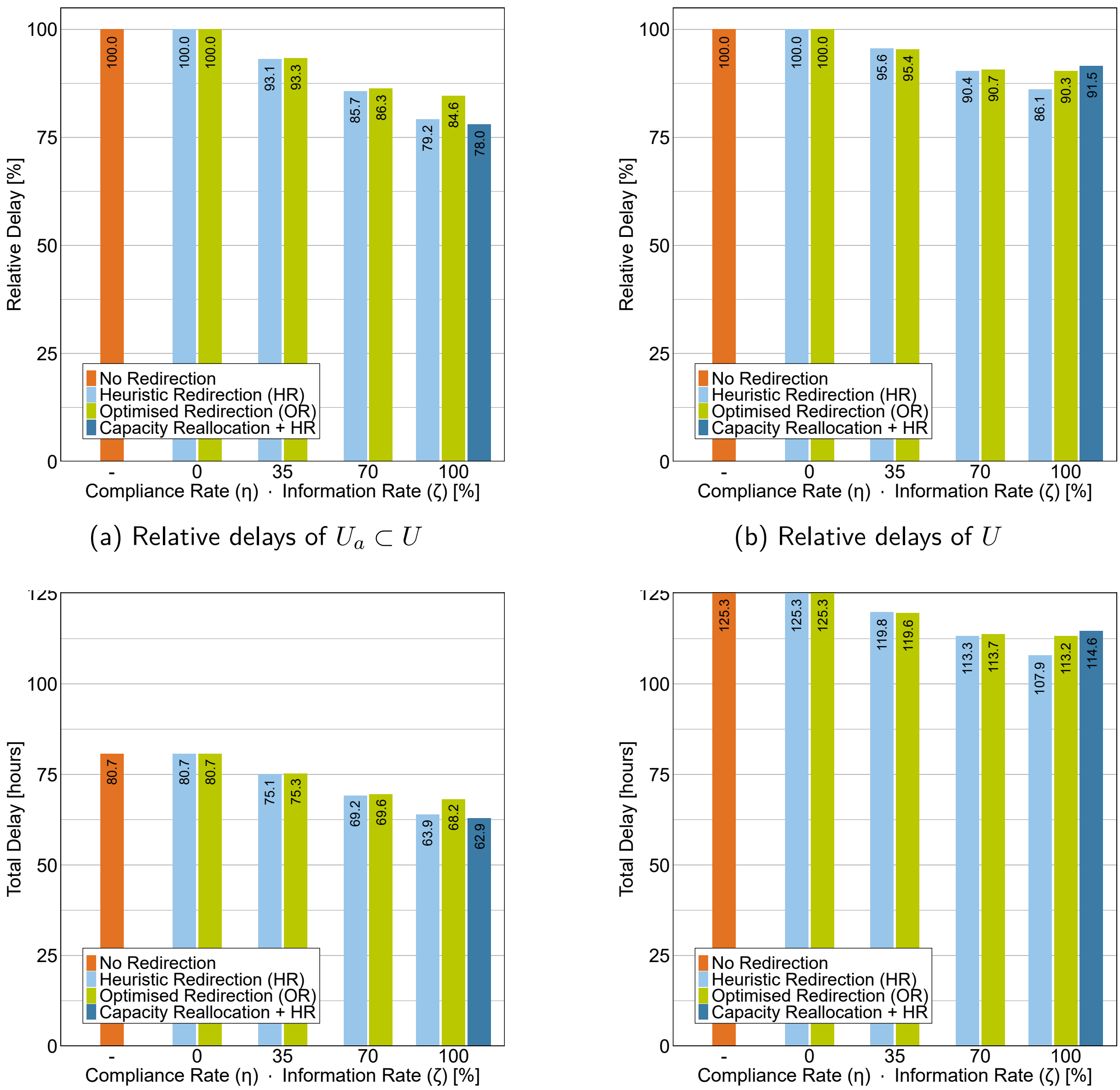
Figure 5.7: Overall relative delays of $U_a \subset U$ with $\xi > 0\%$ in Scenario LS ($\psi = -1$)



(a) $U_a \subset U$

(b) U

Figure 5.8: Overall relative delays of $U_a \subset U$ and U with $\eta \cdot \zeta$ in 10% steps with $t_i = 60$ minutes in Scenario LS ($\psi = -1$)



(a) Relative delays of $U_a \subset U$

(b) Relative delays of U

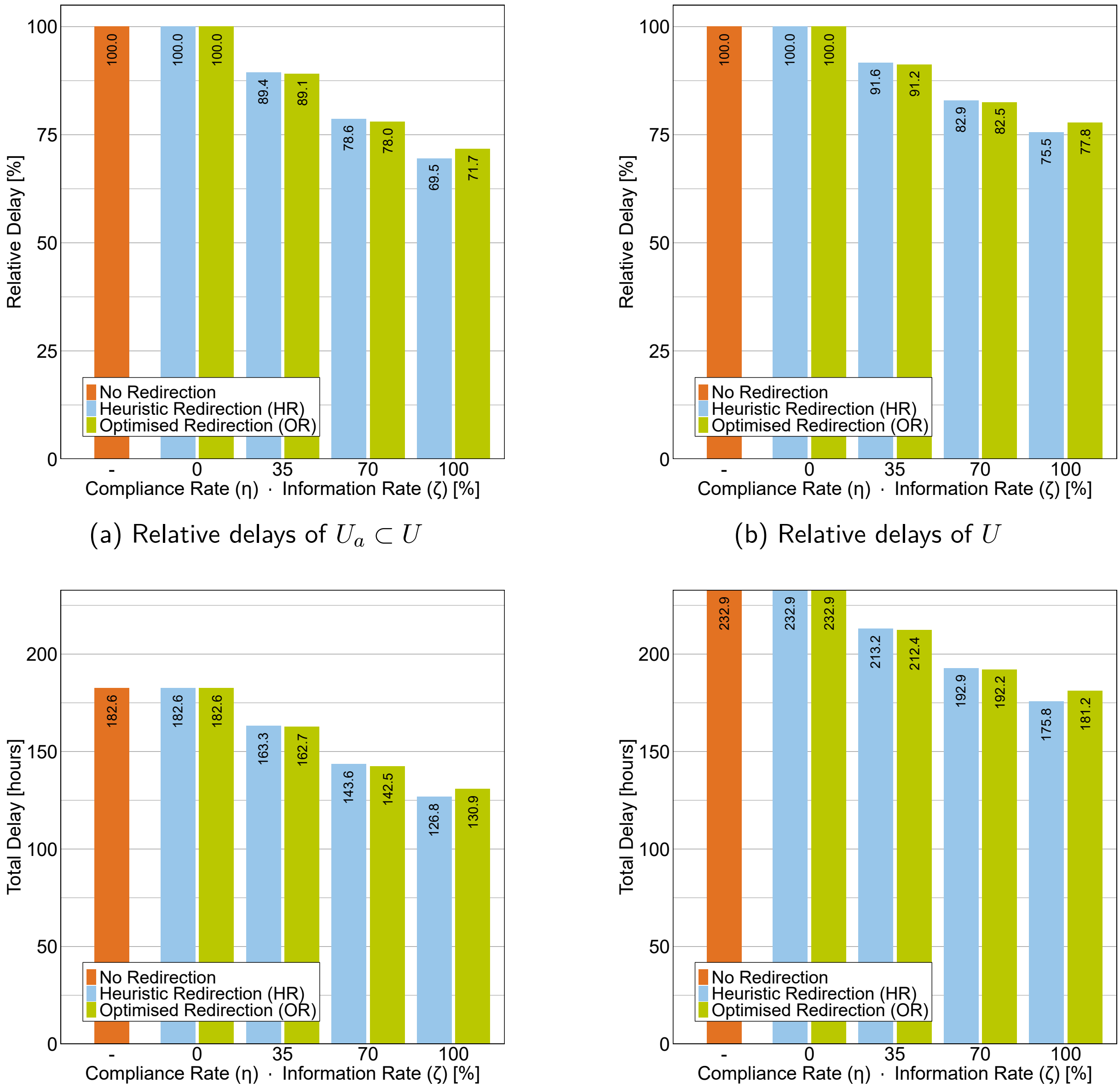
(c) Total delays of $U_a \subset U$

(d) Total delays of U

Figure 5.9: Overall relative and total delays of $U_a \subset U$ and U with $t_i = 30$ minutes and $\xi = 0\%$ in Scenario LR ($\psi = 0$)

As previously pointed out, the Scenario LR is a less disruptive disposition measure than LS. This is especially true if the additional travel time on the rerouted PT lines is not considerably prolonged, as is the case here with an additional travel time of about 3.5 minutes for the red line between Nodes 8 and 10. The yellow line skips Stop 8 in the scenario of the rerouting which means that passengers cannot reach this node by using the yellow line. The delay of the buses of this line is 3 minutes between Nodes 10 and 15. Therefore, a shorter recovery time is to be expected which is why for Scenario LR results with $\psi = 0$ are presented.

The total delays in Figure 5.9 support the statement that line-rerouting is less disruptive



(a) Relative delays of $U_a \subset U$

(b) Relative delays of U

(c) Total delays of $U_a \subset U$

(d) Total delays of U

Figure 5.10: Overall relative and total delays of $U_a \subset U$ and U with $t_i = 60$ minutes and $\xi = 0\%$ in Scenario LR ($\psi = 0$)

than line-splitting. Whereas in Scenario LS, an incident duration of 30 minutes causes a total delay of all passengers of 1097.1 hours (Figure 5.4d), in Scenario LR, however, it causes a total delay of 125.3 hours (Figure 5.9c). Furthermore, the difference between the total delays of all passengers (U: 25,486, Figure 5.9d) and the delays of the affected passengers ($U_a \subset U$: approximately 1,100, Figure 5.9c) is noticeably lower than in the Scenario LS (Figures 5.4d and 5.4c). Since the rerouting is less disruptive for the affected passengers $U_a \subset U$, it is also less disruptive for the indirectly affected passengers $U_{ida} \subset U$. Looking at the results in Scenario LR with incident durations of 60 and 90 minutes (Figures 5.10 and 5.11), it is evident that the effectiveness of REPACK rises with an increase of the incident duration, as in Scenario LS. Therefore, even in situations with less disruptive disposition measures such as line-rerouting, REPACK becomes more reasonable with longer incident durations.

The relation between the total delays of all passengers U and of the affected passengers $U_a \subset U$ shows a similar development as in Scenario LS, with an increase in the incident duration, the influence of the delays of the indirectly affected passengers ($U_{ida} \subset U$) shrinks. In case of $t_i = 30$ minutes the delays of the affected passengers amounts to 64% of all passengers, with $t_i = 60$ minutes to 78% and with $t_i = 90$ minutes to 82%. Again this effect shrinks with an increase of the incident duration, here, more obvious than in Scenario LS.

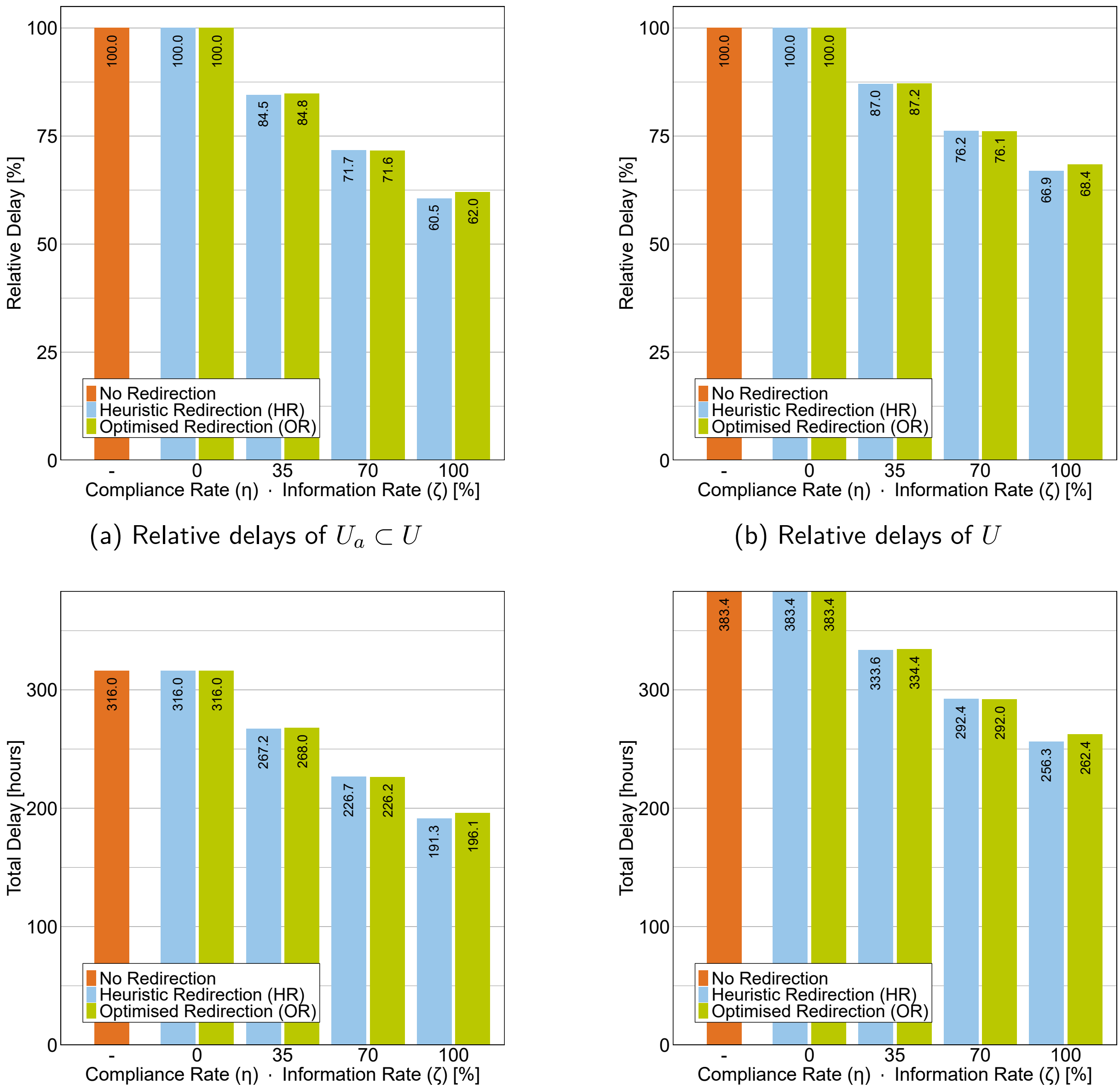
Another interesting observation is that only CR+HR, but not CR+OR, is executed in the cases with $t_i = 30$ minutes and that neither CR+HR nor CR+OR is executed in any other of the cases with a self-redirection rate ξ of 0%. This is probably due to the same reasons which have been discussed before concerning the execution criteria of the capacity reallocation process. Furthermore, even though CR+HR performs best from the perspective of the affected passengers, it worsens the situation of all passengers. Hence, the disadvantages for the line from which the reallocated buses have been withdrawn seem to be higher than the advantages for the supported line.

The results with a self-redirection rate of $\xi > 0\%$ show that the increase in the self-redirection rate does not have a significant effect on the relative passenger delay in Scenario LR which again can be explained by the less disruptive nature of this scenario, as well as with by the fact that for most affected passengers, the rerouted lines might still be the best alternative path which possesses the same capacity as in the undisrupted scenario. This fact might lead to most of the affected passengers being redirected onto them. Hence, the difference between self-redirected travellers and travellers redirected by given path advice is lower than in Scenario LS.

Among these cases, there is only one in which an approach with capacity reallocation is executed. With $\xi = 10\%$ and $t_i = 30$ minutes, CR+HR performs best and accomplishes a delay reduction of 22.3% in the case with $\eta \cdot \zeta = 100\%$. Through the self-redirected travellers who occupy room on the fastest alternative paths, the positive effects of CR+HR seem to outweigh its disadvantages better than with $\xi = 0\%$, which means no self-redirected PT users. At least for the affected passengers, whereas for all passengers, Approach HR performs best. This indicates that also the level of severity and taken disposition measures might be a support to decide on which redirection approach to use. However, the differences between the results of Approach HR compared to OR are insignificant in most cases, in Scenario LR.

The presentation of the relative delays in 10% steps shows a relatively linear development with respect to an increase of $\eta \cdot \zeta$, as in Scenario LS. However, here, the trend line is flatter, which fits well with the previously presented results. As argued before, this makes the execution of REPACK less reasonable in case of a less disruptive disposition measure, especially with $\eta \cdot \zeta < 40\%$, for which cases the delay reduction is less than 10%.

In summary, REPACK demonstrates a significant positive effect on the overall relative and total delay of affected passengers with a relative delay reduction of up to 90% under ideal circumstances. However, the results also show certain factors that influence REPACK's performance perceivably such as the severity and duration of an incident, as well as the level of disruptiveness of the disposition measures. The product of compliance and information rates also shows significant influence on the results with a somewhat linear relation. Moreover, a rising number of self-redirected passengers decreases the effectiveness of REPACK.



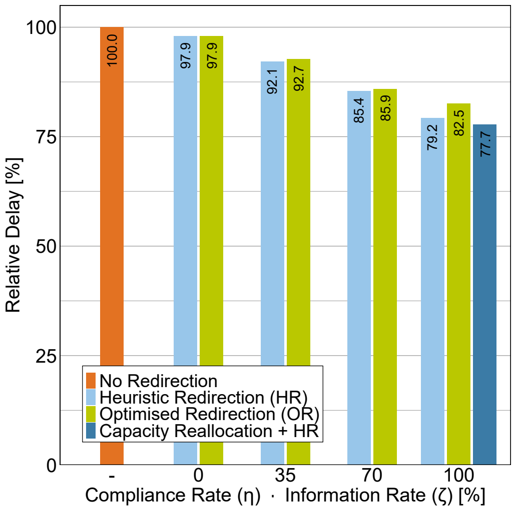
(a) Relative delays of $U_a \subset U$

(b) Relative delays of U

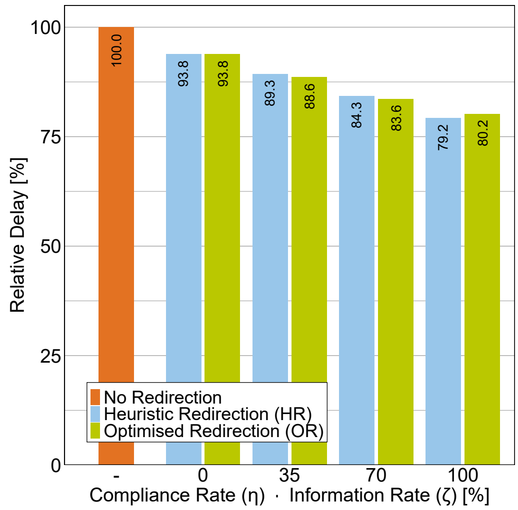
(c) Total delays of $U_a \subset U$

(d) Total delays of U

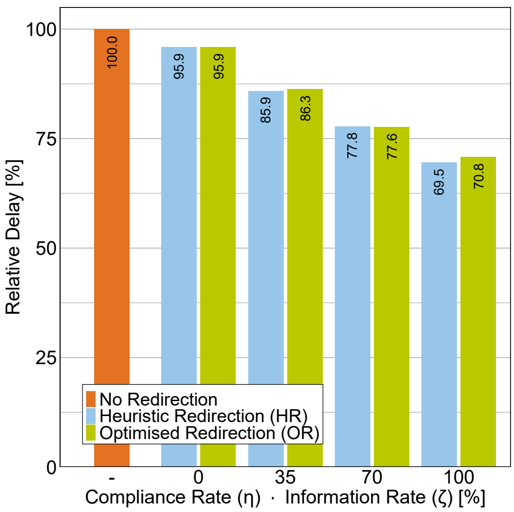
Figure 5.11: Overall relative and total delays of $U_a \subset U$ and U with $t_i = 90$ minutes and $\xi = 0\%$ in Scenario LR ($\psi = 0$)



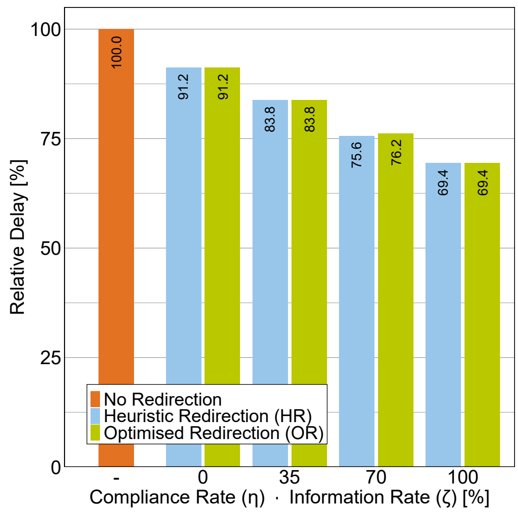
(a) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 10\%$



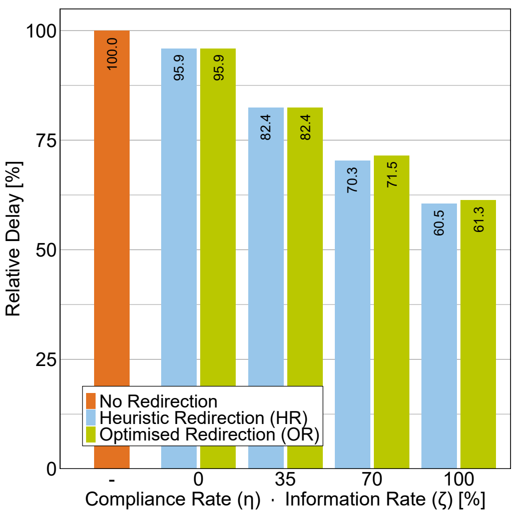
(b) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 30\%$



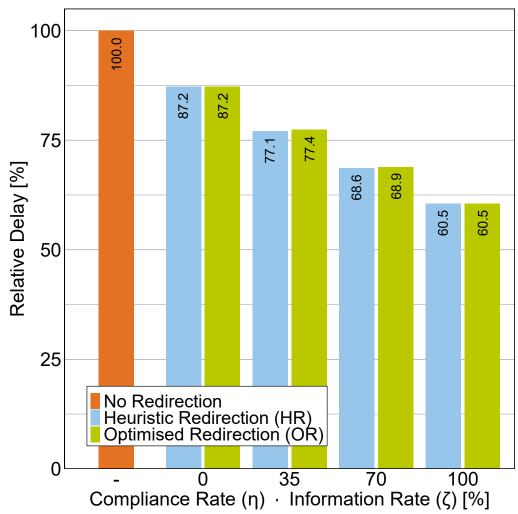
(c) $U_a \subset U$; $t_i = 60$ minutes; $\xi = 10\%$



(d) $U_a \subset U$; $t_i = 60$ minutes; $\xi = 30\%$

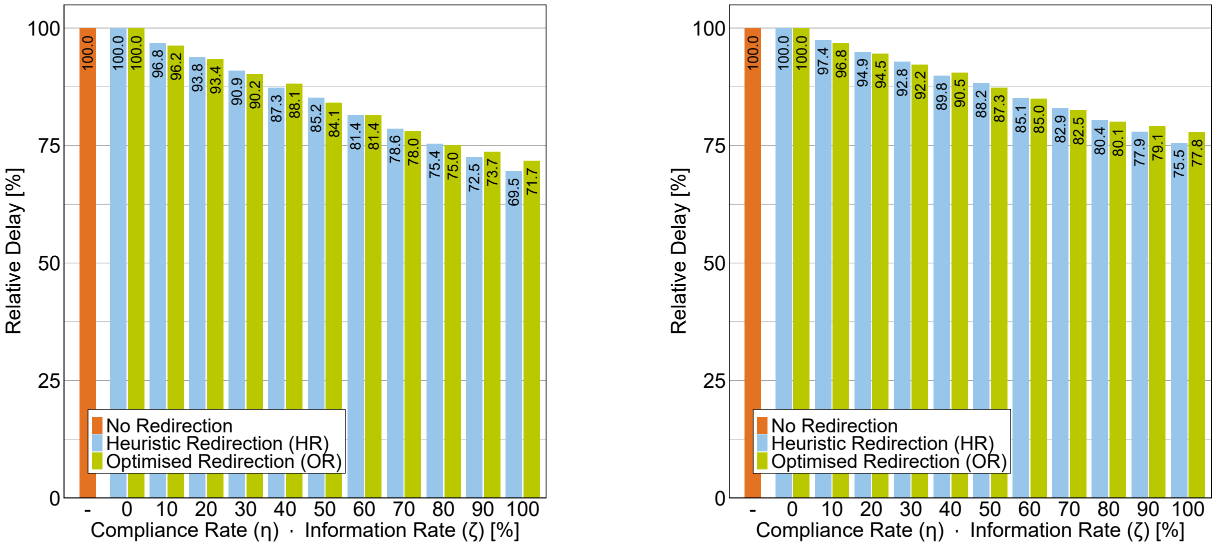


(e) $U_a \subset U$; $t_i = 90$ minutes; $\xi = 10\%$



(f) $U_a \subset U$; $t_i = 90$ minutes; $\xi = 30\%$

Figure 5.12: Overall relative delays of $U_a \subset U$ with $\xi > 0\%$ in Scenario LR ($\psi = 0$)



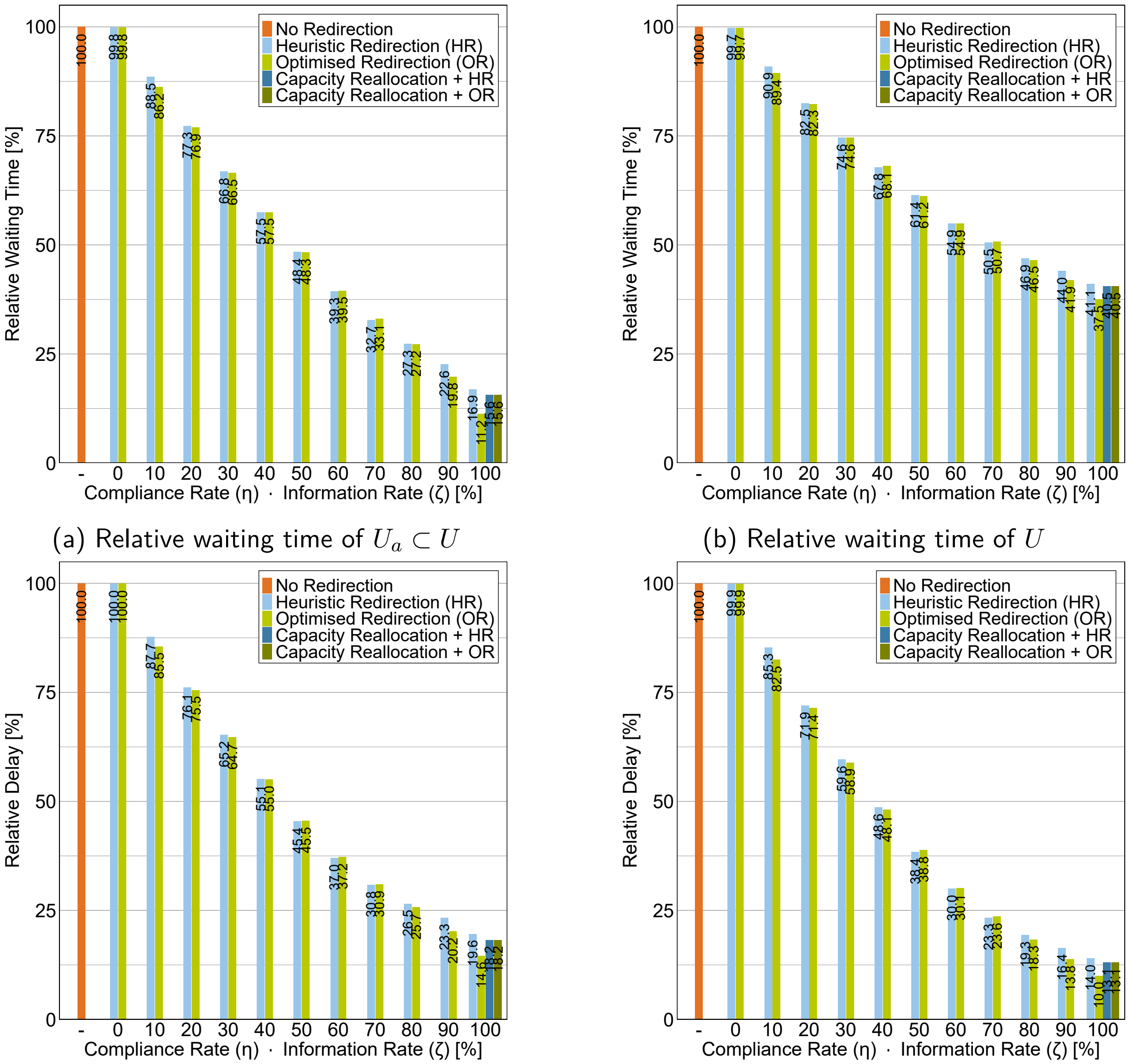
(a) $U_a \subset U$

(b) U

Figure 5.13: Overall relative delays of $U_a \subset U$ and U with $\eta \cdot \zeta$ in 10% steps with $t_i = 60$ minutes in Scenario LR ($\psi = 0$)

Relative Waiting Time

In the following the waiting time in dependence of the product of compliance and information rates is presented in order to evaluate the effect of REPACK on the waiting time of passengers (Figure 5.14). The waiting time is a part of the travel time of each PT user. As explained in Section 2.1.2 the waiting time is less convenient than the riding or in-vehicle time of a passenger. It is the accumulated time during which travellers are waiting at stops for the PT service they intend to take. For the affected passengers $U_a \subset U$ (left side), the waiting time similarly decreases compared to the relative delay. For all passengers U (right side), the relative delay decreases more rapidly than the relative waiting time. Therefore, the waiting time decreases more quickly for the affected passengers with an increase in the product of compliance and information rates compared to all passengers. This indicates that REPACK also caters for an advantage in waiting time for the redirected passengers. This reduces their perceived travel time even quicker than the actual travel time (Section 2.1.2).



(a) Relative waiting time of $U_a \subset U$

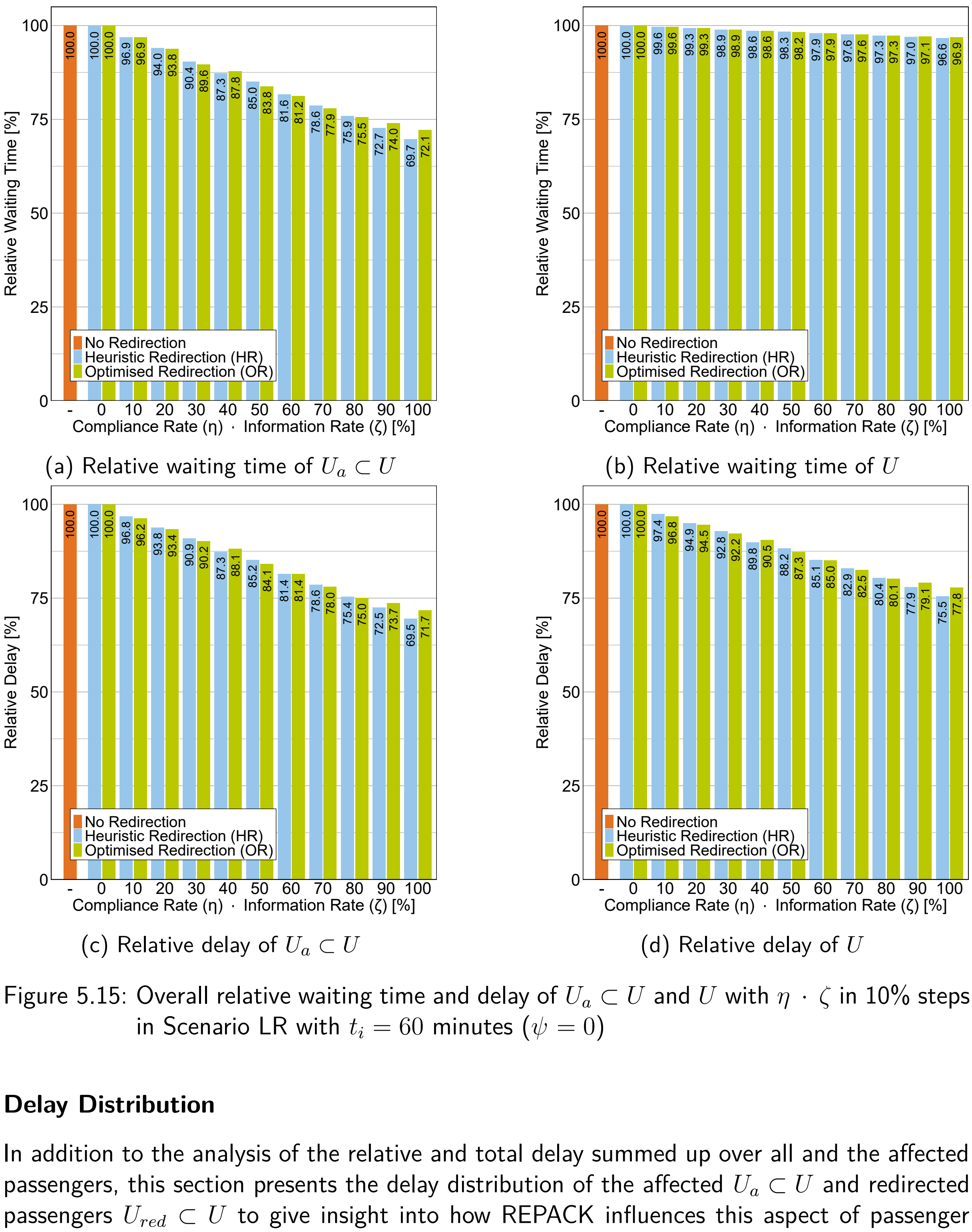
(b) Relative waiting time of U

(c) Relative delay of $U_a \subset U$

(d) Relative delay of U

Figure 5.14: Overall relative waiting time and delay of $U_a \subset U$ and U with $\eta \cdot \zeta$ in 10% steps in Scenario LS with $t_i = 60$ minutes ($\psi = -1$)

As for Scenario LR, the relative waiting time drops quicker for the affected $U_a \subset U$ (left side) than for all passengers U (right side). In general, the development of the waiting time in this scenario fits well to the development of the relative delay and the fact that the line-rerouting is less disruptive than the line-splitting (Figure 5.15a).



(a) Relative waiting time of $U_a \subset U$

(b) Relative waiting time of U

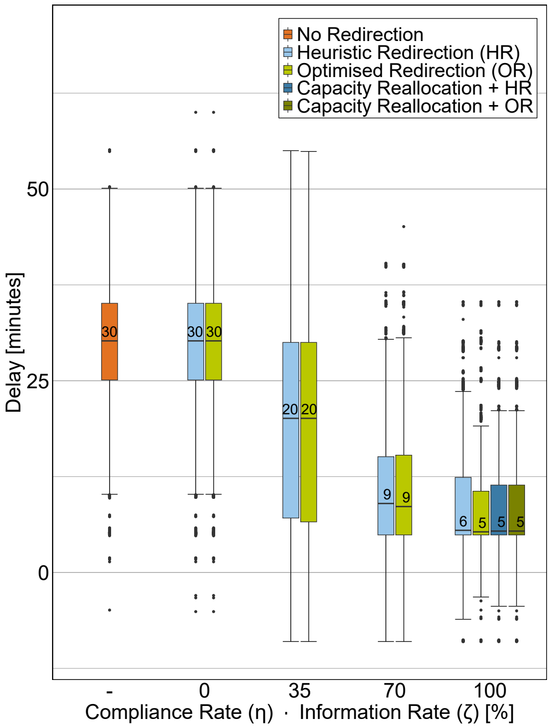
(c) Relative delay of $U_a \subset U$

(d) Relative delay of U

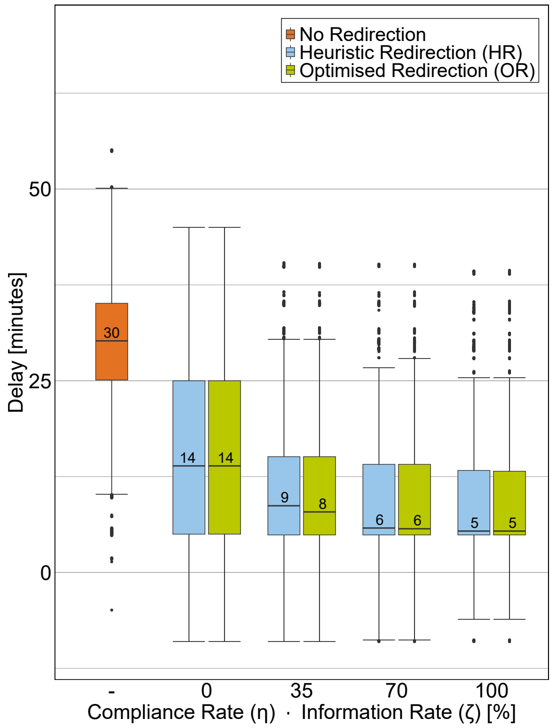
Figure 5.15: Overall relative waiting time and delay of $U_a \subset U$ and U with $\eta \cdot \zeta$ in 10% steps in Scenario LR with $t_i = 60$ minutes ($\psi = 0$)

Delay Distribution

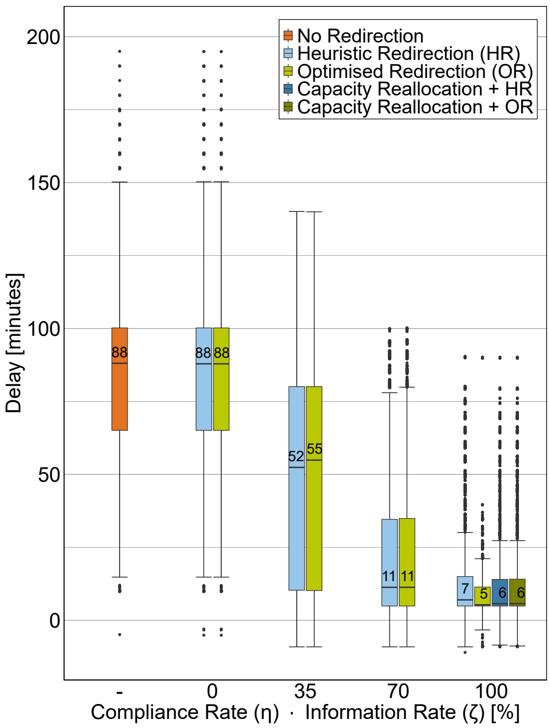
In addition to the analysis of the relative and total delay summed up over all and the affected passengers, this section presents the delay distribution of the affected $U_a \subset U$ and redirected passengers $U_{red} \subset U$ to give insight into how REPACK influences this aspect of passenger delays. Figure 5.16 shows the delay distribution of the affected passengers, again with $\psi = -1$. The figures on the left side are the cases with a self-redirection rate ξ of 0% and on the right side with $\xi = 30\%$. The two figures at the top have an incident duration of 30 minutes and at the bottom of 90 minutes.



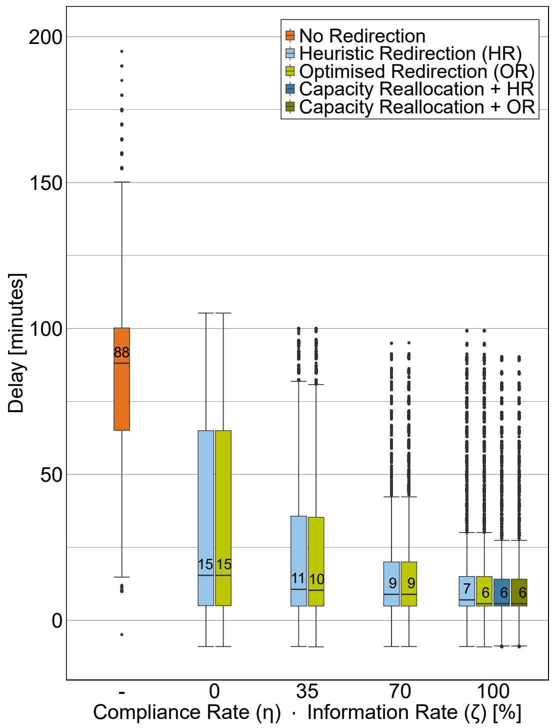
(a) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 0\%$



(b) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 30\%$



(c) $U_a \subset U$; $t_i = 90$ minutes; $\xi = 0\%$



(d) $U_a \subset U$; $t_i = 90$ minutes; $\xi = 30\%$

Figure 5.16: Delay distribution of $U_a \subset U$ in Scenario LS ($\psi = -1$)

For these results box plots are used. The bottom border of the box represents the 25th percentile (first quartile) of the passengers, and the top border delineates the 75th percentile (third quartile). The horizontal line within each box is the median (i.e. the 50th percentile, second quartile). The bottom whisker describes the 0th percentile (zeroth quartile) and the top whisker the 100th percentile (fourth quartile). The data points outside the whiskers represent outliers. To define outliers, here, the 1.5IQR rule is used. The inter quartile range (IQR) is the range from the first to the third quartile. If a value lies beyond the product of 1.5 times IQR plus the third quartile (75th percentile) or minus the first quartile (25th percentile), the value is defined as an outlier [Dawson, 2011; Wikipedia, 2023].

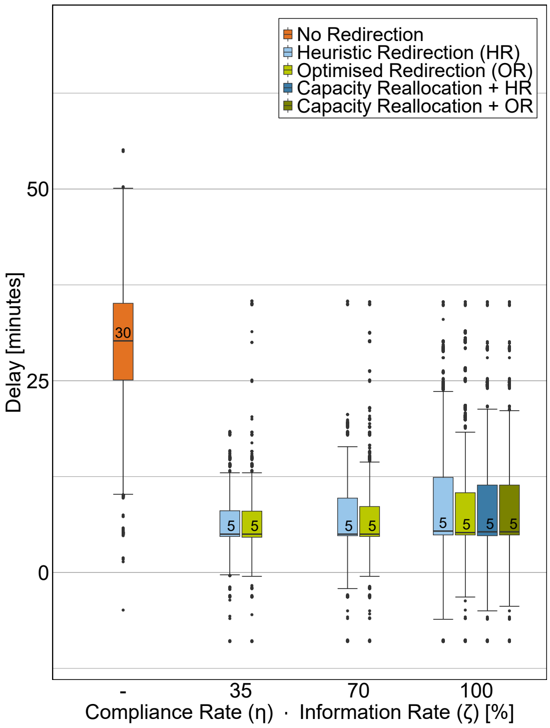
Generally, it is apparent that a reduction in the number of waiting travellers also reduces the distribution of passenger delays. This goes along with an increase in the number of outliers that are above the top whisker. The more redirected travellers, the fewer waiting travellers due to the absence of available alternative paths or due to their late arrival at the origin of the redirection after the redirection duration elapsed (Section 4.5). However, if there is no available alternative path for a certain OD pair, the corresponding passenger delay is rather severe, compared to the delay of the redirected passengers.

For the cases with $\xi = 0\%$ and $\eta \cdot \zeta = 35\%$, the IQR is the largest (Figures 5.16a and 5.16c). This can be explained by the fact that in these cases the number of waiting people is higher than that of the redirected passengers. Furthermore, the waiting travellers include those who arrive at the incident site not just shortly before the dissolution of the incident, but also during its entire duration. With a rising product of compliance and information rates, the number of these long-waiting passengers decreases and consequently does the IQR. However, it also raises the number of outliers who are most likely these few still present long waiting passengers for whom no alternative path is available. The case in which $t_i = 90$ minutes shows that the optimised redirection performs best in this matter. Since the more severe delay of long waiting travellers can perceivably increase the average overall delay of all affected passengers, the optimisation rather redirects these passengers than a bigger group that faces a shorter delay.

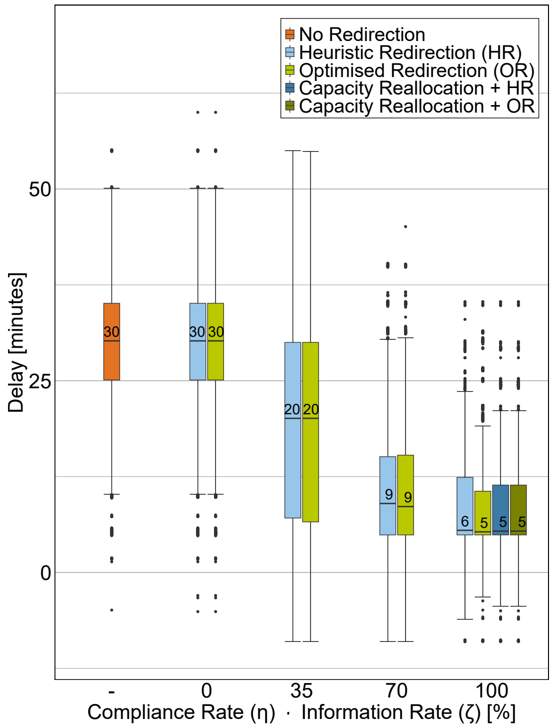
The results of the cases with $\xi = 30\%$ show a similar picture. Nonetheless, in these cases, the distribution starts to decline even with $\eta \cdot \zeta = 0\%$, which shows the largest IQR in these cases, even with a product of compliance and information rates of 0%. This can be explained through the 30% of the affected passengers who redirect themselves and thereby stretch the deviation of passenger delays. Interestingly, in these cases, the optimised redirection does not show a smaller range of outliers. The reason for this might be the fact that those passengers who redirect themselves occupy relevant space that outliers might take when redirected.

With an increase of the incident duration, the development of the results from the cases with $\eta \cdot \zeta = 0\%$ to 100% becomes slightly more obvious, but its course is similar.

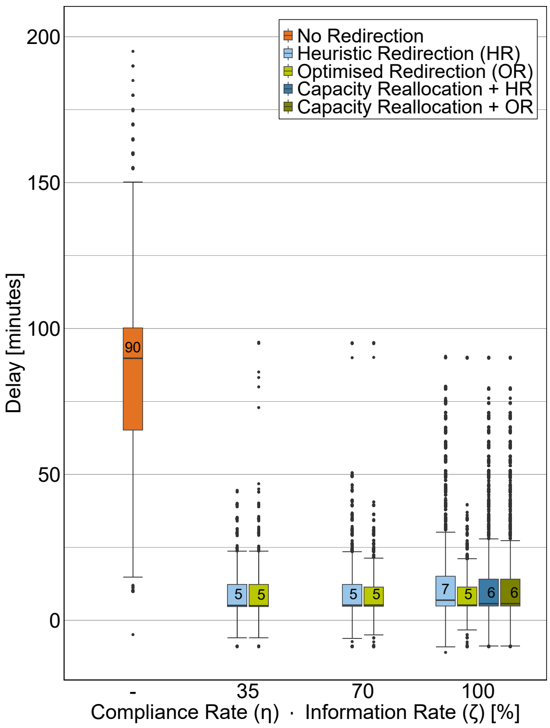
Another striking observation that can be made is the fact that some travellers show a negative delay which means that their travel time is shorter than in the lower benchmark scenario without an incident. The zero line runs between first and second quartile for $\eta \cdot \zeta >= 35\%$ with $\xi = 0\%$ and for $\eta \cdot \zeta >= 0\%$ with $\xi = 30\%$. For $\eta \cdot \zeta = 100\%$ this effect shrinks, which means that for some of the affected passengers it is best if not all $u \in U_a$ follow path advice or are informed. This indicates that through passenger redirection that causes a



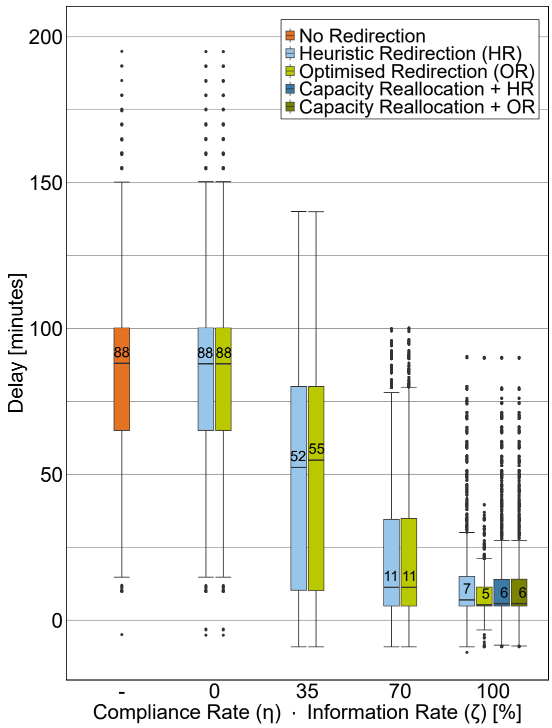
(a) $U_{red} \subset U$; $t_i = 30$ minutes; $\xi = 0\%$



(b) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 0\%$



(c) $U_{red} \subset U$; $t_i = 90$ minutes; $\xi = 0\%$



(d) $U_a \subset U$; $t_i = 90$ minutes; $\xi = 0\%$

Figure 5.17: Delay distribution of $U_{red} \subset U$ and $U_a \subset U$ in Scenario LS ($\psi = -1$)

redistribution of passengers within the PT network, for some of the affected passengers the situation is even better than without an incident in terms of their travel time.

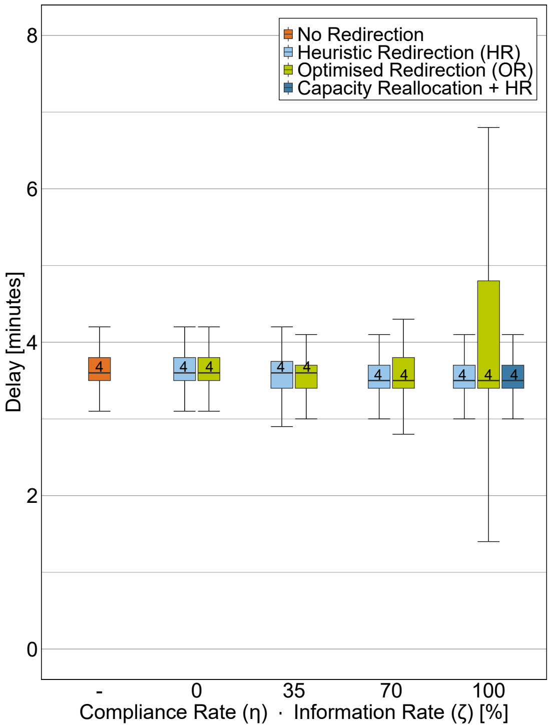
The Braess paradox could also be an explanation for this phenomenon. This paradox expresses that a disturbed system sometimes performs better than the undisturbed [Ameli et al., 2020]. In contrast to this, however, is the fact that the disrupted PT system without passenger redirection does not show this phenomenon, or at most for individual passengers.

To compare the delay distribution of the affected passengers $U_a \subset U$ to the delay distribution of the redirected passengers $U_{red} \subset U$, in Figure 5.17 the redirected passengers' delay distribution with $\xi = 0\%$ and incident durations of 30 and 90 minutes is presented in comparison to the results of the affected PT users $U_a \subset U$. The figures on the left show the results for $U_{red} \subset U$ and the ones on the right for $U_a \subset U$. These figures help to explain the right shift of the median of the delay distribution of the affected passengers, as for the redirected passengers the IQR is lower and with an increasing product of compliance and information rates from left to right, the delay distribution of the redirected passengers moves closer and closer to the distribution of the affected passengers. This is logical, as with an increase in the number of redirected passengers, the number of waiting passengers decreases and with $\eta \cdot \zeta = 100\%$, most of the affected passengers are redirected.

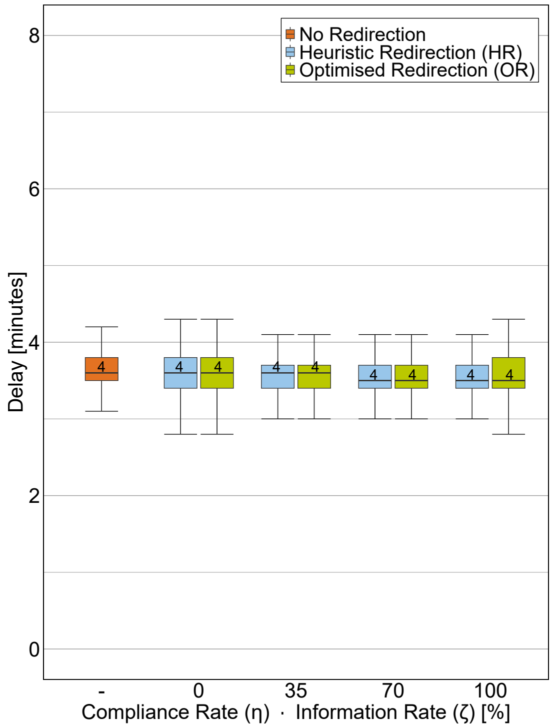
For Scenario LR, the delay distribution of the affected passengers looks noticeably different compared to Scenario LS (Figure 5.18a). The negative consequences of the line-rerouting are significantly lower in terms of delays for most of the affected passengers compared to the line-splitting. This can also be seen in the delay distributions. Therefore, the outliers extend the range of the occurred delays greatly through which the boxes shrink to an almost unreadable size. Therefore, the outliers are removed here. Some of these diagrams with outliers are to be found in Annexe C.

Due to the reduced overall delays even without passenger redirection, the differences between the various cases with a range of used products of compliance and information rates are also smaller than in Scenario LS. The median only drops minimally in the cases with $\eta \cdot \zeta > 35\%$. However, this can only be seen through the position of the median line in the diagram, since the change occurs exclusively in the decimal range without any change to the rounded value depicted in the diagram. It is noticeable that the optimised redirection has a higher IQR in the cases with $\eta \cdot \zeta = 100\%$. This is especially true for the cases with $\xi = 0\%$. Again, it might be the case that through the less precise calculation of the alternative paths' remaining capacities, the redirection worsens the situation for a few passengers. This also fits the results with $\xi = 30\%$, for which this occurs less often as more passengers take their fastest alternative path and do not follow the path advice. Generally speaking, the delay distribution in Scenario LR is insignificant, which is not surprising, as the difference in additional travel time of the rerouted lines is 3.5 minutes.

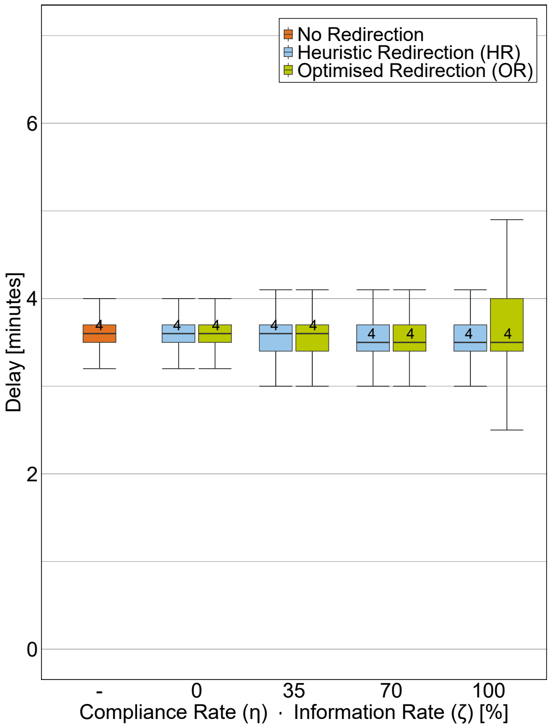
For the same reason, there is almost no difference in the delay distribution of the redirected passengers $U_{red} \subset U$, which is presented in Figure 5.19 in comparison to the results of the affected passengers $U_a \subset U$. The results for the redirected PT users are on the left side, whereas the results for the affected PT users are on the right side.



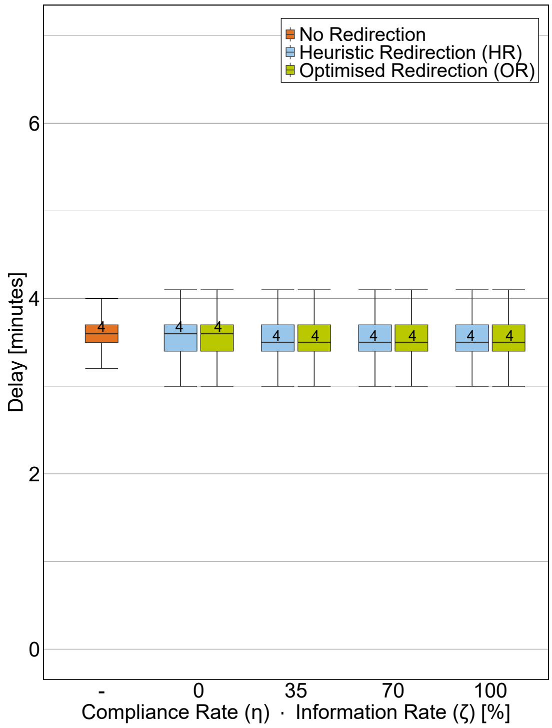
(a) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 0\%$



(b) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 30\%$

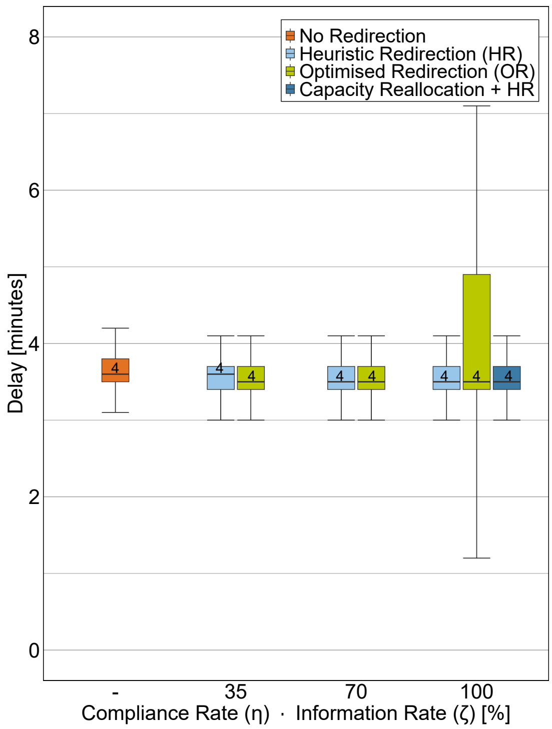


(c) $U_a \subset U$; $t_i = 90$ minutes; $\xi = 0\%$

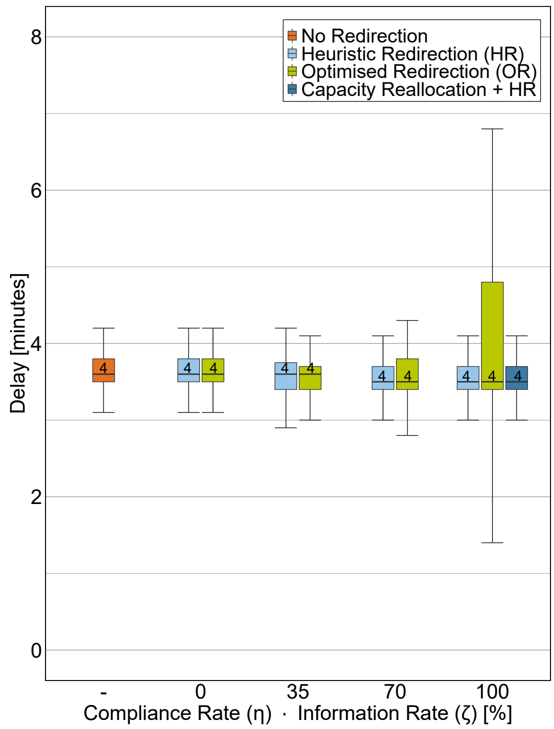


(d) $U_a \subset U$; $t_i = 90$ minutes; $\xi = 30\%$

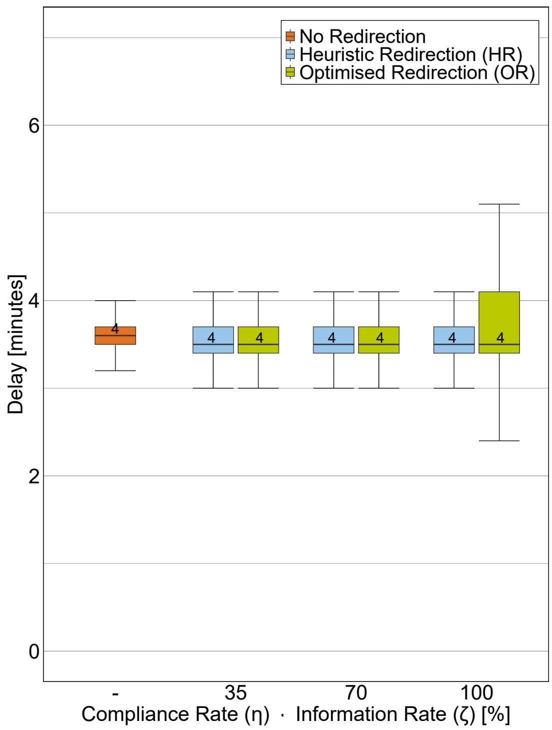
Figure 5.18: Delay distribution of $U_a \subset U$ in Scenario LR ($\psi = 0$)



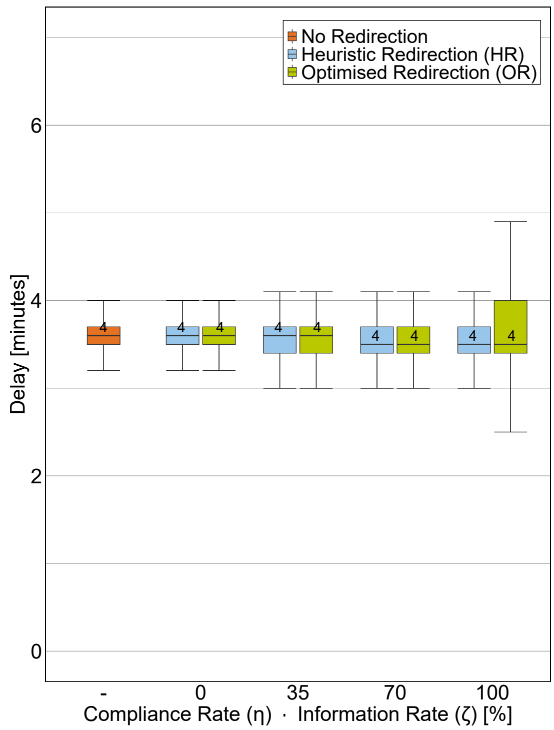
(a) $U_{red} \subset U$; $t_i = 30$ minutes; $\xi = 0\%$



(b) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 0\%$



(c) $U_{red} \subset U$; $t_i = 90$ minutes; $\xi = 0\%$



(d) $U_a \subset U$; $t_i = 90$ minutes; $\xi = 0\%$

Figure 5.19: Delay distribution of $U_{red} \subset U$ and $U_a \subset U$ in Scenario LR ($\psi = 0$)

Delay per Departure Time

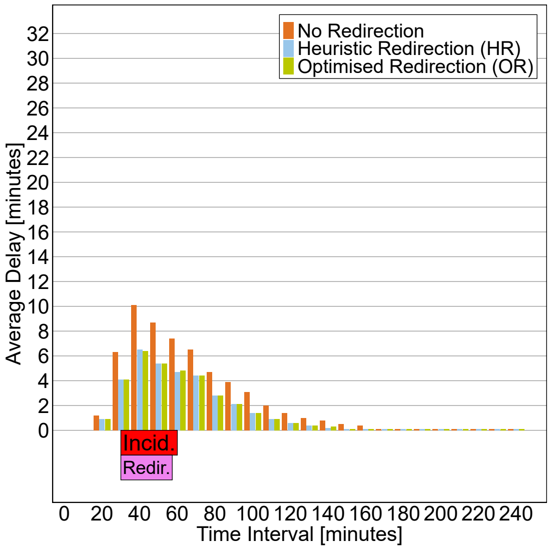
The total and relative delay as well as the delay distribution grants insight into the delays over the whole simulation period of each case study. However, those results do not cast any light on the development of the passenger delay over time. Therefore, Figures 5.20a to 5.20d show the average delay of all passengers per time interval. The delays are averaged in 10-minutes steps of the passengers' departure times. The red bar at the bottom of the diagram shows the incident duration and the violet bar shows the redirection duration. Since the redirection duration varies for the redirection groups of the different affected OD pairs depending on the alternative path they are redirected onto (Section 4.5), the end of the violet bar is determined by the mean of the departure times of the respective last redirected passenger in each case over all five random seeds.

The figures demonstrate that the course of the development of the passenger delays is similar between all the conducted approaches. However, an obvious gap exists between the case with no redirection and the ones in which passengers have been redirected. Logically, this gap is bigger in the cases with a product of compliance and information rates of 100% (Figures 5.20b and 5.20d) than in the cases with a rate of 35% (Figures 5.20a and 5.20c). As in these cases the delay reduction is more substantial due to the larger number of passengers that are redirected. Furthermore, the more travellers follow the path advice, the quicker the delay decrease at the end and shortly after the incident. For the cases with no redirection the delays fall slowly and go far beyond the end of the incident which makes a negative value for ψ, which prolongs the redirection duration, reasonable.

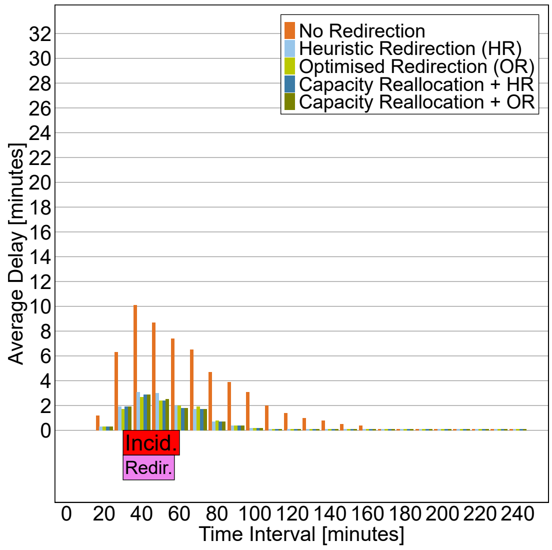
Through a negative value of ψ the redirection duration T^p_{od} is prolonged by $|\psi| \cdot \breve{h}_p$. With $\psi = -1$ this still caters for a redirection duration shorter than the incident duration. Due to the fact that the rest of Equation 4.2, to calculate T^p_{od}, mainly depends on the travel time difference between the fastest alternative path $\hat{p} \in P_{od}$ and the assigned alternative path $\tilde{p} \in P_{od}$ of an affected OD pair $od \in OD_a$. This also explains the fact that the redirection durations in the two Scenarios LS and LR are nearly the same at about 57 minutes. Even though the value for factor ψ is set differently (-1 versus 0). This is because the differences in travel time between $\hat{p} \in P_{od}$ and $\tilde{p} \in P_{od}$ are likely to be greater in the more disruptive Scenario LS than in Scenario LR.

The approaches with the capacity reallocation are only executed in the cases with $\eta \cdot \zeta = 100\%$. As in the results for the relative delays the optimised redirection performs best.

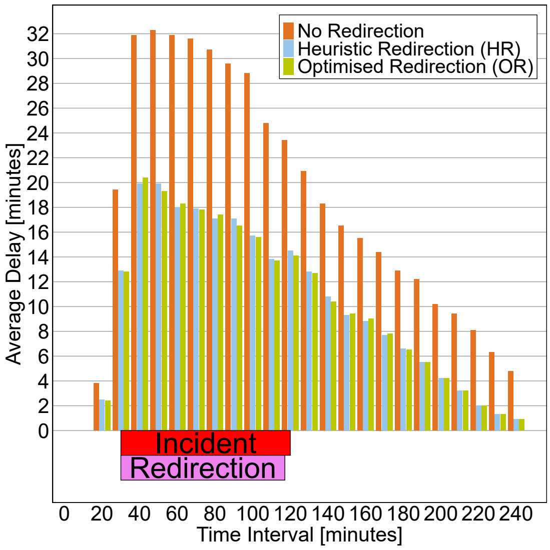
Figure 5.21 fits well with the previously presented results of the relative and total delays as well as the delay distributions in Scenario LR. The gaps between the case with no redirection and the cases with a passenger redirection are perceptible but insignificant. The delays end with the end of the incident, even in the case of $t_i = 90$ minutes. This makes a negative value for ψ unreasonable in Scenario LR as there is no or an insignificant recovery time. This supports the decision for a value of $\psi = 0$.



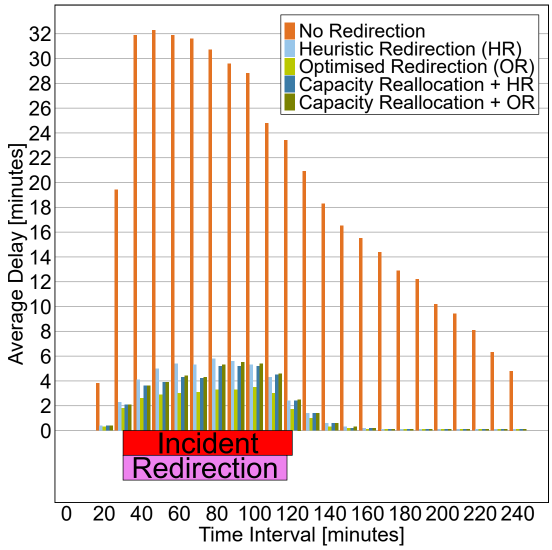
(a) U; $\eta \cdot \zeta = 35\%$; $t_i = 30$ minutes



(b) U; $\eta \cdot \zeta = 100\%$; $t_i = 30$ minutes

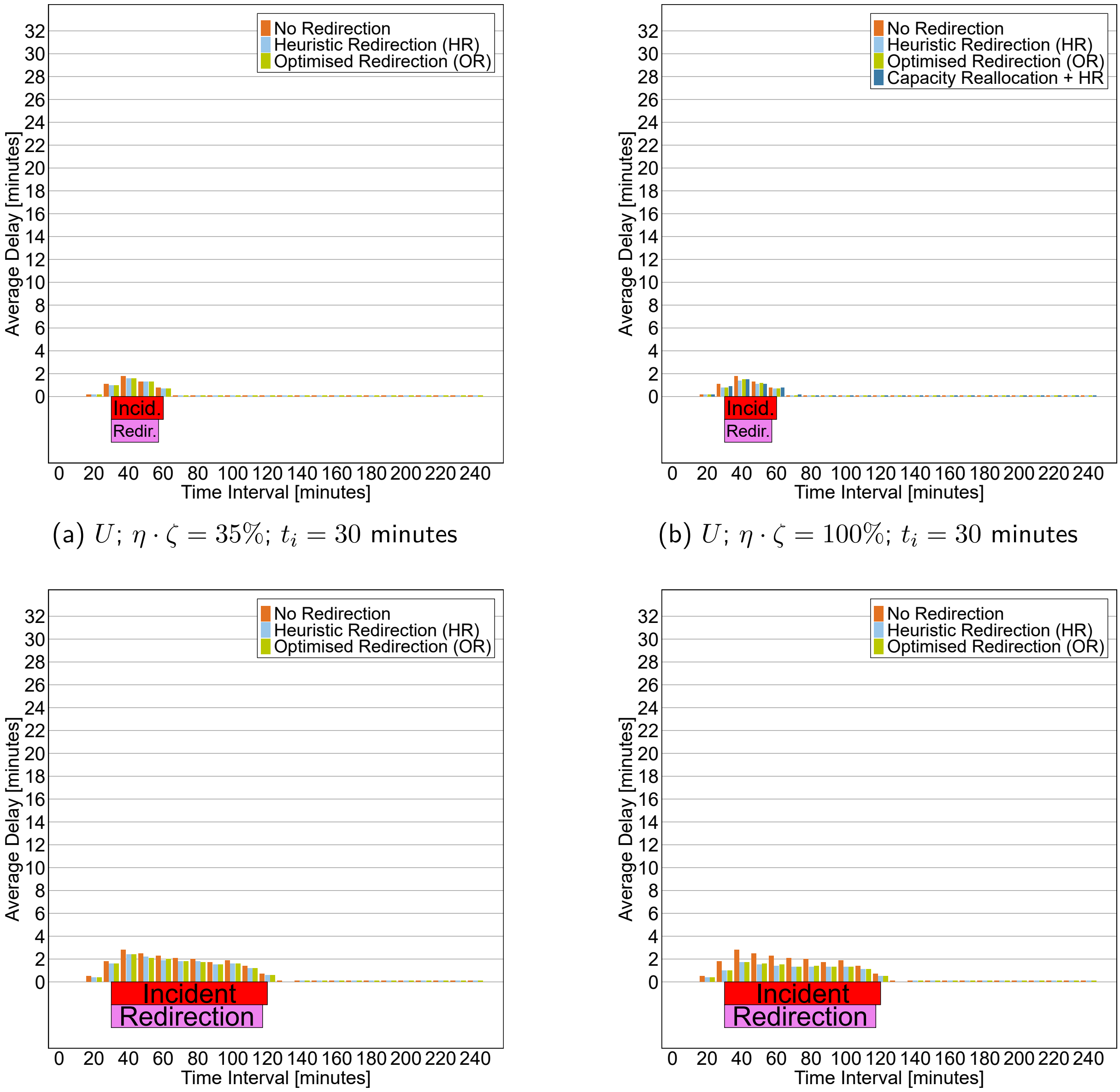


(c) U; $\eta \cdot \zeta = 35\%$; $t_i = 90$ minutes



(d) U; $\eta \cdot \zeta = 100\%$; $t_i = 90$ minutes

Figure 5.20: Average delays by departure time of $u \in U$ with $\xi = 0\%$ in Scenario LS ($\psi = -1$)



(a) U; $\eta \cdot \zeta = 35\%$; $t_i = 30$ minutes

(b) U; $\eta \cdot \zeta = 100\%$; $t_i = 30$ minutes

(c) U; $\eta \cdot \zeta = 35\%$; $t_i = 90$ minutes

(d) U; $\eta \cdot \zeta = 100\%$; $t_i = 90$ minutes

Figure 5.21: Average delays by departure time of $u \in U$ with $\xi = 0\%$ in Scenario LR ($\psi = 0$)

PT User Crowding at Stops

As explained in Section 5.2.2, REPACK also reduces the waiting time of affected passengers. This can also lead to a decrease in passenger crowding at stops, as affected travellers wait for a shorter duration at a stop before they can board a PT vehicle. For this, the six stops which are directly before and after the incident site at Nodes 8 and 10 in the Mandl network have been picked for this investigation, as the crowding is likely to be most severe at these stops.

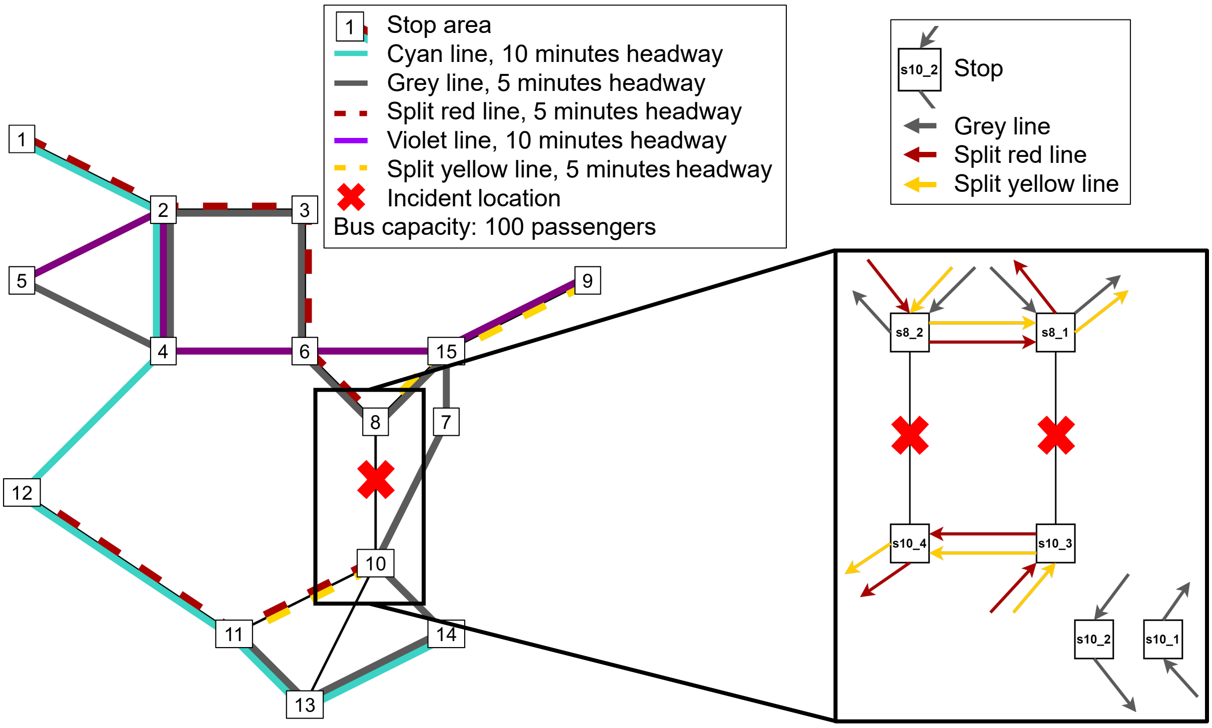


Figure 5.22: Stop setup at Nodes 8 and 10 in Scenario LS

Figures 5.22 and 5.23 show the location of the investigated stops concerning their position in the network. As described in Section 4.3, each node in the network represents a stop area that contains at least two stops (i.e. one for each line direction at the opposite sides of a street or respective link). At junctions with several links where different PT lines meet, this number can be even higher. As Figures 5.22 and 5.23 show, Node 8 includes two stops, whereas Node 10 includes four. The coloured arrows show how the PT lines that serve these nodes approach and leave a stop area and which stop is served by which line and by which direction of a line. Figure 5.22 shows the setup in Scenario LS and Figure 5.23 in Scenario LR.

Passengers are able to walk between the stops of a stop area which is not depicted here to avoid confusion through overlapping lines. However, this is shown in Figure 4.3. In Scenario LS, the split lines serve two stops of each stop area before the vehicles turn around to drive along the line route in the opposite direction. In Scenario LR, only one stop is served. Which stop depends on the direction of the line route.

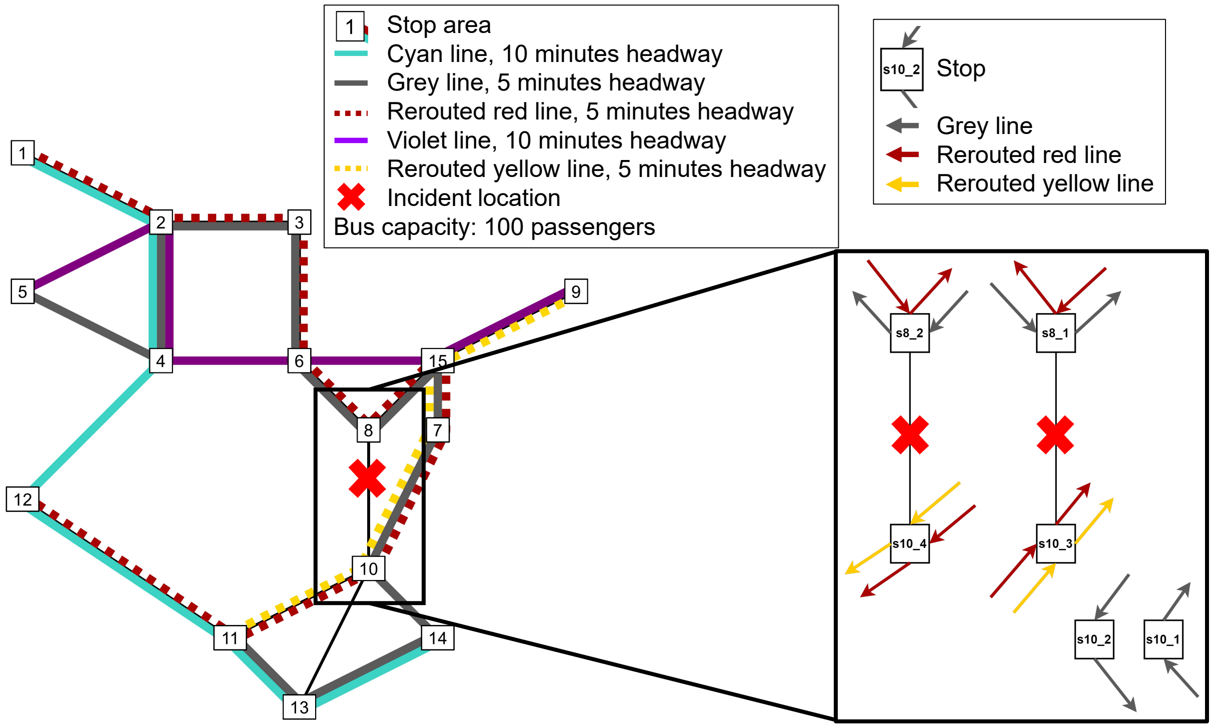


Figure 5.23: Stop setup at Nodes 8 and 10 in Scenario LR

Figures 5.24a to 5.24d show the number of passengers at the chosen stops over time. The left side shows Scenario LS and the right side Scenario LR. The upper two figures show the corresponding cases with no redirection, the middle two with the heuristic redirection approach, and the bottom two with the optimised redirection approach. The product of compliance and information rates is 100% in these results, the self-redirection rate 0%, $\psi = -1$ for Scenario LS, and $\psi = 0$ for Scenario LR. The incident duration is 60 minutes. These results are taken from the simulation runs are performed for a single random seed.

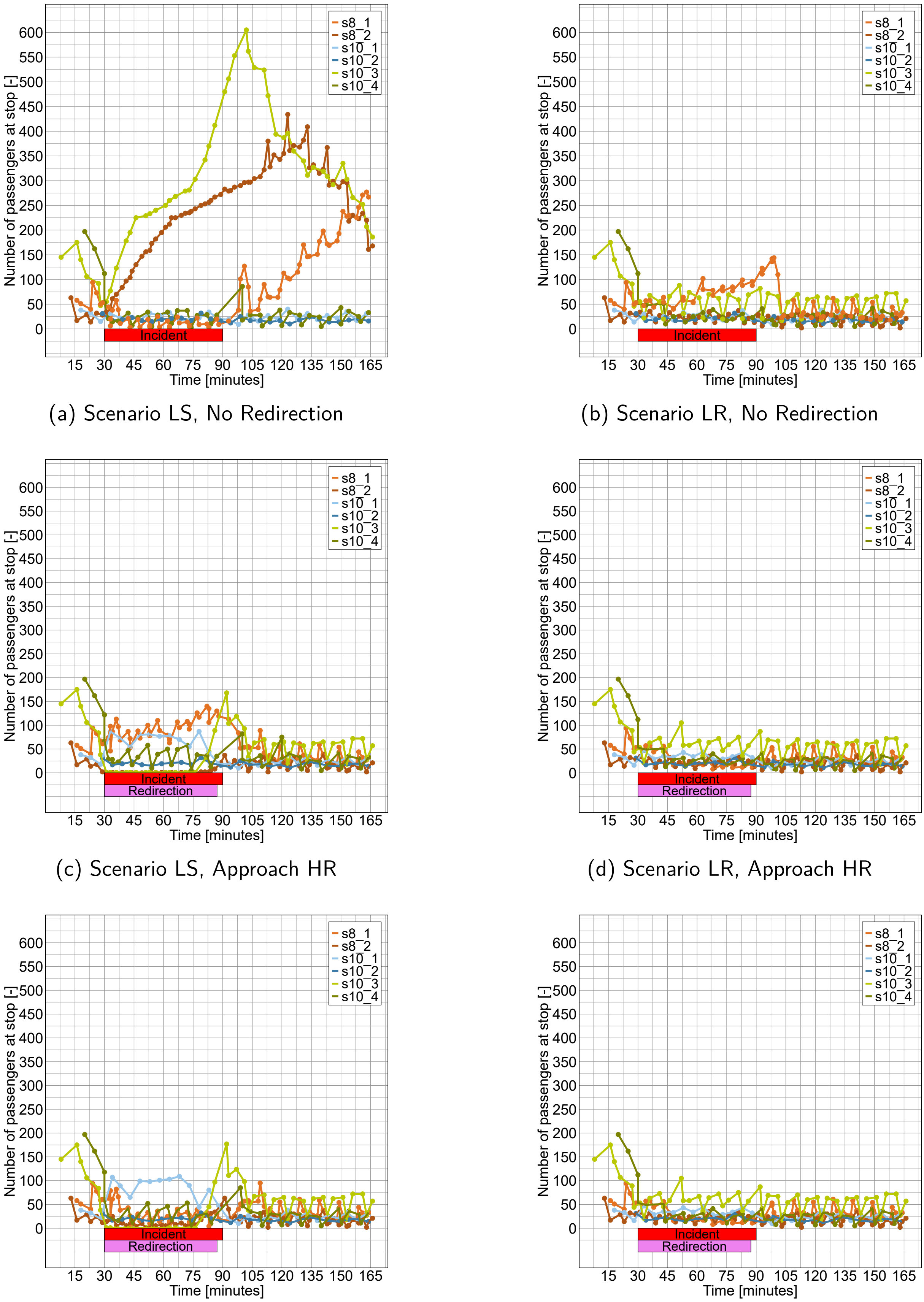
Each data point in the diagrams indicates a bus stopping at the respective stop, its departure time determines the x-value of the data point, whereas the number of passengers who have been waiting at that time at the stop defines the y-value. The orange and brown lines describe the crowding at the stops of Node 8, and the blue and green lines show the crowding at the stops of Node 10. The relatively high number of people waiting at the stops at the beginning of the scale can be explained by the fact that the passengers start to enter the network right at the beginning of the simulations, whereas the PT service starts later with different departure times for each PT line and direction. Once the PT service starts, the number of passengers at stops drops rapidly.

The crowding effects of the incidents underline the previous statement of the stronger severity of Scenario LS compared to Scenario LR. As in the latter, the service is not turning around, but keeps serving the same stops, just with an additional travel time of 3.5 minutes, the crowding is limited, even without passenger redirection. In Scenario LS the crowding increases quickly at Stops s10_3 and s8_2. These are the last two stops before the PT service would enter the edge which is disrupted due to the assumed incident. Even after the incident, it takes time until the crowding decreases as travellers continuously enter the network and the number of waiting PT users at the stops exceeds the capacity of one bus of 100 passengers. These observations also fit with the results from the previous section about the delays per time interval, as in the case with no redirection, the delays decay slowly and far beyond the end of the incident.

Since the split lines serve the rest of their routes, the Stops s8_1 and s10_4, as well as the stops served by the not disrupted grey line, do not show a significant rise in the number of waiting passengers. After the dissolution of the incident, the crowding at Stop s8_1 increases. It is the stop behind the incident site. After the dissolution of the incident, passengers travel again along the edge between Nodes 8 and 10. The red and yellow lines start to pick up the strongly accumulated traveller demand at Stop s10_3. Some of them get off at Stop s8_1 to transfer from the red line to the grey or yellow line, or from the yellow to the grey or red line. As it can be seen in Figure 5.2b a lot of passengers are travelling from Node 8 to Node 6. If however, passengers travel on the yellow line between Nodes 8 and 10, they transfer to the grey or red line at Stop s8_1. This rising number of passengers at this stop will likely to continue until the accumulated traveller demand at Stops s10_3 is completely dissipated. As the accumulated demand at Node 8 is lower, so is the crowding effect at Stop s10_4. Furthermore, this crowding development after the dissolution depends on the OD relations. As most of the passengers who travel from Node 8 to 10 have Node 10 or 11 as their destination (Figure 5.2b), they do not transfer at Node 10, hence, the low crowding at Stop s10_4 compared to Stop s8_1.

Comparing the passenger crowding in the case of HR to the case of OR in Scenario LS, it is noticeable that the crowding a Stop s8_1 is more severe during the incident in the case of HR. Hence, more passengers transfer at this stop during the heuristic redirection than in the optimised redirection which might be an indication that the optimised redirection redirects more passengers to the cyan line (Figure 5.3a) than Approach HR.

In Scenario LR, the effects of the incident on the crowding levels of the depicted stops are significantly lower. Only Stop s8_1 shows a small rise after the end of the incident. As previously implied by the results from Scenario LS, this stop is used by some passengers to transfer to another line (Figure 5.24b). This peak is not to be found in the results from the case with passenger redirection, shown in Figure 5.24d. So, even though the crowding levels are already very low during the case with no redirection they are even lower in the case with passenger redirection in Scenario LR. These observations again fit well with the results of the delays per time interval in the previous section, in which Scenario LR also shows insignificant delays during and no delays right after the incident. Comparing the case of HR to OR in this scenario, there are no noticeable differences as the crowding in general in Scenario LR is insignificant.



(a) Scenario LS, No Redirection

(b) Scenario LR, No Redirection

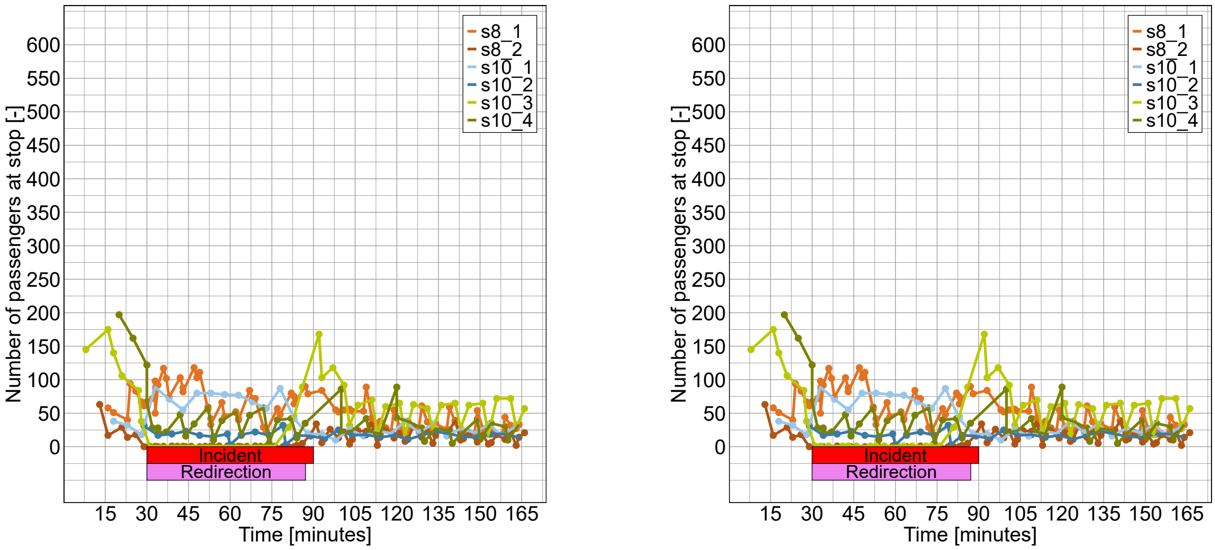
(c) Scenario LS, Approach HR

(d) Scenario LR, Approach HR

(e) Scenario LS, Approach OR

(f) Scenario LR, Approach OR

Figure 5.24: Passenger crowding at Nodes 8 and 10 with $t_i = 60$ minutes in both scenarios



(a) Scenario LS, Approach CR+HR

(b) Scenario LR, Approach CR+OR

Figure 5.25: Passenger crowding at Nodes 8 and 10 with $t_i = 60$ minutes in Scenarios LS and LR

Regarding the Approaches CR+HR and CR+OR, Figure 5.25 shows the crowding for these approaches at the investigated stops. However, only for Scenario LS as the capacity reallocation has not been executed in Scenario LR for the set of parameters used here. There are no noticeable differences in the stop-crowding levels between the two approaches with capacity reallocation. This indicates that in these cases, the noticeable differences in the results between the heuristic and optimised redirection might be eliminated through the capacity reallocation process, which uses a similar heuristic procedure as the heuristic redirection (Section 4.6).

Compared to the approaches without capacity reallocation, it is noticeable that the levels of some of the crowding lines change. This is explainable by the reallocated buses. The orange line which shows the passenger crowding at Stop s8_1 is higher with Approach HR than with Approaches CR+HR and CR+OR. In Scenario LS, buses have been reallocated onto the grey line. These cater for extra pick-ups at Stop s8_1, which lowers the crowding line accordingly. The comparison of Approaches CR+HR and CR+OR with the optimised redirection (OR) is more complex. Whereas the levels of the light green and light blue crowding lines for Stops s10_1 and s10_3 decrease, the orange crowding line for Stop s8_1 increases. As the capacity reallocation process redirects the passengers similarly to the heuristic redirection, more passengers transfer at Stop s8_1 as in the heuristic redirection, hence, the increase of the level of the orange line. Due to the same reason, the light blue line also develops in the same way as in the heuristic redirection. However, the lower level of the light green line might be caused by reallocated buses serving the grey line. Therefore, these results indicate a positive effect of the Approaches CR+HR and CR+OR on the crowding levels at stops which is logical due to the extra runs.

Nevertheless, what these diagrams do not show is how the reallocation of capacities might increase the crowding at the stops of the lines from which the reallocated buses are withdrawn. As shown in previous results, the approaches with a capacity reallocation only lead in a few cases to stronger reductions of passenger delays than the Approaches HR and OR without capacity reallocation, which indicates an increase in passenger crowding at those stops.

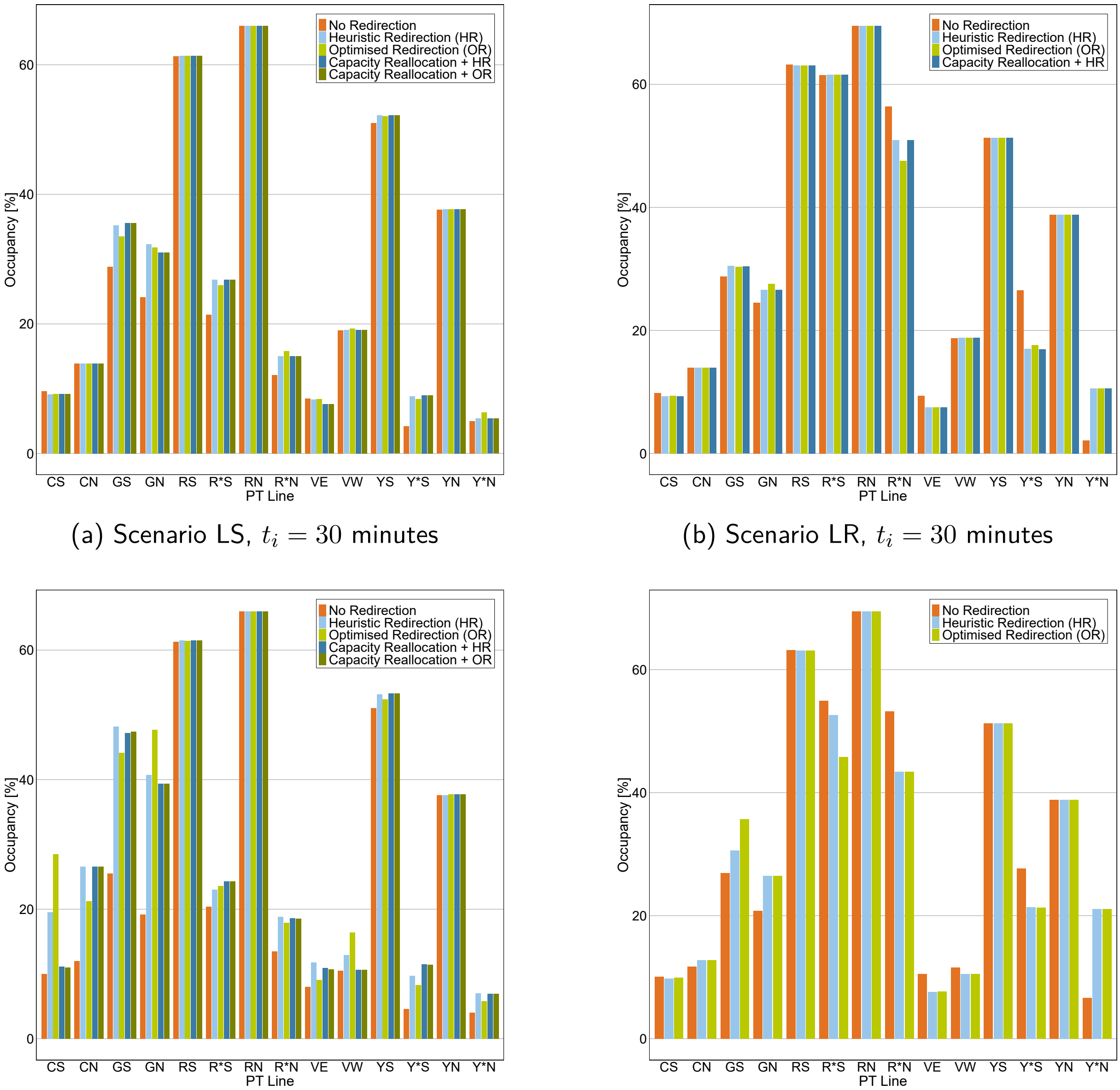
On the whole, it can be said that REPACK has a noticeable positive effect on the crowding levels at stops. This effect becomes more significant with an increase in the severity of an incident. With an increase in the self-redirection rate, a decrease in crowding at stops is likely, whereas, with an increase in the incident duration, a rising in the crowding effect is to be expected as more travellers are affected for a longer period. This leads to more people waiting at the stops for longer durations.

PT Line Occupancy

This section presents the effects of REPACK on the occupancy of the different operating PT lines. Again, $\psi = -1$ for the results of Scenario LS and $\psi = 0$ for the results in Scenario LR. A self-redirection rate of $\xi = 0\%$ is set. Furthermore, a product of compliance and information rates of 100% is used. The incident durations of 30 and 90 minutes are considered to also see an effect of the increase in the incident duration. Figures 5.26a and 5.26c on the left show the results for Scenario LS and Figures 5.26b and 5.26d on the right show the results for Scenario LR. The upper two show the cases with an incident duration of 30 minutes, and the lower two with $t_i = 90$ minutes. The first letter of the line identifications refers to the line colour (e.g. Y: yellow line), and the second letter refers to the direction of the corresponding line route (N: northward; S: southward; E: eastward; W: westward). The lines which have been split or rerouted are marked with a star (*). For the evaluation of the line occupancy, the period of the incident has been chosen in correspondence to the arrival of the PT vehicle. Hence, the results of the red and yellow line without a disposition measure depict buses that already passed the incident site, but have not yet arrived at their destination at the time when the incident occurs.

In Scenario LS the different approaches show a similar picture regarding the occupancy of the different PT lines. The most noticeable differences are to be seen in a shift towards the split red and yellow lines as well as the grey line when comparing the no redirection case with the redirection and reallocation approaches. This shift is more obvious in the case with an incident duration of 90 minutes. Here, there is also a shift towards the cyan line. The cyan and the grey line are the two obvious choices if one wants to travel around the incident site in Scenario LS. The line occupancies indicate that for shorter incident durations, most redirected passengers use the grey line. For a longer incident duration, the capacity of the grey line might not fit all redirection groups for which the cyan line is also increasingly used.

In Scenario LR, more people travel with the rerouted red and yellow line. As argued before, in this scenario, this is likely to still be the fastest path for some or even most of the affected passengers. Interestingly, in the case with an incident duration of 30 minutes, when comparing the no-redirection case with the passenger-redirection and capacity-reallocation approaches, the occupancy of the rerouted southward yellow line is reduced whereas the occupancy of the



(a) Scenario LS, $t_i = 30$ minutes

(b) Scenario LR, $t_i = 30$ minutes

(c) Scenario LS, $t_i = 90$ minutes

(d) Scenario LR, $t_i = 90$ minutes

Figure 5.26: PT line occupancies in Scenarios LS and LR

rerouted northward yellow line increases. Logically, this cannot be due to the same passengers. Therefore, it might be the case that affected passengers travelling southward are redirected onto other lines than the yellow line, whereas affected passengers travelling northward are redirected onto the yellow line. This phenomenon can also be observed in the case with an incident duration of 90 minutes, however, as in Scenario LS, here, there is also a shift towards the grey line.

By and large, the changes in the line occupancy are most significant between the no-redirection cases and the other cases with passenger redirection. The size of the network and the number of lines, which limits the number of alternative travel options, are possible reasons. Nevertheless, the results show a noticeable shift and point out some lines which are of importance to the passenger redirection, such as the grey line, for instance. The capacity reallocation approaches do not show a significantly different picture of the line occupancy than the redirection approaches. However, there are some peaks in the Scenario LR in the case with an incident duration of 30 minutes of Approach CR+OR which might be an indication of vehicles being withdrawn. In Scenario LS most reallocated vehicles have been withdrawn from the violet line and dispatched to the grey line, whereas for Scenario LR, most reallocated vehicles have been withdrawn from the cyan and violet lines to support the red line.

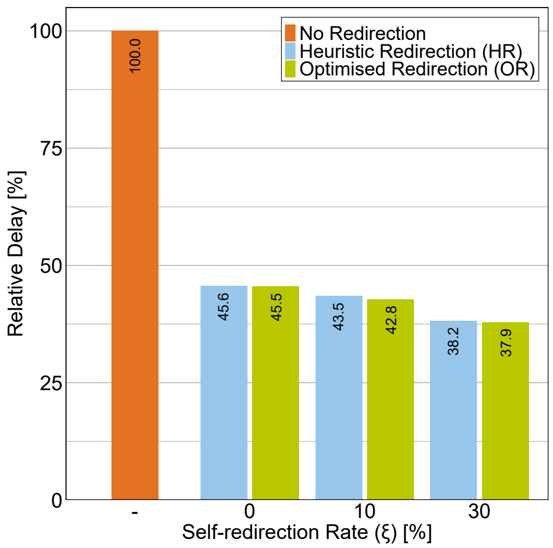
Special Cases with Limited Information Availability

In addition to the cases which have been previously presented in this section, special cases for each scenario – LS and LR – are conducted in which the information rate ζ is dependent on the size of the redirection group on the fastest alternative path of each affected OD pair $od \in OD_a$ ($rg_{od}^{\hat{p}}$) (Section 4.5). Only a limited number of OD pairs has an information rate of 100%.

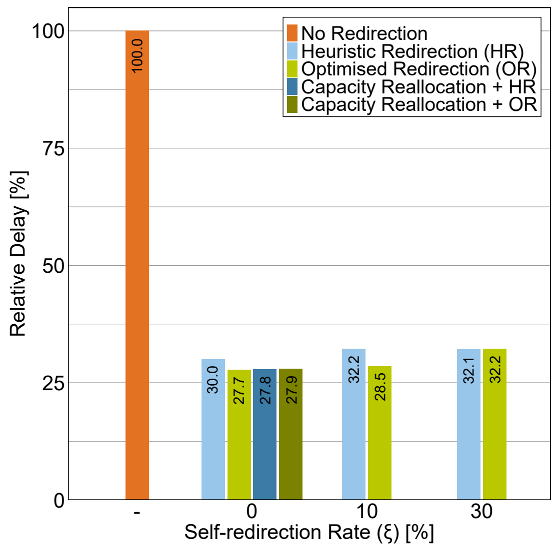
Since dynamic PI displays do not have unlimited space to disseminate information and speaker announcements cannot continuously broadcast information, as it would rather confuse than help, only a limited number of OD pairs can be informed via the collective PI channels. This is unfortunate, as these channels are preferred by the survey participants for receiving information during incidents (Figure 3.7). It is reasonable that the OD pairs with the biggest redirection groups $rg_{od}^{\hat{p}}$ are chosen, as in this way more people profit from the path advice. It is assumed that these OD pairs have an information rate of 100%. For the rest of the OD pairs, an information rate of 25% is considered, as this is about the share of survey participants who prefer social media, websites, and PT smartphone apps as PI channels during incidents. This is tested for the first five OD pairs with the largest $rg_{od}^{\hat{p}}$. The compliance rate η is set to 100%.

Figures 5.27a and 5.27c show the case in which only the aforementioned five OD pairs are completely reachable; Figures 5.27b and 5.27d show the case in which for all OD pairs $\zeta = 100\%$. The two figures on the top show the cases with $t_i = 30$ minutes and the two on the bottom with $t_i = 90$ minutes. The self-redirection rate ξ increases from left to right from 0% to 30%. The results express that for a disruptive event such as in Scenario LS, REPACK is also useful, even if only the five OD pairs with the largest redirection groups completely receive the path advice and of the redirection groups of the remaining OD pairs, only a quarter receives the path advice. However, this is for $\eta = 100\%$. For lower compliance rates, which are likely according to the results of the PT user survey presented in Section 3.2.3, the relative delay increases.

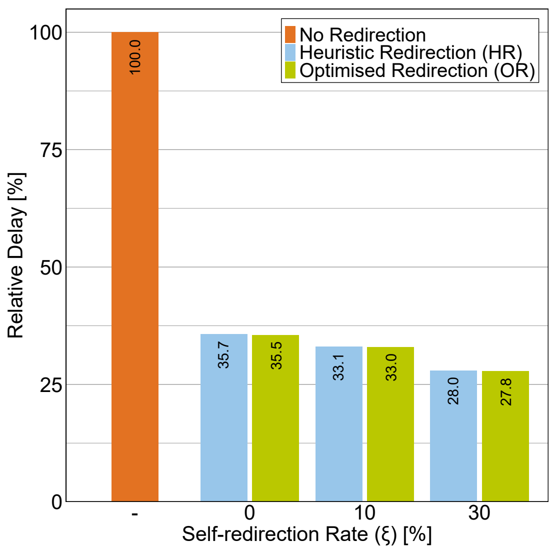
For Scenario LR this is not the case (Figure 5.28a). With a rising incident duration, the positive effect of REPACK on the relative passenger delay increases. In addition to the fact that a longer incident duration leads to more severe delays and therefore to stronger reductions in delays for the informed passengers. For example, in Scenario LS and Approach HR



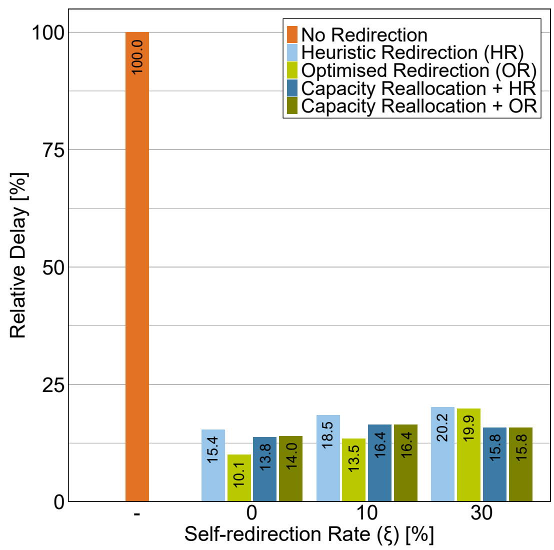
(a) $U_a \subset U$; Scenario LS; $t_i = 30$ minutes; 5 OD



(b) $U_a \subset U$; Scenario LS; $t_i = 30$ minutes; all OD



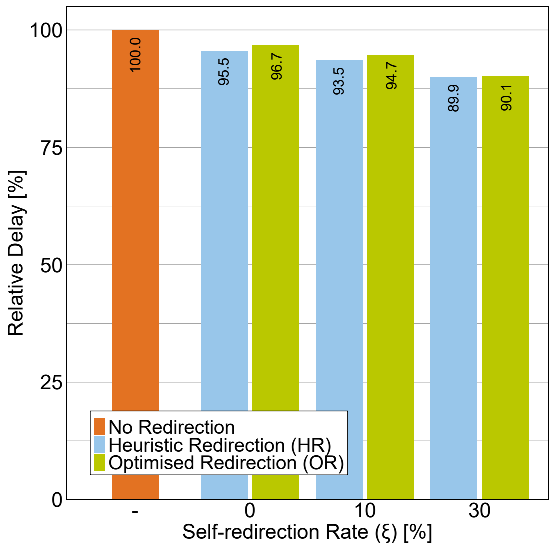
(c) $U_a \subset U$; Scenario LR; $t_i = 90$ minutes; 5 OD



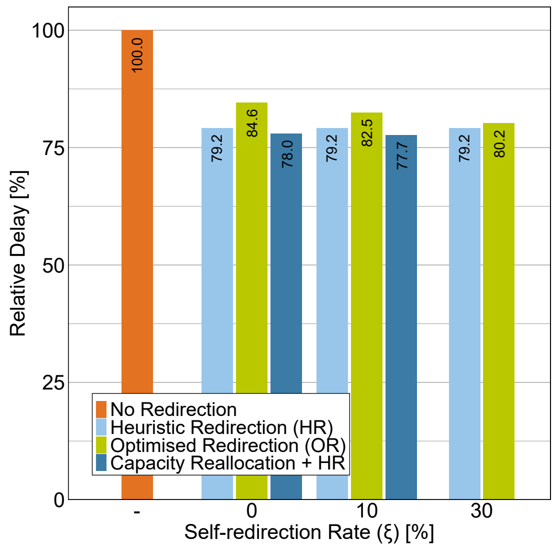
(d) $U_a \subset U$; Scenario LR; $t_i = 90$ minutes; all OD

Figure 5.27: Relative delays of $U_a \subset U$ comparing merely five $od \in OD_a$ to all $od \in OD_a$ informed with $\zeta = 100\%$ in Scenarios LS ($\psi = -1$)

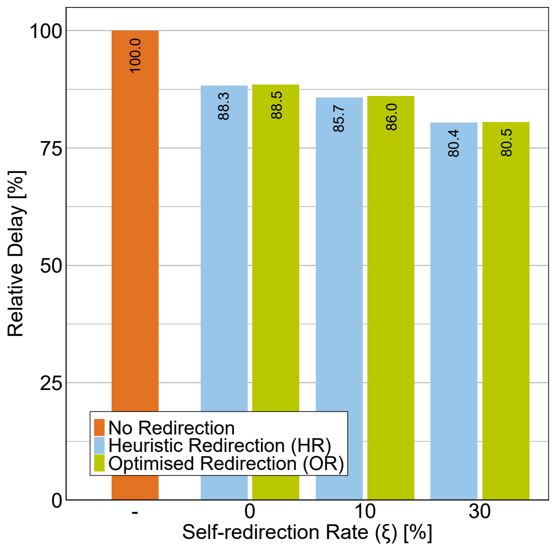
with $t_i = 30$ minutes, the number of redirected passengers is 666, which is about 60.5% of the 1,100 affected passengers. With $t_i = 90$ minutes, the number of redirected passengers is about 1,971, which is 58% of the 3,410 affected passengers. Therefore, there is a higher chance that the remaining capacity on the fastest alternative paths is raised due to a reduced number of informed passengers. This improves the situation for the informed travellers. For comparison, in Scenario LS and heuristic passenger redirection with a product of compliance and information rates of 100%, the number of redirected passengers is about 1,100 for $t_i = 30$ minutes and 3,357 for $t_i = 90$ minutes. Hence, in the former case, all affected passengers (1,100) are redirected and in the latter, almost all affected passengers (3,410) are redirected. Thus, the results are better for the cases with no limitations on the information availability.



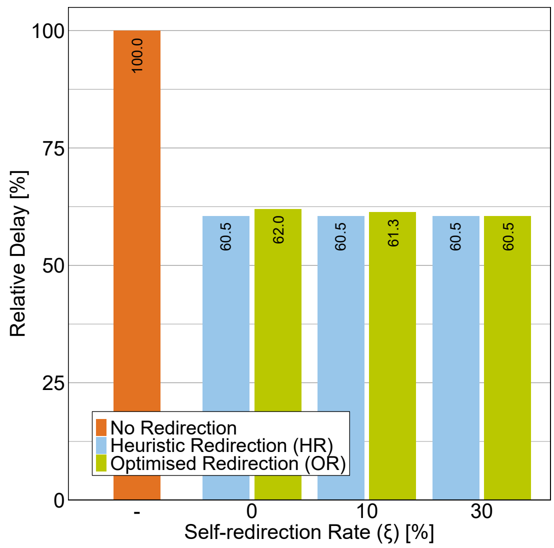
(a) $U_a \subset U$; Scenario LS; $t_i = 30$ minutes; 5 OD



(b) $U_a \subset U$; Scenario LS; $t_i = 30$ minutes; all OD



(c) $U_a \subset U$; Scenario LR; $t_i = 90$ minutes; 5 OD



(d) $U_a \subset U$; Scenario LR; $t_i = 90$ minutes; all OD

Figure 5.28: Relative delays of $U_a \subset U$ comparing merely five $od \in OD_a$ to all $od \in OD_a$ informed with $\zeta = 100\%$ in Scenarios LR ($\psi = 0$)

5.2.3 Implementation in an Autonomous PT System

In the previous case study, all PT lines have been served by buses. In addition, in this section, the setup and results of a case study are described in which the PT lines are served by the aforementioned DART system. Rau, Tian et al. [2018] and Rau, Jain et al. [2019] introduce the setup and properties of the DART system. It is an autonomous and connected PT system with a modular setup. Instead of buses, PT lines are served by autonomous bus modules which offer a capacity of 30 passengers. The general idea behind the system is that the timetable is designed in a way that single modules serve different feeder lines and meet at the beginning of a common section, a trunk line, to couple and serve this common section as a platoon of modules.

Platooning of vehicles describes the driving of several vehicles behind each other with small intra-platoon gaps between the vehicles within a platoon. Through vehicle-to-vehicle (V2V) communication, vehicles are capable of sharing certain information such as location, speed, and acceleration with each other. This enables them to keep a smaller gap between each other, compared to mandatory safety gaps which need to be kept by human drivers.

The platooning of trucks on highways is an especially well-researched area in literature. Two investigated advantages of truck platooning are energy and space savings through the reduced gap size between the vehicles and the resulting improved slipstream effect [Bachmann, 2017; Bachmann and Sethuraman, 2019; Larsen et al., 2019].

In addition, in recent years more and more investigations regarding platooning in urban traffic have been conducted. One finding, for instance, is the advantages concerning the increased throughput of vehicles as well as advantages for traffic light signalling as an electronically coupled platoon needs less time to cross an intersection than the members of such a platoon would need as individually driving vehicles [Lioris et al., 2017; Y. Wu et al., 2022].

Moreover, there also have been investigations regarding platooning in PT systems in recent years. Cao et al. [2022], for instance, introduce a coupling and decoupling process of PT vehicles and its integration in the PT schedule planning process. This is also a concept used in the DART system. Sethuraman et al. [2019] conclude that platoons of DART modules cater for energy savings as well as an increase in the effectiveness of PT prioritisation at signalised intersections. This is argued through the fact that coupled modules arrive together at intersections which reduces the number of arrivals of PT vehicles at intersections.

In addition to the aforementioned advantages of platooning concerning energy and space savings as well as the improvement of traffic flow, Bachmann, Rau et al. [2021] imply that platooning of DART modules can also improve capacity reallocation during incidents, which has been tested in a numerical example. The conceptional framework of the capacity reallocation process by Bachmann, Rau et al. [2021] has been further developed into an applicable model and is presented in Section 4.6. It is used here to implement the DART system into a simulation study in the Mandl network.

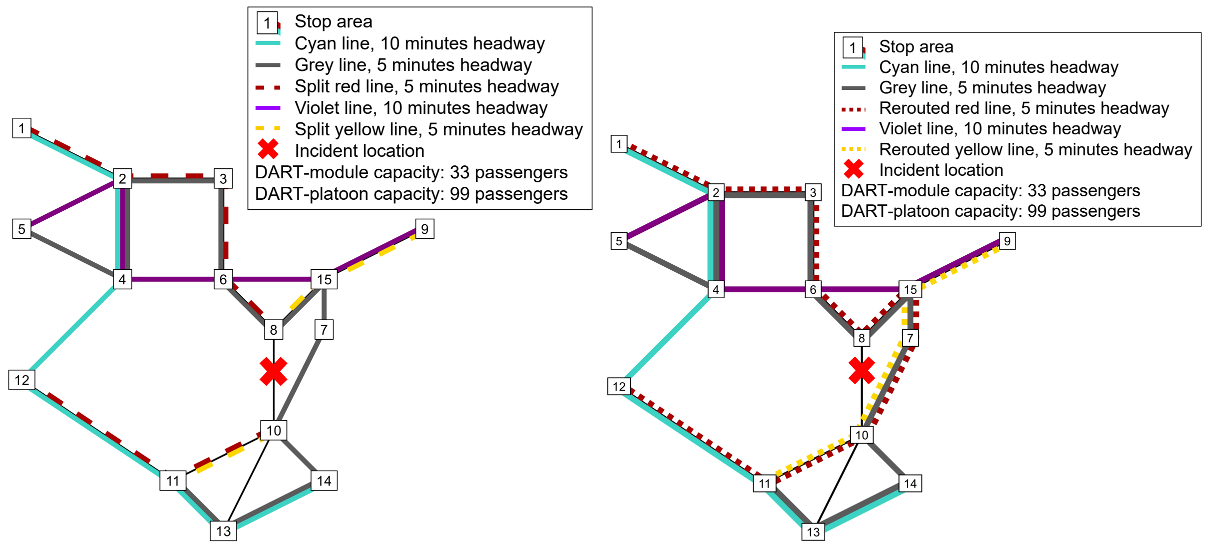
Case Study Setup in the DART System

Instead of 30 passengers per module, a capacity of 33 passengers is assumed here and the lines are served by platoons of three DART modules. In this way, a platoon has about the same capacity as one bus in the previous case study (99 versus 100 passengers). This improves the comparability between both PT systems. Due to the modular setup of the DART system, a capacity reallocation can be undertaken here by just reallocating one or two modules to the PT lines with insufficient capacity, instead of the whole platoon. Therefore, in contrast to the process in a PT bus system as described in Section 4.6 when searching the PT system for dispensable capacities, it is not checked whether the following platoon can take the passengers of the previous one to then reallocate the complete platoon of three modules. Instead, it is checked if the occupancy of a platoon is below one-third or two-thirds of its capacity of 99 passengers. In the former case, two of the three modules, which form a platoon, can be reallocated. In the latter case, one module can be reallocated. In this way, the decay of service quality through the reallocation on the line, from which the modules are withdrawn, is smaller compared to the previous studies, in which whole buses have been withdrawn. This is due to the fact that even though the capacity is reduced, the headway is not extended as still one module or a platoon of two modules serves their original line.

Please note that the dynamics of platooning have not been implemented in SUMO. Instead, modules and platoons are represented by buses of corresponding size and capacity. Whole platoons of three modules have the same size as the buses in the previous study, but with a capacity of 99 passengers. If dispensable capacity is identified and matched with an affected OD pair $od \in OD_a$, such a bus, representing a whole platoon of three modules, is reduced to one-third or two-thirds of its size as well as its capacity (i.e. 33 or 66 passengers), depending on whether a platoon can spare one-third or two-thirds of its capacity. In addition, a second vehicle is inserted in the simulation with a corresponding size and capacity, representing the decoupled module or modules which are reallocated. As in the previous case study, for this procedure, SUMO's API TraCI has been used [DLR, 2022]. It is assumed that the dynamics of platooning as the coupling and decoupling process do not have a significant influence on the passengers' travel time and that it can therefore be represented in this way without significant effects on the passenger delays.

Unfortunately, for $\psi = -1$ in Scenario LS and $\psi = 0$ in Scenario LR, the capacity reallocation is not executed in the case study with the DART system. Therefore, to be able to compare the two PT systems concerning the capacity reallocation process, factor ψ has been set here to -2 in both scenarios – LS and LR – through which the capacity reallocation is executed. The redirection duration T^p_{od} is thereby longer in the following case study than in the previous one (Equation 4.2). For Scenario LS, the study is done with an incident duration of 60 and 90 minutes and for Scenario LR with $t_i = 30$ minutes.

For these cases, a self-redirection rate ξ of 10% as well as products of compliance and information rates of 0%, 35%, 70%, and 100% are used. The timetable, demand, and disposition measures are as set as in the previous case study (Figure 5.29).



(a) Scenario LS

(b) Scenario LR

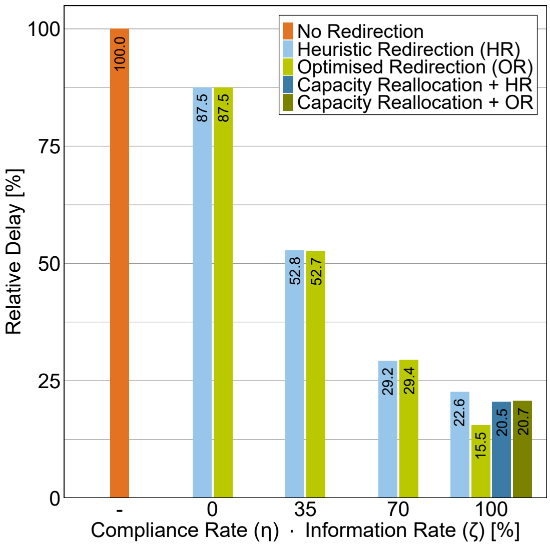
Figure 5.29: Mandl PT network served by the DART system with disposition measures

Results of the Case Study in the DART System

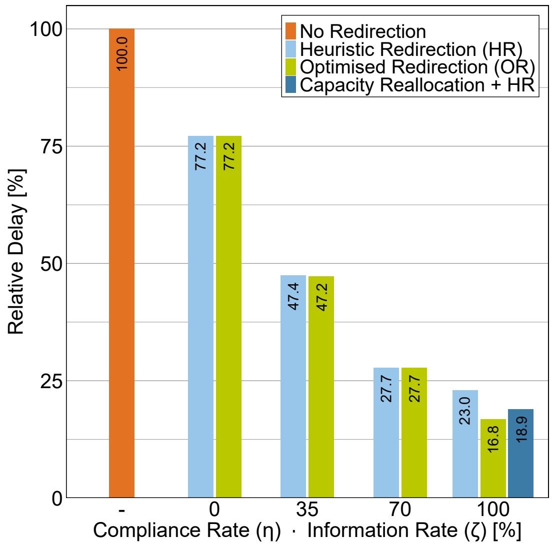
Due to the similar vehicle capacity and the same timetable and disposition measures, it can be expected that the results for the passenger redirection Approaches HR and OR are somewhat similar to those in the previous case study, in which the PT lines have been served by buses. Additionally, minimal or no differences can be expected regarding the total delay in the no-redirection case. For the capacity reallocation approaches – CR+HR and CR+OR – however, an improvement in the results might be expected due to the improved flexibility in reallocating capacities due to the modular setup of the DART system. Still, these advantages are more likely to be seen in the results for all passengers than for the affected passengers, as the main advantage of the modular setup of the DART system is that the headway on the original lines of reallocated modules can be maintained even during the reallocation process.

As expected, the total delays in the no-redirection case show merely insignificant differences. For Scenario LS with $t_i = 60$ minutes and $\xi = 10\%$, the total delays in the bus system are 2075.1 hours, whereas they are 2093.6 hours in the DART system. For Scenario LR with $t_i = 30$ minutes and $\xi = 10\%$, the total delay of the affected passengers is 80.7 hours in the bus system and 81.2 hours in the DART system.

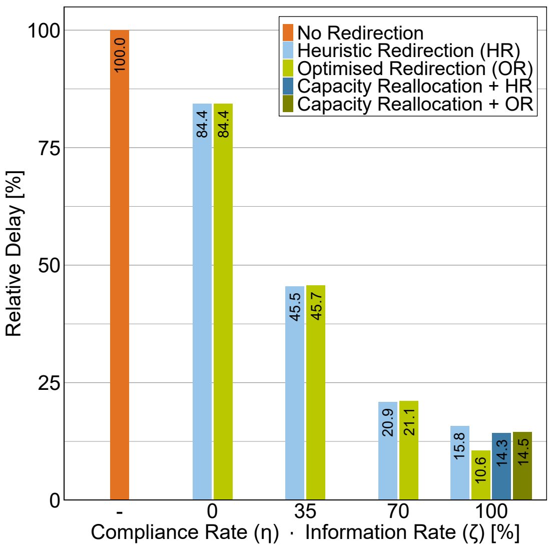
Figure 5.30 presents the relative delays in Scenario LS with $t_i = 60$ minutes and $\xi = 10\%$. The upper two figures show the relative delays of the affected passengers $U_a \subset U$, whereas the lower two pictures present the relative delays of all passengers U. On the left side there are the results of the case study in the DART system and on the right side there are the results of the case study in the bus system. Generally, the results develop similarly from $\eta \cdot \zeta = 0\%$ to $\eta \cdot \zeta = 100\%$ for both PT systems. With an increase in the product of compliance and information rates, the delay reduction improves. However, in contrast to the expectations, there are already visible differences between the results of the two systems concerning the



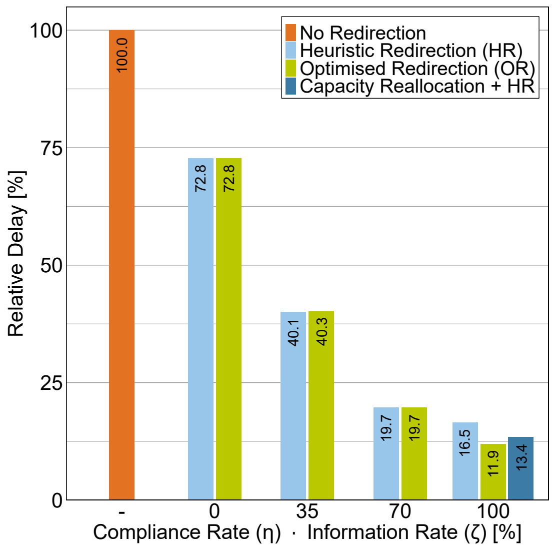
(a) Relative delay of $U_a \subset U$; DART system



(b) Relative delay of $U_a \subset U$; bus system



(c) Relative delay of U; DART system



(d) Relative delay of U; bus system

Figure 5.30: Overall relative delays in Scenario LS in a bus and the DART system with $t_i = 60$ minutes and $\xi = 10\%$ $(\psi = -2)$

passenger redirection approaches – HR and OR – without the capacity reallocation. The bus system performs better in all cases with $\eta \cdot \zeta < 100\%$. It is rather doubtful that this difference can be explained by the reduced capacity of the DART modules by one place, but is rather due to simulation dynamics of random interactions between the travellers and the PT vehicles.

Another obvious observation is that for the DART system, both capacity reallocation approaches – CR+HR and CR+OR – are executed, whereas for the bus system, merely Approach CR+HR is done. However, in contrast to the expectations, the bus system performs better in the cases with a capacity reallocation than the DART system. This is true for the affected as well as all passengers. Reasons for this can be that this kind of micromanagement of capacities is over-shooting the intentions of providing better service during incidents or that sending smaller vehicles with less capacity to the line with insufficient capacity does not makes sense if not all affected passengers at a stop can board the additional vehicle due to insufficient capacity. Another possible explanation for this might be the differences in the process of the identification of dispensable capacity as explained in the previous section. Through this, the timings of the DART modules might be different and less fitting than the timings of the buses. As discussed before in Section 5.2.2, when reallocated vehicles arrive shortly before or after a regularly scheduled bus of the supported PT line, the reallocation process might worsen the situation for the passengers rather than improve it. This effect might be stronger for the DART than for the PT bus system in these cases.

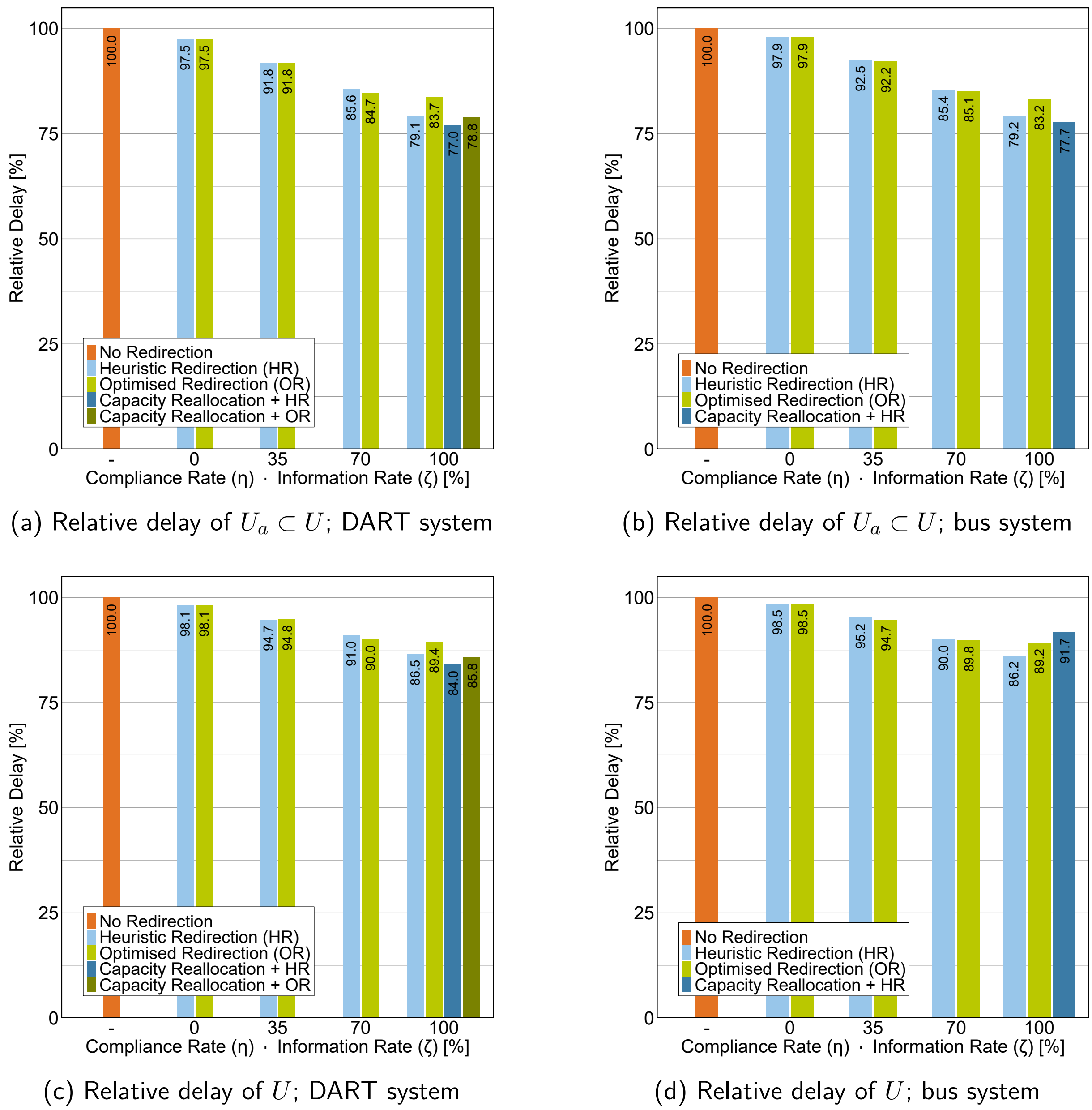
Interestingly, Approach OR performs best in DART system in the compared cases with a delay reduction of 89.4%, which again, can only be explained by the variances through simulation dynamics. Nevertheless, the differences between the results of both systems are rather insignificant and motivate further investigations to find out the reasons for the differences.

In Figure 5.31 the results for Scenario LR with $t_i = 30$ minutes and $\xi = 10\%$ are presented for both PT systems. The results for the DART system are again on the left side and for the bus system on the right side, with the relative delays of $U_a \subset U$ on top and of U on the bottom of this set of figures.

Here, the differences in the passenger redirection approaches – HR and OR – are less noticeable between the two PT systems compared to the results from Scenario LS. Furthermore, the DART system performs here slightly better than the bus system with $\eta \cdot \zeta < 100\%$. With full compliance and information availability, the bus system performs insignificantly better.

As in Scenario LS, Approach CR+HR is executed in both systems whereas CR+OR is only executed in the DART system. Here, the DART system accomplishes the best result among all cases with a relative delay of 77.0% for the affected passengers $U_a \subset U$ and 84.0% for all passengers U. This means that the circumstances for the advantage of the modular setup of the DART system have been right or at least better in this case. This invites further research to find out which circumstances need to be met for the DART system to be able to unfold its full potential during capacity reallocation, especially because the difference to the second best result in the case of the bus system with Approach HR, with a relative delay of 79.2% for the affected passengers and 86.2% for all passengers, is just insignificantly worse.

In summary, it can be said that the DART system performs similarly to the bus system during the capacity reallocation, in Scenario LS slightly worse, in Scenario LR slightly better. As the previous case study in Section 5.2.2 point out, the capacity reallocation process needs further research and adjustment to better fit its task of supporting passenger redirection during incidents. This is further discussed in Chapter 6.



(a) Relative delay of $U_a \subset U$; DART system

(b) Relative delay of $U_a \subset U$; bus system

(c) Relative delay of U; DART system

(d) Relative delay of U; bus system

Figure 5.31: Overall relative delays in Scenario LR in a bus and the DART system with $t_i = 30$ minutes and $\xi = 10\%$ ($\psi = -2$)

5.3 Implementation in the Network of the City of Kassel

In addition to the Mandl network, REPACK has also been implemented for the network of the city of Kassel, Germany, to test it in a more complex and more realistic network. Kassel is a big city with 207,622 inhabitants [City of Kassel, 2023]. The Kassel region special purpose association [Translated from German: Zweckverband Raum Kassel] (ZRK), of which the city administration of Kassel, the North Hessian transport association [Translated from German: Nordhessischer Verkehrsverbund] (NVV), and the Kassel transport company [Translated from

German: Kasseler Verkehrsgesellschaft] (KVG) are members, have provided a transport model of the operating area of the NVV. This area includes the northern half of the federal state of Hesse. As the focus of this thesis lies on urban PT systems, the city centre of Kassel has been extracted from the transport model. Since this model is implemented in PTV Visum, the used part of it was extracted using the "Subnetworkgenerator". This is a tool to cut out a part of a PTV Visum transport model [PTV Group, 2023].

However, the transport model was not directly convertible into a SUMO network, therefore, the "OSMWebWizard", which is a tool to extract networks from Open Street Map (OSM) and to save them as SUMO network, has been used to build the basis of the simulation model used here [DLR, 2022; OSM Foundation, 2023]. Nevertheless, the transport model from Kassel contains the OD zones from which traffic originates and to which traffic flows. The geographical definition of these zones has been transferred to the created SUMO network. The transport model also contains OD matrices for pedestrian, cyclist, car, and truck demand, as well as PT user demand of 24 hours of a usual weekday.

If the demand has been assigned onto corresponding paths before the subnetwork has been extracted, the corresponding demand for the subnetwork can be exported from the transport model in PTV Visum. For this process, PTV Visum creates so-called cordon zones. These represent the origin and/or destination of OD relations which lie outside the created subnetwork to be able to also include this demand. Unfortunately, these do not contain geographical area information and have therefore not been transferred to the SUMO network. Nonetheless, since in the model used here, only urban PT services have been simulated, and demand beyond the borders of the subnetwork also uses regional and long-distance PT services, it would not have been possible to assign the external demand appropriately. The PT users who travel within the city is about 70% of the overall demand (including the cordon zones). Therefore, this demand has been increased accordingly, to compensate for the missing trips from outside the city centre.

Furthermore, the period of the day during which the demand is simulated has been chosen to be the four hours from 6 am to 10 am. This period is about the period of the morning peak during which the traffic demand is highest throughout the day [Heimböckl, 2005; Klein, 2021]. So, even though 4 hours are about 16.7% of the day, it has been assumed that about 35% of the daily PT users are travelling in this period. This leads to a demand of about 31,390 people. Since the focus of this work lies on PT, people who only use walking as a transport mode have been filtered out, which leaves a demand of about 25,300 PT users, depending on the random seed. The same number of random seeds as in the Mandl network have been used. To limit the complexity of this case study, cyclists, motorised individual traffic, and freight transport have not been considered, as it would have also caused the need for calibrating the traffic lights. These have been set to actuated signalling which means that they react to the traffic demand, which in this case are the PT vehicles.

The transport model of Kassel also contains PT line routes and timetables which have further been complemented by schedule information from KVG's website [KVG, 2023]. The city centre of Kassel that has been used here comprises a complex PT network which is served by 20 bus lines (10, 11, 12, 13, 14, 16, 17, 21, 25, 26, 27, 30, 32, 37, 38, 51, 52, 100, 110, 500), 7 tram lines (1, 3, 4, 5, 6, 7, 8) and 3 "RegioTram" lines (RT1, RT4, RT5) [KVG, 2023]. The "RegioTram" is a regional tram service that also serves suburban areas. However, in the transport model used here, only the parts of the lines which are in the simulated area are considered. The level of complexity is therefore a lot higher than the level of complexity of the Mandl network (Figure 5.2). Figure 5.32 shows a map of the simulated part of the city of Kassel with the PT services that have been taken into account here. The bus lines are depicted by cyan lines, the tram lines by violet lines, and the regional tram lines by yellow lines. A capacity of 100 passengers is assumed for the buses, a capacity of 180 passengers for the tram trains and a capacity of 220 passengers for the regional tram trains.

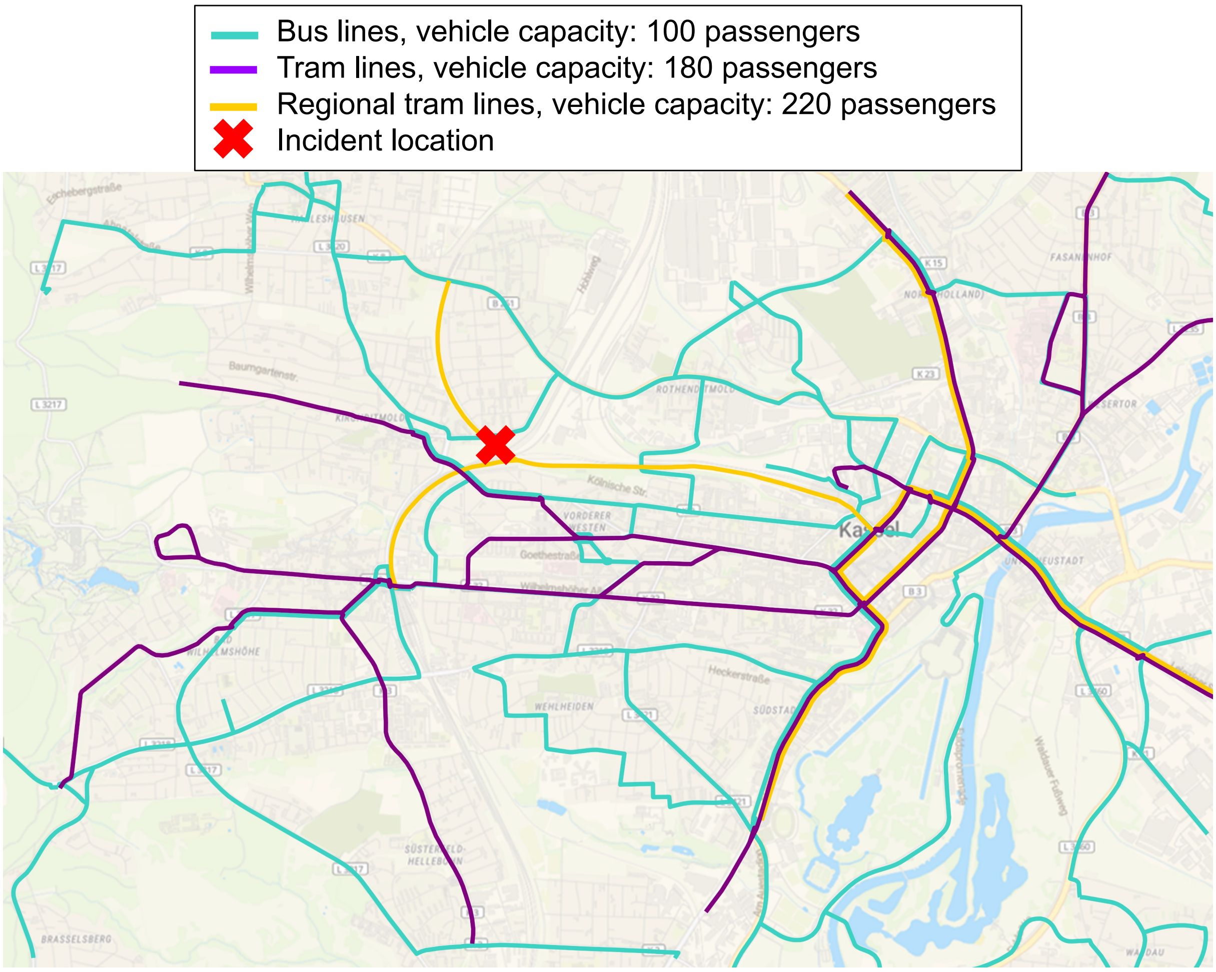


Figure 5.32: PT network of the city of Kassel

5.3.1 Case Study Setup in the Kassel Network

As has been discussed in Section 5.2.2, factor ψ, which influences the redirection duration T^p_{od} (Equation 4.2), is difficult to set probably and needs further research. Moreover, in the Kassel network, the headways of the lines vary between 10 minutes and a full hour, which increases the influence of ψ on T^p_{od} immensely. Therefore, to ensure that T^p_{od} is not set illogically, as it could lead to PT users being redirected for a too-short or too-long period, ψ has been set here to 0. The incident duration t_i is 60 minutes.

The results from the case study in the Mandl network show that REPACK is more reasonable in situations with more disruptive disposition measures such as PT line-splitting than less disruptive such as PT line-rerouting. Therefore, for the case study in the Kassel network, a scenario with line-splitting is set. Since this disposition measure is more common in railway operations, as the rail network offers fewer diversion options than the more closely meshed road network (Section 2.2.1), the regional tram lines RT1 and RT4 have been split in this Scenario LS. A track-switch failure is assumed between the central station and the stop "Kirchditmold" as shown by the red cross on the map in Figure 5.32. The two lines can short-turn on both ends of the incident site but not serve the stops as scheduled during the incident. The two split lines RT1 and RT4 run with a headway of 60 minutes.

As said in Section 4.4, the implementation of the all-simple-paths algorithm, which has been used to create a set of all simple paths in the Mandl network [Sryheni, 2022], is too complex for a network as large as the network of Kassel. The complexity of the algorithm is $O(|n|!)$, where $|n|$ is the number of nodes in the network. Therefore, to collect the necessary set of alternative paths for Kassel, a k-shortest path algorithm (Section 2.1.2) has been used [Meooow, 2022]. K indicates the number of paths that are supposed to be found for one OD relation, if available. This value has been set to 100, to ensure that enough alternative paths are found for the affected OD pairs. However, in a network as complex and as large as this network, even with $k = 100$, there might be paths that are not considered due to this limit on the number of alternative paths. Furthermore, instead of searching the network for all OD relations, only those have been searched which are needed for the affected OD pairs $od \in OD_a$. In this case, just about 200 relations have been searched, instead of over 200,000. Due to the five random seeds, some of the origins of redirection are different in the various simulation runs.

5.3.2 Results of the Case Study in the Kassel Network

The results of the case study conducted in the Kassel network show a smaller reduction of the delay of the affected and all passengers than the results from the case studies in the Mandl network. However, in case of a product of the information and compliance rates of 100%, the delays of the affected passenger can still be reduced by 38.5% for the affected and 50.9% for all passengers. As in the case studies in the Mandl network, the delay reduction grows with an increase in the product of compliance and information rates. One reason for the lower effect of REPACK might be the less central location of the incident than in the previous case studies. This caters for a lower level of severity of the incident's disturbances for example in terms of fewer affected passengers of about 180 passengers with $t_i = 60$ minutes. The previous case studies show that the more severe the incident, the better the effectiveness of REPACK. Furthermore, even though the incident is not severe for the system, it is severe for the affected passengers through the line-splitting of the PT lines RT1 and RT4. Hence, a negative value for factor ψ might lead to better results than $\psi = 0$ as it is set here. Nevertheless, this case also shows that REPACK has a positive effect on passenger delays if an incident is less centrally located.

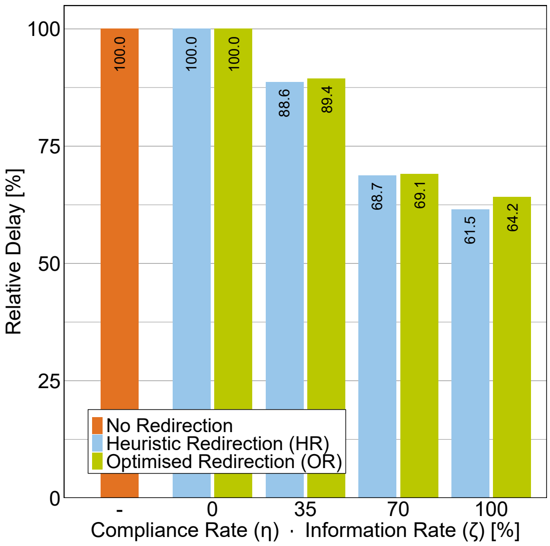
Another striking observation is that for all passengers U, the heuristic redirection approach (HR) performs significantly better than the optimised redirection (OR). This becomes continuously more obvious with a rising product of compliance and information rates. Moreover, it is a noticeable difference to the results of the case studies in the Mandl network in which the OR performed better than the HR with $\eta \cdot \zeta > 80\%$ (Section 5.2.2).

Another significant difference is that this observation is more true for all passengers rather than for the affected ones, meaning that HR shows a smaller negative effect on the indirectly affected passengers $U_{ida} \subset U$ than OR. This can be explained by the different procedures of calculating the remaining capacities when comparing Approach HR with OR (Section 4.5). Through a segment-wise calculation of the remaining capacity in Approach HR, which takes the travel time of the redirection groups (rg_{od}^{p}) on the alternative paths into account, the estimation of it is more precise than in Approach OR. In this approach, the incident duration is used as the period to calculate the remaining capacity. Due to the longer headways, this might be a bigger disadvantage in more complex scenarios with a larger range of headways. In this case, this probably leads to passengers being redirected to services with insufficient remaining capacity. This causes an increase in the delays of the indirectly affected passengers. Another possibility might be that the complexity of a network might be another decision support factor to decide whether Approach HR or OR is used for passenger redirection. This is further discussed in Section 6.1.

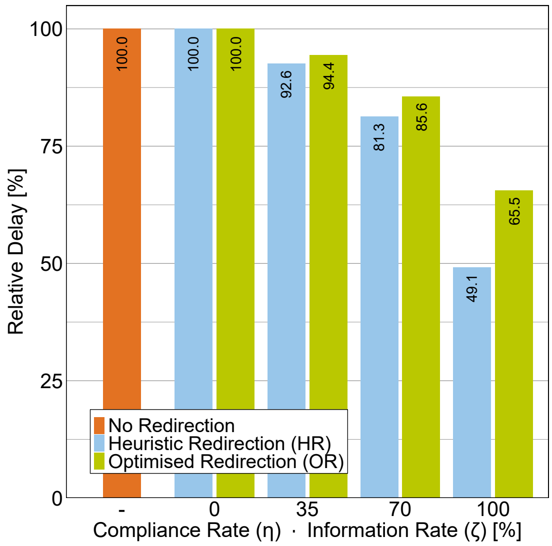
Moreover, the difference between the total delay of the affected passengers compared to all passengers is striking for the case with $\eta \cdot \zeta = 100\%$ in which the total delay of all passengers U is lower than for the affected passengers $U_a \subset U$ in the case of the heuristic redirection approach. This means that the redirection improves the situation for the unaffected $U_{una} \subset U$ and/or indirectly affected passengers $U_{ida} \subset U$ more than for $U_a \subset U$. The fact that this only happens in the case of the heuristic redirection (HR) but not in Approach OR might be again due to the differences in the calculation of the remaining capacity of alternative paths among these two approaches, which is more precise in the latter than in the former (Section 4.5).

Another explanation can be that REPACK needs further adjustments and development to be more suitable for an application in more complex and more realistic networks.

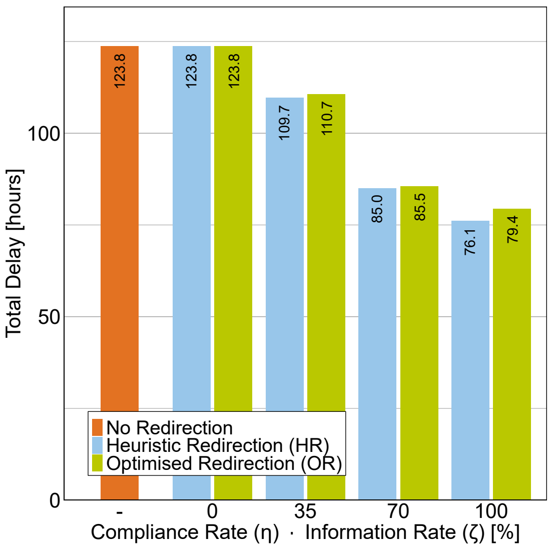
The representation of the PT service by the network graph as explained in Section 4.3 might be too simple for such a complex case. For example, traffic lights could lead to delays of the buses and a later arrival at stops which is not considered in the graph. A representation that takes the actual arrival times of PT services into account would be more precise. This becomes even more important when the demand for individual traffic modes such as cars and freight transport is considered. Additionally, some aspects such as calibrating the traffic lights and implementing PT prioritisation at traffic lights have not been taken into account here, which also probably influences the outcome. Moreover, implementing the PT service exactly as it is in practice likely influence the results. In this case study, only a simplified version of the actual timetable which considers the headways but not additional services during peak hours might be a reason for these results.



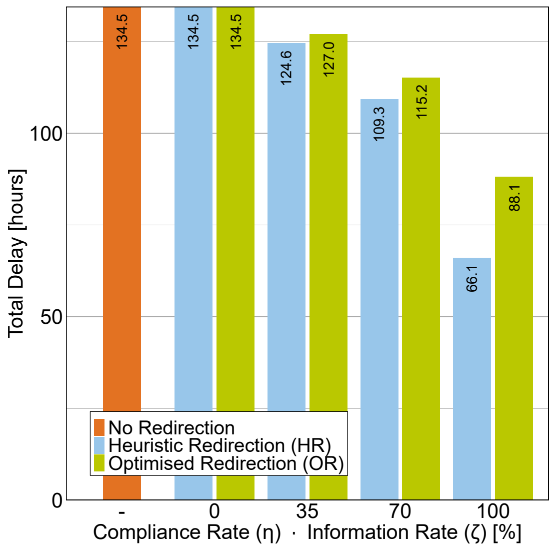
(a) Relative delays of $U_a \subset U$



(b) Relative delays of U



(c) Total delays of $U_a \subset U$



(d) Total delays of U

Figure 5.33: Overall relative and total passenger delays with an incident duration (t_i) of 60 minutes and $\xi = 0\%$ in Scenario LS $(\psi = 0)$

Furthermore, factor ψ and the consideration of the recovery time need more investigation and might play a bigger role in more complex networks than they do in more simple networks such as the Mandl network. In addition, the fact that not all possible alternative paths are considered to reduce the computational effort for calculating them might cause that better alternative paths are not taken into consideration.

These explanations might also be elements which influence the Approaches CR+HR and CR+OR, which have not been executed in the Kassel network. Furthermore, this can be due to the following reasons:

first, Kassel is served by bus, tram, and regional tram lines, however, for the reallocation of capacities, merely buses have been considered in the search for dispensable capacities. This is due to the fact that only buses have the necessary flexibility to be reallocated in the way proposed in Chapter 4. Furthermore, buses are not capable to run on tram tracks, at least if these are not integrated in the road. Therefore, only path segments with insufficient capacity which are served by bus lines have been considered for the deployment of dispensable buses. This reduces the possibilities to find matching dispensable capacities.

Second, the bigger network also means that the start and end of lines are more distant from each other, which means it takes buses longer to get from their original line to the lines with insufficient capacity. Moreover, it is less likely that they get there in time before the respective redirection duration elapses. If the reallocation of capacities during their run would be considered, it could lead to a higher chance for matches, especially if they also would just serve a certain segment of a line with insufficient capacity, which might be more applicable in practice. However, it also lifts the level of complexity of the capacity reallocation problem.

Third, in the Kassel network, headways vary between 10 minutes and a full hour. For relatively long headways of for example more than 10 minutes, depending on the network and situation, a capacity reallocation is probably not expedient, as the negative effects on passenger delays through the withdrawal of vehicles from their original line. Further, it makes it harder to find buses in the incident period. However, such situations might be the ones in which autonomous modular system such as the aforementioned DART system is able to make full use of its advantages. Through the modular setup a platoon of modules can be split and a line with insufficient capacity can be supported while the rest of the platoon can still serve the originally assigned line. In this case, the headway stays the same on the original line and also longer headways are not a problem. Hence, a bigger, denser, and more complex PT network might lead to better results for the DART system compared to the results presented in Section 5.2.3.

Nevertheless, REPACK caters for a significant reduction in the delays of the affected as well as all passengers and shows thereby a potential for an application in practice. Furthermore, the applicability of REPACK in a multimodal PT network is demonstrated.

5.4 Key Findings from the Case Studies

Firstly, the results imply that the application of REPACK is especially reasonable if the incident and the consequential disposition measures are sufficiently disruptive. This is because the results of the cases in Scenario LS in which the disrupted PT lines are split show a significantly stronger delay reduction than the results of the cases in Scenario LR in which the lines are rerouted.

Secondly, with an increase in the incident duration the effectiveness of REPACK grows significantly. Therefore, the incident duration is an important aspect of setting a minimum threshold for the execution of passenger redirection as well. BMVI [2019] presents the outcome of an approach in practice concerning passenger redirection. The consortium which conducted this investigation is mainly composed of practitioners. One finding of this work is the definition of a minimum incident duration of 30 minutes. This fits well with the results of the previously presented case studies. However, shorter incident durations are not tested here or by any of the works presented in Section 2.2.2. Nevertheless, as already mentioned, an incident must have a certain minimum level of disturbance for the execution of REPACK to be meaningful. Even though each incident has its characteristics according to the outcome of the aforementioned observations in OCCs [Bachmann, Briem et al., 2022], the definition of a generally valid minimum threshold for the execution of REPACK is appropriate and makes it more applicable in practice. In terms of the incident duration, 30 minutes seems to be a good choice as the minimum, however, the severity of the incident needs to be considered in this decision.

Thirdly, another factor that influences the effectiveness of REPACK is the availability of alternative paths and the travel time differences between these paths and the disrupted original path of affected passengers. If no alternative paths are available, passengers cannot be redirected. Therefore, the closer to the city centre an incident happens, where the PT network is close-meshed, the more likely the availability of alternative paths. The fact that the passenger delays are more severe in the case study in Kassel than in the case study in the Mandl network might also be caused by the less centrally located incident and fewer available alternative paths.

Furthermore, as demonstrated by the comparison of the two Scenarios LS and LR in the Mandl network (Section 5.2.2), the more severe the disturbances in terms of length of delays on the originally planned path of the affected passengers and the bigger the difference in travel time between the disturbed original path and the available alternative paths, the longer the redirection duration T^p_{od} (Equation 4.2). With a longer redirection duration, more passengers are redirected and profit from REPACK, hence, increasing its effectiveness. In Scenario LR, for instance, the PT lines are rerouted and the additional travel time due to the detour is just 3.5 minutes. Therefore, for less disruptive scenarios, passenger redirection might not be appropriate for shorter incident durations of less than 60 minutes. This indicates that the previously mentioned definition of a minimum incident duration should be set in accordance with the level of severity of an incident.

Fourthly, as previously mentioned, the difference in travel times between the disturbed original path and the alternative paths of the affected passengers also influences the redirection duration T^p_{od}; the bigger the difference, the shorter the redirection duration. However, it is also influenced by the factor ψ. A positive value for it shortens T^p_{od}; a negative value prolongs it (Equation 4.2). The previously presented results show that a negative value for ψ leads to better results with more severe incident situations such as in Scenario LS whereas for Scenario LR $\psi = 0$ is a good setting. Still, the presented results indicate that a deterministic value for ψ might be a too simple approach, as it needs to be set according to the recovery time. This is further discussed in the next chapter.

Lastly, the capacity reallocation process has merely been executed in cases with a product of compliance and information rates of 100%, which is a rather unlikely rate according to the outcome of the PT user survey presented in Chapter 3 (Figure 3.9). It might be that the reallocation process is only applicable in cases in which the capacity on the alternative paths is strongly exceeded or in which rail replacement services must be supported (Section 2.2). As pointed out by Bachmann, Briem et al. [2022], finding drivers becomes continually more difficult for PT operators, which leads to the unavailability of standby and extra vehicles. If extra capacity is needed as presented here or in the form of rail replacement services to bridge disrupted railway services, it might be necessary to withdraw it from other lines. For such a situation, the introduced capacity reallocation process might be very suitable. However, as the results show, this process also gives room for improvement. This is discussed in the following chapter.

Chapter 6

Discussion

The previous chapter presents and explains the results of case studies conducted in the Mandl network as well as the network of the city of Kassel. The first section of this chapter elaborates on the limitations of the REPACK model introduced here, followed by a section underlining the contribution of this work and comparing it to the literature presented in Section 2.2.2. The final section discusses steps needed to implement REPACK in practice.

6.1 Model Limitations

"All models are wrong, but some are useful" [Box, 1979]. It is the author's conviction that the REPACK model is useful. However, as valid for all models, it has some limitations which are elaborated on and discussed in the following.

First, REPACK is not yet capable of adjusting to changes in the estimated incident duration. Whenever an incident occurs and is reported to the OCC, dispatchers estimate its duration. The return of the PT service to its schedule depends on various factors such as the severity of the incident, its location and closeness to a depot or standby services, the availability of staff and extra vehicles, and the traffic condition, just to name a few. Therefore, it is difficult to estimate an incident duration, which is why this estimation strongly relies on the experience of the dispatchers in OCCs, as pointed out by Bachmann, Briem et al. [2022]. In any case, an incident can evolve differently than expected. Therefore, the capability of adjusting the estimated incident duration is useful. When the estimated incident duration is adjusted, the set redirection strategy needs to be taken into account. Sudden changes in the path advice might lead to confusion and mistrust. Therefore, the advised paths need to stay the same and just the redirection duration is adjusted if the alternative paths possess sufficient remaining capacity for the changed redirection duration. However, this might be an issue for cases in which the redirection duration is prolonged and the remaining capacities on the alternative paths cannot accommodate the consequential additional demand.

Second, related to the issue of the estimated duration is the prediction of the recovery time, which expresses the period between the end of the incident and the point of time at which no further delays induced by the incident are caused. Tsuchiya et al. [2006] introduce a linear function to predict the development of the recovery time, however, their approach heavily relates to rescheduling of railway services. Furthermore, here, this is rather understood as part of the incident duration, as rescheduling is a disposition measure in railway operations (Section 2.2). Nevertheless, including a prediction for the recovery time is expedient to accomplish a more precise redirection duration. Factors that influence the recovery time are the demand and the occupancy of services, which influence how quickly the accumulated passenger demand at stops can be picked up.

Concerning the calculation of the redirection duration T^p_{od}, such a prediction would also help to improve Equation 4.2. This can be achieved due to a further development of factor ψ from a deterministic value to a recovery-time-dependent sub-model. Such a sub-model probably needs to be adjusted to the characteristics of a PT system, as well as the location and duration of an incident, and the demand and occupancy levels at the point of time the incident occurs.

Third, REPACK merely considers one incident, however, it is possible that more than one incident occurs at the same time. Furthermore, an initial incident can also trigger secondary disturbances (Section 2.1.3). Similarly to the previously described case of adjusting the estimated incident duration, the set redirection strategy needs also to be taken into account if a second incident or disturbance occurs. Changing the redirection strategy, meaning the already provided path advice for the OD pairs, is inappropriate as mentioned before, at least if it happens within a short period. The minimum incident duration for a switch in the redirection strategy is yet to be determined. Otherwise, the passenger redirection for the second disturbance is more restricted due to the already disseminated path advice.

Fourth, Approach HR gives room for improvement. The heuristic sorts the affected OD pairs $od \in OD_a$ by the corresponding size of its respective redirection group $rg^{\hat{p}}_{od}$ (Section 4.5). Another reasonable approach would be to organise the $od \in OD_a$ by the potential savings of their overall delays, which are not only dependent on the size of $rg^{\hat{p}}_{od}$, but also on the difference in travel time between the alternative paths. Especially with smaller products of compliance and information rates of $\eta \cdot \zeta < 80\%$, which are more likely according to the results from the PT user survey (Figure 3.9, Section 3.2.3), the heuristic approach performs better than Approach OR, which indicates the expediency of redirecting the affected OD pairs in a certain order. Nevertheless, as pointed out here, delays could be further reduced with a different definition of this order of OD pairs.

Fifth, the aforementioned statement about Approach HR is therefore also an argument for the advancement of the optimised approach of the passenger redirection process (Approach OR). The consideration of a certain order of the affected OD pairs $od \in OD_a$ during the redirection or a stronger inclusion of the product of compliance and information rates into the optimisation, especially into the optimisation function, might be useful. Further, in the optimisation approach, the travel time of the redirection groups rg^p_{od} along a path $p \in P_{od}$ when calculating the remaining capacity is not considered as in Approach HR, in which the capacities are calculated segment-wise (Section 4.5).

When a redirection group travels on an alternative path, the start and end time of the journey on a certain path segment are determined by the departure of the first passenger of the corresponding redirection group at the beginning of the segment and the arrival of the last group member at the end of a segment. This is true for each path segment, defined by the used PT lines, which are used along the path. The period in which a certain rg^p_{od} needs free room on the first path segment is earlier than the period for the second and third segments. This can lead to the remaining capacity being over- or underestimated. Consequently, the achievable reductions can decrease in the overall passenger delays, which is also an explanation for the Approach HR performing better in some cases than Approach OR, which was especially evident in the case study conducted in the network of Kassel (Section 5.3). Therefore, the optimisation can be improved by including the travel time of the redirection groups when calculating the remaining capacity on alternative paths.

The fact that Approach HR performs in some cases better than Approach OR also invites investigations for a hybrid model in which both approaches are integrated into one. In the previous chapter, factors which influence which approach performs better are already mentioned – e.g. product of compliance and information rates, network complexity, and incident duration.

Sixth, this thesis merely presents a heuristic approach to the reallocation process. As the heuristic passenger redirection process, the heuristic reallocation process might also be improved by the previously described order of the redirection groups, sorted by the potential reduction in passenger delay rather than by the size of the respective redirection group $rg_{od}^{\hat{p}}$ of the affected OD pairs $od \in OD_a$. Furthermore, just like the redirection process, the reallocation process is mainly a matching problem, however, the matching of affected passengers with available alternative paths is more complex when including the possibility of reallocating dispensable capacities. Nevertheless, it is an optimisable problem that invites the development of an optimisation approach for the capacity reallocation process.

Moreover, the passenger redirection and capacity reallocation process have been presented separately to investigate which element of REPACK has which effect. However, a merger of the approaches would be expedient as it might lead to an acceleration of the process and better results through the consideration of dispensable capacities during the passenger redirection procedure.

Seventh, in the case studies conducted, the Approaches CR+HR and CR+OR, which include the reallocation of capacities, are only executed if all missing places could be provided by dispensable capacities. Another approach could also be that if this is not achievable, the available dispensable capacities are used. In this way, at least some of the corresponding redirection groups could be redirected for a correspondingly shorter redirection duration. As some of the results indicate, capacity reallocation not only increases the remaining capacity on alternative paths, but also lowers the waiting time for some passengers through the extra departures at the corresponding stops at the supported PT line. Moreover, capacity reallocation is only considered for the whole stretch of the line with insufficient capacity ($pl \in PL_{ins}^{ps}$) and only if a bus is dispensable from the beginning of its original assignment. To enhance the level of flexibility and increase the chance for the execution of the capacity reallocation process, the possibility of reallocating a bus during its run on its original line and just for the part of the insufficient line $pl \in PL_{ins}^{ps}$ which serves the path segment $ps \in \bar{PS}_p$ with insufficient remaining capacity might improve the process. Another advantage of increased flexibility during this process can be the timing of the reallocation. As discussed in the previous chapter, the fact that the capacity reallocation approaches perform best merely in a few cases might also derive form reallocated buses arriving right before or after regularly scheduled buses at stops. This limits the positive effect of the process while still causing additional delays on the lines from which the reallocated buses are withdrawn.

Eighth, REPACK is developed for mass PT services and does neither consider other modes and services such as walking, cycling as well as bike, e-scooter, or car sharing, nor on-demand services. Especially when the remaining distance to a traveller's destination is short, walking is probably the best alternative. Additionally, walking to a nearby alternate stop might lead to bigger delay reductions for some passengers. In particular, for small redirection groups of one or a few affected passengers, mode-sharing and on-demand services probably offer a suitable alternative and reduce the demand on the mass PT system during the incident. However, these services have a significantly smaller capacity than mass PT services and are therefore not suitable for the redirection of bigger groups. That being said, including several on-demand vehicles such as taxis in the capacity reallocation process could probably help to reduce the overall delay of affected passengers more efficiently. According to the aforementioned interviews and observations in OCCs, this is also done in practice [Bachmann, Briem et al., 2022].

Ninth, a path choice model is not included in REPACK. Works such as Cats and Jenelius [2014] and Leng and Corman [2020], which are introduced in Section 2.2.2, use a path choice model to predict the reaction of passengers to incident information. However, these works do not consider concrete path advice. Extending a path choice model accordingly might help to better predict the compliance rate η of affected passengers. This is further discussed in the following.

Tenth, even though an information rate is considered, differences in the information rate concerning different locations in the network are just mentioned, but not implemented in the methodology. This would also be a useful extension for the special case in which only five OD pairs have an information rate of 100% and the rest of 25% (Section 5.2.2).

The model limitations clearly show a wide range of possibilities of improvement. Even though REPACK already shows mainly a strong positive effect on the passenger delays during incidents, it is likely that even better results can be accomplished when the listed limitations are removed or at least weakened. The following section discusses this work's contribution as well as the comparison to other works in the field of PCIM.

6.2 Contribution and Comparison

Section 2.2.2 introduces the to-date academic investigations and approaches in practice in the field of *passenger-centric* incident management (PCIM) in PT systems. Among the academic investigations presented are four that propose the provision of path advice and are thereby closest to the methodology presented here. However, two of them, Bachmann, Rau et al. [2021] and Bachmann, Dandl et al. [2023] present earlier stages of the PCIM method described here. Bachmann, Rau et al. [2021] show the conceptional framework of a PCIM method including heuristic passenger redirection and capacity reallocation, and test the method in a numerical example in a simple toy network (STN) which is used here to tell the real-life story in Section 4.1. Bachmann, Dandl et al. [2023] present a further developed version of the passenger redirection heuristic and introduce an optimised approach to it. These two approaches of the passenger redirection process from Bachmann, Dandl et al. [2023] as well as the framework of the capacity reallocation process from Bachmann, Rau et al. [2021] are merged and further developed into the REPACK model presented here. The most significant advancements are the consideration of self-redirected passengers through ξ, the advanced version of Equation 4.2 to calculate the redirection duration T^p_{od} through which factor ψ is introduced as well as the development of the conceptional framework of the capacity reallocation process into an applicable algorithm. The latter upgrade makes the reallocation process applicable for simulation studies and brings it closer to implementation in practice. Furthermore, here, REPACK is tested in a multimodal PT network model which is based on an actually existing network.

The other two works which present methods for the provision of path advice are by van der Hurk et al. [2018] and Mo, Koutsopoulos, Shen et al. [2023]. The former publication demonstrates a PCIM method to provide customers of railway services with path advice in case of severe disruption. The introduced algorithm, called ARSRU, includes also a rolling-stock rescheduling model, based on the work of Kroon et al. [2015], which are connected through an iterative loop to accomplish an ideal outcome.

The most noticeable difference to REPACK is the environment for which the methods have been developed. Whereas van der Hurk et al. [2018] focus on regional and long-distance railway operations, REPACK is meant for multimodal urban PT systems. Railway networks, especially of regional and long-distance services, are more coarse-meshed than urban PT networks. Moreover, the headways are often longer, and incidents that include the blockage of a track are often more severe, as trains cannot overtake each other like buses can in a close-meshed street network. The situations in the two systems are therefore different but comparable. Also, the work by van der Hurk et al. [2018] as well as most of the other works introduced in Section 2.2.2 consider indivisible passenger groups in accordance with the origin and destination of passengers or by their origin of redirection and destination.

The authors also consider a compliance rate of several deterministic values as well as a logarithmic calculated value. The latter takes the travel time difference between the suggested and the fastest path into account. As argued before, the difference between the fastest and the suggested path is certainly one factor that influences the willingness of affected passengers to follow given path advice, but other influencing factors are likely too. As elaborated in Section 2.1.4, weather, bike and car ownership, closeness to the destination, and further aspects influence the reaction of passengers to incident situations and therefore can also have positive or negative effects on the compliance rate of affected passengers.

Furthermore, the aforementioned difference in path travel times rather influences the willingness of experienced travellers, such as daily commuters, who are aware of the fastest alternative path, than that of the rest. REPACK takes PT users who prefer to redirect themselves separately into account through the self-redirection rate ξ. Moreover, van der Hurk et al. [2018] do not consider PI channels or an information rate to take into account the reachability of affected passengers. As the survey results in Section 3.2.3 show, most of the participants prefer a collective PI channel (i.e. dynamic PI displays or speaker announcements) as the source of information during incidents.Therefore, in Section 5.2.2 a special case is presented where only five of the affected OD pairs are fully reachable, while of the rest only 25% of the passengers of each affected OD pair $od \in OD_a$ are reachable. Nevertheless, ARSRU considers uncertainties in the estimation of the incident duration which is yet to be implemented in REPACK.

The general idea behind the rolling stock rescheduling model is similar to the capacity reallocation process presented here, which is the provision of additional capacity to support passenger redirection. However, as rolling stock rescheduling faces more restrictions due to the boundaries of the deployment of trains and the usually coarse-meshed nature of railway networks, the reallocation of buses is more flexible, which however induces a certain further complexity. Through REPACK, buses are withdrawn from their original assignment and deployed to other lines to support passenger redirection. Among all the works done in the field of PCIM, van der Hurk et al. [2018] present the method which is the closest to REPACK, however, as discussed in this section, the method shows several differences to REPACK.

Mo, Koutsopoulos, Shen et al. [2023] present a mathematical formulation of passenger flow distribution in an urban PT network. The authors consider full compliance, and even though PI channels such as mobile phones and websites are mentioned, no information rate or information schemes are taken into account. As with most of the works presented in Section 2.2.2, Mo, Koutsopoulos, Shen et al. [2023] do consider indivisible passenger groups as well as capacity constraints. Other than that, through the mathematical approach to flow distributions, the work by Mo, Koutsopoulos, Shen et al. [2023] is significantly different from the other publications presented in Section 2.2.2.

The rest of the academic investigations introduced in Section 2.2.2 do not consider path advice, but either assume that affected travellers inform themselves about alternative connections [Müller-Hannemann et al., 2019] or inform passengers about an incident and changes to the arrival times of PT services or taken disposition measures.

Cats and Jenelius [2014] and the *Corman group*[1] implement the availability of this kind of information in path choice models through which the affected PT users are then assigned to paths. Therefore, there is no room for a compliance rate, as on the one hand, no concrete path advice is given to which the travellers could comply, and on the other hand, how the passengers react to the given incident information is decided by the path choice model.

Path choice models are sophisticated and helpful tools to predict travellers' path choices. This reveals the possibility of combining parts of the presented methodologies by implementing path advice into path choice models (Section 2.1.2). However, for this, the factors which influence the compliance to given path advice need further research to complement the work by Wilke [2023], who investigates incentives to influence passengers' willingness to follow path advice, in the context of urban PT services (Section 2.1.4).

Furthermore, Cats and Jenelius [2014], Zhu and Goverde [2019a], as well as the *Corman group*[1] consider different locations and schemes of information. Cats and Jenelius [2014], for instance, compare information dissemination at stops and at transfer hubs as well as network-wide dissemination. Zhu and Goverde [2019a] take into account information being available at stations and/or trains. The *Corman group*[1] tests different information schemes concerning the time at which the information is disseminated. As mentioned in the previous section, location-dependent information rates are an especially expedient advancement for REPACK.

The results of the case studies presented in the various investigations concerning relative passenger delay reduction show a wide range of outcomes from negative values [Cats and Jenelius, 2014; van der Hurk et al., 2018; Bachmann, Dandl et al., 2023; Mo,

[1] Leng and Corman [2020], Leng, Liao et al. [2020], M. Rahimi et al. [2021] and Rahimi Siegrist and Corman [2021]

Koutsopoulos, Shen et al., 2023], to reduction of almost 100% [Leng and Corman, 2020] (Section 2.2.2, [Bachmann, Tsakarestos et al., 2023]). With a range of relative delay reductions from less than 10% with $\eta \cdot \zeta = 35\%$ in Scenario LR to a reduction of 90% with $\eta \cdot \zeta = 100\%$ in Scenario LS, the results of REPACK fit well with the published works in the field of PCIM. However, all these works use different simulation environments, networks, and inputs, which makes a direct comparison inadequate and unreasonable. The usage of the same publicly available benchmark networks, such as the Mandl or the Mumford networks, as used for the comparison of algorithms to solve the PT network design problem [Ul Abedin et al., 2018], would be desirable.

In the approaches in practice which are introduced in Section 2.2.2, the focus is different from that of the previously mentioned academic investigations, even though the general idea and aim of reducing passenger delays through adequate PI during incidents are the same. As pointed out by Bachmann, Tsakarestos et al. [2023] as well as in Section 2.2.2, most well-equipped PT systems to date provide their users with information about the occurrence of an incident as well as the consequential disturbances. The provision of concrete path advice is not state-of-the-art in practice yet. Tsuchiya et al. [2006] present a prototype of a passenger guidance system for the railway system in Japan. Affected passengers receive the information on whether they should wait or take another path to their destination in case of an incident. Considered PI channels are dynamic displays at stations and mobile phones. However, the system's capacity is only qualitatively taken into account, and the developed algorithms are not disclosed, optimisation not mentioned.

BMVI [2019] presents the outcome of a PCIM project with several phases in Germany. Over the development of the project, the consortium, mainly composed of practitioners, moved continuously away from the use of collective PI channels towards individual information channels such as smartphone apps [BMVBW, 2001; BMVBS, 2009; BMVBS, 2011; BMVI, 2019]. This contradicts the findings of the PT user survey presented in Section 3.2.3, which imply the importance of collective PI channels, especially during incidents. The system's capacity is also only qualitatively considered and as in the previously mentioned work, algorithms are not disclosed either and optimisation is not mentioned. All approaches in practice, which are introduced in Section 2.2.2 mention the necessity of an integration of a PCIM method into the OCC of a PT system, as also suggested by Bachmann, Tsakarestos et al. [2023].

Besides the aforementioned publications by Bachmann, Rau et al. [2021] and Bachmann, Dandl et al. [2023], this work presents the first approach in the field of PCIM focussing on bus operations and includes a capacity reallocation process which withdraws dispensable buses from PT lines to dispatch them to other lines to support passenger redirection. This has been done, since the interviews and observations in OCCs give evidence of the fact that finding drivers who cater for the availability of standby and extra vehicles has constantly become harder [Bachmann, Briem et al., 2022]. This could also be a problem when an incident in the railway part of an urban PT network occurs and a rail replacement service needs to be established to bridge the disrupted segment of the railway service (Section 2.2). If not enough extra buses are available, such a bridging service could be supported by the capacity reallocation process to withdraw buses from other lines to dispatch them to the bridging service. It goes without saying that the passenger redirection process should also be executed in such a situation to give the affected passengers adequate path advice.

One of the most decisive contributions of this thesis is that it brings academic research and approaches in practice in the field of PCIM one step closer together. As pointed out by Bachmann, Tsakarestos et al. [2023] and also explained in Section 2.2.2, there is a gap between these two perspectives. Academic research presents optimised procedures with which optimal paths are found for affected passengers, but it lacks the connection to practice in terms of available data and information dissemination equipment. Approaches in practice strongly focus on the available infrastructure, but fail the implementation of state-of-the-art research.

Through interviews and observations in OCCs (Section 2.2.1), the base of understanding of PT operations – the supply side – is built. Additionally, through the PT user survey, presented in Chapter 3, insight into the passengers' perception of incidents and incident management is given that supports the understanding of the passenger side. The supply and passenger sides are to be connected through PCIM methods such as REPACK, as also implied in Figure 1.1. This connection is elaborated in the following.

The redirection duration T^p_{od} which is introduced here is important information for the dispatchers in OCCs. During the information dissemination process, described in Section 4.7, available PI channels for the affected OD pairs are identified. The redirection duration T^p_{od} then defines for each of the affected OD pairs $od \in OD_a$ for how long the path advice is disseminated. After the redirection duration is elapsed, the advice to wait can be broadcast until the incident is resolved or alternatively until the recovery time is elapsed. In addition, the presented PT user survey gives insight into the users' preferences regarding PI channels during incidents. As these are mostly collective channels – i.e. dynamic PI displays and speaker announcements (Section 3.2.3) – the reachability of all affected OD pairs might not be certain. Therefore, the information rate ζ enables the inclusion of this limitation. Furthermore, the option that for only a limited number of the affected OD pairs, the information rate is higher since they can be informed via the collective channels, whereas for the rest, the information rate is lower, as they are dependent on other PI channels, is implemented. In Section 5.2.2, such a case has been tested with five affected OD pairs that have an information rate of 100% and the rest a rate of 25% following the results from the aforementioned survey (Section 3.2.3).

Nevertheless, works by Cats and Jenelius [2014], Zhu and Goverde [2019a], as well as the *Corman group*[1] couple the location of information dissemination with the reachability of PT users. Hence, connecting the information rate in REPACK with the location where affected passengers receive the path advice would be expedient. As argued before, the availability of collective PI channels is different within a PT network depending on the kind, size, and location of a stop. Whereas large transfer hubs in the city centre are often well-equipped with PI channels, small bus stops at the outskirts of a network might not be equipped with any

[1] Leng and Corman [2020], Leng, Liao et al. [2020], M. Rahimi et al. [2021] and Rahimi Siegrist and Corman [2021]

PI channels. Depending on how well a PT network is generally equipped in this matter, even stops in the city centre might not be equipped adequately.

However, even though REPACK already presents a method that is relatively close to implementation in practice compared to other works in the field of PCIM, further steps are necessary and need to be considered before an application of REPACK in practice is thinkable. These steps are discussed in the following section.

6.3 Implementation in Practice

As pointed out by Bachmann, Tsakarestos et al. [2023] as well as by the investigations of practitioners presented in Section 2.2.2, when implementing a PCIM method into practice, it is useful to integrate it in the system architecture of an ITCS. The ITCS is the overall system connecting the OCC with the vehicles and the PI systems [VDV, 2001, pp. 182–183; Pangilinan et al., 2008]. The OCC is the heart of a PT system where important information is gathered, especially during and about incidents (Section 2.2.1), which is important input for REPACK. Hence, a logical first step is the consideration of the sources for necessary inputs. Incident information such as location and an estimation of duration as well as the disrupted PT lines are important inputs. It is conceivable that this information is manually provided by the dispatchers when they receive the information over the radio from the PT drivers. However, this makes an already stressful situation even more stressful for the dispatchers. Another opportunity to provide for the necessary information is to establish an interface to the ITCS as proposed by Bachmann, Tsakarestos et al. [2023]. Through a connection to the ITCS also information regarding the disposition measures taken by the dispatchers as *supply-centric* reaction to the incident can be passed and thus the disposition timetable, which is necessary to find alternative paths for affected passengers, can be made available. Therefore, a coupling of a PCIM method like REPACK with ITCS is expedient.

Figure 6.1 by Bachmann, Tsakarestos et al. [2023] shows a high level system architecture of an ITCS in which CAPR is integrated. The incident reporting and instructing the disposition measures are done verbally via radio. The PT vehicles' positions and capacities are transmitted automatically. The OCC feeds back the vehicles delays, based on the delay calculation, which compares vehicles' positions with the timetable [Bachmann, Briem et al., 2022]. The disposition measures are decided by the dispatcher. The consequential disposition timetable, the incident information (i.e. location, duration), the vehicles' capacities, and the passenger demand can then be entered in the ITCS. Afterwards, PCIM methods like REPACK can compute path advice based on the given information as described in Chapter 4. Together with other information such as departure times and free text written by a dispatcher, path advice can be sent to all available PI channels (e.g speakers, dynamic PI displays, PT trip planners).

Therefore, in addition to connecting REPACK with the OCC and integrating it in the system architecture of the ITCS, the PI channels need to be capable of disseminating path advice. This also concerns the aforementioned interfaces, the GTFS and the VDV454 (Sections 2.1.5 and 2.2.2) [VDV, 2018b; Mobility Data, 2022].

Moreover, the reallocation process of an PCIM method such as REPACK would profit from such an interface through which important information about the fleet and its occupancy can

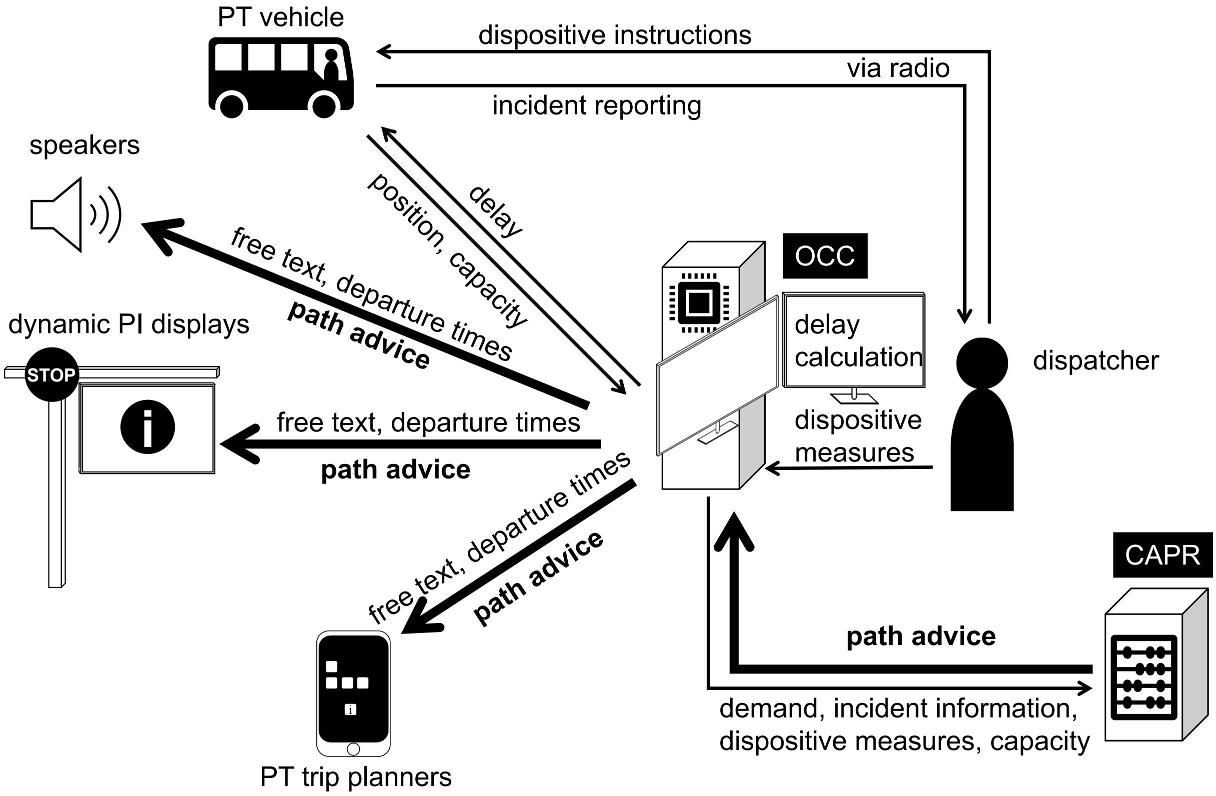


Figure 6.1: CAPR integrated in the ITCS architecture [Bachmann, Tsakarestos et al., 2023]

be transmitted. Hence, not only CAPR but all elements of REPACK should be integrated.

A related second step concerns the incident duration. As described by Bachmann, Briem et al. [2022] and in Section 2.2.1, a great extent of incident management relies on the experience of dispatchers, as does the estimation of the incident duration, which is an important input for REPACK. This might lead to wrong estimations and readjustments of the estimated incident duration. As pointed out in Section 6.1, the ability of REPACK to adjust to changes in the incident duration is yet to be implemented and is a sensible advancement. However, as far as a categorisation of incidents regarding their location in the network as well as the type of incident, time of day, and other aspects are concerned, it would be expedient if an OCC can provide a corresponding database, which contains information about common and rare incidents. In accordance with factors such as the time of the day, weekday, and to be expected demand level, the database could then provide an estimation for the incident duration.

The demand is subject of the third step. To be able to check alternative paths for sufficient remaining capacity, at least an estimation of the demand is needed. Most PT operators have at least some historical travel data through ticket sales, random samples, or censuses, as this data is also needed for planning purposes [Ul Abedin, 2019]. It is thinkable that a database of such historical travel data is prepared and categorised by the day of the week and the time of day to get a demand estimation for the time when an incident occurs. Such a database could also include the unusual demand levels which are caused due to special events such as festivals or sport competitions. Furthermore, in well-developed PT systems, there is the possibility of connecting REPACK with real-time demand data that can be collected through AFC and APC. With the help of such real-time data the precision of REPACK could be further improved.

Speaking of redirecting demand onto alternative paths, the provision of a set of available paths is another necessary input for REPACK and defines the fourth step. As pointed out in Sections 4.4 and 5.3 as well as by Müller-Hannemann et al. [2019], the calculation of paths can be computationally expensive and take a long time, which is not convenient for a system that needs to react quickly. Therefore, also in the case of paths' provision, a database could be set up, preparing possible sets of paths regarding certain incident situations. In a construction kit manner, such a database could be built with certain incident locations, incident types, and estimations of durations to then select a possible set of paths. The building procedure of such a database could be guided by link vulnerability analysis such as the one by Cats and Jenelius [2014] to start with the incidents with the most severe consequences for the PT system and the links at which an incident is most likely.

Regarding the paths, an advancement of REPACK is also necessary concerning the destination of redirection groups rg^p_{od} of the affected OD pairs $od \in OD_a$. So far, REPACK considers the final destination stops of affected passengers. In a large real-life PT network such as the one used in Section 5.3, this is not reasonable as it leads to more OD pairs and thereby smaller redirection groups, which can limit the number of reachable travellers as pointed out before. Hence, it would be more considerate to use the last transfer hub or relatively centrally located stop of affected passengers as the destination of redirection. In this way, more passengers could be associated with the same OD pair, even though their final stop is not the same.

A thinkable fifth step concerns computational time. As previously pointed out, looking for paths is computationally expensive. However, also in this regard, REPACK needs improvement. With an Intel Xeon W-2133 CPU with 3.60 Gigahertz and 32.0 Gigabytes of RAM, the assignment process from Step 6 in the situation analysis process (Figure 4.4) to Step 23 in the passenger redirection process (Figure 4.5) needs about 20 seconds in the Mandl network, as also mentioned by Bachmann, Dandl et al. [2023]. However, most of the time needed, about 18 seconds, is used for the retrieval and processing of the simulation output from the higher benchmark scenario, which can probably be accelerated. If the capacity reallocation process is executed, an additional 30 seconds are needed from Step 24 to Step 46 (Figure 4.6). So, in total REPACK would need about one minute in practice, not including the accessing and processing of the data coming from the ITCS and aforementioned databases concerning the available alternative paths and the demand, which will likely also add processing time. Furthermore, in the network of Kassel (Section 5.3), Steps 6 to 23 need about 5 minutes. As REPACK is supposed to react quickly on suddenly occurring incident situations, this process needs to be accelerated.

Speaking of timing, Figure 6.2 combines Figure 2.1 which presents the incident management procedure of an OCC (left track) with Figure 4.2 presenting the procedure of REPACK (right track). It is supposed to give an idea of the timing of REPACK's execution in relation to the processes in an OCC. At the point of time at which the dispatcher decided on the disposition measures (Step 3, left track) on which basis the disposition timetable is created, REPACK can be executed to start analysing the situation (Step A). As indicated by the not existing gaps between the processes of REPACK, it continues with the subsequent Steps B, C, and D without any delay. This is in contrast to the steps conducted in the OCC during which the dispatchers have to wait until certain events occur, such as the arrival of the transport warden at the incident site.

In Step 7, the OCC updates the instructions to the PT drivers. If an incident develops differently than expected or the dispatchers receive additional information from the transport warden, disposition measures might need to be adjusted and the estimation of the incident duration might also change. As discussed before, it is therefore expedient if REPACK is also capable of adjusting to changes in the inputs such as the incident duration, which happens in Step E and update the redirection strategy accordingly. At the same time, also the instruction to the drivers is updated. This step is not yet implemented in REPACK. Once the situation is cleared, REPACK ends as well, until the next incident occurs.

A sixth step is the consideration of staff management. As pointed out by Carrel, Mishalani et al. [2010] and Bachmann, Briem et al. [2022], shortages in staff can worsen incidents and play a vital role in incident management. The capacity reallocation process does not yet consider the legal constraints concerning the driving hours of the PT drivers. Certain reallocations might therefore not be possible if they extend the driving times significantly.

A possible seventh step concerns a REPACK smartphone app or app add-on by which the passengers could be redirected. Figure B.7 shows that the survey participants are willing to share some information about their trips and travel habits for the service of getting path advice during incidents. Furthermore, such an app could consider travellers' preferences regarding redirection as also suggested by Ceder and Jiang [2019] for path searches under undisturbed conditions. In any case, as argued in Section 3.2.5, path advice should be disseminated through all available PI channels.

The eighth and last necessary step for REPACK's implementation into practice is a rather minor one but still needs consideration. When such a PCIM method is rolled out in practice, the PT users need to first build up trust in the system before most of them would follow given path advice. As shown in Figure 3.9, most of the passengers answered that they *might* follow given path advice. Additionally, the presented results in Chapter 5 reveal that the effectiveness of REPACK grows with an increase in the product of compliance and information rate. Being "REPACKed" might therefore not be a promising term to gain trust. On the users' end of REPACK, a more appealing name, such as Path Advice for Passengers during Incidents (PAPI) or Passenger ROUting during Distruption (PROUD), should be established. Another thinkable way to motivate people to follow path advice is by monetary incentives for travellers who follow path advice by reducing the fare of the corresponding rides as also the survey results from Wilke [2023] suggest. In urban PT systems that are equipped with AFC such an approach is technically feasible.

In general, further investigations could help to better understand travellers' reactions to incidents and path advice. For example if these would examine factors which influence the passengers' willingness to follow given path advice and develop a model to predict such behaviour, such as the work by Wilke [2023] for long-distance railways services. Furthermore, such knowledge could be implemented in path choice models and improve the effectiveness of PCIM methods such as REPACK as pointed out before.

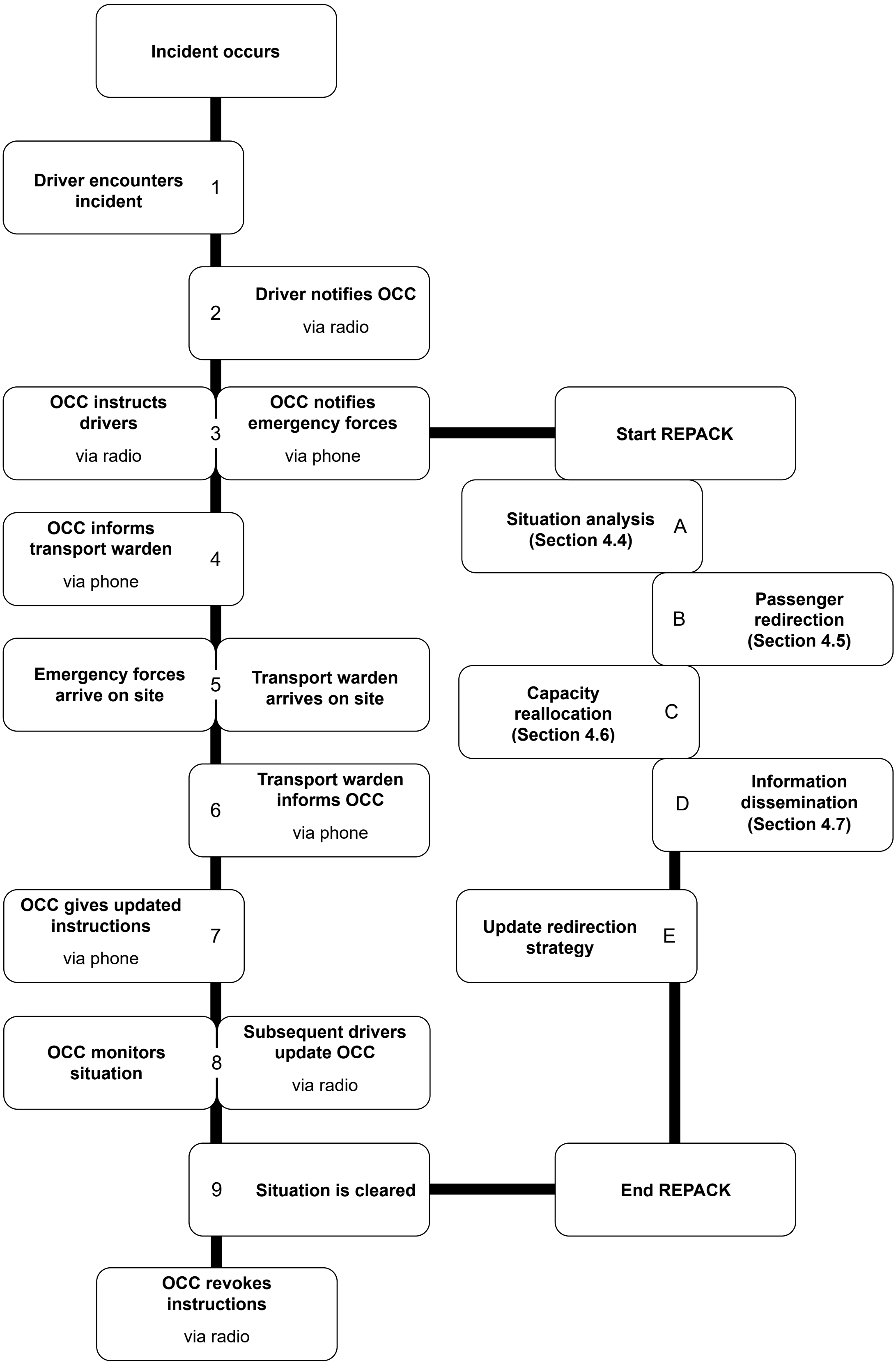


Figure 6.2: REPACK integrated in the incident management procedure of OCCs, extended from BACHMANN, BRIEM et al. [2022]

Chapter 7

Conclusions

7.1 Summary

This dissertation presents the background as well as the state-of-the-art of incident management in public transport (PT). Here, incident management is divided into two parts: *supply-centric* incident management that describes the supply side during incidents in PT, and *passenger-centric* incident management (PCIM) that connects the supply side with the passenger side as Figure 1.1 implies. To better understand the passenger side, especially during incidents, a PT user survey has been conducted, the setup and results of which are described in this thesis as well.

The knowledge which has been gained through the aforementioned elements of this thesis is the basis for the development of the model for REdirecting Passengers and reAllocating Capacities Knowingly (REPACK) during incidents in urban PT systems. This model is a new contribution to the research area of PCIM. The results of several case studies in the Mandl network as well as one case study in the network of the city of Kassel, Germany, are presented and discussed. Furthermore, the reallocation of capacity is tested in an autonomous PT system.

This has been done to answer the following research questions, which are also introduced in Chapter 1:

1. To what extent does path advice lower the overall passenger delay during incidents?

This question can be answered through the literature review on PCIM in PT. From the works presented in Section 2.2.2, four consider path advice, also including the two investigations presenting earlier stages of the REPACK model [van der Hurk et al., 2018; Bachmann, Rau et al., 2021; Bachmann, Dandl et al., 2023; Mo, Koutsopoulos, Shen et al., 2023]. The outcomes of the studies by van der Hurk et al. [2018] and Mo, Koutsopoulos, Shen et al. [2023] show a relatively wide range from -6.4% to 30% relative delay reduction for affected passengers, which indicates that path advice has the potential to conceivably reduce passenger delays during incidents. However, the outcomes also indicate limitations and cases in which it is not reasonable to redirect passengers.

Also, REPACK shows great potential to reduce passenger delays induced by incidents in urban PT systems. Under ideal circumstances, the relative delay of affected passengers can be reduced by 90%, which is significantly more than the aforementioned results. But, a direct comparison of the results of different works is inappropriate and inadequate as the models have been tested with different inputs, in diverse networks, and simulation environments. Nevertheless, it is evident that path advice can reduce overall passenger delays during incidents to a great extent.

2. Under which circumstances is the redirection of passengers reasonable?

The fact that path advice can also lead to an extension of passenger delays as implied by the previously mentioned negative results. This means that the circumstances for a passenger redirection to be reasonable need to be met. The results presented in Chapter 5 express that the location of an incident plays a decisive role as it influences the number of available alternative paths. Passengers can only be redirected if alternative paths are available.

Moreover, the type of incident and the taken disposition measures play an important role as well. The comparison of the two tested scenarios – LS, in which the disrupted PT lines are split; LR, in which the disrupted PT lines are rerouted – show that the more disruptive the incident and the taken disposition measures, the more effective is REPACK. Furthermore, the longer the incident duration, the more people are affected by it, and hence, the more affected passengers can profit from REPACK, which also increases its effectiveness. In some cases in the less disruptive Scenario LR, the effect of REPACK was very low and therefore it is probably not expedient to employ it in these cases. As discussed in Chapter 6, the definition of an incident's minimum level of disruptiveness as the threshold for the execution of REPACK is useful.

3. What are factors that influence the effectiveness of passenger redirection?

In addition to the incident-related circumstances such as location, duration, and taken disposition measures, factors are also identified that influence the effectiveness of REPACK.

Firstly, the product of the two parameters compliance and information rates shows a significant influence on the outcome of passenger redirection. The more people who are reachable and follow provided path advice, the higher the effectiveness of REPACK.

Secondly, a growing share of affected passengers who redirect themselves lowers the effectiveness of REPACK. About these matters, the presented results of the PT user survey also give a useful insight into the passengers' willingness to follow given path advice as well as into preferences regarding the passenger information (PI) channels through which they retrieve information during an incident.

Thirdly, the quality of the calculation of the redirection duration introduced here influences how much REPACK can lower passenger delays. In this regard, factor ψ plays a role. For the more disruptive Scenario LS -1 is a good set, and for the less disruptive Scenario LR 0 is a good set, as the more disruptive a scenario is, the longer is the respective recovery time. The recovery time is the time between the dissolution of the incident and the end of the delays induced by an incident. A negative value for factor ψ prolongs the redirection duration through which it can be adjusted to the recovery time. However, as discussed before, a deterministic value for factor ψ might be a too simple approach. Therefore, more research is needed concerning this matter.

4. Does capacity reallocation support passenger redirection?

In addition to the two passenger redirection approaches – heuristic redirection (HR) and optimised redirection (OR) – introduced here, these are tested in combination with the capacity reallocation process described in Section 4.6. Bachmann, Rau et al. [2021] imply that through reallocating capacities, passenger redirection can be supported and passenger delays further reduced. However, this work which presents the conceptional framework of REPACK is merely tested in a numerical example, in contrast to the simulation case studies in this thesis, in which REPACK is tested at its present stage.

The results show that only in rare cases the aforementioned criteria for the execution of the capacity reallocation process are met. It only happens with a product of compliance and information rates of 100%, which indicates that in cases in which fewer people are redirected, there is no need for capacity reallocation. Therefore, it might be more interesting for cases in which the remaining PT system's capacity is smaller than in the cases conducted here or the PT system is stronger demanded, respectively.

Furthermore, among the cases in which the capacity reallocation is done, there are only a few cases in which it performs better than the passenger redirection process. Consequently, in most cases, the disadvantages of the capacity reallocation of reducing the service quality on the lines from which reallocated buses are withdrawn outweigh the advantages on the lines to which they are dispatched to support the passenger redirection. The fact that this is also true for the cases in an autonomous PT system with a modular setup, called DART, in which these disadvantages are weakened through the flexibility of the modular setup, indicates that other factors also influence the performance of the capacity reallocation. For example, the timing of the deployment at the supported line as discussed before. Nevertheless, in some cases, the capacity reallocation reduces passenger delays further as suggested by Bachmann, Rau et al. [2021], but gives also room for further research.

In summary, REPACK shows great potential for reducing passenger delays during incidents. Performance-influencing circumstances such as the incident duration and factors such as the compliance rate have been identified. Due to the closeness of this work to practice, as discussed in Chapter 6, this thesis presents a contribution to PCIM in PT which is another step closer to implementation in practice. The presented work supports the statement that PCIM methods such as REPACK can improve the reliability of PT systems and by that their attractiveness. This can lead to a rise in ridership, which consequently lead to a reduction in greenhouse gas emissions.

7.2 Outlook

First of all, REPACK needs further evaluation and testing in different cases, especially regarding the complexity of the network and variety of available mass PT modes (i.e. metro, trams, bus) as well as the characteristics of the incident concerning its location in the network and its duration. Furthermore, only two disposition measures are considered here in combination with REPACK. As Section 2.2.1 presents, there are a variety of *supply-centric* measures taken by dispatchers in OCCs to mitigate the negative effects of incidents. Chapter 6 reveals that factor ψ needs further development from a deterministic value to a more sophisticated sub-model considering the recovery time and severity of an incident. To do so, it needs to be investigated which factors influence the recovery time and to which extent.

Additionally, the presented limitations of REPACK need to be removed or at least weakened. These include the possibility of adjusting to an altered estimation of the incident duration, being able to handle more than one incident, further improving the heuristic passenger redirection approach by sorting the affected origin-destination (OD) pairs in another manner, improving the optimised passenger redirection approach by considering the travel time of redirection groups when calculating the remaining paths' capacities, and further develop the calculation of the redirection duration as previously mentioned.

Moreover, the capacity reallocation needs further research to improve its performance through better timing of the deployment and redefining its criteria for execution. Furthermore, an optimisation approach for the capacity reallocation approach is yet to be developed as well as the integration of the passenger redirection and capacity reallocation processes into one. Additionally, the capacity reallocation process provides the possibility of also including on-demand services, such as taxis to support passenger redirection. Speaking of other modes, the passenger redirection process only considers mass PT services and not other modes like walking, cycling, or shared mobility, such as bike, car, or e-scooter sharing services. Those can lead to further path alternatives, especially for smaller redirection groups and, thereby, to even stronger delay reductions. In addition, this can exploit new alternative paths for coarse-meshed areas of the PT network.

The results from the case study in the Kassel network indicate that further adjustments are needed for REPACK to function well in more complex and realistic networks. The representation of the disposition timetable through the network graph described in Section 4.3 might be a good point to start in this matter. A representation that takes into account the actual arrival times of PT vehicles is necessary when REPACK is to be implemented in practice. This would also consider the influences through mixed traffic which additionally includes private and freight vehicles. Once REPACK is implemented into practice, the experience can be used to further improve and validate it.

Finally, factors influencing the compliance rate of affected passengers need further research. If these are better understood, such knowledge can be used to develop path choice models which can take path advice during incidents into account and to better predict travellers' reactions to incidents and path advice.

As stated in this section, the research area of PCIM has just been opened up and gives plenty of room for further improvement to accomplish even stronger delay reductions.

7.3 Own Publications

This last section of this dissertation presents the studies that have been conducted or supported by the author of this thesis. As indicated in Table 7.1, most of them are already published and further are planned. In the following, it is described how these works contributed to this thesis or, in case of the planned papers, on basis of which section of this thesis they will be developed.

Most importantly the works by Bachmann, Rau et al. [2021] and Bachmann, Dandl et al. [2023] presenting earlier stages of the REPACK model are to be pointed out. Therefore, they are cited accordingly in the Chapters 4 and 5.

Furthermore, the publication by Bachmann, Briem et al. [2022] gives profound insight into the daily practice of dispatchers in OCCs of urban PT systems. Thereby, it contributes to Section 2.2.1.

In addition, a literature review about CAPR is conducted by Bachmann, Tsakarestos et al. [2023] which is the basis of Section 2.2.2.

One case study of this thesis is conducted in the autonomous modular PT system, called DART, which, among other things, uses the advantages of vehicle platooning. The explanation of platooning in general and its advantages in the context of PT systems is supported by the works of Bachmann [2017], Bachmann and Sethuraman [2019] and Sethuraman et al. [2019] in Section 5.2.3.

Moreover, Weinsziehr et al. [2023] study the detection of the phenomenon of bus bunching, which is mentioned in Section 2.1.3.

Generally speaking, these works as well as the peer review they went through, helped to improve the quality of this thesis.

Regarding the planned publications, the first listed planned work will present an updated version of REPACK shown in Chapter 4. It will include an improvement of the heuristic as well as optimisation approach as discussed in Section 6.1 and an optimised approach for the capacity reallocation process. These upgrades probably further reduce the passenger delays.

The second planned paper will couple REPACK with the model FleetPy which is introduced by Engelhardt et al. [2022] to manage fleets of on-demand services. It will investigate how passenger redirection can be supported by reallocating on-demand services during incidents. As mentioned in Section 2.2.1 this is already done in practice but not yet supported by algorithms or optimisation. As on-demand services are more flexible than buses due to their smaller size and the fact that they are not assigned to a scheduled PT lines, this might lead to better results compared to the reallocation of buses. Even better results might be gained by a combination of buses and on-demand services. Therefore, it will be an extension of the capacity reallocation process explained in Section 4.6.

In addition to the potential of REPACK, also room for further research and improvements is shown. If the aforementioned limitations can be removed or at least weakened and the aforementioned extensions are implemented, REPACK can lead to an even greater reduction in passenger delays than it already does. Furthermore, the steps listed in Section 6.3 can help to build the bridge between practice and research in the field of PCIM. The time is right to use the existing realisations to implement PCIM methods such as REPACK into practice. As this dissertation and aforementioned studies in the field of PCIM (Section 2.2.2) show, this can improve PT systems' reliability and by that their attractiveness. An increase in the attractiveness of more environmentally friendly means of transport, such as PT, motivates people to use it instead of motorized individual means such as cars. This reduces greenhouse gas emissions and thus contributes to the achievement of humanity's greatest challenge of adjusting our way of life to a sustainable one so that planet Earth remains habitable for our kind and for other living beings.

Reference	Title	Place of publication
Published		
Bachmann [2017]	Simulative assessment of the impact of a platoon assistant on the capacity of motorways	Master's Thesis at Technical University of Munich
Bachmann and Sethuraman [2019]	Simulative Assessments of Energy and Space Savings due to Platooning	mobil.TUM Conference 2019
Sethuraman et al. [2019]	Effects of Bus Platooning in an Urban Environment	IEEE Intelligent Transportation Systems Conference
Bachmann, Rau et al. [2021]	Redirecting Passengers and Reallocating Capacities during Incidents in Public Transport	100th Annual Meeting of the Transportation Research Board
Bachmann, Briem et al. [2022]	Dynamics and Processes in Operations Control Centers in Urban Public Transport: Potentials for Improvement	IEEE Transactions on Intelligent Transportation Systems
Bachmann, Dandl et al. [2023]	Optimized Passenger Redirection During Incidents in Urban Public Transportation Systems	102nd Annual Meeting of the Transportation Research Board
Bachmann, Tsakarestos et al. [2023]	State of the Art of Passenger Redirection during Incidents in Public Transport Systems, Considering Capacity Constraints	Public Transport
Weinsziehr et al. [2023]	Detection of Bus Bunching through the Analysis of Prevalent Public Transport Control Data	11th Symposium of the European Association for Research in Transportation
Planned		
Planned	REPACK: REdirecting Passengers and ReAllocating Capacities Knowingly during incidents in public transport systems	Transportation
Planned	Integration of On-Demand Services in the Reallocation of Capacities During Incidents in Public Transport Systems	Transportation Research Part B: Methodological

Table 7.1: Published and planned studies

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List of Abbreviations

AFaO adapted fix and optimise 31
AFC automatic fare collection 7, 79, 167, 168
APC automatic passenger count 7, 40, 79, 167
API application programming interface 15, 39, 95, 144
ARSRU advice and rolling stock rescheduling problem with uncertainty 31, 36, 161
AVL automatic vehicle location 7, 19, 20

BMVBS German Federal Ministry of Transport, Building, and Urban Development [Translated from German: Bundesministerium für Vekehr, Bauen und Stadtentwicklung] 39
BMVBW German Federal Ministry of Transport, Building, and Housing [Translated from German: Bundesministerium für Vekehr, Bauen und Wohnen] 39
BMVI German Federal Ministry of Transportation and digital Infrastructure [Translated from German: Bundesministerium für Vekehr und digitale Infrastruktur] 28, 40
BVG Berlin transport company [Translated from German: Berliner Verkehrsbetriebe] 47, 57, 61

CAPR capacity-aware passenger redirection 23, 75, 165, 166, 175, 207
CR+HR capacity reallocation in combination with heuristic redirection 102, 104, 106, 110, 111, 116, 137, 145–147, 153, 159, 209, 226, 232
CR+OR capacity reallocation in combination with optimised redirection 102, 104, 106, 110, 111, 116, 137, 140, 145–147, 153, 159, 209, 210, 227, 233

DART Dynamic Autonomous Road Transit 4, 18, 28, 60, 143–148, 154, 173, 175, 207
DB German rail [Translated from German: Deutsche Bahn] 25, 38
DLR German Aerospace Center [Translated from German: Deutsches Zentrum für Luft- und Raumfahrt] 93

EFA electronic timetable information [Translated from German: Elektronische Fahrplan Auskunft] 40

GPS global positioning system 15, 19, 21
GTFS general transit feed specification 15, 78, 165

HAFAS Hanover consulting timetable information system [Translated from German: Hannover Consulting Fahrplan Auskunftssystem] 40

HR heuristic redirection 102, 104, 116, 135–138, 140, 145–147, 152, 158, 159, 173, 209, 224, 230

IC incident channel 66, 67

IPCC Intergovernmental Panel on Climate Change 1

IQR inter quartile range 125, 127

ITCS intermodal transport control system 19, 39, 78, 95, 165–167, 207

KVG Kassel transport company [Translated from German: Kasseler Verkehrsgesellschaft] 148, 149

LR PT line-rerouting 98, 99, 102–104, 114–116, 118–120, 122, 123, 127–130, 132–142, 144, 145, 147, 148, 154, 155, 163, 172, 206, 207, 209, 210, 230–236

LRT light rail transit 53, 54

LS PT line-splitting 98, 99, 102–105, 108, 109, 112–116, 122, 124, 126, 127, 130, 131, 133–142, 144–147, 151, 153–155, 163, 172, 206, 207, 209, 224–229

MaaS Mobility-as-a-Service 38

MATSim Multi-Agent Transport Simulation 27, 31, 36

MRT mass rapid transit 52–55, 58

NTU Nanyang Technological University 61

NVV North Hessian transport association [Translated from German: Nordhessischer Verkehrsverbund] 148, 149

OCC operations control centre 4, 12, 16, 19–22, 24, 33, 34, 39–43, 46, 71, 74, 76–78, 80, 95, 155, 157, 160, 163–169, 173, 175, 205, 207, 212

OD origin-destination 7, 25, 29, 74–76, 79, 80, 82, 83, 85–87, 89–92, 95–98, 100, 101, 106, 107, 111, 125, 130, 135, 140–142, 144, 149, 151, 158–161, 164, 167, 174, 202, 203, 207, 209, 221–223

OR optimised redirection 102–104, 106, 116, 135–138, 145–147, 152, 158, 159, 173, 209, 225, 231

OSM Open Street Map 149

PAPI Path Advice for Passengers during Incidents 168

PCIM *passenger-centric* incident management 3, 4, 16, 21, 23–28, 30–34, 36, 38–43, 46, 64, 71, 73, 75–77, 85, 96, 160–165, 168, 171, 173–175

PDA passenger demand assignment 7, 8
PI passenger information 10, 13–15, 23–27, 29–31, 38–40, 42, 43, 46, 48, 53, 54, 56, 66–68, 71–73, 75, 77, 80, 82, 91–93, 96, 100, 140, 161–165, 168, 172
PMD personal mobile device 49
PROUD Passenger ROUting during Distruption 168
PSC path search channel 66
PT public transport v, 1–4, 7–21, 23–33, 36, 38–43, 46–50, 52–67, 71–81, 83, 85–87, 89–101, 103, 104, 107, 110, 111, 114, 116, 121, 127, 133–135, 138–140, 143–147, 149–152, 154–168, 171–175, 201–203, 205–207, 209, 211
PTV PTV Planning Transportation Traffic [Translated from German: Planen Transport und Verkehr GmbH] 93, 149

RAPTOR round-based public transit optimized router 31, 36
RATP the autonomous administration of the Paris transport services [Translated from French: Régie Autonome des Transports Parisiens] 38
REPACK REdirecting Passengers and reAllocating Capacities Knowingly 71–74, 76–78, 83, 91–99, 102, 106, 107, 109, 111, 116, 117, 121, 123, 133, 138, 140, 148, 151, 152, 154, 155, 157–169, 171–176, 205, 207

SMS short message service 15
STM Montréal transport company [Translated from French: Soviété de Transport de Montréal] 39
STN simple toy network 71, 72, 160, 205
SUBT suburban train 52, 54
SUMO Simulation of Urban MObility 28, 31, 36, 93, 95, 97, 144, 149

TfL Transport for London 38
TfNSW Transport for New South Wales 38
TraCI traffic contol interface 95, 144

UK United Kingdom 38
USA United States of America 29, 32

V2V vehicle-to-vehicle 143
VBB transport association Berlin/Brandenburg [Translated from German: Verkehrsverbund Berlin/Brandenburg] 40
VDV association of German transport companies [Translated from German: Verband Deutscher Verkehrsunternehmen] 39, 78, 165

ZRK Kassel region special purpose association [Translated from German: Zweckverband Raum Kassel] 148

List of Symbols

B	Set of all buses 87
$b \in B_{sup}^{pl}$	Bus in set of support buses, assigned to PT support line $pl \in PL_{sup}$ 90
$b \in B_{sup}$	Bus in set of support buses 89–91, 202, 203
$b \in B$	Bus in set of all buses 89, 90
c_l	Remaining link capacity of link $l \in L$ 77, 85, 86
c_p	Remaining path capacity of path $p \in P$ 77, 83, 89
$G = (N, L)$	Network graph existing of set of all nodes N and set of all links L 77, 80
$rg_{od}^{\hat{p}}$	Group of passengers, associated with od, being redirected onto their respective fastest path $\hat{p} \in P_{od}$ 82, 85, 87, 106, 140, 158, 159, 201
rg_{od}^{p}	Group of passengers, associated with od, being redirected onto path $p \in P_{od}$ 82, 83, 85–87, 89–91, 100, 101, 106, 152, 158, 167, 202
sg_{od}	Group of self-redirected passengers, associated with od 81, 82, 85, 89
$wg_{od}^{\hat{p}}$	Group of passengers, associated with od, waiting for the dissolution of the incident and staying on their respective $0 \in P_{od}$, while respective $rg_{od}^{\hat{p}}$ on $p \in P_{od}$ 82
wg_{od}^{p}	Group of passengers, associated with od, waiting for the dissolution of the incident and staying on their respective original path $0 \in P_{od}$, while respective $rg_{od}^{\hat{p}}$ on the respective fastest path $\hat{p} \in P_{od}$ 82, 83, 85, 86, 89, 90, 100
$\breve{h}_p$	Longest headway among the PT lines which are serving of path $p \in P$ 81, 101, 103, 130, 203
$L_i \subset L$	Set of links disrupted by an incident, subset of L 77
$L_p \subset L$	Set of links which are part of $p \in P$, subset of L 77
L	Set of all links 77, 201
$l \in L_p$	Link in set of links which are part of path $p \in P$ 85, 86, 201
$l \in L$	Link in set of all links 77, 85, 86, 201
$M \in 0, 1^{P_{od}xL}$	Path-link matrix, in which the element m_{pl} is 1 if link $l \in L_p$ 85, 86, 201
m_{pl}	Binary element of $M \in 0, 1^{P_{od}xL}$ which is 1 if link $l \in L_p$ 85, 86
$N_L \subset N$	Set of line nodes, PT lines serving corresponding stop nodes 77

$N_P \subset N$	Set of stop nodes, reflecting physical PT stops 77
N	Set of all nodes 77, 201
OD	Set of all OD pairs 80, 202
$OD_a \subset OD$	Set of affected OD pairs, subset of OD 75, 80, 82, 85–87
$od \in OD_a$	OD pair in the set of all affected OD pairs 75, 80–83, 85–87, 90–92, 95, 100, 101, 106, 111, 130, 140–142, 144, 151, 158, 159, 161, 164, 167, 206
$0 \in P_{od}$	Original path of od 81–83, 85, 90, 95, 100, 201
$P_{od} \subset P$	Set of alternative paths, associated with od, subset of P 80, 83
P	Set of all paths 202
$\tilde{p} \in P_{od}$	Assigned path of rg^p_{od} associated with od 83, 87, 90, 91, 95, 100, 106, 130, 203
$\hat{p} \in P_{od}$	Fastest path among $p \in P_{od}$, associated with od 80–83, 86, 87, 100, 101, 130, 201
$p \in P_{od}$	Path in set of available alternative paths for od 81–83, 85–87, 89, 90, 106, 158, 201–203
$p \in P$	Path in set of all paths 77, 201
$PL_{ins} \subset PL$	Set of insufficient lines, subset of PL 86
$PL_{sup} \subset PL$	Set of support lines, subset of PL 86, 87, 89, 90, 202
PL	Set of all PT lines 86, 202
$pl \in PL^{ps}_{ins}$	PT line in the set of insufficient lines, associated with path segment ps, subset of PL_{ins} 89, 90, 159, 203
$pl \in PL_{sup}$	PT line in set of support lines $PL_{sup} \subset PL$ 90, 201, 202
$ps \in \bar{PS}_p$	Path segment in set of path segments of path p with insufficient remaining capacity 89, 90, 159, 202, 203
$ps \in PS_p$	Path segment in set of path segments of path p 83, 89
TT^p_{od}	Total travel time of od, if assigned to $p \in P_{od}$ 85
Δtt_u	Delay of PT user $u \in U_a$ 76
t^e_i	End time of the incident 77, 81, 85, 203
t^s_i	Start time of the incident 77, 79, 81, 82, 85
t^o_{arr}	Arrival time at the origin of redirection 82
t^b_{dep}	Original departure time of bus $b \in B_{sup}$ at $pl \in PL_{sup}$ 90
t_{con}	Time constant to consider delays due to missed PT vehicles and interference with other passengers [Bachmann, Dandl et al., 2023] 81
t_i	Incident duration 102–105, 107–116, 118–120, 122–126, 128–132, 136–142, 144–148, 151, 153, 206, 207, 224–236
$t^p_{e,ps}$	End time of passenger redirection at $ps \in \bar{PS}_p$ of $p \in P_{od}$ 90
$t^p_{s,ps}$	Start time of passenger redirection at $ps \in \bar{PS}_p$ of $p \in P_{od}$ 90
T^p_{od}	Redirection duration of passengers associated with od for path $p \in P_{od}$ 81–83, 85, 87, 92, 95, 100, 101, 106, 130, 144, 150, 155, 158, 160, 164, 203

tt_0^{od}	Travel time needed for the original path 0 by od 81, 85
$tt_{\tilde{p}}^{od}$	Travel time needed for assigned path $\tilde{p} \in P_{od}$ by od 87
tt_{pl}^b	Travel time of bus $b \in B_{sup}$ from its original PT line route to the insufficient PT line route of $pl \in PL_{ins}^{ps}$ of $ps \in \bar{PS}_p$ 89, 90
tt_{ps}^b	Travel time of bus $b \in B_{sup}$ along the insufficient PT line $pl \in PL_{ins}^{ps}$ to the start of path segment $ps \in \bar{PS}_p$ 90
tt_p	Travel time needed for path p 81–83, 85, 87
t_u^i	Waiting time of PT user $u \in U_{od}$ until the end of the incident (t_i^e) 85
$U_a \subset U$	Set of affected PT users, subset of U 74, 76, 101, 102, 104, 105, 107–116, 118–124, 126–129, 141, 142, 145–148, 152, 153, 206, 207, 209, 210, 224–236
$U_{ida} \subset U$	Set of indirectly affected PT users, subset of U 74, 85, 107, 108, 110, 115, 116, 152
$U_{od} \subset U$	Set of PT users associated with od, subset of U 85
$U_{red} \subset U$	Set of redirected PT users, subset of U 123, 126, 127, 129, 206
$U_{una} \subset U$	Set of unaffected PT users, subset of U 74, 152
U	Set of all PT users 101, 104, 105, 107–109, 111, 113–116, 118, 120–123, 131, 132, 145–148, 152, 153, 203, 206
$u \in U_a$	PT user in set of all affected PT users 74, 76, 85, 125, 202
$u \in U_{ida}$	PT user in set of all indirectly affected PT users 76
$u \in U_{od}$	PT user in set of all PT users associated with od 85, 203
$u \in U$	PT user in set of all PT users 74, 131, 132, 206
x_{od}^p	Binary decision variable which is 1 if OD pair od is assigned to path $p \in P_{od}$ 86
η	Compliance rate, which expresses the share of passengers who comply with given path advice 82, 83, 85, 100, 102–106, 108, 110, 111, 113, 116, 120, 122, 123, 125, 127, 130–132, 140, 145–147, 152, 158, 160, 163, 206, 224–235
ψ	Factor by which $\breve{h}_p$ is multiplied to adjust redirection duration T_{od}^p 81, 83, 85, 101–105, 108, 109, 112–115, 118–120, 122–124, 126, 128–132, 134, 138, 141, 142, 144, 146, 148, 150, 151, 153, 155, 158, 160, 172, 174, 206, 207, 224–236
ξ	Self-redirection rate, which expresses the share of self-redirected passengers 80, 83, 85, 99, 102, 104, 105, 108–112, 114–116, 118, 119, 123–129, 131, 132, 138, 140, 144–148, 153, 160, 161, 206, 207, 209, 210, 224–236
ζ	Information rate, which expresses the share of passengers who receive path advice 82, 83, 85, 100, 102–106, 108, 110, 111, 113, 116, 120, 122, 123, 125, 127, 130–132, 140–142, 145–147, 152, 158, 163, 164, 206, 224–235

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Annexe

A Incident Examples in Detail

One example of an often occurring kind of incident is falling passengers. For instance, if a bus driver needs to break hard or takes a turn too rapidly, sometimes, passengers standing in the bus and not holding on tightly enough fall during the ride. In most cases, they do not severely hurt themselves. However, in any case, the bus driver needs to check whether the passenger needs medical attention and/or wants to file a complaint. If fallen passengers hurt themselves severely and they need medical attention, the bus needs to wait until the doctor arrives and takes care of the passengers. In such cases, the bus cannot continue as planned and the run might even have to be cancelled. This is even worse if the bus needs to wait at a stop that is consequently blocked.

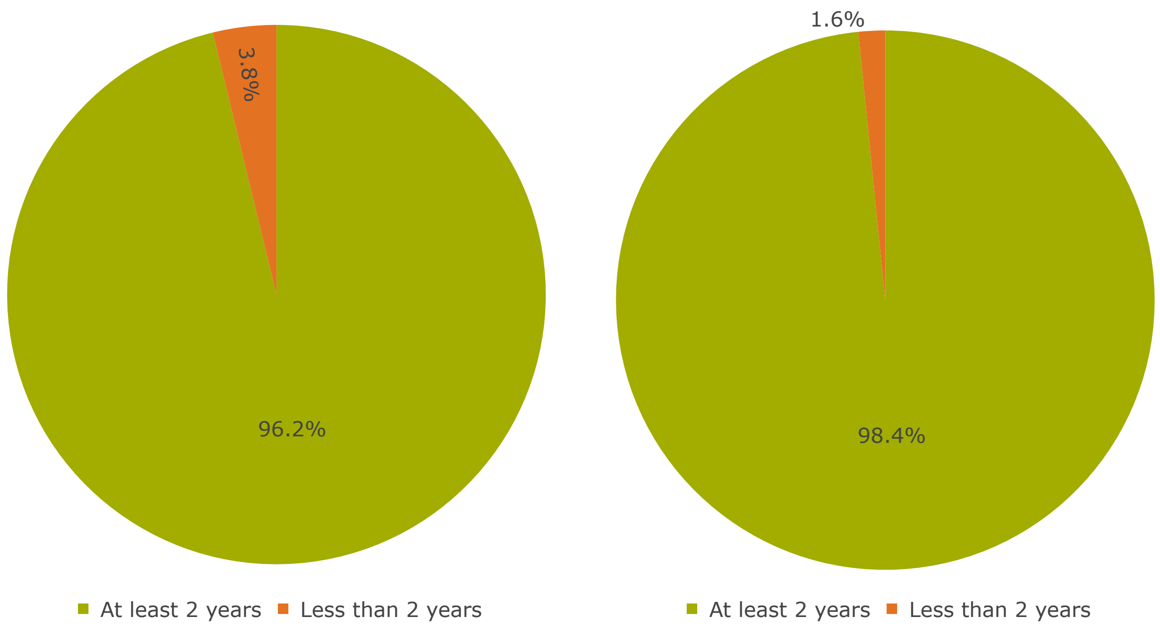
Another example of an often occurring kind of incident is a traffic accident. In the event of a traffic accident on a road or at an intersection where bus lines operate the accident might block the way for the buses of the according PT line. Consequently, those have to wait or take a detour which takes additional travel time which results in delays for the PT service and the passengers. This kind of situation worsens if a bus is involved in an accident itself. In this case, the bus needs to wait until the police arrive and document the accident before the bus can continue its trip, provided the bus and driver are still fit for duty. In severe cases with a broken-down bus and injured people, the run needs to be cancelled, and subsequently runs need to be rerouted for a longer period.

Buses are rather flexible, and a lot of incident situations can be easily dissolved, or their impact at least mitigated by rerouting them. Rail-bound services such as trams and metro, however, are considerably more restricted and therefore limited in their responses to incidents. An incident occurs sometimes just due to a parking offender standing too close to tram tracks. The tram needs to wait until the parking car is removed which can take some time. Due to fewer rerouting options in railway networks, this situation easily causes queuing of trams. In rare cases, such an incident also occurs through the deployment of emergency forces such as ambulance, the fire department, or police, if these park their vehicles on tram tracks.

One last description of a typical incident is about signal failures in rail-bound PT services. For example, if a metro signal fails, metro trains need to stop and wait until the signal is fixed. Since metro trains usually operate at a high frequency and possess a high vehicle capacity and high occupancies, especially during peak hours, such an incident can easily cause severe disturbances, depending on how quickly the signal can be fixed. Knowledge about incidents has been gained through the author's experiences and visits to OCCs [Bachmann, Briem et al., 2022].

B Further Survey Results

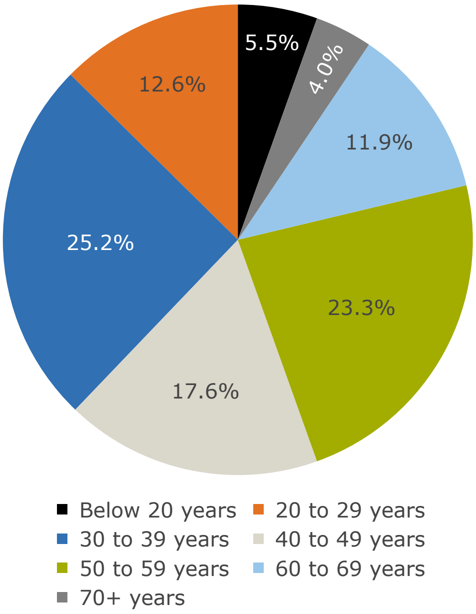
B.1 Sample Description



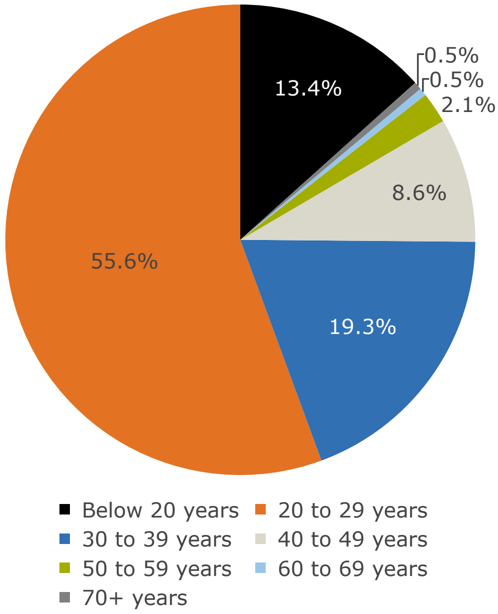
(a) Berlin (N=658)

(b) Singapore (N=189)

Figure B.1: How long have you been resided in the respective city or its suburban area?

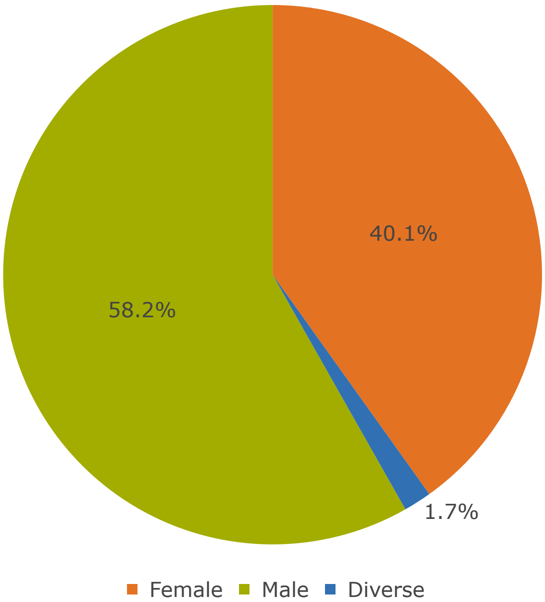


(a) Berlin (N=658)

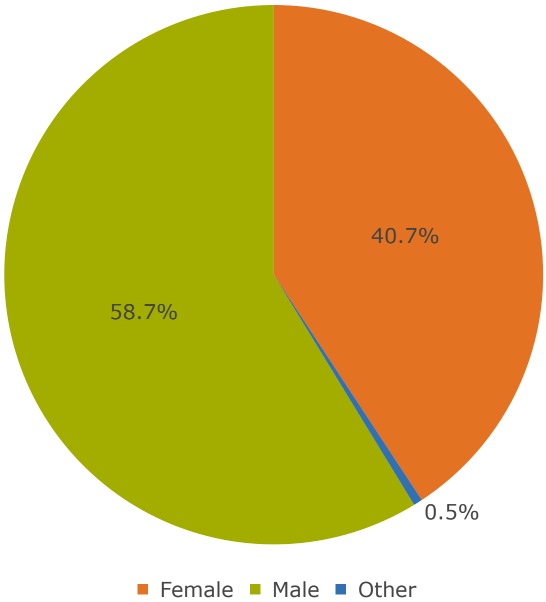


(b) Singapore (N=187)

Figure B.2: How old are you?

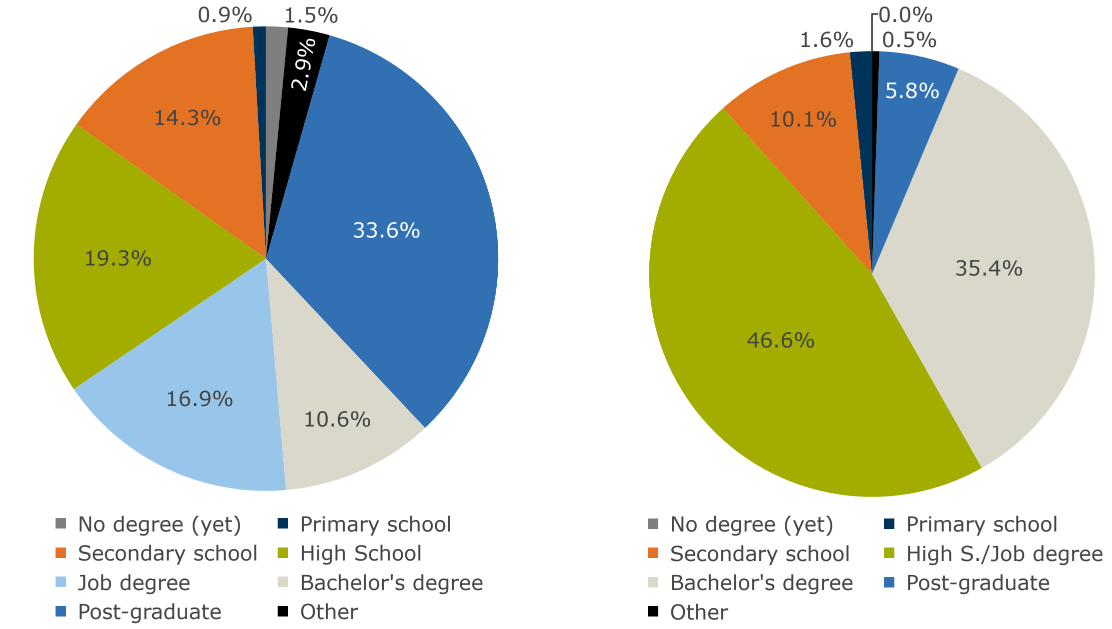


(a) Berlin (N=658)



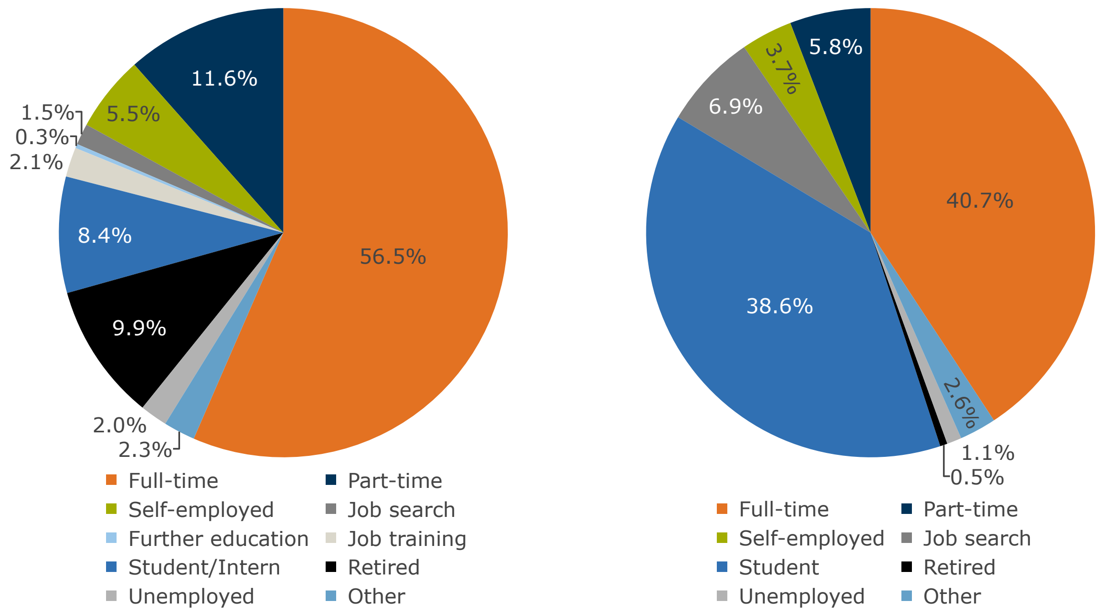
(b) Singapore (N=189)

Figure B.3: What is your gender?



(a) Berlin (N=658) (b) Singapore (N=189)

Figure B.4: What is the highest level of education you have completed?



(a) Berlin (N=658) (b) Singapore (N=189)

Figure B.5: Which of these best describes your current labour status?

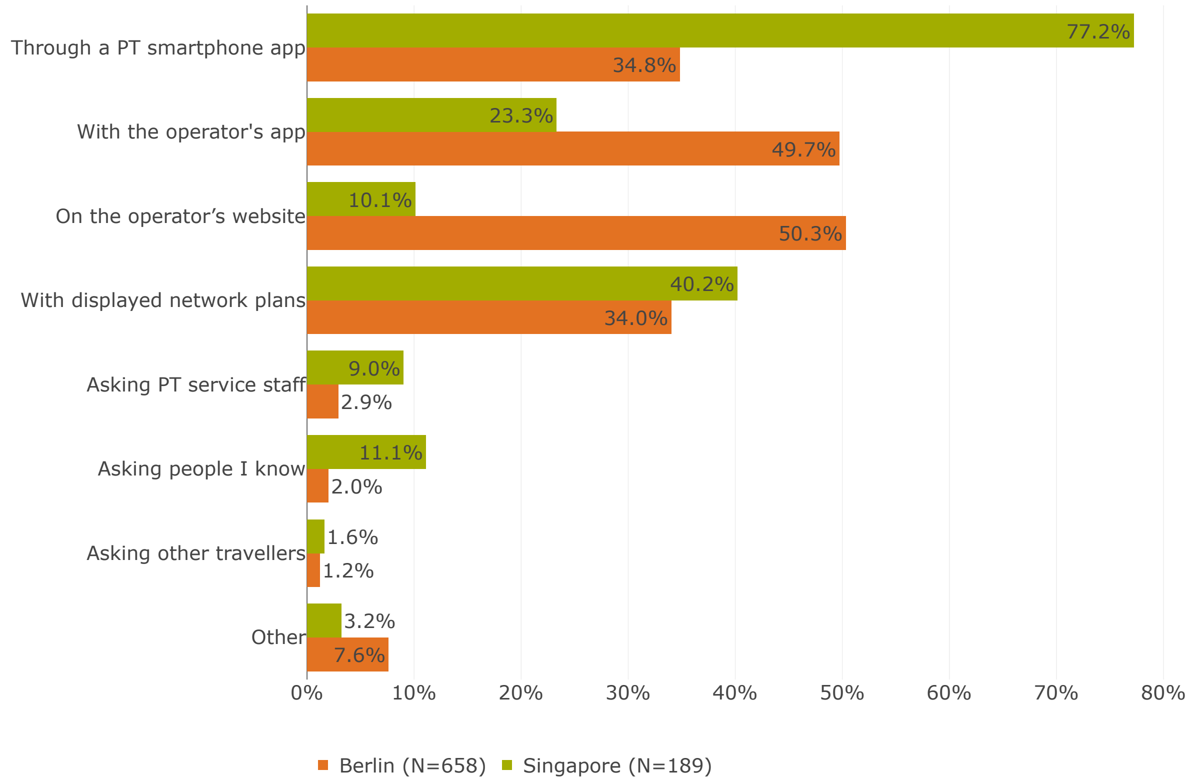


Figure B.6: How do you usually find your transit route within the mass public transport network?

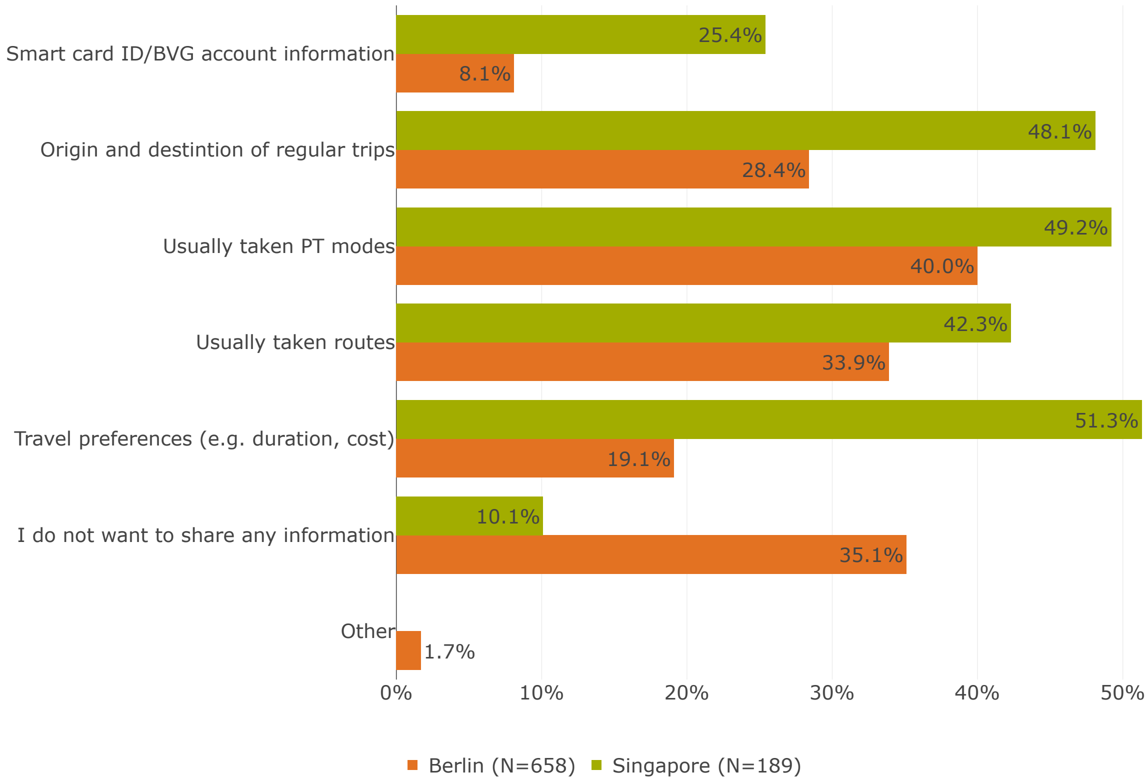
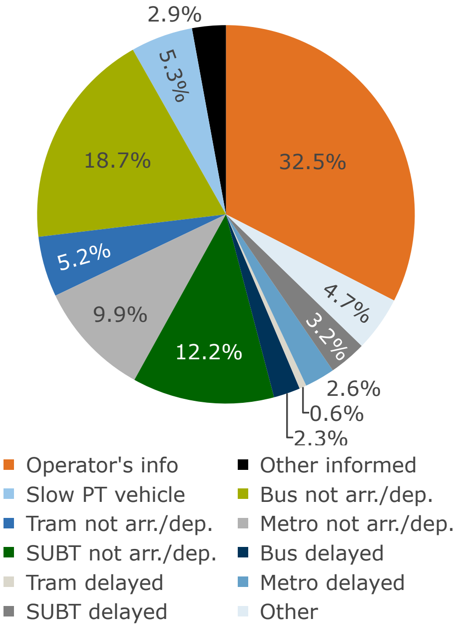
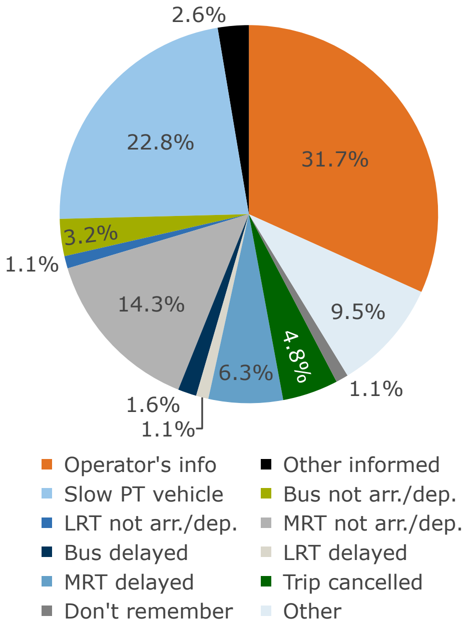


Figure B.7: If the operator were able to give you a route suggestion tailored to your travel needs and preferences, which information would you be willing to share?

B.2 Experienced Incidents



(a) Berlin (N=658)



(b) Singapore (N=189)

Figure B.8: How did you notice that there was an incident?

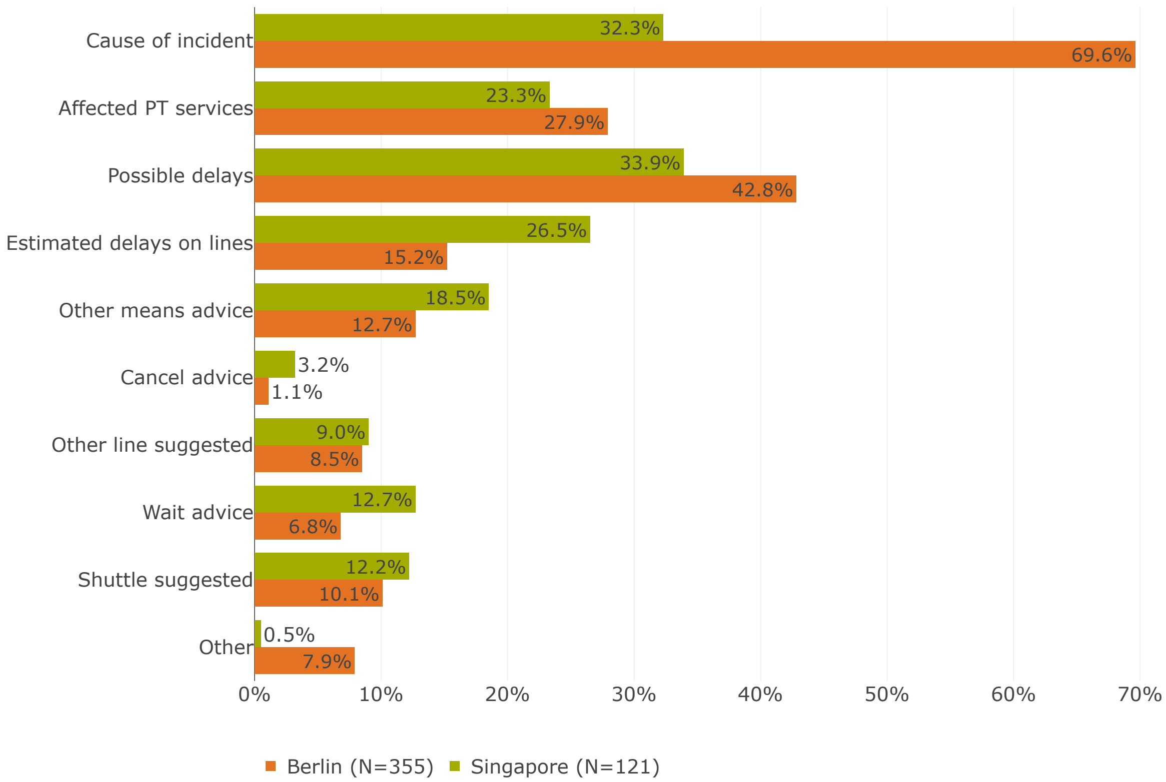
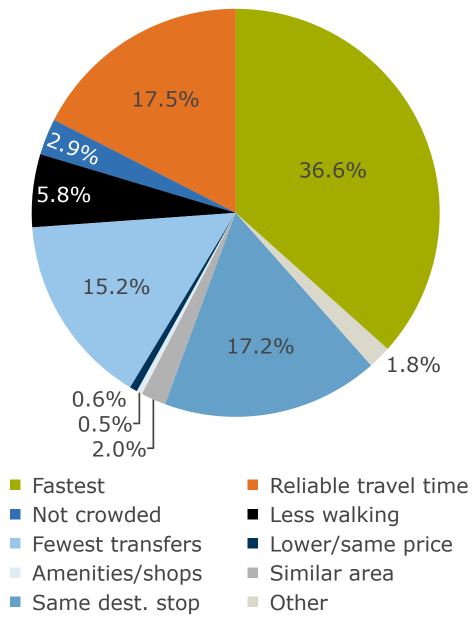
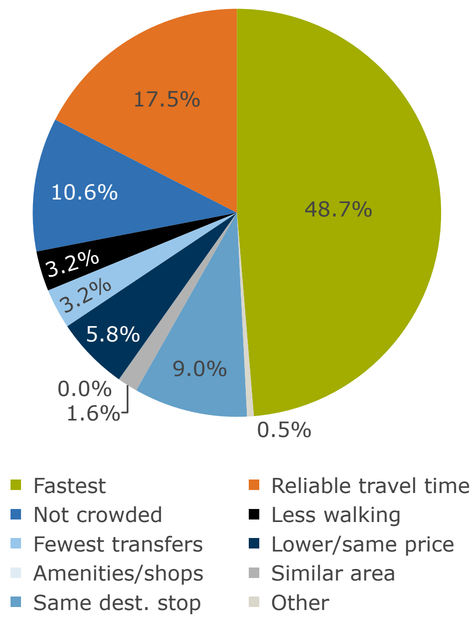


Figure B.9: What information was given to you?

B.3 Passengers' Preferences



(a) Berlin (N=658)



(b) Singapore (N=189)

Figure B.10: Which of these characteristics is most important to you in the alternative path?

C Further Information About the Case Studies

C.1 The Original Mandl Network

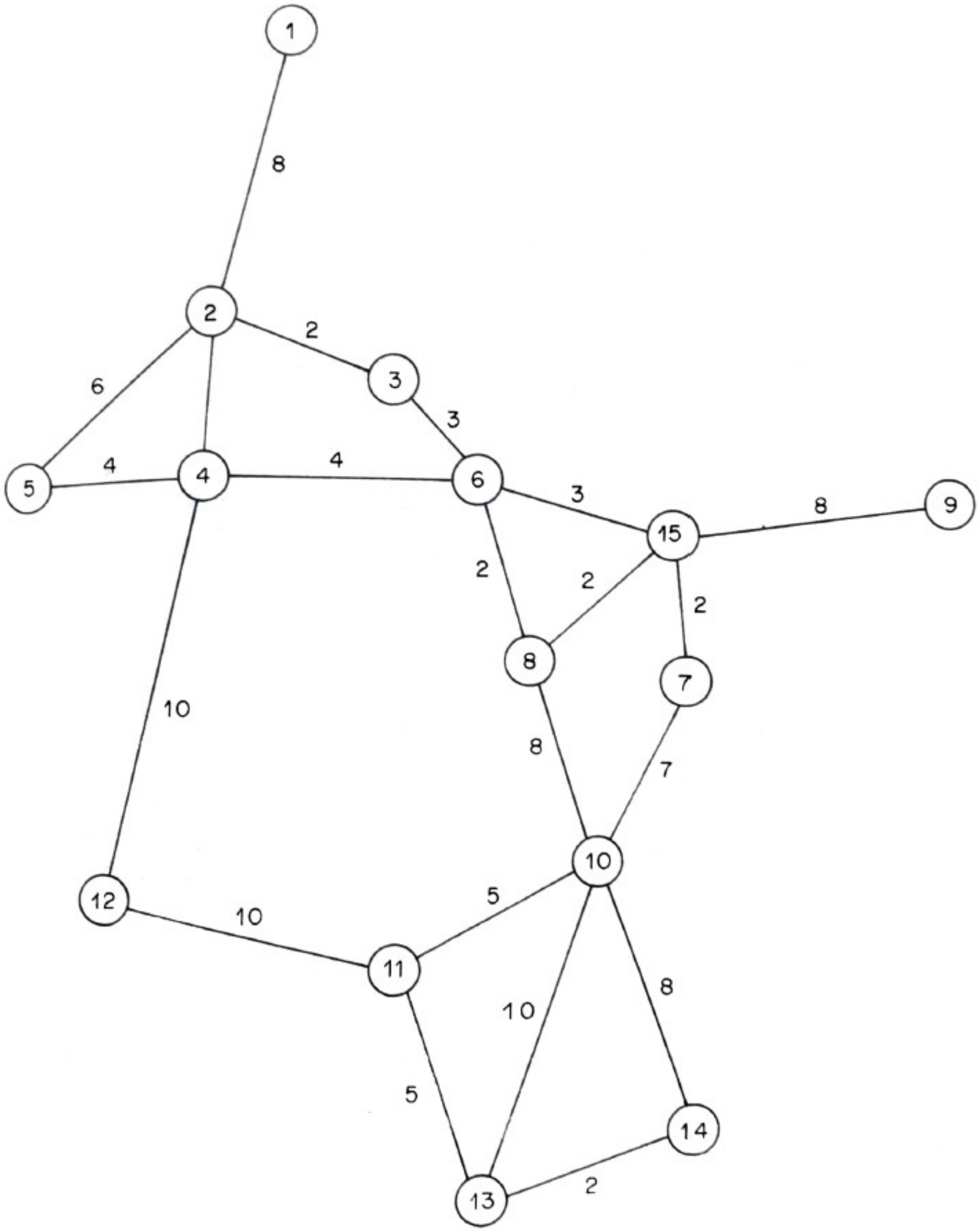


Figure C.1: The original Mandl network [MANDL, 1979]

	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	400	200	60	80	150	75	75	30	160	30	25	35	0	0
2		50	120	20	180	90	90	15	130	20	10	10	5	0
3			40	60	180	90	90	15	45	20	10	10	5	0
4				50	100	50	50	15	240	40	25	10	5	0
5					50	25	25	10	120	20	15	5	0	0
6						100	100	30	880	60	15	15	10	0
7							50	15	440	35	10	10	5	0
8								15	440	35	10	10	5	0
9									140	20	5	0	0	0
10										600	250	500	200	0
11											75	95	15	0
12												70	0	0
13													45	0
14														0

Figure C.2: The original OD matrix of the Mandl network [MANDL, 1979]

C.2 Demand in the Mandl Network

Node-IDs	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	600	300	90	120	225	112	112	45	240	45	37	52	0	0
2	600	0	75	180	30	270	135	135	22	195	30	15	15	7	0
3	300	75	0	60	90	270	135	135	22	675	300	15	15	7	0
4	90	180	60	0	75	150	75	75	22	360	60	37	15	7	0
5	120	30	90	75	0	75	37	37	15	180	30	22	7	0	0
6	225	270	270	150	75	0	150	150	45	1320	90	22	22	15	0
7	112	135	135	75	37	150	0	75	22	660	52	15	15	7	0
8	112	135	135	75	37	150	75	0	22	660	525	15	15	7	0
9	45	22	22	22	15	45	22	22	0	210	300	7	150	0	0
10	240	195	67	360	180	1320	660	660	420	0	900	375	750	300	150
11	45	30	300	60	30	90	52	52	300	900	0	112	142	22	150
12	37	15	15	37	22	22	15	15	75	375	112	0	105	0	150
13	52	15	15	15	7	22	15	15	0	750	142	105	0	67	0
14	0	7	7	7	0	15	7	7	0	300	22	0	67	0	0
15	0	0	0	0	0	0	0	0	0	0	150	150	0	0	0

Table C.1: OD matrix for Mandl network, as used in this thesis

Node-IDs	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5
2	x1.5	0	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5
3	x1.5	x1.5	0	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x15	x15	x1.5	x1.5	x1.5	x1.5
4	x1.5	x1.5	x1.5	0	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5
5	x1.5	x1.5	x1.5	x1.5	0	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5
6	x1.5	x1.5	x1.5	x1.5	x1.5	0	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5
7	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	0	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5
8	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	0	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5
9	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	0	x1.5	x15	x1.5	+100; x1.5	x1.5	x1.5
10	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x3	0	x1.5	x1.5	x1.5	x1.5	+100; x1.5
11	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x15	x1.5	0	x1.5	x1.5	x1.5	+100; x1.5
12	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x15	x1.5	x1.5	0	x1.5	x1.5	+100; x1.5
13	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	0	x1.5	x1.5
14	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	0	x1.5
15	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	x1.5	+100; x1.5	+100; x1.5	x1.5	x1.5	0

Table C.2: Changes to the original OD matrix in Figure C.2

C.3 Results

PT line-splitting

ψ	t_i	$\xi = 0\%$				$\xi = 10\%$				$\xi = 30\%$			
		$\eta \cdot \zeta$											
		0%	35%	70%	100%	0%	35%	70%	100%	0%	35%	70%	100%
1	30 minutes	100.2	72.1	50.0	38.7	79.6	65.5	46.3	36.7	49.8	52.5	39.4	34.1
	60 minutes	100.0	63.6	34.7	19.4	77.2	56.4	32.1	20.2	43.5	42.9	28.2	21.2
	90 minutes	100.1	61.2	30.9	15.3	76.7	54.0	28.5	15.7	42.2	40.5	24.7	17.4
0	30 minutes	100.2	67.7	42.6	31.2	79.6	56.6	38.6	31.9	49.8	39.5	33.8	32.2
	60 minutes	100.0	61.7	32.2	18.8	77.2	49.0	28.9	21.6	43.5	31.5	24.9	23.0
	90 minutes	100.1	59.8	29.1	14.2	76.7	47.0	25.7	17.8	42.2	28.9	21.7	20.0
-1	30 minutes	100.2	65.2	39.0	30.0	79.6	54.6	36.6	32.2	49.8	38.7	33.1	32.1
	60 minutes	100.0	60.2	30.8	19.6	77.2	47.9	28.1	22.0	43.5	31.2	24.7	23.2
	90 minutes	100.1	59.0	28.1	15.4	76.7	46.5	25.1	18.5	42.2	28.7	21.6	20.2
-2	30 minutes	100.2	64.2	37.8	31.9	79.6	53.3	35.7	32.5	49.8	38.5	33.0	32.4
	60 minutes	100.0	59.0	30.2	21.7	77.2	47.4	27.7	23.0	43.5	31.0	24.8	23.4
	90 minutes	100.1	58.6	27.8	16.8	76.7	46.2	24.8	18.7	42.2	28.5	21.5	20.3
-3	30 minutes	100.2	63.7	37.1	32.2	88.9	57.6	36.1	32.2	67.9	47.2	34.0	32.2
	60 minutes	100.0	58.7	29.9	22.3	87.5	52.2	28.6	22.7	64.0	40.9	26.2	23.3
	90 minutes	100.1	58.3	27.5	17.9	87.3	51.5	25.9	18.2	63.4	38.7	23.4	19.5

Table C.3: Relative delay of $U_a \subset U$; Scenario LS; Approach HR

ψ	t_i	$\xi = 0\%$				$\xi = 10\%$				$\xi = 30\%$			
		$\eta \cdot \zeta$											
		0%	35%	70%	100%	0%	35%	70%	100%	0%	35%	70%	100%
1	30 minutes	100.2	71.5	49.9	38.1	79.6	64.9	46.3	36.4	49.8	51.6	39.3	34.5
	60 minutes	100.0	63.3	34.8	17.9	77.2	56.0	32.3	18.1	43.5	42.6	28.2	19.5
	90 minutes	100.1	61.1	30.8	12.4	76.7	54.0	28.5	13.3	42.2	40.3	24.7	15.3
0	30 minutes	100.2	66.8	42.4	30.6	79.6	56.1	38.5	30.4	49.8	38.9	33.7	32.3
	60 minutes	100.0	61.7	32.4	15.3	77.2	48.8	29.1	17.8	43.5	31.1	24.9	22.9
	90 minutes	100.1	59.7	29.1	10.7	76.7	46.8	25.6	13.9	42.2	28.7	21.6	19.7
-1	30 minutes	100.2	64.9	39.3	27.7	79.6	54.3	36.7	28.5	49.8	38.3	33.0	32.2
	60 minutes	100.0	59.8	30.9	14.6	77.2	47.7	27.9	17.0	43.5	30.9	24.8	23.0
	90 minutes	100.1	59.0	28.2	10.1	76.7	46.3	25.2	13.5	42.2	28.4	21.6	19.9
-2	30 minutes	100.2	64.7	39.2	28.6	79.6	53.6	36.9	28.8	49.8	38.5	33.6	33.1
	60 minutes	100.0	59.3	30.7	14.4	77.2	47.2	27.7	16.8	43.5	30.8	24.8	23.2
	90 minutes	100.1	58.5	27.8	10.0	76.7	45.9	25.0	13.4	42.2	28.4	21.6	19.9
-3	30 minutes	100.2	65.5	41.7	29.5	88.9	58.7	38.8	27.9	67.9	47.3	36.1	30.6
	60 minutes	100.0	58.2	30.0	14.6	87.5	52.2	28.7	15.3	64.0	40.6	26.3	17.4
	90 minutes	100.1	58.1	27.6	10.1	87.3	51.4	26.0	11.2	63.4	38.7	23.4	13.8

Table C.4: Relative delay of $U_a \subset U$; Scenario LS; Approach OR

ψ	t_i	$\xi = 0\%$				$\xi = 10\%$				$\xi = 30\%$			
		$\eta \cdot \zeta$											
		0%	35%	70%	100%	0%	35%	70%	100%	0%	35%	70%	100%
1	30 minutes	NA	NA	NA	36.8	NA	NA	NA	34.8	NA	NA	NA	NA
	60 minutes	NA	NA	NA	18.2	NA	NA	NA	17.9	NA	NA	NA	18.6
	90 minutes	NA	NA	NA	13.3	NA	NA	NA	13.9	NA	NA	NA	15.6
0	30 minutes	NA	NA	NA	29.5	NA	NA	NA	29.1	NA	NA	NA	NA
	60 minutes	NA	NA	NA	17.9	NA	NA	NA	18.7	NA	NA	NA	18.6
	90 minutes	NA	NA	NA	13.4	NA	NA	NA	16.3	NA	NA	NA	16.0
-1	30 minutes	NA	NA	NA	27.8	NA	NA	NA	NA	NA	NA	NA	NA
	60 minutes	NA	NA	NA	18.2	NA	NA	NA	18.7	NA	NA	NA	18.7
	90 minutes	NA	NA	NA	13.8	NA	NA	NA	16.4	NA	NA	NA	15.8
-2	30 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	60 minutes	NA	NA	NA	18.9	NA	NA	NA	18.9	NA	NA	NA	NA
	90 minutes	NA	NA	NA	14.1	NA	NA	NA	16.5	NA	NA	NA	NA
-3	30 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	60 minutes	NA	NA	NA	18.9	NA	NA	NA	18.9	NA	NA	NA	NA
	90 minutes	NA	NA	NA	15.4	NA	NA	NA	15.9	NA	NA	NA	NA

Table C.5: Relative delay of $U_a \subset U$; Scenario LS; Approach CR+HR

ψ	t_i	$\xi = 0\%$				$\xi = 10\%$				$\xi = 30\%$			
		$\eta \cdot \zeta$											
		0%	35%	70%	100%	0%	35%	70%	100%	0%	35%	70%	100%
	30 minutes	NA	NA	NA	36.3	NA	NA	NA	NA	NA	NA	NA	NA
1	60 minutes	NA	NA	NA	18.2	NA	NA	NA	18.3	NA	NA	NA	NA
	90 minutes	NA	NA	NA	13.5	NA	NA	NA	14.3	NA	NA	NA	16.3
	30 minutes	NA	NA	NA	29.8	NA	NA	NA	29.1	NA	NA	NA	NA
0	60 minutes	NA	NA	NA	17.9	NA	NA	NA	18.7	NA	NA	NA	NA
	90 minutes	NA	NA	NA	14.9	NA	NA	NA	16.3	NA	NA	NA	15.4
	30 minutes	NA	NA	NA	27.9	NA	NA	NA	NA	NA	NA	NA	NA
-1	60 minutes	NA	NA	NA	18.2	NA	NA	NA	18.7	NA	NA	NA	NA
	90 minutes	NA	NA	NA	14.0	NA	NA	NA	16.4	NA	NA	NA	15.8
	30 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
-2	60 minutes	NA	NA	NA	18.9	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	14.8	NA	NA	NA	16.5	NA	NA	NA	NA
	30 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
-3	60 minutes	NA	NA	NA	18.8	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	15.9	NA	NA	NA	15.9	NA	NA	NA	NA

Table C.6: Relative delay of $U_a \subset U$; Scenario LS; Approach CR+OR

ψ	t_i	$\eta \cdot \zeta$			
		0%	35%	70%	100%
1	30 minutes	HR, OR: 79.6	OR: 64.9	HR, OR: 46.3	**CR+HR: 34.8**
	60 minutes	HR, OR: 77.2	OR: 56.0	HR: 32.1	**CR+HR: 17.9**
	90 minutes	HR, OR: 76.7	HR, OR: 54.0	HR, OR: 28.5	**OR: 13.3**
0	30 minutes	HR, OR: 79.6	OR: 56.1	OR: 38.5	**CR+HR, CR+OR: 29.1**
	60 minutes	HR, OR: 77.2	OR: 48.8	HR: 28.9	**OR: 17.8**
	90 minutes	HR, OR: 76.7	OR: 46.8	OR: 25.6	**OR: 13.9**
-1	30 minutes	HR, OR: 79.6	OR: 54.3	HR: 36.6	**OR: 28.5**
	60 minutes	HR, OR: 77.2	OR: 47.7	OR: 27.9	**OR: 17.0**
	90 minutes	HR, OR: 76.7	OR: 46.3	HR: 25.1	**OR: 13.5**
-2	30 minutes	HR, OR: 79.6	HR: 53.3	HR: 35.7	**OR: 28.8**
	60 minutes	HR, OR: 77.2	OR: 47.2	HR, OR: 27.7	**OR: 16.8**
	90 minutes	HR, OR: 76.7	OR: 45.9	HR: 24.8	**OR: 13.4**
-3	30 minutes	HR, OR: 88.9	HR: 57.6	HR: 36.1	**OR: 27.9**
	60 minutes	HR, OR: 87.5	HR, OR: 52.2	HR: 28.6	**OR: 15.3**
	90 minutes	HR, OR: 87.3	OR: 51.4	HR: 25.9	**OR: 11.2**

Table C.7: Lowest relative delays of each case for $U_a \subset U$ with $\xi = 10\%$ in Scenario LS

ψ	t_i	$\eta \cdot \zeta$			
		0%	35%	70%	100%
1	30 minutes	HR, OR: 49.8	OR: 51.6	OR: 39.3	**HR: 34.1**
	60 minutes	HR, OR: 43.5	OR: 42.6	HR, OR: 28.2	**CR+HR: 18.6**
	90 minutes	HR, OR: 42.2	OR: 40.3	HR, OR: 24.7	**OR: 15.3**
0	30 minutes	HR, OR: 49.8	OR: 38.9	OR: 33.7	**HR: 32.2**
	60 minutes	HR, OR: 43.5	OR: 31.1	HR, OR: 24.9	**CR+HR: 18.6**
	90 minutes	HR, OR: 42.2	OR: 28.7	OR: 21.6	**CR+OR: 15.4**
-1	30 minutes	HR, OR: 49.8	OR: 38.3	OR: 33.0	**HR: 32.1**
	60 minutes	HR, OR: 43.5	OR: 30.9	HR: 24.7	**CR+HR: 18.7**
	90 minutes	HR, OR: 42.2	OR: 28.4	HR, OR: 21.6	**CR+HR, CR+OR: 15.8**
-2	30 minutes	HR, OR: 49.8	HR, OR: 38.5	HR: 33.0	**HR: 32.4**
	60 minutes	HR, OR: 43.5	OR: 30.8	HR, OR: 24.8	**OR: 23.2**
	90 minutes	HR, OR: 42.2	OR: 28.4	HR: 21.5	**OR: 19.9**
-3	30 minutes	HR, OR: 67.9	HR: 47.2	HR: 34.0	**OR: 30.6**
	60 minutes	HR, OR: 64.0	OR: 40.6	HR: 26.2	**OR: 17.4**
	90 minutes	HR, OR: 63.4	HR, OR: 38.7	HR, OR: 23.4	**OR: 13.8**

Table C.8: Lowest relative delays of each case for $U_a \subset U$ with $\xi = 30\%$ in Scenario LS

PT line-rerouting

ψ	t_i	$\xi = 0\%$				$\xi = 10\%$				$\xi = 30\%$			
		$\eta \cdot \zeta$											
		0%	35%	70%	100%	0%	35%	70%	100%	0%	35%	70%	100%
1	30 minutes	100.0	93.5	87.0	80.8	97.9	91.1	86.3	80.7	93.8	89.2	84.4	80.3
	60 minutes	100.0	89.9	78.4	70.1	95.9	87.7	77.6	70.0	91.2	84.2	75.8	69.8
	90 minutes	100.0	85.5	71.4	60.8	95.9	82.6	71.0	60.8	87.2	76.9	68.8	60.7
0	30 minutes	100.0	93.1	85.7	79.2	97.9	92.1	85.4	79.2	93.8	89.3	84.3	79.2
	60 minutes	100.0	89.4	78.6	69.5	95.9	85.9	77.8	69.5	91.2	83.8	75.6	69.4
	90 minutes	100.0	84.5	71.7	60.5	95.9	82.4	70.3	60.5	87.2	77.1	68.6	60.5
-1	30 minutes	100.0	93.4	86.1	79.2	97.9	92.5	85.4	79.2	93.8	89.4	84.1	79.2
	60 minutes	100.0	89.1	77.9	69.4	95.9	85.9	77.3	69.4	91.2	83.6	75.9	69.4
	90 minutes	100.0	85.0	71.6	60.5	95.9	82.2	71.2	60.5	87.2	77.1	68.4	60.5
-2	30 minutes	100.0	93.4	86.1	79.2	97.9	92.5	85.4	79.2	93.8	89.4	84.1	79.2
	60 minutes	100.0	89.1	77.9	69.4	95.9	85.9	77.3	69.4	91.2	83.6	75.9	69.4
	90 minutes	100.0	85.0	71.6	60.5	95.9	82.2	71.2	60.5	87.2	77.1	68.4	60.5
-3	30 minutes	100.0	93.4	86.1	79.2	97.9	92.5	85.4	79.2	93.8	89.4	84.1	79.2
	60 minutes	100.0	89.1	77.9	69.4	95.9	85.9	77.3	69.4	91.2	83.6	75.9	69.4
	90 minutes	100.0	85.0	71.6	60.5	95.9	82.2	71.2	60.5	87.2	77.1	68.4	60.5

Table C.9: Relative delay of $U_a \subset U$; Scenario LR; Approach HR

ψ	t_i	$\xi = 0\%$				$\xi = 10\%$				$\xi = 30\%$			
		$\eta \cdot \zeta$											
		0%	35%	70%	100%	0%	35%	70%	100%	0%	35%	70%	100%
1	30 minutes	100.0	93.7	86.9	83.9	97.9	91.6	86.3	82.7	93.8	89.3	84.0	80.5
	60 minutes	100.0	89.3	79.4	71.9	95.9	87.8	77.5	70.9	91.2	84.1	76.5	69.8
	90 minutes	100.0	85.8	71.9	61.8	95.9	82.2	71.5	61.0	87.2	77.6	68.4	60.7
0	30 minutes	100.0	93.3	86.3	84.6	97.9	92.7	85.9	82.5	93.8	88.6	83.6	80.2
	60 minutes	100.0	89.1	78.0	71.7	95.9	86.3	77.6	70.8	91.2	83.8	76.2	69.4
	90 minutes	100.0	84.8	71.6	62.0	95.9	82.4	71.5	61.3	87.2	77.4	68.9	60.5
-1	30 minutes	100.0	93.6	86.4	85.1	97.9	92.2	85.1	83.2	93.8	88.7	82.7	80.1
	60 minutes	100.0	88.9	79.2	71.6	95.9	86.5	77.3	70.8	91.2	83.4	76.6	69.4
	90 minutes	100.0	84.5	72.6	62.0	95.9	82.1	70.9	61.3	87.2	77.6	68.9	60.5
-2	30 minutes	100.0	93.6	86.3	85.1	97.9	92.2	85.1	83.2	93.8	88.7	82.7	80.1
	60 minutes	100.0	88.9	79.2	71.7	95.9	86.5	77.3	70.8	91.2	83.4	76.6	69.4
	90 minutes	100.0	84.5	72.6	62.0	95.9	82.1	70.9	61.3	87.2	77.6	68.9	60.5
-3	30 minutes	100.0	93.6	86.3	85.1	97.9	92.2	85.1	83.2	93.8	88.7	82.7	80.1
	60 minutes	100.0	88.9	79.2	71.6	95.9	86.5	77.3	70.8	91.2	83.4	76.6	69.4
	90 minutes	100.0	84.5	72.6	62.0	95.9	82.1	70.9	61.3	87.2	77.6	68.9	60.5

Table C.10: Relative delay of $U_a \subset U$; Scenario LR; Approach OR

ψ	t_i	$\xi = 0\%$				$\xi = 10\%$				$\xi = 30\%$			
		$\eta \cdot \zeta$											
		0%	35%	70%	100%	0%	35%	70%	100%	0%	35%	70%	100%
1	30 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	60 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
0	30 minutes	NA	NA	NA	78.0	NA	NA	NA	77.7	NA	NA	NA	NA
	60 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
-1	30 minutes	NA	NA	NA	77.9	NA	NA	NA	77.7	NA	NA	NA	NA
	60 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
-2	30 minutes	NA	NA	NA	77.9	NA	NA	NA	77.7	NA	NA	NA	NA
	60 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
-3	30 minutes	NA	NA	NA	77.9	NA	NA	NA	77.7	NA	NA	NA	NA
	60 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

Table C.11: Relative delay of $U_a \subset U$; Scenario LR; Approach CR+HR

ψ	t_i	$\xi = 0\%$				$\xi = 10\%$				$\xi = 30\%$			
		$\eta \cdot \zeta$											
		0%	35%	70%	100%	0%	35%	70%	100%	0%	35%	70%	100%
1	30 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	60 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
0	30 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	**32.4**
	60 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
-1	30 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	**32.4**
	60 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
-2	30 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	**32.4**
	60 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
-3	30 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	**32.4**
	60 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	90 minutes	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

Table C.12: Relative delay of $U_a \subset U$; Scenario LR; Approach CR+OR

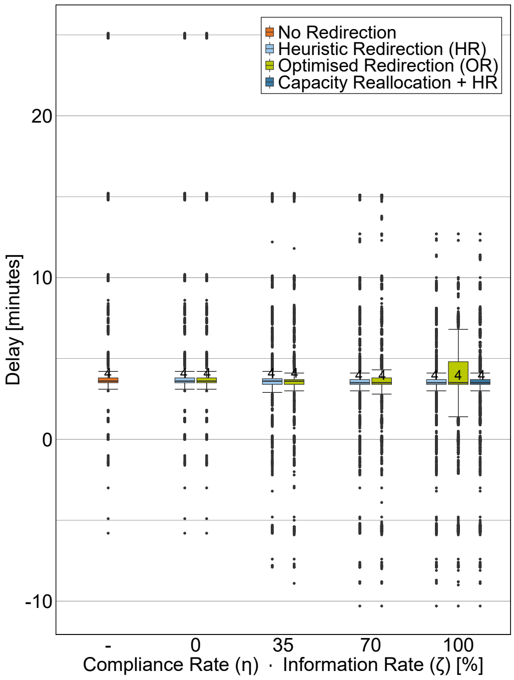
ψ	t_i	$\eta \cdot \zeta$			
		0%	35%	70%	100%
1	30 minutes	HR, OR: 97.9	HR: 91.1	HR, OR: 86.3	**HR: 80.7**
	60 minutes	HR, OR: 95.9	HR: 87.7	OR: 77.5	**HR: 70.0**
	90 minutes	HR, OR: 95.9	OR: 82.2	HR: 71.0	**HR: 60.8**
0	30 minutes	HR, OR: 97.9	HR: 92.1	HR: 85.4	**CR+HR: 77.7**
	60 minutes	HR, OR: 95.9	HR: 85.9	OR: 77.6	**HR: 69.5**
	90 minutes	HR, OR: 95.9	HR, OR: 82.4	HR: 70.3	**HR: 60.5**
-1	30 minutes	HR, OR: 97.9	OR: 92.2	OR: 85.1	**CR+HR: 77.7**
	60 minutes	HR, OR: 95.9	HR: 85.9	HR, OR: 77.3	**HR: 69.4**
	90 minutes	HR, OR: 95.9	OR: 82.1	OR: 70.9	**HR: 60.5**
-2	30 minutes	HR, OR: 97.9	OR: 92.2	OR: 85.1	**CR+HR: 77.7**
	60 minutes	HR, OR: 95.9	HR: 85.9	HR, OR: 77.3	**HR: 69.4**
	90 minutes	HR, OR: 95.9	OR: 82.1	OR: 70.9	**HR: 60.5**
-3	30 minutes	HR, OR: 97.9	OR: 92.2	OR: 85.1	**CR+HR: 77.7**
	60 minutes	HR, OR: 95.9	HR: 85.9	HR, OR: 77.3	**HR: 69.4**
	90 minutes	HR, OR: 95.9	OR: 82.1	OR: 70.9	**HR: 60.5**

Table C.13: Lowest relative delays of each case for $U_a \subset U$ with $\xi = 10\%$ in Scenario LR

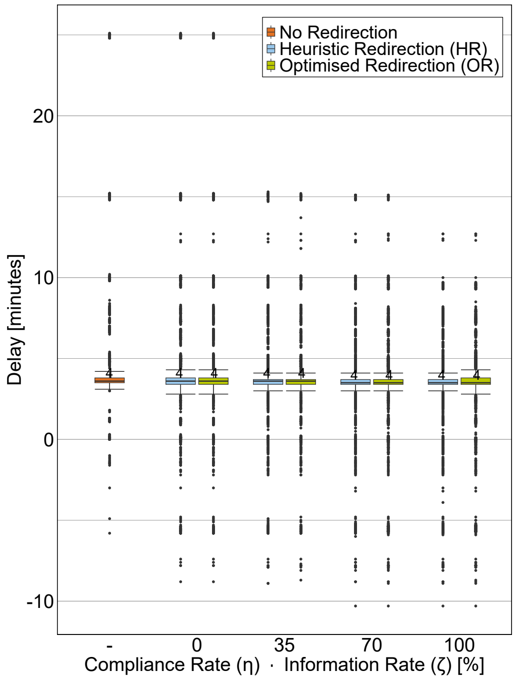
ψ	t_i	$\eta \cdot \zeta$			
		0%	35%	70%	100%
1	30 minutes	HR, OR: 93.8	HR: 89.2	OR: 84.0	**HR: 80.3**
	60 minutes	HR, OR: 91.2	OR: 84.1	HR: 75.8	**HR, OR: 69.8**
	90 minutes	HR, OR: 87.2	HR: 76.9	OR: 68.4	**HR, OR: 60.7**
0	30 minutes	HR, OR: 93.8	OR: 88.6	OR: 83.6	**HR: 79.2**
	60 minutes	HR, OR: 91.2	HR, OR: 83.8	HR: 75.6	**HR, OR: 69.4**
	90 minutes	HR, OR: 87.2	HR: 77.1	HR: 68.6	**HR, OR: 60.5**
-1	30 minutes	HR, OR: 93.8	OR: 88.7	OR: 82.7	**HR: 79.2**
	60 minutes	HR, OR: 91.2	OR: 83.4	HR: 75.9	**HR, OR: 69.4**
	90 minutes	HR, OR: 87.2	HR: 77.1	HR: 68.4	**HR, OR: 60.5**
-2	30 minutes	HR, OR: 93.8	OR: 88.7	OR: 82.7	**HR: 79.2**
	60 minutes	HR, OR: 91.2	OR: 83.4	HR: 75.9	**HR, OR: 69.4**
	90 minutes	HR, OR: 87.2	HR: 77.1	HR: 68.4	**HR, OR: 60.5**
-3	30 minutes	HR, OR: 93.8	OR: 88.7	OR: 82.7	**HR: 79.2**
	60 minutes	HR, OR: 91.2	OR: 83.4	HR: 75.9	**HR, OR: 69.4**
	90 minutes	HR, OR: 87.2	HR: 77.1	HR: 68.4	**HR, OR: 60.5**

Table C.14: Lowest relative delays of each case for $U_a \subset U$ with $\xi = 30\%$ in Scenario LR

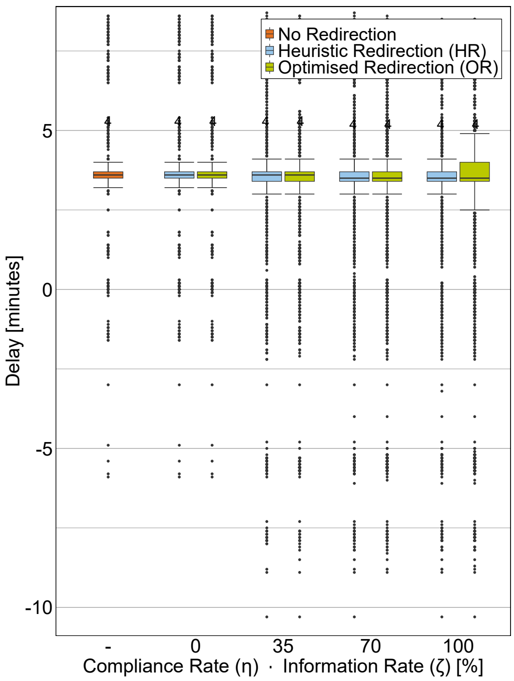
Delay Distribution with Outliers



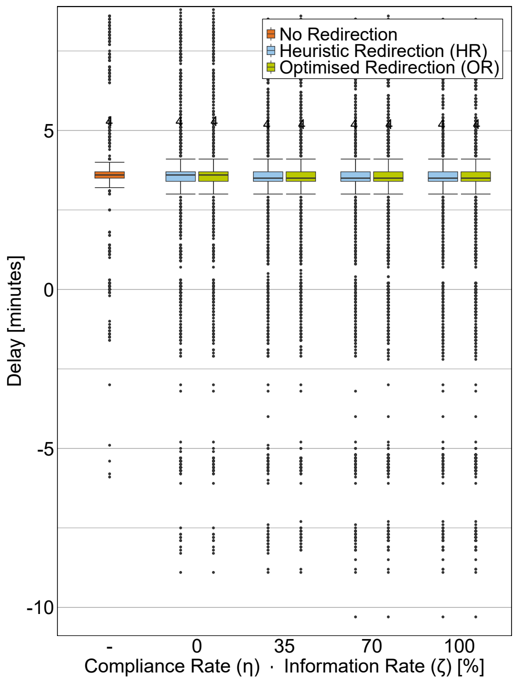
(a) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 0\%$



(b) $U_a \subset U$; $t_i = 30$ minutes; $\xi = 30\%$



(c) $U_a \subset U$; $t_i = 90$ minutes; $\xi = 0\%$



(d) $U_a \subset U$; $t_i = 90$ minutes; $\xi = 30\%$

Figure C.3: Delay distribution of $U_a \subset U$ with outliers in Scenario LR ($\psi = 0$)