DISS ETH NO. 27050

THE ROLE OF INFORMATION TO PASSENGERS IN PUBLIC TRANSPORT DISRUPTIONS

A dissertation submitted to attain the degree of

DOCTOR OF SCIENCES of ETH ZURICH

(Dr. sc. ETH Zurich)

presented by

NUANNUAN LENG

Master of Engineering, Beijing Jiaotong University (BJTU)

born on 24.11.1989

citizen of Shandong (CHINA)

accepted on the recommendation of

Prof. Dr. Francesco Corman, examiner

Prof. Dr. Ulrich Weidmann, co-examiner

Prof. Dr. Anita Schöbel, co-examiner

Dr. Paul Bouman, co-examiner

2020

Abstract

During public transport disruptions, the performance of the public transport network is degraded due to unexpected events, resulting in delays and inconvenience for passengers. Therefore, the infrastructure managers and operating companies typically generate a new public transport timetable, called disposition timetable, to reduce passengers' delays, thereby limiting a negative impact on passengers' activities and related satisfaction. To generate the new timetable, different rescheduling strategies are considered, such as retiming, rerouting, partial or full cancellation of services, possibly needing to take into account the feasibility of rolling stock circulation.

In this context, disseminating information about the running services is critical. This information is not only the bridge for infrastructure managers and operating companies to provide an updated timetable to passengers, but also the link for them to understand passengers' behaviours in case of disruptions so that they can reschedule timetable and rolling stock more efficiently to offer passengers better quality services. However, the disseminated information in reality could be incomplete or inaccurate, that is, not all the passengers immediately receive all the information about the disposition timetable. This incompleteness of information could jeopardise the efforts of infrastructure managers and operating companies to improve passengers' satisfaction.

In this dissertation, we study the effects of information provision to passengers in public transport disruptions, taking into account information availability, quality, passenger heterogeneity, passenger behaviours, disposition timetables and multi-modal transport network. The main contribution of this dissertation is three-fold. First, we propose rigorous mathematical relations to formalise the effects of information availability to passengers in public transport disruptions, including user equilibrium and non-equilibrium solutions. These relations allow simulating and analysing passengers' behaviours in a multi-modal network using an agent-based micro-simulation model (MATSim). Second, we combine in an innovative manner MATSim with an optimisation model to explore passengers' satisfaction towards different disposition timetables and information strategies. The results from this integrated model can be helpful for infrastructure managers and operating companies to offer better services to passengers in public transport disruptions. Third, we propose a novel multi-layer time-event-graph method to quantify and identify the effects of incomplete information to passengers' delays and route feasibility.

Part I summarises the information availability in public transport disruptions in a "who-when-where-what" four-dimensional framework. Based on the proposed rigorous mathematical descriptions of the effects of information availability to passengers, including user equilibrium and non-equilibrium solutions, we apply MATSim to the city of Zürich, Switzerland, to assess the benefit of activity-based simulation in a multi-modal network. We use an existing day-to-day replanning method, and further extend it by a within-day replanning approach, to study agents' route choices responding to public transport disruption in one single iteration. The disruption is assumed as the rail track blockages between two major stations, Zürich HB and Zürich Oerlikon. We simulate three scenarios based on different information availability, and compared with a benchmark of agents' behaviours without disruption. Statistic results are analysed for all the agents who are involved in the defined disruption. Agents' flow in related transit routes and transport modes shows their adaptations to the corresponding information availability. Our analysis on delays and other statistics reveal that information availability significantly influences agents' satisfaction in public transport disruption.

Part II applies a mixed integer programming (MIP) model to generate different disposition timetables following a disruption, with the objective to minimise the total delay of passengers. The timetable rescheduling includes the strategies of retiming, reordering, rerouting, cancellation of train services. The rolling stock circulation is checked to ensure the feasibility of the disposition timetable. We solve this MIP model using a commercial solver. We then apply MATSim to simulate the activity-based agents' behaviours with different disposition timetables and information strategies in a multi-modal network, and analyse agents' delays and other performance indicators for the city of Zürich. We find that the earlier the information of disposition timetable is disseminated to passengers, the larger the improvements of satisfaction they can gain during disruption. We also find that, compared to a straightforward full cancellation of train services, computing a precise feasible rolling stock circulation that is able to handle partial train cancellations can significantly benefit the passengers. In particular, the delay of passengers whose planned services are disrupted decreases substantially, whereas other passengers that are not directly affected by the disruption may experience minor delays. At system level, the realistic operation strategy can considerably reduce the impact of the disruption, with a utility impact of the disruption reduced to a fifth only, instead of the original negative impact.

Part III studies the effects of incomplete information to passengers and proposes a novel multi-layer time-event-graph method to describe heterogeneous passengers' thinking about disposition timetable under different types of incomplete information. Specifically, the information we consider varies based on time and location that passengers receive as well as content. Moreover, we consider different passengers' beliefs on delay propagation (i.e. impacts of disposition timetable). Using our graph-based route choice model, we are able to describe passengers' behaviours incorporating the impacts of incomplete information (perfect or on-route) and their belief (schedule-stubborn or delay-extended). We then examine the feasibility of passengers' routes and passengers' delays. The results show that the on-route information causes more infeasible routes and larger passengers' delays compared to the perfect information. The effects of passengers' belief with on-route information are negligible; but are large in case of perfect information: schedule-stubborn belief causes less passengers' delay with a short available information, otherwise delay-extended belief works better.

To sum up, this dissertation provides insights on how the information (e.g. availability, completeness) affects passengers' satisfaction during public transport disruptions. We quantify the value of early information and richer information to the satisfaction/ delays of specific passenger groups. The results can be useful to infrastructure managers and operating companies to understand and evaluate the effects of different information and rescheduling strategies during public transport disruptions. This dissertation can be beneficial for passengers, infrastructure managers, operating companies and the public transport industry.

Zusammenfassung

Während Störungen von öffentlichen Verkehrssystemen ist die Leistung des öffentlichen Verkehrsnetzwerkes infolge von unerwarteten Ereignissen reduziert. Diese Reduzierung führt zu Unannehmlichkeiten und Verspätungen für die Passagiere. Daher erstellen die Infrastrukturmanager und Betriebsgesellschaften typischerweise einen Dispositionsfahrplan um die Verspätung der Passagiere zu minimieren. Dadurch wird der negative Einfluss der Störungen auf die Aktivitäten der Passagiere limitiert und die Zufriedenheit erhöht. Um einen neuen Fahrplan zu erstellen, werden verschiedenen Neuplanungsstrategien in Betracht gezogen. Diese Strategien beinhalten eine Neubeurteilung der Route, der Abfahrtszeiten, sowie den partiellen oder vollständigen Ausfall der Linien. Diese Strategien müssen möglicherweise die Rollmaterialzirkulation berücksichtigen.

In diesem Kontext ist es zentral, Informationen über die verkehrenden Linien zu verteilen. Diese Information stellt nicht nur die Brücke von Infrastrukturmanager und Betriebsgesellschaften zu den Passagieren dar. Sie wird auch verwendet um das Verhalten der Passagier im Störungsfall zu verstehen. Somit können die Fahrpläne und Rollmaterialzuweisung effizient geplant werden und die Qualität für die Passagiere erhöht werden. Die verteilten Informationen können aber in der Realität inkomplett und ungenau sein, so dass nicht alle Passagiere die Informationen bezüglich des Dispositionszeitplanes nicht in Echtzeit erhalten. Diese Unvollständigkeit der Information könnte die Anstrengungen der Infrastrukturmanager und Betriebsgesellschaften, die Fahrgastzufriedenheit zu erhöhen, gefährden.

In dieser Dissertation betrachten wir die Effekte von dem zur Verfügung stellen von Informationen im Zuge von Störungen von öffentlichen Verkehrssystemen, unter Berücksichtigung von der Verfügbarkeit und Qualität von Informationen, Passagierheterogenität, Passagierverhalten, Dispositionsfahrplan und multimodalen Transportnetzwerken. Diese Dissertationen macht drei Hauptbeiträge an die Wissenschaft. Erstens, stellen wir rigorose mathematische Formulierungen auf, um den Effekt der Verfügbarkeit von Informationen für Passagiere während Störungen der öffentlichen Verkehrssysteme zu formalisieren. Diese Formulierungen beinhalten Lösungen für den Fall von Nutzergleichgewicht und Nutzerungleichgewicht. Diese

Formulierungen erlauben die Simulation und Analyse von Passagierverhalten in multimodalen Netzwerken unter Verwendung einer Agent-basierten Simulationssoftware (MATSim). Zweitens, kombinieren wir auf eine innovative Art MATSim mit einem Optimierungsmodell um die Passagierzufriedenheit in Bezug auf verschiedenen Dispositionsfahrpläne und Informationsstrategien zu erforschen. Die Resultate der Verwendung dieses integralen Models können für Infrastrukturmanager und Betriebsgesellschaften nützlich sein, um einen besseren Service für Passagiere während einer Störung zu bieten. Drittens, zeigen wie eine neuartige, mehrlagige Zeit-Ereignis-Graph-Methodik auf, um die Effekte von unvollständigen Informationen bezüglich Passagierverspätung und Machbarkeit von Verbindungen zu identifizieren und quantifizieren.

Der erste Teil der Arbeit fasst die Informationsverfügbarkeit während Störungen von öffentlichen Verkehrssystemen, in einem vierdimensionalen "wer-wann-wo-was" Framework, zusammen. Basierend auf der vorgeschlagenen rigorosen mathematischen Beschreibung der Effekte der Informationsverfügbarkeit, welches Lösungen für das Nutzergleichgewicht und Nutzerungleichgewicht beinhalten, werden wir MATSim auf die Stadt Zürich, Schweiz, an. Somit können wir die Vorteile einer auf Aktivitäten basierenden Simulation in einem multimodalen Netzwerk beurteilen. Wir verwenden eine bereits existierende Neuplanungsmethode mit dem Planungshorizont von einem Tag. Zusätzlich erweitern wir die Methode, um Neuplanungen während eines Tage zu ermöglichen. So können die Routenwahlen der Agenten während einer Störung des öffentlichen Verkehrssystems in einer einzigen Iteration untersucht werden. Es wird eine Störung in Form einer Blockierung der Eisenbahnverbindung zwischen Zürich HB und Zürich Oerlikon angenommen. Wir simulieren drei Szenarien mit verschieden Verfügbarkeiten von Informationen und vergleichen die Resultate mit den Verhalten der Agenten bei einem normalen Betrieb (Betrieb ohne einer Störung). Die Resultate werden für alle Agenten, die von der definierten Störung berührt werden, ausgewertet. Die neue Wahl der Agenten in Bezug auf Route und Verkehrsart zeigt ihre Adaption an die verfügbaren Informationen an. Unsere Analyse der Verspätungen und anderen Kennwerten zeigt, dass die Verfügbarkeit von Informationen die Zufriedenheit der Agenten während einer Störung signifikant beeinflusst.

Im zweiten Teil der Arbeit generieren wir verschiedene Dispositionsfahrpläne als Reaktion auf eine Störung mittels eines gemischt-ganzzahligen Programmierung (MIP) Modelles. Das Ziel dieses Modelles ist die Minimierung der totalen Verspätung der Passagiere. Die Neuplanung des Fahrplanes beinhaltet eine Neubeurteilung der Routen, der Abfahrtszeiten, sowie den partiellen oder vollständigen Ausfall von Linien. Die Rollmaterialverwendung wird überprüft um die Machbarkeit des Dispositionsfahrplanes zu garantieren. Wir lösen das MIP Modell mittels eine kommerziell verfügbaren Solvers. Danach wenden wir MATSim an, um das Verhalten der Agenten mit verschiedenen Dispositionsfahrplänen und Informationsstrategien in einem multimodalen Netzwerk zu simulieren. Im Anschluss analysieren wir die Verspätung der Agenten sowohl auch die weiteren Kennwerte für die Stadt Zürich. Wir zeigen auf, dass je früher die Information bezüglich des Dispositionsfahrplans verfügbar ist, desto grösser ist die Erhöhung der Zufriedenheit der Passagiere. Zusätzlich zeigen wir, dass, im Verglich zu einem kompletten Ausfall aller Fahrten, bei einer genauen Berechnung der machbaren Rollmaterialszirkulationen Lösungen gefunden werden können, welche einen signifikanten Mehrwert für die Passagiere darstellen. Insbesondere die Verspätung von Passagieren, deren geplante Fahrten von der Störung betroffen sind, nehmen erheblich ab, während andere Passagiere, die nicht direkt von der Störung betroffen sind, geringfügige Verspätungen haben können. Auf Systemebene kann die realistische Betriebsstrategie die Auswirkungen der Störung erheblich reduzieren, wobei die negativen Auswirkungen der Störung auf ein Fünftel der ursprünglichen Auswirkungen reduziert werden kann.

Der dritte Teil untersucht die Auswirkungen von unvollständigen Informationen auf Passagiere und schlägt eine neuartige mehrlagige Methode vor, welche auf dem Zeit-Ereignis-Graph basiert. So kann das heterogene Interpretierend des Dispositionsfahrplanes der Passagiere unter verschiedenen Variationen von unvollständiger Informationen beschrieben werden. Insbesondere variieren die Informationen, die die Passagiere erhalten nach Zeit und Ort. Darüber hinaus berücksichtigen wir unterschiedliche Ansichten der Passagiere zur Verspätungsausbreitung (d. H. die Auswirkungen des Dispositionsfahrplans). Mithilfe unseres grafischen Routenwahlmodells können wir das Verhalten der Passagiere unter Berücksichtigung der Auswirkungen unvollständiger Informationen (perfekt oder im Verlauf der Route) und ihrer Überzeugung (am ursprünglichen Fahrplan orientierend oder an der Verspätung orientierend) beschreiben. Anschliessend prüfen wir die Machbarkeit der Routen der Passagiere und die zugehörigen Verspätungen. Die Ergebnisse zeigen, dass die Informationen auf der Route im Vergleich zu den perfekten Informationen mehr undurchführbare Routen und grössere Verspätungen verursachen. Die Auswirkungen der Interpretation der Passagiere der Informationen auf der Route sind vernachlässigbar. Bei perfekten Informationen sind sie jedoch gross: Orientieren sich Passagiere am ursprünglichen Fahrplan und wird kurzfristig informiert, treten weniger Verspätungen auf, andernfalls ist es besser, wenn sich die Passagiere an der Verspätung orientieren.

Zusammenfassend bietet diese Dissertation Einblicke, wie sich Informationen (z.B. Verfügbarkeit, Vollständigkeit) auf die Zufriedenheit der Fahrgäste bei Störungen des öffentlichen Verkehrs auswirken. Die Ergebnisse können für Infrastrukturmanager und Betriebsgesellschaften nützlich sein, um die Auswirkungen von verschiedenen Informations- und Neuplanungsstrategien bei Störungen des öffentlichen Verkehrs zu verstehen und zu bewerten.

Riassunto

Le prestazioni di una rete di trasporti possono essere ridotte considerevolmente a causa di eventi imprevisti, con conseguenti ritardi e disagi per i passeggeri. Quando ciò accade, i gestori dell'infrastruttura e le società operative solitamente producono un nuovo orario dei trasporti, chiamato “orario dispositivo”, per ridurre i ritardi dei passeggeri, limitando così l’impatto negativo sulle loro attività e sulla loro soddisfazione verso l’utilizzo della rete di trasporti. Per produrre il nuovo orario, vengono prese in considerazione diverse strategie di rischedulazione dei mezzi, quali variazioni degli orari di arrivo e/o partenza alle stazioni, variazioni del percorso, annullamento parziale o totale dei servizi, tenendo conto nel caso della rete ferroviaria dei vincoli necessari affinché i veicoli ferroviari possano circolare correttamente.

In questo contesto, divulgare le informazioni relative ai servizi in corso è fondamentale. Queste informazioni non costituiscono solo il mezzo per i gestori dell'infrastruttura e le società operative per fornire un orario aggiornato ai passeggeri, ma anche uno strumento per comprendere i comportamenti dei passeggeri in caso di interruzioni o riduzioni dei trasporti pubblici, in modo da poter riprogrammare gli orari ed i veicoli in modo più efficiente ed offrire un servizio migliore in caso di interruzioni future. Tuttavia, le informazioni diffuse potrebbero essere incomplete o imprecise: non tutti i passeggeri potrebbero ricevere immediatamente tutte le informazioni sul nuovo orario. Questa incompletezza ed imprecisione delle informazioni potrebbe compromettere gli sforzi dei gestori dell'infrastruttura e delle società operative per migliorare la soddisfazione dei passeggeri.

In questa tesi vengono studiati gli effetti della divulgazione di informazioni ai passeggeri durante interruzioni o riduzioni dei trasporti pubblici, tenendo conto della disponibilità e tempistica delle informazioni, della loro qualità, dell'eterogeneità dei passeggeri, dei comportamenti dei passeggeri, dell’orario dispositivo e della rete di trasporto multimodale. I contributi principali di questa tesi sono i seguenti. In primo luogo, vengono proposte relazioni matematiche rigorose per formalizzare gli effetti della disponibilità di informazioni ai passeggeri in caso di interruzioni o riduzioni dei trasporti pubblici, includendo soluzioni di equilibrio e non equilibrio per i passeggeri. Queste relazioni hanno permesso di simulare e analizzare i comportamenti dei passeggeri in una rete multimodale utilizzando un modello di micro-simulazione basato sull’agente (MATSim). In secondo luogo, vengono integrati in modo innovativo MATSim ed un modello di ottimizzazione, con lo scopo di studiare la soddisfazione dei passeggeri nei confronti di diversi orari dispositivi e strategie di informazione. I risultati di questo modello integrato possono essere utili per i gestori dell'infrastruttura e le società operative per offrire servizi migliori ai passeggeri in caso interruzioni o riduzioni dei trasporti pubblici. In terzo luogo, nella tesi viene proposto un nuovo metodo basato su un diagramma ad eventi temporali a più livelli per identificare e quantificare l’effetto che

un’informazione incompleta può avere sui ritardi dei passeggeri e sulla possibilità di usare percorsi differenti.

La parte I della tesi è rivolta a sintetizzare la disponibilità di informazioni durante le interruzioni o riduzioni dei trasporti pubblici in uno schema quadridimensionale "chi-quando-dove-cosa". Sulla base delle relazioni matematiche introdotte per descrivere gli effetti della disponibilità di informazioni sui passeggeri, incluse soluzioni di equilibrio e non equilibrio, abbiamo applicato MATSim alla città di Zurigo (Svizzera) per valutare i vantaggi della simulazione delle loro attività in una rete multimodale. Abbiamo utilizzato sia un metodo esistente di ripianificazione giornaliera, sia una nuova estensione di questo metodo dove la ripianificazione avviene più volte al giorno. Questa estensione permette infatti di studiare in un'unica iterazione le scelte di percorso degli agenti che reagiscono ad un'interruzione dei trasporti. Nello specifico, l'interruzione considerata è il blocco della linea ferroviaria tra due stazioni principali di Zurigo (Stazione Centrale ed Oerlikon). Abbiamo simulato tre scenari in base alla diversa disponibilità delle informazioni e abbiamo confrontato il comportamento degli agenti con il caso in cui non ci sia stato il blocco. Abbiamo analizzato in modo statistico i risultati della simulazione per tutti gli agenti coinvolti nel blocco della linea. Il flusso degli agenti nei relativi percorsi e la loro scelta dei mezzi di trasporto mostra che gli agenti adattano le proprie scelte alle informazioni disponibili. Un’ulteriore analisi su ritardi e altre statistiche ha rivelato che la disponibilità di informazioni influenza in modo significativo la soddisfazione degli agenti durante il blocco della linea.

La parte II applica un modello di programmazione lineare mista intera (MIP) per generare diversi orari dispositivi a seguito di un'interruzione dei trasporti, con l'obiettivo di ridurre al minimo il ritardo totale dei passeggeri. La ridefinizione dell'orario dei trasporti comprende le strategie di modifica degli orari di arrivo/ partenza, riordinamento delle precedenze dei veicoli, modifica del percorso e cancellazione di servizi ferroviari. Per garantire la fattibilità dell’orario dispositivo, il modello verifica anche che la circolazione dei veicoli ferroviari sia ammissibile. Il modello MIP viene risolto con un solutore commerciale. In seguito, MATSim viene applicato alla città di Zurigo per simulare i comportamenti degli agenti e le loro attività in base a diversi orari dispositivi e strategie di informazione in una rete multimodale. Inoltre, la simulazione serve per analizzare i ritardi degli agenti ed altri indicatori di prestazione della rete di trasporti. I risultati mostrano che prima le informazioni sul nuovo orario sono divulgate ai passeggeri, maggiori sono i miglioramenti della soddisfazione ottenibili durante l'interruzione o riduzione dei trasporti. Inoltre, comparato ad una cancellazione totale dei servizi ferroviari, includere cancellazioni parziali e calcolare in modo preciso l’ammissibilità della circolazione dei veicoli ferroviari può portare vantaggi notevoli ai passeggeri. In particolare, il ritardo dei passeggeri i cui servizi previsti sono stati interrotti diminuisce sostanzialmente; allo stesso tempo, passeggeri che non sono direttamente coinvolti dall'interruzione possono subire ritardi minori. A livello di sistema, una strategia operativa realistica può ridurre considerevolmente l'impatto dell'interruzione: la misura di utilità dei trasporti durante l'interruzione viene ridotta solamente di un quinto anziché essere negativa come in caso mancata informazione.

La parte III della tesi studia gli effetti di un’informazione incompleta sui passeggeri. Viene proposto un nuovo metodo basato su un diagramma ad eventi temporali a più livelli per descrivere diversi tipi di incompletezza di informazione e passeggeri eterogenei nel modo di reagire all’orario dispositivo. In particolare, l’informazione che consideriamo varia in base all'orario e posizione dei mezzi che i passeggeri ricevono nonché al contenuto. Inoltre, consideriamo le diverse convinzioni dei passeggeri riguardo la propagazione dei ritardi (ovvero l’impatto dell’orario dispositivo). Utilizzando il modello di scelta del percorso basato sul nostro nuovo metodo, siamo stati in grado di descrivere comportamenti dei passeggeri che incorporano l’effetto di un’informazione incompleta (perfetta oppure durante il percorso – “on-route”) e la loro tendenza ad affidarsi all’orario iniziale (“orario-iniziale”) piuttosto che all’ultima informazione disponibile sul ritardo (“ritardo-esteso”). Abbiamo quindi esaminato la fattibilità dei percorsi dei passeggeri ed i loro ritardi. I risultati mostrano che l’informazione on-route causa un maggior numero di percorsi non più ammissibili e ritardi dei passeggeri maggiori rispetto ad un’informazione perfetta. Gli effetti della convinzione dei passeggeri con informazione on-route sono trascurabili ma sono invece significativi in caso di informazione perfetta: la convinzione orario-iniziale provoca un ritardo minore dei passeggeri mentre la convinzione ritardo-esteso funziona meglio.

Per riassumere, questa tesi fornisce analisi su come la divulgazione di informazioni (ad esempio, la loro disponibilità o completezza) influenzano la soddisfazione dei passeggeri durante un’interruzione o riduzione dei trasporti pubblici. Questo studio è il primo a quantificare l’impatto che un’informazione tempestiva e completa produce sulla soddisfazione e sui ritardi di diverse categorie di passeggeri. I risultati contenuti in questa tesi possono essere utili ai gestori dell'infrastruttura e alle società operative per comprendere e valutare gli effetti di diversi tipi di informazione e per meglio definire le strategie di rischedulazione durante un’interruzione o riduzione dei trasporti pubblici. Più in generale, i risultati di questa tesi possono essere utili per i passeggeri, i gestori dell'infrastruttura, le società operative e l’intera industria dei tra sporti pubblici.

Acknowledgements

My deepest gratitude goes to Prof. Francesco Corman, for your constant help, strong support, enlightening guidance and kindly encouragement. Without your great help, I could not imagine how many difficulties I still would have to overcome. I really appreciate your supervision during the past three years. Thank you for giving me quick feedback each time, including many innovative thoughts and detailed comments. The meetings and discussions with you have always been very inspiring and fruitful. Your questions and insights from diverse perspectives inspired me to think more comprehensively and increased my more knowledge of different fields of expertise. I learned from you that how to progressively solve a complex problem, starting from a simple approach, understanding the mechanism before implementations. I also learned from you that how to clearly improve my explanations to avoid the confusion and misunderstandings of the readers. Your profound knowledge, insightful criticism, novel ideas and illuminating instruction have greatly improved my academic interest and ability. I also thank you for providing me with many opportunities to cooperate with other researchers. I feel very lucky and grateful to have you as my supervisor.

I would like to express my heartfelt gratitude to Prof. Ulrich Weidmann, who has offered me such a precious opportunity to come to Switzerland for my doctoral study at ETH Zurich. I deeply acknowledge your patient instruction, expert guidance and continuous encouragement, which have helped and benefited me a lot during the whole process of my study. Despite your many duties as vice-president of ETH Zurich, you have spent much time to regularly discuss my research progress, carefully review each draft and provide me with many valuable suggestions. Your comprehensive knowledge and deep understanding of the Swiss railway system have helped me to broaden my horizon and provided me with a solid foundation for my academic research. Thank you for guiding me to understand the real needs from railway industry, the meaning of my current research, and relevance to the previous research in IVT. I feel greatly fortunate to be one of your students. What I have learned from you would impose profound impacts on me to be a better researcher.

My sincere gratitude goes to Prof. Anita Schöbel, for your instructive advice and useful suggestions on my research. You are always friendly to me and give me warm encouragement. Even though we only meet a few times, your rigorous attitude towards research and unique insights to questions have inspired my thinking and helped me a lot for deep research.

I am greatly indebted to Dr. Paul Bouman, for your patient guidance and insightful advice in the process of my study. Especially when I was trapped in MATSim, your tremendous help has offered me a great cornerstone of my research. I was very impressed and encouraged for your willingness to embrace challenges as well as the openness to share new research ideas. Thank you for the thought-provoking discussions about the research field of public transport passengers.

I am deeply grateful to Prof. Lei Nie, the supervisor of my master study. Thank you for giving me numerous projects and opportunities to study passenger flows of Chinese high-speed railway, in which I have learned knowledge and formed insights for my further research. I honestly appreciate your enlightening teaching, unwavering trust, constant encouragement and warm concern about my study and daily life.

My special gratitude goes to Zhengwen Liao, for your strong help and the fruitful cooperation during my doctoral study. I have learned a lot thanks to your admirable knowledge and insights about railway optimisation. Thank you for your timely feedback and each efficient discussion.

I sincerely thank Beda Büchel, for inspiring me in statistics and plotting, helping me writing the German abstract. Your sunny life attitude, kindness, good sense of humour and small surprises have always created a friendly atmosphere in our group. Thank you for the discussions about research, culture, sport, psychology and even philosophy. I would also like to thank Alessio Marra for sharing your knowledge about computer science with me. Your explanations about the case study of Dutch railway helped me to understand quickly the research background. I was impressed by your rigorous work attitude and delighted for your willingness to share interesting topics in life. I gratefully acknowledge Aoyong Li, for numerous tips about coding as well as your patient assistance in my research. Thank you for your time and efforts. I am very grateful to Xiaojie Luan, for your time to discuss about my research and your friendly help with the mathematical formulas. I also appreciate your understanding and encouragement, which helped me building confidence in research. Many sincere thanks go to Alessio Trivella, for kindly helping me revising my formulas, improving my English writing and writing the Italian abstract. I am truly grateful for your useful advices, warm encouragement and strong support.

My heartfelt thanks also go to my officemate Valerio De Martinis, for your patience and availability in helping me discussing my research topics and answering my multiple questions about the general life in IVT. I am very fortunate and grateful to meet my sincere colleagues, Ambra Toletti, Xiaolu Rao and Kaidi Yang, who have friendly shared me much valuable guidance, help and support about both my research and general life. I am also thankful to Marc Sinner, Michael Schwertner and Martin Huber who have helped me in assisting teaching, learning German language and adapting to the life in Switzerland. I would also like to thank Yizhe Huang, Sihui Long, Yanan Li and Xin Hong, for the delightful discussions and plentiful experiences. I wish you could have stayed for a longer time at IVT. My gratitude goes also to the colleagues Francesco Ciari, Ilahi Anugrah, Patrick Bösch, Sebastian Hörl, Milos Balac and Thibaut Dubernet, who have helped and supported me in my study of MATSim. I am very obliged to Peter Lorch who has given me great support for the computational needs during this research.

I am sincerely grateful to Lingxuan Zhang, for giving me great help and warm companionship during my work and life in Switzerland. I exceptionally liked the talks with you about different topics and enjoyed the time spent together with you. Thank you for understanding me, encouraging and supporting me. I deeply appreciate our precious friendship. I would like to thank Mengmeng Zhang particularly, for inspiring and helping me when I was in difficulties. I definitely like your wisdom and smartness regarding to life. I owe my sincere gratitude to my friend Xiao Li, who has been always understanding and supporting me. Special thanks should go to my friends Tianyuan Ge, Yu Cong and Wenjie Ma, who have always cared about me during the long-term friendship.

My warmest gratitude goes to my beloved parents, for their endless trust, support and encouragement all through these years. I am deeply grateful to my father for always giving me enlightenment in my life. The same gratitude also goes to my mother for giving me eternal love and care. Thank you for having raised me into what I am today. I love you both beyond melodies, beyond words.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Research motivation

The number of public transport passengers are estimated to continue growing rapidly (+51% public transport passenger-kilometres by 2040 with respect to 2010, Federal Office for Spatial Development, 2016). The higher usage of public transport, especially for the use of passengers, increases the vulnerability of public transport, the probability of disruptions and the operation complexity. Public transport operation might be disrupted by diverse reasons, such as infrastructure maintenance, accidents, natural disasters, malfunctions of facilities, etc. (Dorbritz, 2012). In case of public transport disruptions, the resources, necessary for running the public transport system as planned, become insufficient. These insufficient resources can be tracks, rolling stock, staff, power supply, information or train protection systems (Schranil, 2013). So far, research on public transport operation has connection with many diverse fields, such as capacity, train automation, energy supply, environmental and safety issues. However, the links to passengers, especially in case of severe disruptions of services, are still in the initial stage. With the comparison of the improved services of road traffic, the customers expect that public transport services can also make progress with a higher quality system. The passenger-friendly public transport operations are of great importance for the future.

Public transport disruptions can cause passengers' time lost and dissatisfaction as well as the service providers' reimbursement costs and revenue losses. Cats et al. (2016) identify that the yearly costs can exceed 1.9 million euros, due to rail disruptions in a metropolitan public transport network of the Netherland. Yap (2020) summarises the refund policies in case of delays and disruptions in different countries and illustrates that disruption propagation costs are responsible for up to 8% of the total passenger disruption costs. Transport for London (2019) reports the disruptions of the underground network of London have caused 4.9 million lost customer hours during a four-week period (from 10

November to 7 December) in 2019. The public transport systems actually continue to face the challenge of improving the service qualities. European countries define challenging targets in terms of quality of services to customers (ERRAC 2012). Ojo (2019) reviews the research related to the quality of services of different type of public transport in different region of the world. To benefit the quality of services, Strässle and Schneeberger (2017) explain the customer information for the entire public transport system in Switzerland, including regional and city networks, railways, buses in different operating companies. The prime motivation of this research is to increase passengers' satisfaction, especially in public transport disruptions, and improve quality of public transport services.

Managing public transport disruptions is a complex task because of the multiple-objectives of different stakeholders, the intricate interactions of the managing process, the diverse information disseminating the supplied services to passengers, passengers' choices and behaviours in multi-modal network, etc. Figure 1.1 explains the complexity of public transport management, especially in case of disruptions. The services and feasibility are legally separated in railway (Federal Council, 2009), but the issues exist also for other public transport. The main three stakeholders are passengers, train operators and infrastructure managers. Passengers are the clients of public transport, whose travel demand should be satisfied in terms of punctuality, routes, stops, transfers, comfort, etc. However, disruptions generally result in passengers' inconvenience, such as impossibility to reach the destination, increased travel time or compelled transfers. Passengers' behaviours are diverse with reaction to disruptions (e.g. cancelling schedules directly, waiting for recovery or transferring to other trains, or even leaving the public transport system). Operating companies aim at both reducing operating costs and providing passengers with satisfactory services. Infrastructure managers need to ensure the operational feasibility, in charge of eliminating timetable conflicts from the network-wide perspectives.

The relationships of the three stakeholders are described briefly as follows. Taking passengers' quantities and priorities into consideration, operating companies design adapted services (e.g. lines, stops, connections) with the checked operational feasibility by infrastructure managers. The interactions among these three stakeholders, in case of public transport disruptions, are linked by the information. The information can be the inner communication between the two stakeholders who define and offer the supply services. From operating companies to infrastructure managers, the information includes the adaptation to the running/ planned services; the reverse direction confirms their feasibility from network perspectives. Furthermore, the information can be between these two stakeholders and passengers in public transport disruptions. The information, from operating companies and infrastructure managers to passengers, includes the feasible adapted services in disruptions; the reverse information flow is the feedback about passengers' behaviours and satisfaction to the provided services.

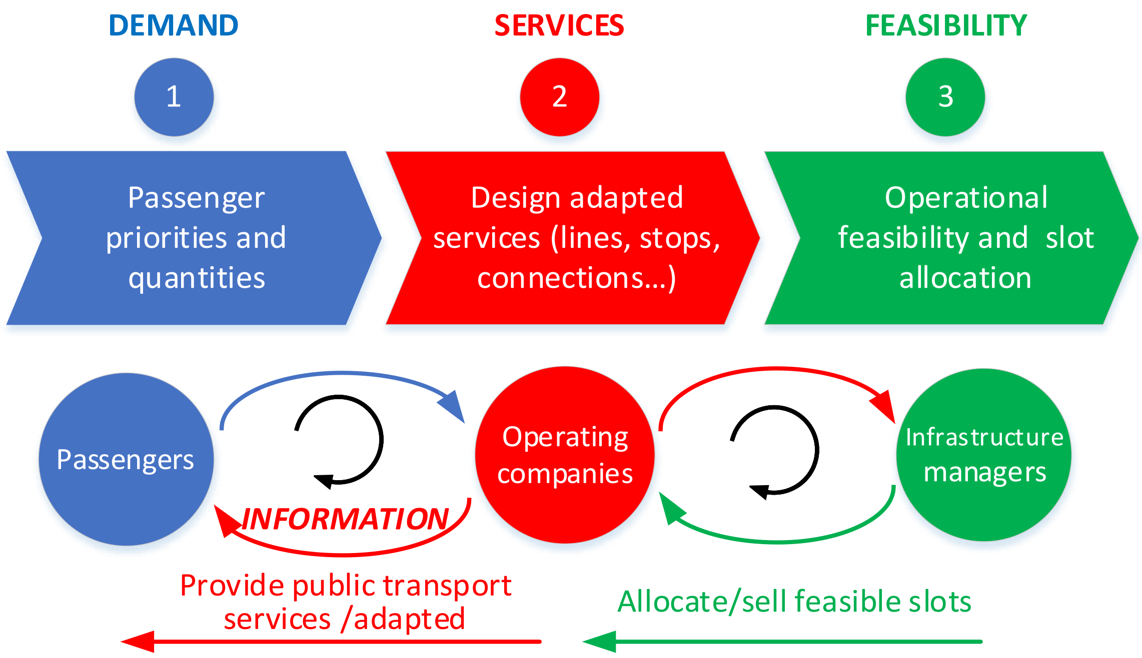

Figure 1.1: Interactions in public transport disruptions

In this dissertation, we mainly focus on the information, with the direction from operating companies and infrastructure managers to passengers, in case of public transport disruptions. This information to passengers can contain diverse contents, such as the start and the end time of disruptions, even the details of the rescheduled timetable, routes, stops or alternatives. Different information system or channels can disseminate the information to passengers, such as station display and radio broadcast, in-vehicle display, or the mobile apps for passengers' check and request or for pushing notifications (e.g. Scherer, 2019). This diversity of information is due to different rescheduling and information strategies in specific public transport disruptions, which results in different information availability to passengers, and then influences passengers' behaviours. Especially in a multi-modal urban network, passengers have autonomy to decide how they react to the disruptions and the available information, such as choosing the adaptations provided by operating companies and infrastructure managers, or looking for other alternatives on their own in terms of transport modes/ routes, or waiting, or even cancelling the trip, etc.

The focus of this dissertation is to understand and quantify the effects of information to passengers' behaviours in public transport disruptions, which is barely discussed in current academic research. This research can not only help passengers to understand how the information influences their choices, but also can assist infrastructure managers and operating companies to understand passengers' behaviours with the effects of information, trade off the interests to make more passenger-friendly decisions in case of public transport disruptions.

1.2 Research challenges

To study the effects of information to passengers in public transport disruptions, the following several challenges are tackled:

(1) The complexity of information in public transport disruptions.

As the important bridge between supply and passengers in case of public transport disruptions, information can be described from different perspectives. The term *information availability* is from the perspective of passengers, to express the details of information that passengers received, which are disseminated by the infrastructure managers and operating companies. In case of public transport disruptions, this can be for instance what information about the planned/ updated supply is disseminated to passengers, when and where passenger can receive updated information. The term *information strategies* is from the perspective of infrastructure managers and operating companies, to depict their efforts to improve the information availability to passengers. For instance, Kroon et al. (2015) study how the information available to passengers can be complete or partial. As a more specific description, the term *incomplete information* refers to the delayed, imprecise, missing, partial information, which is common and inevitable in case of disruptions, including diverse aspects: the delayed information availability to passengers, the limited information content about specific public transport services at specific stations within specific time horizon, etc. For instance, Ben-Elia and Avineri (2015) review the literature about inaccurate information under conditions of uncertainty, including information either before departure or once on the move.

The research challenge is to understand the factors of complexity of information, and to classify and study the effects of diverse information using mathematical notations, formulas and appropriate methods.

(2) Passenger heterogeneity cannot be neglected.

In public transport disruptions, information can have different effects to different passengers, with different origin, destination, planned departure time, planned transport mode and planned transport route, etc. For instance, information may affect the passengers who pass the disrupted route more significantly, compared to other passengers who travel very far away or passengers who are already at that moment at home. There are also passengers whose initial plan is to pass the disrupted route multiple times, increasing the complexity and meaning of detailing passenger heterogeneity in the research. The findings in Carrel et al. (2013) show that passengers value delays differently depending on the available information during disruptions, e.g. the reasons of disruptions or where the disruptions occur within their trip. However, most literature simplify to model passengers as groups based on origins and destinations, considering only the aggregated passengers in the process of timetable or rolling stock rescheduling (e.g. Binder et al, 2017). This strong assumption simplifies the complexity of what passengers might do in a real multi-modal network.

The research challenge is to consider the passenger heterogeneity, especially throughout the entire day, over multiple trips and activities, including the detailed description of their transport modes, routes, time and activities.

(3) Passengers’ adaptations in case of public transport disruptions.

Passenger adaptations, especially in case of public transport disruptions, with the impacts of information, need to be precisely explored in detail. Paulsen et al. (2018) show that passengers’ behaviours in multi- modal network are not limited to route changes (e.g. as considered in Hickman and Bernstein, 1997), but also include transport modes, activities and time change. In case of public transport disruptions, considering the impacts of information strategies/ information availability, the above-mentioned passengers’ adaptations need to be studied. The solutions of passengers’ behaviours from a system level could result in a user equilibrium or non-equilibrium depending on whether each passenger can figure out his/ her best solution with the guidance of information in public transport disruptions.

Furthermore, in case of incomplete information, passengers’ belief influences their behaviours. The belief is passengers’ expectation/ projection about the future unknown operations, based on the known information. For instance, Arentze and Timmermans (2005) model passengers’ belief about activity locations based on the limited information. Consequently, passengers’ route choices in case of incomplete information can be different to that with the assumption of complete information. Parvaneh et al. (2014) mention that passengers are not always aware of all available alternatives with the uncertain information and different passengers’ belief.

The research challenge is to model mathematically the impacts of information to passengers’ behaviours in public transport disruptions, either about the possible adaptations in multi-modal network, or passengers’ belief in case of incomplete information.

(4) Quantify the effects in a large-scale multi-modal network.

Passengers' actions in reality happen in a multi-modal network, and quantifying the effects of available information in disruptions should reflect this. Some literature consider realised travel behaviour by means of passenger tracking approaches (e.g. Marra et al., 2019) or smart card data usage (e.g. van der Hurk et al., 2018) as a possible way to collect real data about public transport disruptions. However, a comprehensive study of those factors and real wishes of passengers through e.g. revealed preferences is difficult due to rare, unexpected occurrence of disruptions, and possible answers' bias from passengers under pressure and or skewed perception of disruption events. The evaluation of complex choices by a multitude of heterogeneous passengers is often too complex to be included explicitly in optimisation models, and is instead tackled by means of simulation techniques. Among those, agent-based simulation models consider each passenger as an agent, able to take independent decisions maximising some utility function, based on the understanding they have of the transport network.

The research challenge is to realistically quantify the effects of information to passengers' behaviours and corresponding satisfaction in a large-scale multi-modal network, apply passenger simulation technique, such as agent-based simulation.

(5) Timetable and rolling stock rescheduling in public transport disruptions.

Infrastructure managers and operating companies have different objectives and functional requirements in the process of disruption management. The adjusted supply during disruptions typically includes a combination of rescheduling of public transport resources (optimising infrastructure capacity, vehicles, drivers, etc.), which have a strong effect to passengers. The different possible actions of infrastructure managers and operating companies include such as retiming, rerouting (e.g. Binder et al., 2017), full/ partial cancellation of train services (e.g. Cacchiani et al., 2014) and rolling stock rescheduling (e.g. Veelenturf et al., 2017).

The challenge is to take advantage of these strategies to generate better disposition timetables in public transport disruptions, applying optimisation model to quantify the optimised solution in each case with different supply strategies.

(6) The quantification of benefits to passengers with different rescheduling and information strategies.

In order to improve passengers' satisfaction in public transport disruptions, infrastructure managers and operating companies can apply different strategies, such as information strategies, timetable and rolling stock rescheduling strategies. Different strategies might result in different level of services to passengers. In the process of considering strategies, different stakeholders have different objectives, which may conflict to each other. For instance, ensuring the disrupted passengers' feasible route to destination may cause larger delay propagation to other passengers who are on the alternative routes. Some rescheduling methods may result in high cost, but result in few improvements to passengers in case of disruptions; for others, it might be the opposite. Trying to quantify the effects of information and rescheduling strategies is not only beneficial for infrastructure managers and operating companies to make decisions, but also beneficial for the improvement passengers' satisfaction in public transport disruptions. To link passengers, train operators and infrastructure managers in public transport disruption management, one method is to combine passenger simulation and the optimisation model of timetable and rolling stock rescheduling.

The challenge is to demonstrate the benefits of this holistic process, and to explore and study the trade-off towards the satisfaction of passengers in case of different supply and information strategies in public transport disruptions.

1.3 Research question and hypotheses

This dissertation aims at answering the following overarching question:

What are the influences of information to passengers in case of public transport disruptions on a large-scale multi-modal network, considering the interplay of information availability about the disruption, updated operation strategies, incomplete information about future conditions?

In detail, the sub-questions are given as follows:

(1) How to model passengers' adaptations under different information availability in public transport disruptions and estimate the corresponding passengers' satisfaction?

(2) What are passengers' satisfaction under different information strategies and disposition timetables (considering different rescheduling strategies and the feasibility of rolling stock circulation) in public transport disruptions?

(3) How to model passengers' behaviours under different incomplete information (Inc. passengers' belief) and quantify passengers' satisfaction?

In order to answer these questions, the following hypotheses are proposed:

H1 Information is main enabler of passengers' behaviours in case of public transport disruptions; the effects of information to passengers' behaviours can be described and modelled.

H2 Passengers are rational and able to choose the maximum utility (e.g. the least travel time) to reach their destination with the given specific information about public transport disruptions.

H3 The behaviours of passengers in a large-scale multi-modal network in case of public transport disruptions can be simulated based on some functional requirements within a time horizon of one full day, and considering different possibilities of mode/ route/ time/ activity change.

H4 Heterogeneous passenger's delay and satisfaction in public transport disruptions can be quantified from the results of passenger simulation.

H5 The public transport disruptions can be described to include the change of planned schedules as input to passenger simulation or route/ time changes in the process of timetable and rolling stock rescheduling.

H6 An optimisation approach can be used to support the rescheduling process, matching the functional requirements of infrastructure managers and operating companies, by designing adapted services and ensuring the operational feasibility of supply in public transport disruptions.

H7 The adaptation of passengers to different, possibly optimised timetable and rolling stock plans, in case of public transport disruptions, can be modelled and simulated.

H8 The incomplete information in public transport delays, passengers' belief and the consequent effects to passengers' behaviours and satisfaction can be modelled as a sequence or successive states over time.

1.4 Research contributions

1.4.1 Scientific contributions

The main scientific contributions of this dissertation are as follows:

(1) We define the mathematical notations and formulas to describe the effects of information availability to passengers' adaptations. The rigorous mathematical descriptions are able to describe user equilibrium and non-equilibrium solutions corresponding to different information availability scenarios. Furthermore, a framework for the classification of information availability is proposed for the sake of passenger-oriented disruption management in transport networks. This framework can represent how many passengers know

about public transport disruptions, where they get to know this (e.g. at the disrupted station), when they know it (e.g. in advance or after disruption) and what they know (e.g. precise start and end time of public transport disruption). This framework allows determining many intermediate cases, between two extremes of information dissemination in public transport disruptions: agents have no knowledge about disruptions; or agents know all the detailed information about disruptions in advance (Chapter 3).

(2) The use of agent-based micro-simulation approach, to study passenger behaviours during public transport disruptions, brings the following benefits. The first is the consideration of movements of agents in a multi-modal network, not only including choices within the public transport network, but also including switching to private modes, cancelling trips, and even cancelling or changing activities throughout a daily plan. The second is the explicit consideration of heterogeneity of users in the activity-based micro-simulation of an entire day, where detailed activities and trips are simulated. Therefore, the specific and heterogeneous reaction of passengers in disruptions can be precisely understood (Chapter 3, 4).

(3) A novel within-day replanning module within the agent-based simulation approach is specifically designed to address passengers' behaviours in public transport disruptions. This within-day replanning is fundamentally different from the traditional day-to-day replanning, as the simulation is in a single iteration; there is no equilibrium to be determined, but only a best adaptation, corresponding to a non-equilibrium solution. (Chapter 3).

(4) An optimisation approach is applied to solve the timetable rescheduling problem with the feasibility of rolling stock circulation in a railway hub and explores alternative train routes to be used in case of disruptions. A mixed integer programming (MIP) model is applied with train order binary variables, which can be solved by a commercial solver. The objective of the optimisation model is to minimise the total delay of passengers. The timetable rescheduling includes the strategies retiming, reordering, rerouting, cancellation of train services. In addition, the rolling stock circulation is checked to ensure the feasibility of the disposition timetable (Chapter 4).

(5) This dissertation innovatively combines an optimisation model and an agent-based micro-simulation model (Chapter 3) to explore passengers' satisfaction of different information strategies and disposition timetables in public transport disruptions (Chapter 4). This combination quantifies the benefits to passengers with different information and rescheduling strategies in case of public transport disruptions. This combination is fast enough to be practically applicable, even for a large multi-modal network, for both planned and unplanned disruptions.

(6) We propose a novel multi-layer time-event-graph method to describe the incomplete information (e.g. information issue time, duration, information contents) and belief (internal, own perspective of future operations, based on e.g. schedule or delay belief) for heterogeneous passengers, to evaluate more realistically passengers' behaviours on public transport network in case of delays. The proposed multi-layer time-event-graph method and graph-based route choices are described with rigorous mathematical notations and formulas (Chapter 5).

1.4.2 Societal contributions

The main contributions to society of this dissertation are as follows:

For the benefits of passengers:

(1) Passengers could get better services (both operation and information services) in case of public transport disruptions.

The main goal of passengers in case of public transport disruptions is to have feasible routes to reach their destination and to reduce their inconvenience (e.g. delays or extra transfers) as much as possible. This is studied in our research by considering different information availability and different rescheduling strategies. The research results are in view of heterogeneous passengers in a large-scale multi-modal network, including diverse passengers' adaptations (mode/ route/ time/ activity changes). In other terms, the research results are based on a relatively realistic model of the actual passengers' behaviours in the real multi-modal transport system. In this sense, these results are valuable for the service providers to estimate how to improve the service quality to passengers in case of disruptions, including both the operation services and information services.

The better operation services for passengers refer to fewer cancelled trains/ buses, fewer skipped stops, smaller delays of the running trains/ buses, and so on, in case of public transport disruptions. For instance, our research results (Chapter 4) show the following improvement of services to passengers. First, passengers who cross the disrupted area multiple times can benefit if the running trains are partially cancelled, instead of full cancellation. Second, passengers who are directly affected by disruptions can reduce a large delay if the disrupted trains are rerouted to the alternative routes. This may cause a slight delay for passengers on the alternative route.

The better information services mean that passengers can get the information via more available channels (e.g. station display, mobile apps) as early as possible in case of disruptions. The provided information contains more details about disruptions (e.g. the locations/ train routes of disruption, the start and end time), and the adjusted train operations (e.g. time/ route change), etc. For instance, the results of our research show that the information services affects passengers' satisfaction in case of disruptions. First, the negative impact of disruption is reduced with the available information, compared to without information. Second, the earlier the passengers can receive the disposition timetable, the smaller the delay they will suffer in disruption (Chapter 3, 4). Third, either partial information about adjusted train operations or the information only available at station has negative effects to passengers. This incomplete information causes more infeasible routes and more delays to passengers, and results in the deviations between the delay that passengers think they will face and the actual delay in reality. (Chapter 5).

(2) Passengers can understand that which approximation of the future unknown operations brings better results.

In case of incomplete information about train delays, passengers' beliefs about further train operations affect their route choices and their delays. Our results can help passengers to know which approximation/ belief brings better results in specific incomplete information case (e.g. information type, information time horizon) (Chapter 5).

For the benefits of infrastructure managers and operating companies:

(1) To estimate passengers' behaviours better in large-scale network in disruptions.

The infrastructure managers and operating companies can estimate passengers' behaviours, delays and satisfaction in the large-scale multi-modal network more comprehensively in case of planned or unplanned public transport disruption. It includes passengers' route choices within the disrupted transport mode (e.g. railway), mode share in other public transport modes (e.g. bus or tram) or even the private mode (e.g. car or bike). In other terms, they can know the percentage of passengers who keep stay in the public transport system and how many passengers prefer to leave and choose other alternative transport modes (Chapter 3).

(2) To quantify the benefits of different operating and information strategies in disruptions.

The infrastructure managers and operating companies can test and quantitatively understand which kind of rescheduling strategies and information strategies can offer better services to passengers in public transport disruptions. They can also know the trade-offs between different groups of passengers (e.g. disruption affected passengers or passengers on the alternative routes) from the research results. From system level, they can quantitatively know how much the impacts of disruption can be reduced with the efforts of rescheduling timetable and rolling stock, as well as offering passengers information (Chapter 4). Moreover, this research is crucial for infrastructure managers and operating companies to determine the trade-offs and balance the benefits of the rescheduling and information strategies with their costs (e.g. cost for vehicle short-turn, cost for information channels, or cost for improved prediction or predictable processes in case of disruptions).

(3) To understand quantitatively the effects of incomplete information to passengers in case of delays.

The infrastructure managers and operating companies can understand the quantitative loss of benefits due to the incomplete information in case of public transport delays (Chapter 5). It is helpful for them to trade off the benefits and costs of information and public transport operations in order to improving the service quality to passengers. This result is also helpful for them to decide the long-term investment about building the information system, such as station displays, train/ bus information facilities and mobile information to alarm delays.

1.5 Outline

The overall methodologies adopted in this research and the corresponding findings are presented. The structure of the rest of this dissertation is shown in Figure 1.2, including the following chapters.

Chapter 2 reviews the related literature based on research question and hypotheses in order to synthesize the current research gap, with the characteristic of public transport disruptions, information generation and supply, information availability and passengers' adaptations. In detail, we review the multiple objectives of stakeholders, the existing methods for timetable and rolling stock rescheduling, how to integrate passengers in the process of generating information, what are the typical information contents provided to passengers, the information channels and dissemination, passengers' behaviours with the guidance of information, as well as the agent-based simulation approach.

Chapter 3 defines the mathematical notations and formulas to describe the effects of information availability to passengers' adaptations. We also show how to compute performance indicators of user equilibrium and non-equilibrium solutions corresponding to different information availability scenarios. In addition, a framework for classification of information availability is proposed for passenger-oriented disruption management in transport networks. An agent-based micro-simulation model (MATSim), including a novel within-day replanning module, simulates heterogeneous passenger behaviours in a multi-modal network in case of disruptions.

Chapter 4 combines an optimisation model and an agent-based micro-simulation model to estimate passengers' satisfaction of different disposition timetables and information strategies. A mixed integer programming (MIP) model is applied to calculate the disposition timetable. The timetable rescheduling includes the strategies retiming, reordering, rerouting, cancellation of train services. The rolling stock circulation is checked to ensure the feasibility of the optimised disposition timetables. The agent-based simulation with MATSim platform (from Chapter 3) is used in case of different information strategies and different disposition timetables generated by an optimisation model of timetable and rolling stock rescheduling.

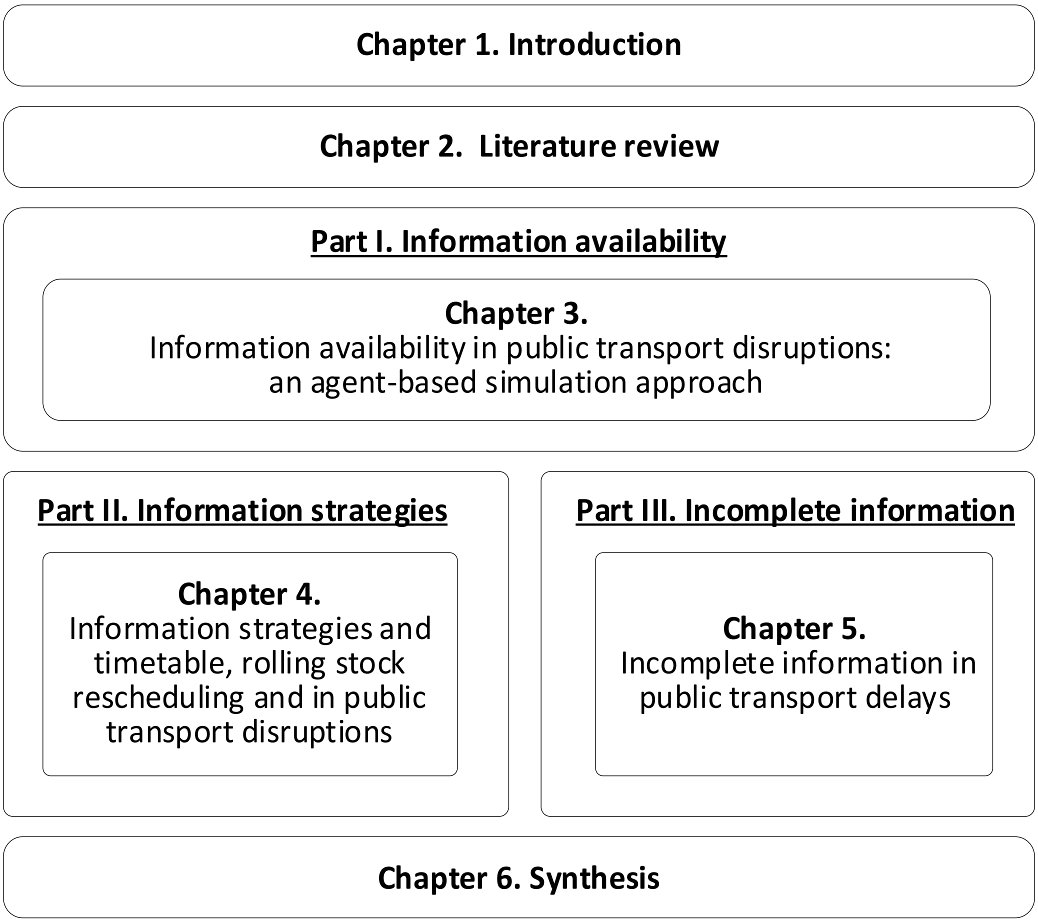

Figure 1.2: Overview of the dissertation structure

Chapter 5 is a more in-depth study about information availability (from Chapter 3), discussing the effects of incomplete information to passengers. A novel multi-layer time-event-graph method is proposed to describe the incomplete information (e.g. information issue time, duration, information contents) and belief (internal, own perspective of future operations, based on e.g. schedule or delay belief) for heterogeneous passengers.

This method can evaluate more realistically passengers' behaviours in public transport network in case of delays. The graph-based route choices are described with rigorous mathematical notations and formulas.

Chapter 6 concludes research results, answers the research questions and gives insights to future research on public transport disruption management.

Chapter 2

Literature review

To answer the research question in Section 1.2, one significant step is to comprehend the current research state and common research methods. First, we clarify the concepts of public transport disruptions and delays in Section 2.1 to understand the complexity of the corresponding management process. Moreover, information plays an important role in the field of passenger-oriented delay and disruption management, as the bridge linking the supply from infrastructure managers and operating companies to passengers. The information in this dissertation focuses on the transmission, processing, messaging, and communication systems, with the direction from the infrastructure managers and operating companies to passengers. In general, information provision can be particularly advantageous to passengers when things do not work as planned in the case of service disruptions (Cats et al., 2016). The process of passenger-oriented disruption management, which we follow in the structure of this review, can be summarised as:

(1) Information generation and supply: infrastructure managers or operating companies gather the information about the disrupted operation, determine and implement some disposition timetables; (Section 2.2)

(2) Information contents: infrastructure managers or operating companies decide which aspects about disruptions and disposition timetables will be disseminated to passengers; (Section 2.3)

(3) Information channels and dissemination: the service providers disseminate the information via some specific channels; (Section 2.4)

(4) Information availability and passengers' behaviours: then the information becomes available to passengers; passengers adapt their behaviours based on information; (Section 2.5)

(5) Effects of information: passengers' behaviours determine the outcome in a large network and reveal the relation between the quality of available information and passengers' satisfaction in the real-life.

The review in this chapter includes papers related to operations-oriented and passenger-oriented delay and disruption management, in railway, or in general public transport networks or multi-modal (including private transport) networks. Section 2.2 discusses the information generation and supply from infrastructure managers and train operating companies including the topics: multi-objectives of disruption management, timetable and rolling stock rescheduling, the integrations in disruption management. Section 2.3 summarises the information contents in current research about public transport disruptions. Section 2.4 reviews the research about information channels and dissemination. Section 2.5 discusses the information availability and passengers' adaptations in public transport delays and disruptions. We close with a review of agent-based simulation models modelling passengers in public transport disruptions. Finding out the state of literature, Section 2.6 synthesizes the literature and summarises the gaps to fulfil the research targets.

2.1 Public transport disruptions

When a public transport timetable cannot keep the operations as planned, deviations from current plan occur; typically, either disruptions or delays are used to describe this abnormal situation. Delays may be generated by the "disturbances", which are here intended as events that have a small impact on the planned operations. In railway networks, Cacchiani et al. (2014) present in general, a disturbance refers to trains departing or arriving later than planned, while a disruption is usually related to large delays or cancellations of a number of trains. The events called "disruptions" mean the railway malfunctions last long time and partial technical components are unavailable. This section reviews the related research and summarises the differences and connections between public transport disruptions and delays.

Based on literature, the concepts of public transport disruptions and delays are compared in the following aspects.

Resource availability. The first distinction lies in resource availability in the public transport system. Public transport delays refer to the small disturbances of planned operations, but each technical component/ resource is still available, such as tracks, rolling stock, staff, power supply, information and train protection systems. In contrast, disruptions refer to the situation that some technical components are unavailable or some resources mentioned above are insufficient (Schranil, 2013). Durand (2017) summarises different types of disruptions based on line blockage and infrastructure capacity. Some literature investigate the disruption scenario of partial track blockages. For instance, Hirai et al. (2009) explore the accident caused by railway line blockage. Louwerse and Huisman (2014) denote the partial blockage as the situation that some tracks are blocked but some limited traffic is still feasible. Similar scenarios are also in Narayanaswami and

Rangaraj (2013), Binder et al. (2015). Liang et al. (2019) and Zhang and Lo (2020) study the metro services suspended for some time due to unexpected events. Other severe disruptions include the complete blockage of the public transport infrastructure. Wiklund (2007) explores the interruptions of interlocking system destroyed by fire, causing the closure of a railway line. Similar research in Zhan et al. (2015), Veelenturf et al. (2016a) denotes the complete blockage as the situation that all tracks are blocked. The causes of disruptions can be track maintenance (e.g. Albrecht et al., 2013), or planned engineering-based disruptions (e.g. Shires et al. 2019), or natural disasters (e.g. earthquake, Shimizu et al., 2008), extreme weather (e.g. Wang et al., 2019), vandalism, power supplies, malfunctions of facilities (Dorbritz, 2012), etc.

Duration. The second distinction is the duration time of interruptions of planned public transport operations. For instance, in the railway system, Pacciarelli (2013) defines the time window $[t + a, t + b]$. t is the time of a planned operation. a and b are the lower boundary and the upper boundary of time in railway failure, respectively. The challenge is then to find a new conflict free schedule given static information (timetable, railway infrastructure, train characteristics) and dynamic information (disruptions, train positions at time t). Based on different values of a and b, Rao (2015) summarises three focuses:

- When the value $a \leq 2$ mins, $b \leq 45$ mins, the focus is on real-time train rescheduling,
- When the value 2-3 mins $\leq a \leq$ 10-15 mins, $b \leq$ 2-3 hours, the focus is on the delay management,
- When the value $b >$ 2-3 hours, the focus is on the disruption management.

Real-time train rescheduling focuses on conflict detection and resolution (e.g. Rao, 2015). Delay management focuses on deciding whether to keep or drop traffic connections due to delays (e.g. Schöbel, 2007). Disruption management refers to the tasks of new timetable design, rolling stock rescheduling and crew rescheduling (e.g. Cacchiani et al., 2014).

Rescheduling. The differences of rescheduling in public transport delays and disruptions can be summarised as the following aspects:

(1) The main goal in case of public transport delays is to keep and recover the initial schedule (e.g. Lamorgese and Mannino, 2015). In contrast, there is a smaller chance to keep the initial schedule in case of disruptions. The main goal is to provide special alternative plans, during the management of the disruption situation, such as offering passengers feasible routes until the normal operation is restored (e.g. Kroon et al., 2015).

(2) The concept of delay management relates to public transport stability. Based on the statistical results of railway delays in Switzerland, Graffagnino and Labermeier (2016) make a definition of the timetable stability. That is the timetable is stable

when all punctuality goals are achieved. Specifically, for different collections of train runs or sums of decision, different minimal punctuality values are achieved. In contrast, disruption management more relates to public transport robustness; see Weidmann et al. (2015). Andersson (2014) summarises many definitions about robustness in the current literature. Among which, we emphasise the definition of a public transport system where passengers can easily be re-routed if there is a disruption.

(3) Two main phases exist in delay management: delay situation and recovered situation. In contrast, disruption management has four phases: transition phase to disruption, stable disruption situation, transition phase to initial recovered situation, see Ghaemi (2018).

Effects to passengers. The small disturbances of operation generally result in the delays slightly perceived by passengers, with possible impacts to connections (Schöbel, 2007). Disruptions can have a more significant impact on passengers' travel and lead to critical decisions from passengers' perspective, such as cancelling the trip (Nielsen et al., 2012), or even worse, passengers might not reach their destinations.

Moreover, data on public transport delays (e.g. Büchel and Corman, 2020) are easily retrievable when monitoring the normal operation. On the opposite, it is very hard to retrieve passengers' real wishes during disruption both because of the unexpected (and, to some extent, unique) event and because of the answers' bias (e.g. anger) or lack of willingness to answer from passengers (e.g. Leng et al., 2018). Public transport delays can be described mostly on supply characteristics (like the monitoring of arrival time), while disruptions include big changes by the demand.

It has to be mentioned that, these distinctions between delays and disruptions contain small overlapping at the aspects of concepts and methods. Marra and Corman (2020) mention that disruptions can be defined as delayed or failed events. There is no strict boundary existing between delays and disruptions, rather there is a continuous range with the aspects of the features of failure, such as the frequencies, duration, passengers' delays, travel costs to passengers.

2.2 Information generation and supply

We limit ourselves to research in passenger-oriented delay and disruption management in public transport/ multimodal networks, discussing the supply adaptations from the viewpoint of both the operators and passengers, including the role of information as enabler of better performance.

2.2.1 Multiple objectives in disruption management

Many stakeholders interplay in public transport disruptions: passengers who want to move from their origin to their destination and public transport companies who need to keep the feasibility of operation and design better adaptations during the disruptions (e.g. Leng and Weidmann, 2017b). Especially in the railway transport perspective (Federal Council, 2009): train operating companies sell transport services to passengers between stations, and the infrastructure managers sell infrastructure capacity to the train operating companies along railway lines. The viewpoints of different stakeholders are different and translate into different paradigms to determine a best solution in public transport disruptions. From the network viewpoint, infrastructure managers are responsible for network traffic control while train operators are responsible for rolling stock schedule and crew schedule. At stations, infrastructure managers are responsible for train routing and platform assignment while train operators are for shunt planning.

Objectives of infrastructure managers. Current research with regard to disruption management is mainly from *operations-centric* views. The main problem in railway disruption is to reschedule the timetable, which is generally performed by infrastructure managers. The most popular objective is to minimise train delays (e.g. Brucker et al., 2002; Shimizu et al., 2008). There are also some variations to describe train delays more precisely. For instance, Albrecht et al. (2013) propose two criteria to measure the rescheduling objectives. The one is the minimum total delay, consisting of train delays, while the other is to minimise the maximum train delay, avoiding largely attributed delay to one single train. Narayanaswami and Rangaraj (2013) minimise the weighted sum of the difference between the actual and scheduled arrival time at the destination for all trains on both directions of a single track. The second wide-applied objective is to minimise the deviations from original timetable. For example, Hirai et al. (2009) aim at minimising the number of stops outside stations and the deviations from original timetable. To avoid the modifications of scheduled timetable, some papers propose minimising the number of cancelled trains as one objective. Zhan et al. (2015) and Veelenturf et al. (2016a) minimise the number of cancelled trains and the total weighted delay. Except minimising the delays of the operated trains and the number of cancelled trains, Louwerse and Huisman (2014) include another two objectives from the operation viewpoint: balancing the number of trains in both directions, and distributing the operated trains evenly over time. The former objective is specified by the absolute difference between the numbers of cancelled train sub series in each direction while the latter one is demonstrated by the maximum time between two operated trains in the same direction.

Objectives of train operating companies. In addition to timetable rescheduling, the train operating companies need to reschedule the rolling stock at reasonable cost, and then to adjust the crew schedules. The literature review in this section mainly focuses on rolling stock rescheduling. The prime objective of train operating companies is to minimise the operation cost. Sato and Fukumura (2012) seek to minimise the total sum of the costs of selected paths. The traditional objectives of rolling stock planning problem is threefold: efficiency, service and robustness. Fioole et al. (2006) and Cacchiani et al. (2012) employ the objectives containing three major elements: carriage kilometres (efficiency), seat-shortage kilometres (service), and the number of shunting movements (robustness). Among them, carriage-kilometres demonstrate the operational costs of the railway operator. Budai et al. (2010) not only use carriage-kilometres, seat shortage kilometres and the number of composition changes as additional objective, but also propose to resolve as many off-balances as possible in the rescheduling process. Besides, Nielsen et al. (2012) measure the deviation of the rescheduled circulation from the original circulation by employing three objective criteria: cancelled trips, changes to the shunting processes, and off-balances.

Passenger-centric objectives. The literature from *passenger-centric* views, which deal with disruption management, are much scarcer than that from *operations-centric* views. Based on the literature review, there are three objectives from passengers' viewpoint that cannot be neglected: minimising passenger delay, minimising numbers of neglected passengers (seating capacity), minimising general travel time. Jespersen-Groth et al. (2009) propose the objective of the operators in the disruption management process is to minimise the number of passengers affected by the disruption, and to minimise the inconvenience for the affected passengers. Binder et al. (2017) focus on passenger-oriented timetable rescheduling in railway disruptions and integrate three objectives: passenger satisfaction, operational costs and the deviation from the original timetable. The passenger dissatisfaction is given by the generalised travel time including in-vehicle time, waiting time, numbers of transfers, early arrival and late arrival. Zhu (2019) mentions the objective of minimising passenger delays in the process of dispatching decisions. Van der Hurk (2015) uses the objective of minimising passenger inconvenience within a constrained operating cost.

Almodóvar and García-Ródenas (2013) study the rolling stock rescheduling for passenger railways in case of emergencies and minimise the total in-system time of the passengers. The objective function in Kroon et al. (2015) consists of two parts: the system-related costs and the service-related costs. The service-related costs refer to the sum of the individual inconveniences, considering the increase of passenger delay under the limits of train capacity.

2.2.2 Timetable, rolling stock rescheduling

In public transport delay and disruption management, especially in railway disruptions, there are three main problems to be solved from the literature: timetable rescheduling, rolling stock rescheduling and crew rescheduling, see Jespersen-Groth et al. (2009). Here we mainly focus on the first two tasks and summarise the corresponding methods. A short review in the following concerns the models and algorithms for timetable rescheduling in both delay and disruption management, including the methods how train operators allocate resources in order to fulfil rolling stock rescheduling in disruptions.

The methods dealing with the timetable rescheduling can be distinguished from microscopic and macroscopic presentation of railway network. From microscopic viewpoint, alternative graph is a popular method presented in D'Ariano, et al. (2007). In Corman et al. (2011), an optimisation framework is presented to reschedule train services according to different classes of priority, which are used to group train services with similar characteristics. Meng and Zhou (2014) solve train rescheduling containing cumulative flow variables for train rerouting. Herrigel (2015) focuses on algorithms of periodic railway timetables during long- and mid-term planning, based on which Toletti (2018) continues to study algorithms for automated railway traffic dispatching and customer information.

A macroscopic level of detail of the railway network to handle disturbances is considered in Dollevoet et al. (2012), Schöbel (2009) and Törnquist and Persson (2007). Especially considering from passenger-centric view, Schöbel (2007) studies the problem of delay management, which consists of deciding if connecting trains should wait in a station for delayed feeder trains or if they should depart on time. Schöbel (2009) and Schachtebeck and Schöbel (2010) include constraints on the limited capacity of the tracks. A branch-and-bound algorithm and several heuristic approaches are developed in order to solve these problems.

The literature model and produce algorithms to solve the defined disruptions. The mixed integer programming (MIP) model and the train traffic simulation are widely applied. For the focus of timetable rescheduling in disruption management, the rescheduling methods of infrastructure managers can be presented, such as retiming, reordering, cancellations, replacing services, connections, local rerouting and global rerouting. Narayanaswami and Rangaraj (2013) develop a MIP model for rescheduling the train services with the goal of minimising the weighted delay of all train services and solve the problem on a single bidirectional line with disruption blocking the line for some time. Albrecht et al. (2013) use a metaheuristic method to construct an integrated timetable including track maintenance to generate a new feasible schedule for the disrupted system. In Corman et al. (2014), centralized and distributed procedures for train rescheduling are compared, and heuristic algorithms are proposed for coordinating different dispatching areas. In Wiklund (2007), the author describes a simulation procedure for simulating train traffic at a microscopic level to determine the effectiveness of various recovery strategies in case of large-scale disruptions.

For the focus of rolling stock rescheduling in disruption management, the system-related costs in Kroon et al. (2015) refer to three penalties: modifications in rolling stock compositions, modifications in the shunting operations and end-of-day off-balances.

Budai et al. (2010) propose two heuristic solution approaches to solve the rolling stock rebalancing problem, i.e. greedy approach and a two-phase heuristic. The MIP model in Nielsen et al. (2012) is an adapted version of the model by Fioole et al. (2006), rescheduling the rolling stock periodically over a rolling horizon with a limited length concerning the disruption as time progresses. Almodóvar and García-Ródenas (2013) propose a real-time optimisation method for rescheduling rolling stock in case of emergencies. The proposed method is based on a discrete-event simulation model, which determines how to reassign rolling stock from other lines to a line with high demand. The on-line optimisation model is solved using two greedy heuristics, which automatically generates near-optimal decisions about rolling stock reassignments.

In addition, there are literature combining timetable rescheduling and rolling stock rescheduling in public transport disruptions. For instance, Lorek et al. (2011) attempt to integrate models for recovering the timetable and for rescheduling the rolling stock in case of a disruption. They specifically focus on subway networks. A timetable and rolling stock allocation is determined using a MIP model.

2.2.3 Passengers in disruption management

The adjusted supply during disruptions typically includes a combination of rescheduling of public transport resources (optimising infrastructure capacity, vehicles, drivers, etc.), which have a strong effect to passengers. As described in Cacchiani et al. (2014), there are papers dealing with the integration of passengers in different phases of rescheduling, with the aim of determining a good new schedule for the timetable, the rolling stock and crew duties when a disruption occurs. Here we omit the quotes of the literature focusing on crew rescheduling.

Parbo et al. (2015) present a detailed summary of passengers' perspectives and summarise the differences between passenger delay and train delay, showing that maintaining transfers is often the main concern among optimisation studies. Weston et al. (2006) conclude that, due to the missed connections, minimising train delays do not necessarily minimise passenger delays. Nielsen et al. (2008) investigate the differences between passenger delays and train delays by means of traffic assignment model, finding that passengers' on-time performance is significantly lower than that of the trains. Vij et al. (2013) summarise the three impact factors of passengers' travel behaviours. Vromans et al. (2006) examine how travellers perceive the extent of train delays and conclude that a few large delays proved to be more hurtful than several minor delays. Wardman et al. (2012) conduct a meta-analysis of European studies and summarise four variables used to reflect passengers' perception of travel time variability. Hensher et al. (2011) define travel time deviations as either the travellers' risk or uncertainty. Sun et al. (2014) present that the impacts of timetable changes on passengers' travel behaviours should be considered explicitly, in order to accurately quantify the derived impacts. However, most literature consider passenger flows as static or given input (e.g. Binder et al., 2015; Schachtebeck and Schöbel, 2010; Kumazawa et al., 2008). In contrast, Kroon et al. (2015) consider the dynamic passenger flows, i.e. passengers need to wait or re-chose alternative routes if their targeted trains are cancelled or with insufficient seat capacity. Kanai et al. (2011) propose a delay management algorithm considering dynamic interactions between trains and passengers. Kunimatsu et al. (2012) demonstrate a dynamic evaluation method by simulating train operation and passenger flow.

Passengers in timetable rescheduling. Dollevoet et al. (2012) extend the delay management problem with rerouting of passengers who know which connections between trains will be maintained in the near future. Corman and D'Ariano (2012) determine an updated disposition timetable considering microscopic infrastructure capacity. Parbo et al. (2014) propose a genetic-algorithm to reduce passengers' waiting times by changing the departure times of buses; the solutions are evaluated using a detailed passenger assignment model. Binder et al. (2017) consider passengers' rerouting in a railway network by means of a linear programming model, defined for timetable rescheduling in a rail disruption. To solve the problem for different values, a three-dimensional Pareto frontier is explored to understand the trade-offs between passenger satisfaction and operational cost of the disposition timetable. Van der Hurk (2015) develops a model taking into account the probability of boarding and the uncertainty of the duration of large disruptions, proofing the benefits of providing personalised passenger information on alternative routes. Zhu (2019) designs an iterative algorithm to solve the integrated model of passenger re-routing and timetable rescheduling.

Passengers in rolling stock rescheduling. Ghaemi (2018) proposes a model for short turning vehicles during rail disruptions, and studies their simplified effects to passengers' satisfaction. Kroon et al. (2015) combine a passenger assignment problem (only rerouting in a railway network) with a rolling stock rescheduling model in rail disruptions. They approach the problem from the viewpoint of operating company, assuming that the adjusted timetable is given as input in railway disruptions, considering the dynamic passenger flows along the possible detour routes. The solution approach uses a two-stage feedback loop, including solving rolling stock rescheduling as a MIP model and a passenger simulation.

Passengers in timetable and rolling stock rescheduling. Cadarso et al. (2013) consider the integration of timetable and rolling stock rescheduling in a single model. They also consider the inclusion of additional trips, the cancellation of trips, and the possible allocation of additional rolling stock in order to alleviate some of the negative effects of the disruption. A similar approach proposed in Cadarso et al. (2015) considers passenger flows as dynamic; passengers can update their route in a railway network in reaction to a disruption. Leng and Weidmann (2017a) discuss two different rescheduling processes with the difference on who, among infrastructure managers and train operators, makes the definition of passenger services. Veelenturf et al. (2017) integrate the rescheduling of the rolling stock and the determination of a disposition timetable, by considering passenger demand iteratively.

In this dissertation, we consider an optimisation model to generate different disposition timetables based on different possible actions of operating companies, such as retiming, rerouting, full/ partial cancellation of train services, and rescheduling of rolling stock (Chapter 4). The comprehensive effects of the generated disposition timetables are evaluated in a multi-modal network. We also make a step forward in considering individual activities, trips and beliefs of passengers, which relate and influence passenger reaction to disruptions and disposition timetables (Chapter 3, 4, 5).

2.3 Information contents

Infrastructure managers and operating companies need to produce a new timetable and generate information to passengers in disruptions, considering multi-objectives benefiting infrastructure managers, operating companies and passengers (Corman and D'Ariano, 2012). For the contents of the disseminated information, different aspects are discussed in the literature, such as the optimal routes to be communicated to passengers, which disposition timetable is applied in disruptions, the duration time of disruption as well as public transport service capacity.

For instance, Goerigk et al. (2014) study the robust timetable information; i.e., to identify paths that bring the passenger to the planned destination even in the case of delays. Tsuchiya et al. (2006) examine passengers' perception of a support system informing about optimal routes in disruptions. Cheng and Tsai (2014) mention that passengers appreciate being informed about the cause of the delay. When delays were caused by external factors, travellers' negative emotions are alleviated compared to the situation where the operators are responsible for the delay. The information helps passengers to decide whether to wait for resumption or not, if not, which detour to choose. A similar study by means of game theoretical approaches has been presented in Bouman et al (2017), determining that how much the information disclosed and the capacity optimisation mechanism have an impact on the number of passengers utilizing resources and their satisfaction. In Kroon et al. (2015), the information obtained by passengers is complete or partial; for example, the updated timetable, the duration time of disruption or the train capacity. Van der Hurk et al. (2018) combine a passenger simulation mechanism, in which the duration of the disruption is uncertain and train capacity is limited, with an optimisation-based algorithm that aims to minimise passenger inconvenience. Passengers' route choice depends on the route advice that they receive and the timetable information that is available to them. The survey in Zanni and Ryley (2015) shows that more qualitative information can help passengers to better understand the nature of the disruption (the timing and location along the trip, for example), as well as the best reaction to it. Bender et al. (2013) study the online delay management problem of the effects of "additional information" (such as information about the next stations, or information about the distribution of delays) to passengers. Chorus et al. (2007) study by web survey about passengers' need of information including early warnings, full trip assistance, time-related or location-specific information, personalized information, multimodal information, cost-related information, information on other than time- and cost-related aspects. Parvaneh et al. (2014) summarise passengers' information including real-time prescriptive or descriptive, and public or personal information.

The information content can also include some strategies by using other transport modes as alternatives in the disruptions. For instance, Liang et al. (2019) and Wang et al. (2019) provide passengers about the information of the bridging buses in case of expected or unexpected metro disruptions. Foell et al. (2013) study the transport routines of urban bus riders in order to understand in advance the temporal travel needs of individual users. Poulopoulou and Spyropoulou (2019) develop a tool using "variable message signs" acting as an "advanced traveller information systems", aiming to mitigate disruptions and improve traffic flow in the road networks. Bruglieri et al. (2015) design the real time mobility information system for the management of unexpected events, delays and service disruptions concerning public transportation in the city of Milan. Papangelis et al. (2013) identify the requirements of real-time passenger information for each stage and type of disruption, particularly for rural public transport users.

In brief, the different information strategies can vary, for instance, in what information the operating companies disseminate to passengers, when they do so, and where passengers can receive updated information. In this dissertation, a framework for classification of information availability to passengers in public transport disruptions is presented (Chapter 3), able to consider most of those issues, and including the time dynamics of information i.e. what passengers know when (Chapter 3, 4, 5). Then, the influence of information availability to passengers' satisfaction is evaluated.

2.4 Information channels and dissemination

Some research discusses the dissemination channels of information in public transport disruptions, either at static stops/ stations or via mobile channels. Loo and Leung (2017) prove that effective dissemination of information about the severe disruptions and the resulting changes in the transport system, both during the disruptions and considering the effects after it, through different channels, is very important.

Toletti (2018) describes the customer information in Swiss public transport system, which is a centralised platform for the entire public transport system, including regional and city networks, buses, and other train operating companies. It can provide information to stations, online system and staffs about the current traffic situation and the effects on passengers' transport chains. Instead, there are some countries where each train operating company is responsible for information to their own customers. Watkins et al. (2011) show that access to mobile to check real-time information about the updated schedule can reduce passengers' waiting time and increase their satisfaction with the system, by conducting a real-life experiment with the OneBusAway traveller information application. Pender et al. (2014) explore the extent by which social media is beneficial given it provides real-time information. They find that it can only supplement, but not replace conventional information dissemination approaches. Cottrill et al. (2016) study and understand how Twitter can be used as a communication channel during disruption. Findings indicate the potential for future applications of social media by transport operators and authorities in producing a more effective network of communication with passengers. Dziekan and Kottenhoff (2007) use both the questionnaires and behaviour observation method to prove that dynamic at-stop real-time information displays can reduce customers' waiting time and result in adjustments of their walking speeds. Some research discusses the dissemination channels of real-time information in public transport disruptions.

In this dissertation, we first assume and consider the appropriate channels that information dissemination is perfectly available to passengers, and focus only on the information contents, i.e. which information is disseminated, in Chapter 3 and 4. Then, we refine and consider the specific channels that information dissemination might be only available at stations or on-route (Chapter 5).

2.5 Information availability and passengers' behaviours

In this section, we review the research about the relations between information availability and passenger behaviours, as well as passenger simulation methods that can enhance the heterogeneity of passenger in the research of public transport disruptions, including agent-based micro-simulation models.

2.5.1 Passengers' adaptations to information

The findings in Carrel et al. (2013) show that passengers value delays differently depending on the perceived causes as well as where they know information within their trips. In other terms, providing good information to passengers during disruption is a key aspect. The role of information in improving passenger satisfaction in public transport networks has been studied for disturbances and disruptions. For instance, Cats et al. (2016) provide evidence that the provision of real-time information can be especially beneficial in case of service disruption.

There are strong relations between information availability and passengers' adaptations in public transport disruptions. The information in Tsuchiya et al. (2006) helps passengers decide whether to wait for resumption or choose which detour: 94% passengers prefer to have this piece of information as soon as possible, although subject to uncertainty, rather than waiting until the information is certain. Adelé et al. (2019) apply a revealed-preference questionnaire to identify three categories of factors affecting suburban train user behaviours: individual-specific factors, journey-specific factors and information-specific factors. Shires et al. (2019) apply both revealed preference (RP) and stated intentions (SI) data to rail and non-rail users, as well as finding out that, the level of awareness prior to arriving at the station does not seem to have a large impact on the pattern of behavioural response. This may reflect the increased information available from information channels such as mobile devices. In addition, the differences of individual attributes are detailed in some research. Lois et al. (2018) report how the age of participants negatively affects information, indicating that older individuals have some cognitive problems with accessibility in road transport interchanges.

Passengers' possible decisions in disruptions are affected by the way they use the available information with additional assumptions including the regularity of services, passengers' familiarity to services and the strategies considered by passengers. Each combination of assumptions about these aspects links to specific aspects of a public transport research in disruption (see for a broad overview Gentile and Noekel, 2016). In the classical passenger-oriented rescheduling model in Subsection 2.2.3, passengers are assumed to receive perfect information about disruptions (e.g. Binder et al., 2017; Parbo et al., 2014). Their adaptations are typically assumed to find a new fastest path in the disrupted transport network, which means choosing an alternative route in public transport (i.e. a different sequence of public transport services) to fulfil some given passenger journeys from origins to destinations (e.g. Veelenturf et al., 2017; Cadarso et al., 2015). In addition, passengers are often clustered into several groups based on passengers' origin and destination (e.g. Van der Hurk et al., 2018). The grouped passengers' preference in Kroon et al. (2015) obeys probability distribution, including route preference, transfer burden, delay endurance and congestion. Ben-Elia and Avineri (2015) summarises the key theoretical concepts used to explore the relationship between information and passengers' behaviour include: reinforced learning; framing; risk and loss aversion; probability weighting; affect; anchoring and ambiguity aversion; and regret aversion, under the distinction of experiential, descriptive, and prescriptive information sources. Moreover, passengers' beliefs are studied in case of uncertain real-time information. Golledge (2002) shows that individuals make decisions based on their beliefs of reality, their knowledge of the environment and their experiences. Parvaneh et al. (2014) study passengers' route choices, cancellation/ insertion/ resequencing of activities in different travel information and updating belief. Arentze and Timmermans (2005) show that expected information gain tends to favour longer trips and variety seeking in terms of both route and destination choices, especially for individuals who are less familiar with the transport network.

Passengers' adaptations in disruptions are not limited to changes in a single mode of transportation, also can be alternative choices in a multi-modal network including private modes and other public transport. Hickman and Bernstein (1997) develop a path choice model that incorporates both time-dependent and stochastic transit service characteristics, and allows passengers to update path choice decisions while waiting. Schmidt et al. (2017) study passengers' decisions under the uncertainty of disruption duration; either they will wait until the end of disruption or taking a detour route as alternative. Anderson et al. (2014) estimate parameters for route choice in public transport networks by survey data, which requires a detailed estimation of the inconvenience of a route and possibly a distinction between different passenger types and trip purposes. The model with complete travel chain for passengers, including various origins and destinations, different trip purposes and departure times can describe passengers' behaviours with influence of information in public transport disruptions in a more realistic way. Zhang and Lo (2020) focus on the number of passengers who decide leaving the metro system, and study how to serve more passengers by using bus-bridging method in case of metro disruptions.

2.5.2 Agent-based simulation approach

The evaluation of complex choices by a multitude of heterogeneous passengers is often too complex to be included explicitly in optimisation model, but rather approached by means of simulation techniques. Among those, agent-based simulation models consider each passenger as an agent, able to take independent decisions maximising some utility function, based on the understanding they have of the transport network.

Simulation tools. Many different simulation models have been proposed with different modelling behaviour (assuming rationality of users), integrating demand-supply feedback (focusing on demand assignment only, or considering some feedback to supply, and or transport network dynamics), and geographical resolution and time scale (static view, long term dynamics, or short term dynamics at seconds scale). The TRANSIMS (TRansportation ANalysis and SIMulation System) project (Smith et al. 1995) aims at representing reactions of demand to limited supply based on a traffic simulation using cellular automata. It offers detailed simulation of traffic (incl. lanes, traffic signals) and rich activity patterns, but only route choices are used as part of equilibration. Albatross (Arentze and Timmermans, 2000) and FEATHERS (Han et al., 2011) are two similar models based on the idea of decision trees. It represents decisions by a set of rules rather than an optimisation problem and generates activity patterns with external traffic assignment. These simulation tools do not rely on assumption of perfectly rational agents so that parameters of the model are more difficult to interpret. SimMobility (Lu et al., 2015) has a distinguishing feature of "multi-level" simulation including long-term (land use), mid-term (travel demand) and short-term (network simulation). It aims at representing all decisions from traffic tactics to long term and is also activity-based. Adnan et al. (2017) use SimMobility mid-term model to simulate within-day behaviour and agent interactions, where the information propagates to the disrupted transit station and triggers agents' on-route rerouting decision-making processes. BusMezzo is a dynamic transit operations and assignment simulation model, which can be applied to multi-modal metropolitan transit networks. Cats et al. (2011) use BusMezzo to demonstrate that passengers can profit from having real-time information on the current state of the timetable. The structure of MATSim (Axhausen, 2007) is greatly based on TRANSIMS (Smith et al., 1995). It is an activity-based simulation where the decisions of agents are based on some optimisation framework. Meister et al. (2011) present the application of agent-based transport simulation toolkit MATSim to a large-scale scenario of Switzerland.

Disruptions, simulation. Malandri et al. (2018) use BusMezzo to evaluate public transport network vulnerability with a non-equilibrium dynamic transit operations model to quantify temporal and spatial spillover effects of disruptions. Yap (2020) uses BusMezzo to predict disruptions and their impacts on passenger delays of public transport stops. Currently, MATSim includes multiple transport modes to accommodate passengers' behaviours and is suitable for large-scale scenarios. Many papers in recent years apply MATSim to study the effects of unexpected events, but mainly focusing on road transport contexts. For instance, Padgham et al. (2014) couple MATSim with a Belief-Desire-Intention system to allow more extensive modelling of the agent's decision-making. Stahel et al. (2014) show that agent-based simulations represent a promising approach for comprehensively modelling the impacts of unexpected weather on transport systems. Heyndrickx et al. (2016) show via the evaluation and simulation of MATSim that drivers' costs can be reduced by informing them in case of extreme weather. In the public transport field, Paulsen et al. (2018) use MATSim for evaluating passenger delays caused by delayed trains in multi-modal public transport systems.

In this dissertation, we study the heterogeneous passengers' behaviours with information in public transport disruptions. The evaluation of complex choices by a multitude of heterogeneous passengers is tackled by means of simulation techniques. Among those, agent-based simulation models consider each passenger as an agent, able to take independent decisions maximising some utility function, based on the understanding they have of the transport network. We focus on one specific agent-based simulation environment, but our ideas are applicable to any appropriate similar environment. We apply MATSim in a multi-modal network including public and private transport modes, under a public transport disruption, including a novel within-day replanning module for understanding the reaction of agents to disruption and disposition timetables (Chapter 3, 4). We also consider passengers' belief on delay propagation in case that the provided information is incomplete, and propose a novel multi-layer time-event-graph method to study passengers' behaviours in case of public transport delays (Chapter 5).

2.6 Summary and research gaps

In this chapter, we review the gaps of literature related to public transport delay and disruption management. Especially, the passenger-oriented delay and disruption management focuses on understanding and adapting the demand of passengers (activities, trips, preferred modes, preferred arrival time), and the supply from infrastructure managers and operating companies (operating plan, and availability of resources such as vehicles and drivers) to offer better services to passengers. The reviewed literature related to passenger-oriented disruption management, either in public transport networks or multimodal networks, discuss the supply adaptations during disruptions (i.e. operators point of view), demand adaptations during disruption (i.e. passengers point of view) and the relation between the two with information as enabler of better performance.

Information. Literature identify that information plays an important role in improving passenger satisfaction in public transport networks for both disturbances and disruptions. The generated and supplied information contents are diverse in many aspects such as the optimal routes to communicate to passengers, which disposition timetable is applied in disruptions, the duration time of disruption as well as public transport service capacity. The dissemination channels of information in public transport disruptions are also discussed in the literature, either at stops/ stations or via mobile channels.

In brief, the information availability to passengers and the information strategies from service providers can vary, for instance, what is the content of information disseminated to passengers, when and where passengers can receive the updated information. A framework for classification of information availability to passengers in public transport disruptions needs to be defined, which should be able to consider most of those issues, and including the time dynamics of information i.e. what passengers know when. Then, the influence of information availability to passengers' satisfaction can be quantified and evaluated (Chapter 3). In addition, the principles and effects of information availability to passengers in public transport disruptions need to be explained, which should be rigorous and independent of the precise solver used to compute them, with possible formulations and descriptions of (user equilibrium, or non-equilibrium) solutions. This should be applicable to any appropriate similar environment, such as agent-based simulation (Chapter 3, 4).

Moreover, the information about the disposition timetable can be incomplete or imprecise, e.g. the delayed information availability to passengers, the limited information contents about specific public transport services at specific stations within specific time horizon. In case of incomplete information, passengers rely on their belief, i.e. passengers' expectation about the future unknown operations based on their known information. The incomplete information and passengers' belief affects their behaviours, such as route choices. These effects to passengers should be further studied in case of public transport delays and disruptions (Chapter 5).

Passengers. In current research about railway delays and disruptions, there are literature considering passengers in the optimisation model of delay or disruption management. However, most literature simplify to model passengers as homogeneous groups based on origins and destinations to integrate the aggregated passengers in the process of timetable or rolling stock rescheduling. These literature regarding passenger behaviours in railway malfunctions usually consider passenger flows as static or given input, with few papers considering dynamic interactions between trains and passengers. Rerouting of passengers is widely considered, in the literature combining the simulation of train operation and passenger flow together, in public transport disruptions. However, the other changes of passengers' behaviours, such as changing destinations, changing transport modes, are usually neglected.

In other terms, the heterogeneity of individual passenger in public transport disruptions needs deeper study, such as considering individual activities and trips of passengers that relate and influence passenger reactions to disruptions and disposition timetables. The heterogeneous passengers' behaviours with information in public transport disruption needs to be studied. The evaluation of complex choices by a multitude of heterogeneous passengers is often too complex to be included explicitly in optimisation models, and is instead tackled by means of simulation techniques. Among those, agent-based simulation models consider each passenger as an agent, able to take independent decisions maximising some utility function, based on the understanding they have of the transport network (Chapter 3, 4).

Furthermore, more deeply considering the information availability, the incomplete information and passengers' belief (i.e. passengers' inference about the future unknown operations based on the known information) also affects passengers' behaviours, which should be different from the assumption of complete information (i.e. all the operations and delays are known by passengers' immediately as issued).

These effects of incomplete information to passengers' behaviours and satisfaction needs further study (Chapter 5).

Multi-objectives. The methods to study the trade-offs of different objectives of passengers, train operators and infrastructure managers are multiple in the literature. Some establish one holistic mixed-integer programming model to solve the whole problem with the aim to get an optimal solution. With the detailed consideration of modelling three stakeholders, the model size could be large and the computation time of an optimised solution could be considerable. Among which, the metaheuristics methods are applied with an evaluation mechanism to improve solutions from initial ones, where the challenge is to find the optimal solution. There are literature combining passenger simulation and supply optimisation, but they are generally focused on single transport mode instead of multi-modal network.

The infrastructure managers and operating companies would prefer to quantify the effects of different rescheduling strategies and information strategies to passengers in a multi-modal network, in case of disruptions. With the quantitative results, the operating companies can understand the benefits of different strategies and decide to exploit which strategy in public transport disruptions. The optimisation model could generate different disposition timetables based on different possible actions of operating companies, considering retiming, rerouting, full/ partial cancellation of train services and rolling stock rescheduling. The comprehensive effects of the generated disposition timetables and information strategies could be evaluated in a multi-modal network (Chapter 4).

Chapter 3

Information availability in public transport disruptions: an agent-based simulation approach

This chapter is based on the following published article.

Leng, N. and Corman, F. (2020) The role of information availability to passengers in public transport disruptions: An agent-based simulation approach, *Transportation Research Part A: Policy and Practice*, 133 214-236.

3.1 Introduction

Public transport disruptions have typical features of malfunctions of technical components or unavailability of resource allocation, which can be caused by planned maintenance actions, or some unexpected events such as tracks, rolling stock, staff and power supply, failures, weather, etc. Disruptions can have a significant impact on passengers' travel and lead to critical decisions from passengers' perspective, such as delay or even cancelling the trip (Adelé et al., 2019). One main target of public transport disruption management is to improve the services for passengers, with effective methods such as offering information to passengers. The research in Cats et al. (2011) suggests how the provision of information can be especially beneficial to passengers in case of public transport disruptions. The public transport networks are organised in services, which can be used by passengers only as far as they have knowledge of them. In a disruption situation, the disposition timetable should be disseminated to passengers. Based on the information they know, passengers adapt their behaviours to the new situation. In other terms, providing good information to passengers during disruptions is a key aspect; the information availability is an important factor to passengers' satisfaction (Gentile and Noekel, 2016).

The major goal of this chapter is to study the influence of information availability to passengers on a large-scale multi-modal network in case of public transport disruptions, i.e. how to model passengers' adaptations under different information availability and measure the corresponding passengers' satisfaction. This problem is interesting and challenging to solve because of the following aspects. First, the available information can vary, for instance in what they disseminate to people, when they do so, where people can receive updated information. For instance, Kroon et al. (2015) understand how the information available to passengers can be complete or partial. Second, passengers' adaptations are complex under the impact of available information. Paulsen et al. (2018) show that passengers' behaviours in multi- modal network are not limited to route changes (e.g. as considered in Hickman and Bernstein, 1997), also including transport mode, activities and time change. Third, the heterogeneity of passengers' trips cannot be neglected. The findings in Carrel et al. (2013) show that passengers value delays differently depending on where the disruptions occur within their trip. Finally, passengers' behaviours in reality happen in a multi-modal network, and quantifying the available information in disruptions should reflect this. Some literature consider studying that realised travel behaviour by means of passenger tracking approaches (e.g. Marra et al., 2019) or smart card data usage (e.g. van der Hurk et al., 2018) as a possible way to collect real data about public transport disruptions. However, a comprehensive study of those factors and real wishes of passengers through e.g. revealed preferences is difficult due to rare, unexpected occurrence of disruptions, and possible answers' bias (e.g. anger) from passengers under pressure and or skewed perception of disruption events.

Gentile and Noekel (2016) report how the impact of information availability could be possibly studied in a simulation-based approach. We propose to use agent-based micro-simulation, to imitate large-scale passengers' behaviours during public transport disruptions. In such type of simulation, individual passengers and vehicles are modelled through agents that interact with the public transport system according to their individual goals (Bouman, 2017). Heterogeneous passengers in real world are modelled as agents in simulations. Their daily movements are divided as consequent activities and trips: activities represent passengers' destinations in daily plans, such as staying home, at work or do shopping; trips express the connection between two adjacent activities, characterized by transport modes chosen, travel time, etc. With a well-defined description of passengers' movements, an agent-based environment is capable to simulate comprehensive passengers' behaviours in a multi-modal network (i.e. changing transport modes between public transport and private car, bike or walk; adjusting a departure time; changing route in a public transport network; possibly cancel activities) and evaluate the corresponding satisfaction (Horni and Nagel, 2016). We show that the output of agent-based simulations provides a valuable understanding of the differences of information availability to passengers' satisfaction in a given public transport disruption.

The major contributions of this chapter are as follows:

(1) We define the mathematical notations and formulas to describe the effects of information availability to passengers' adaptations. The rigorous mathematical descriptions are able to compute performance indicators of user equilibrium and non-equilibrium solutions corresponding to different information availability scenarios. In addition, a framework for classification of information availability is proposed for passenger-oriented disruption management in transport networks. This is able to model how many passengers know about public transport disruptions, where they get to know this (e.g. at the disrupted station), when they know it (e.g. in advance or after disruption) and what they know (e.g. precise start and end time of public transport disruption). This framework allows determining many intermediate cases, between two extremes about of information dissemination in public transport disruptions: agents have no knowledge about disruptions; or agents know all the detail information about disruptions in advance.

(2) The use of agent-based simulation to study passenger behaviours during public transport disruptions, bringing three key benefits. The first is the consideration of movement of agents in a multi-modal network, including choices within the public transport network, but also including switching to private modes, cancelling trips, and even cancelling or changing activities throughout a daily plan. The second benefit is the explicit consideration of heterogeneity of users, seen in the activity-based micro-simulation of an entire day, where detailed activities and trips are simulated, so that the specific reaction in disruptions can be precisely understood. Third, to allow such analysis, this chapter has to define a few aspects, providing a novel within-day replanning module, specifically designed to address public transport disruption.

(3) The evaluation of the information availability and the proposed MATSim implementation (including key extensions of the software modules of MATSim, determining the within day replanning) on a realistic case study on a large multi-modal network in Zürich, Switzerland, and the detailed evaluation of three different information availability under a large public transport disruption.

This chapter is structured as follows. Section 3.2 proposes rigorous mathematical descriptions of information availability (scenarios), including both user equilibrium and non-equilibrium solutions. In addition, a novel framework for information availability classification is proposed. Section 3.3 describes the detailed agent-based simulation approach to study the information availability and passengers' adaptations. Section 3.4 explains the set-up of Zürich case study and analyses the simulation results. In Section 3.5, conclusions and future work are presented.

3.2 Information Availability and Passengers' Adaptation

In this section, three exemplar scenarios of information availability are introduced: "Advance information", "Timely information" and "No information" in public transport disruption. In case of the same disruption, the different availability of information results in different passengers' adaptations. We use mathematical formulas to explain the mechanisms of passengers' adaptations in detail based on passenger assignment theory. We assume an appropriate channel for this information dissemination is available, and focus only on the content, i.e. which information is disseminated. We propose a "Who-When-Where-What" four-dimension framework for classifying information availability for passengers during public transport disruptions.

3.2.1 Problem Description and User Equilibrium

During public transport disruptions, passengers need to adapt their travel according to diverse information availability to fulfil their intentions to reach their destinations. To explain explicitly these passengers' adaptations, the activity-based models presented in Axhausen (2007) can be applied. In these models, passengers' overall movements are described as plans, dividing into activities and trips. An activity is a continuous interaction with the physical environment, a service or person, within the same socio-spatial environment, such as home, work or other leisure. A trip is the link between two adjacent activities, expressing movement. The concept of "trip" is to represent passengers' efforts and choices to reaching one activity from the previous one. In detail, passengers need to decide transport mode (e.g. public transport or private vehicles) and specific route to finish one trip. Especially if a person chooses public transport, his/ her trip may contain a certain number of transfers and stages. A stage is a continuous movement with one mode of transport; a transfer is the connection between two adjacent stages in one trip. The start and end time of activities and trips can be flexible in a passengers' plan.

Figure 3.1 shows an example of one passenger's daily movements, consisting of three activities and three trips. The x-axis of the Figure 3.1 represents locations, while the y-axis represents time over a day. This passenger starts his/ her day with "Activity 1" (at home) and uses public transport to perform "Trip 1", which allows to reaches the "Activity 2" (Work). The next trip "Trip 2" is from "Activity 2" to "Activity 3", and is composed of two stages ("Stage 1" and "Stage 2") with one transfer "Transfer 1" within the public transport network. The last trip is from "Activity 3" back to "Activity 1" with public transport. The entire sequence over time and space including activities (locations, time) and trips (modes, routes, stages, transfers and time) is called "Plan" of the passenger. In Figure 3.1 we also represent a public transport disruption, which affects the passenger "Trip 2", in specific the first stage. We call trip 2 as the "Directly affected trip" by the disruption.

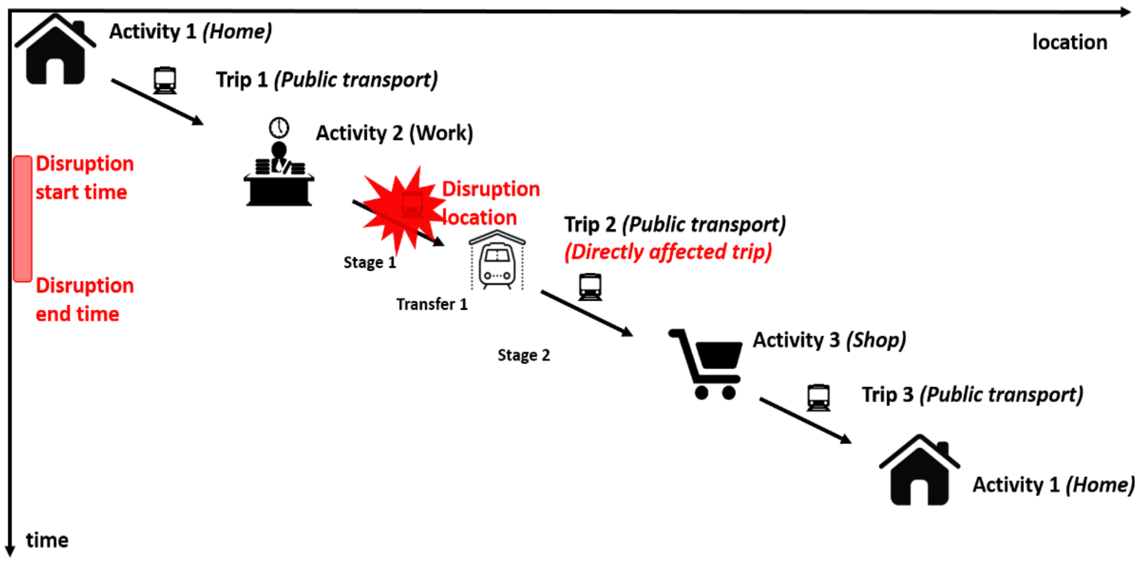

Figure 3.1: Terminology used in this work

We use the following notation. P is the set of all the agents, the total number of agents being $|P|$. For each agent $p \in P$, we define S_p the set of considered k plans, to denote all possible choices they have available to fulfil their demand. We refer to the concepts in the sixth chapter of the book of Gentile and Noekel (2016) for more details. This latter book used "considered paths" to describe passengers' demand of route choices; instead, the "considered plans" in our work include more details about the entire one-day journey, further composed of a sequence of activities A and trips T. The Equation 3.1 shows the detailed components of a "considered plan" $s_{p,k}$. An activity describes the location of activity, start and end time. We hide those details in the following equations when not explicitly needed. A trip is defined by a set of location-time pair in a compact way; we also hide unnecessary detail when possible.

The transport modes, routes, stages are formulaically represented by the "location" of the trip without details. t refers to the time and l refers to the location of the activity or trip.

$$\begin{aligned} & s_{p,k} = (A_1, T_1, A_2, T_2, \cdots A_i, T_i, \cdots), \\ & \quad \text{where } A_i = (t_{start}, l \;, t_{end}),\; T_i = \{(t_j, l_j),\;\; j = 0,1,\cdots,J\}. \end{aligned} \tag{3.1}$$

The total number of the considered plans of agent p is $\left|S_p\right|$. Among all the considered plans, theoretically agents choose one, denoted by $\overline{s}_p$, for actual execution in real life. An assignment solution corresponds to determine one such actual plan for each agent p.

For each specific considered plan $s_{p,k}$, there is a utility $u_{p,k}$ that relates to quality (utility, satisfaction) of this considered plan of the agent p. A larger utility means the agent is more satisfied with their considered plan in the entire multi-modal transport network. In the Equation 3.2, $u_{p,k}$ depends on both the specific considered plan of agent p and the actual plans $\overline{s}_R$ of (in general) all the other agents $r \in P \setminus \{p\}$.These latter have (in general) some dependency on the $\overline{s}_p$, i.e. passengers choice interact, so we identify them as $\overline{s}_r \in S_r \left| \overline{s}_p = s_{p,k} \right.$.

$$u_{p,k} = u_p(s_{p,k}, \overline{s}_R),\; \text{where } \overline{s}_R = \{\overline{s}_r \in S_r \left| \overline{s}_p = s_{p,k}\right., \forall r \in P \setminus \{p\}\}. \tag{3.2}$$

Equation 3.3 shows an example of a set of considered plans $s_{p,1} \cdots s_{p,|S_p|}$ of agent p and the corresponding utility of each considered plan with the impact of other agents in the system. In general, $\overline{s}_{R,1}$ means $\overline{s}_R$ when $s_{p,1}$ is chosen, i.e. the union of all $\overline{s}_r \in S_r \left| \overline{s}_p = s_{p,1} \right.$.

$$S_p = \begin{bmatrix} s_{p,1} = \{A_1, T_1, A_2, T_2 \cdots\} \\ s_{p,2} \\ s_{p,3} \\ s_{p,4} \\ \vdots \\ s_{p,k} \\ s_{p,k+1} \\ \vdots \\ s_{p,|S_p|} \end{bmatrix},\; U_p = \begin{bmatrix} u_p(s_{p,1}, \overline{s}_{R,1}) \\ u_p(s_{p,2}, \overline{s}_{R,2}) \\ u_p(s_{p,3}, \overline{s}_{R,3}) \\ u_p(s_{p,4}, \overline{s}_{R,4}) \\ \vdots \\ u_p(s_{p,k}, \overline{s}_{R,k}) \\ u_p(s_{p,k+1}, \overline{s}_{R,k+1}) \\ \vdots \\ u_p(s_{p,|S_p|}, \overline{s}_{R,|S_p|}) \end{bmatrix} \tag{3.3}$$

Among all possible choices (assignments) for $\overline{s}_p$, the academic literature typically focuses on user equilibrium solutions. Those are specific set of choices, such that each agent achieves his/ her best utility, in the condition that all the other agents also achieve their best utility and nobody else can choose a different actual plan to increase their utility (Gentile and Noekel, 2016). In general, finding a user equilibrium solution is not easy (Nagel and Floetteroed, 2016). We use agent-based approaches to determine (an approximation of) the equilibrium solution.

For each agent p, we can write Equation 3.4, expressing the best choice of the considered plan s_p^* of agent p (i.e. assuming users maximise their utility, the chosen actual plan is the best considered plan $\overline{s}_p = s_p^*$) among all his/ her considered plans S_p in the condition that all the other agents $r \in P \setminus \{p\}$ also choose their best considered plan s_r^*. $\overline{s}_R^*$ compactly represents the best considered plans of the other agents except for agent p.

$$\begin{aligned} s_p^* &= \arg\max_{s_{p,k} \in S_p} u_p(s_{p,k}, \overline{s}_R^*), \\ &\text{where } \overline{s}_R^* = \{ s_r^* \in S_r \mid \overline{s}_p = s_p^*,\ \forall r \in P \setminus \{p\} \}. \end{aligned} \tag{3.4}$$

The plans chosen at user equilibrium lead to a user equilibrium (best) utility u_p^* of agent p (Equation 3.5).

$$u_p^* = u_p(s_p^*, \overline{s}_R^*). \tag{3.5}$$

In Equation 3.6, the total utility U^* of user equilibrium of undisrupted solution in a normal day (from the system perspective) can be computed as the sum of each agent’s utility.

$$U^* = \sum_{p=1}^{|P|} u_p^*. \tag{3.6}$$

3.2.2 Disruption

Once one disruption occurs, the service levels of public transport decrease, they typically remain stable (at a lower level than original) throughout an updated plan of operation named the disposition timetable, and then increase back to original when the disruption is resolved and the network can operate the original timetable again (so called bathtub model, see Ghaemi, 2018). This means that passengers’ utility in the disruption situation decreases from their original utility.

Based on both the intuitive figure expression (Figure 3.1) and mathematical notations introduced, we now describe formally a disruption and the consequences it has towards passengers' adaptations to information availability. We report for a set of considered scenarios, an intuitive figure and a related mathematical formulation of the choices of the users.

We formalize a disruption as follows. D indicates a disruption including the start t^D_{start} and the end time t^D_{end}, as well as a set of disrupted locations L^D (Equation 3.7). The specific services of public transport, which may be affected, are associated to a disruption by means of the "locations".

$$D = (t^D_{start}, t^D_{end}, L^D). \tag{3.7}$$

Without loss of generality, a disruption affects at least one agent p, in the sense that it limits the set of considered plans. Some plans in the set of considered plans S_p of agent p become thus infeasible and unavailable for choice; we denote such set of infeasible plans as $\cancel{S}_p(D)$, adding D as the relevant variable. Specifically, a plan $s_{p,k} \in \cancel{S}_p(D)$ for agent p is infeasible if there exists at least one trip T_i (called affected trip) in this plan, which matches a disrupted location l_j at the time t_j in which the disruption D takes place. More formally (Equation 3.8):

$$\exists T_i \in s_{p,k} : \exists (l_j, t_j) \in T_i \text{ with } l_j \in L^D \wedge t_j \in [t^D_{start}, t^D_{end}]. \tag{3.8}$$

We focus on the agents whose best considered plan s^*_p are affected by the disruption. They are called "involved agents", indicated by the specific set P^D (Equation 3.9). In other words, the disruption makes the involved agents' user equilibrium choice under normal conditions infeasible, and they have to determine another actual plan.

$$\forall p \in P^D : s^*_p \in \cancel{S}_p(D). \tag{3.9}$$

3.2.3 A Framework for Information Availability Classification

We have discussed how passengers' behaviours strongly depend on the information details they know about public transport disruptions in the literature review. We summarise these aspects into a general framework, which analyses the information dissemination along four dimensions, "Who-When-Where-What". Figure 3.2 gives a schematic representation of such a framework, along four axes (corresponding to the four dimensions). For each axis, we picked three possible levels for each dimension highlighted, even though the framework allows for a continuous range of possible levels on each dimension. Such a framework can be used also for other types of disruption, e.g. road disruption affecting private traffic. Our focus on public transport disruption and the need for the passengers to know which services can fulfil their mobility needs makes such a framework especially relevant for public transport services. We consider a single disruption, which can include multiple events, failures, and services not running; we refer to a single disruption, which is completely defined by a disposition timetable for the entire public transport network, used. We do not discuss technologies and costs for information dissemination but only its timely, spatial and content characteristics.

All passengers facing the disruption would ultimately know at least that the disruption is occurring, at the time they try to board a service, which is not running anymore. Similarly, all passengers facing the disruption would know that the disruption is over, at the moment they can board a non-disrupted service which is actually running. All other information might be available to passengers. We discuss the proposed four dimensions in the following.

The ‘Who’ dimension shows the proportion of passengers knowing some information. The worst case is that no passengers know anything about the disruption while the best case is all passengers know. In between, passengers can be grouped by some specific proportion: for instance some know the disruptions (maybe they are more tech-savvy and have continuous access to e.g. mobile data) and others do not know (maybe they are more reactive or unfamiliar with the network). In Figure 3.2, we for instance report three cases of “who”, namely the operating companies is able to reach everybody; some proportion (e.g. half) of the travellers, or none of them.

The ‘Where’ dimension explains the locations of passengers, where they get to know the information. This can represent activities (e.g. I know of the disruption while I am at home or at work), on the transport vehicles (by e.g. announcements) or arriving at the disrupted stations (by e.g. displays). Mobile and social media can be used as the dissemination channel anywhere for passengers. In-vehicle and at-stop real-time information display devices can be helpful for passengers who are involved in public transport disruptions. In Figure 3.2, we for instance report three cases of “where”, namely the operating companies disseminate information through all channels, able to reach all users anywhere; or disseminate information only at the disrupted station; or they do not issue any information at all.

The ‘When’ dimension describes the “issue time” at which the information reaches the users. It can be beforehand, for planned disruptions such as planned public transport maintenances, in which the operating companies broadcast the disposition timetable in detail in advance. In case of unexpected unplanned disruptions (like accidents, failures, etc.), the issue time can only be after the start time of the disruption. In the worst case, the information is never issued and passengers know of the disruption only at the moment they try to board a service, which is not running. A complementary information is also the time at which the disruption is resolved, which can be disseminated at the beginning of the disruption, or later on. These information availability can also be different in the issue time, i.e. when the operating company sends out the announcement and the time the users can receive, which can be even dynamic (see e.g. the review in Corman and Meng, 2015). In Figure 3.2, we for instance report three cases of “when”, namely the operating companies can issue in advance information about the disruption; or disseminate information only when they realise that the disruption is going on; or they do not issue any information at all.

The ‘what’ dimension defines the detailed information that passengers can know in public transport disruption. As is summarised in literature review, the information content can be different in the aspects of the exact disruption going on (e.g. some public transport line is not working), the disposition timetable implemented in this case (e.g. bus line XX is not running), train capacity (e.g. please avoid boarding this train as crowding is expected), additional services planned (e.g. bus bridging is in place between station X and station Y), the duration time of disruption (e.g. we expect that the disruption last at least three hours), and the optimal routes to passengers (e.g. take this service in case you want to go from A to B). In Figure 3.2, we for instance report three cases of “what”, namely the operating companies can issue the precise start time and end time of disruption, and associated disposition timetable; or only the start time (as the ending time in unknown or cannot be precisely specified); or no information at all.

With the classifications by the proposed “Who-When-Where-What” four-dimension framework, diverse information availability can be defined based on passengers’ different level of knowledge for the public transport disruptions. Figure 3.2 shows three exemplar information availability (more examples in Appendix A), which are scenarios analysed in the remainder of this chapter to study the effects of information to passengers’ behaviours and satisfaction in public transport disruptions. The “No information” scenario (red line in Figure 3.2) means passengers do not receive any other information, apart from the fact that a disruption of unspecified length is going on, when they try to board a disrupted service; and that the same disruption is solved, only once it is actually solved. This also implies that no passengers can receive any information anywhere about disruptions. The “Advance information” scenario (blue line in Figure 3.2) means all passengers have a complete knowledge well before the start time of the disruptions. The complete knowledge implies that all the passengers anywhere within the multi-modal network (e.g. not only users of public transport, but also those typically using cars) have access to perfect information, including the disposition timetable, the starting time, ending time, public vehicle capacity. The “No information” “Advance information” scenarios are two extreme types of information availability in public transport disruptions. In between, many scenarios with different information availability can be identified. As an example, we consider a "Timely information" scenario (yellow line in Figure 3.2) which considers that all passengers, anywhere in the multi-modal network, get to know at the precise starting time of the disruption, that a disruption is going on; at the same time they know the disposition timetable, and the end time of disruption.

Figure 3.2: Framework for classification of information availability and three examples of scenarios in public transport disruptions

3.2.4 Advance Information

A relevant case is when passengers have perfect information beforehand, which allows them to adapt at best their plan. A practical case in which disruptions are known in advance and people can react on this, refers to for instance planned maintenance actions, or long term disruptions where people adjust their long term behaviour. Figure 3.3 explains passengers' adaptations in the "Advance information" scenario. The following behaviour rules are assumed.

- First, passengers as reaction to the disruption can change modes. A mode change means that passengers may leave the public transport system and take private car or bike for the affected trip, or even for the entire day.
- Passengers can also change services in disruption. A service change means that passengers who keep using public transport can change the line they use (i.e. bus line 12 instead of 40). Or they can change transfer stations (i.e. Transfer 2 in Figure 3.3 can be the same physical location as Transfer 1 in Figure 3.1, or not). Alternatively, they can take a completely different sequence of services in the public transport network as far as it enables them to reach their destination (in this case Activity 3).
- Additionally, some passengers' activities can be dropped or changed in their locations (e.g. shopping can be done at another location; Activity 3 in Figure 3.3 might not take place at the same physical location as Activity 3 in Figure 3.1).
- Finally, passengers can depart earlier or later than their planned time, for any trip and activity. In the plan of the entire day, passengers can combine any of those reactions for the maximisation of their satisfaction.

The disruption decreases the number of the feasible considered plans. With the help of "Advance information", agents can perfectly know all the feasible considered plans $S_p^{\mathrm{D,AI}} = S_p \setminus \cancel{S}_p(D)$ in the public transport disruption. "AI" is the short hand of "Advance information". In Equation 3.10, we update Equation 3 for an involved agent p under disruption, by representing some of the plans infeasible due to disruption. Without loss of generality and for graphical simplicity, we grouped those latter $\cancel{S}_p(D)$ at the last rows of the S_p.

$$S_p = S_p^{\mathrm{D,AI}} \cup \cancel{S}_p(D) = \begin{bmatrix} s_{p,1} = \{A_1, T_1, A_2, T_2 \cdots\} \\ s_{p,2} \\ s_{p,3} \\ s_{p,4} \\ \vdots \\ s_{p,k} \\ s_{p,k+1} \\ \vdots \\ \cancel{s}_{p,|S_p|} \end{bmatrix}, \; U_p = \begin{bmatrix} u_p(s_{p,1}, \bar{s}_{R,1}) \\ u_p(s_{p,2}, \bar{s}_{R,2}) \\ u_p(s_{p,3}, \bar{s}_{R,3}) \\ u_p(s_{p,4}, \bar{s}_{R,4}) \\ \vdots \\ u_p(s_{p,k}, \bar{s}_{R,k}) \\ u_p(s_{p,k+1}, \bar{s}_{R,k+1}) \\ \vdots \\ \cancel{u}_p(\cancel{s}_{p,|S_p|}, \cancel{\bar{s}}_{R,|S_p|}) \end{bmatrix} \tag{3.10}$$

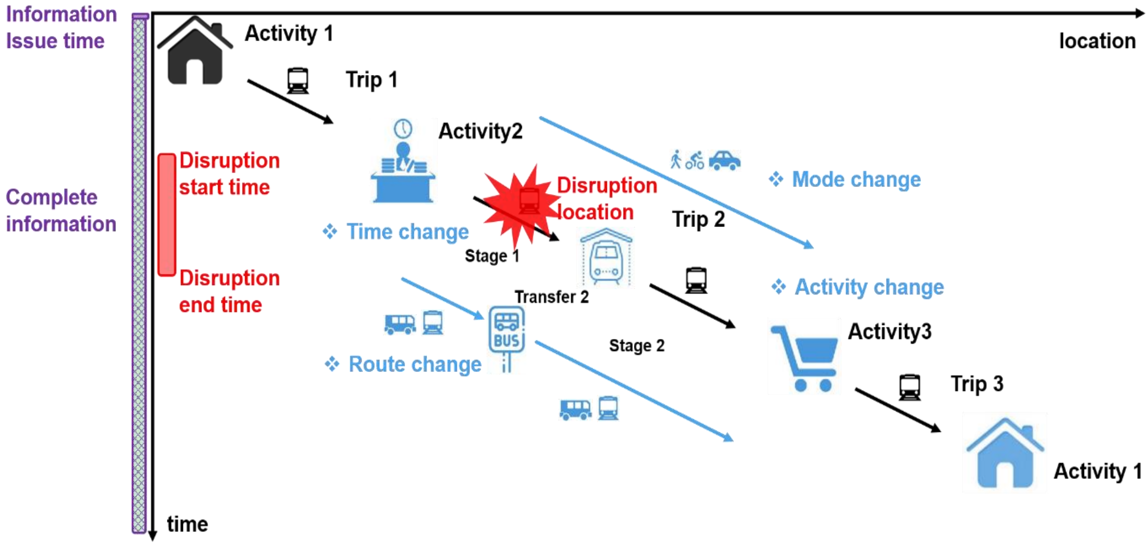

Figure 3.3: The effect of “Advance information”

Thanks to the knowledge of all the feasible considered plans in disruption, the agents will find another solution among the new considered plans $S_p^{\mathrm{D,AI}} = S_p \setminus \cancel{S}_p(D)$. Theoretically, passenger assignment can reach a user equilibrium in the case that passengers can freely change their choices based on learning from other passengers' behaviours after known disruptions (Nagel and Floetteroed, 2016). In fact, the “Advance information” scenario results in another user equilibrium solution. Equation 3.11 indicates the new best considered plan $s_p^{*\mathrm{D,AI}}$ of agent p in the new user equilibrium in the condition that all the other agents $r \in P \setminus \{p\}$ find their best considered plan s_r^* among the decreased considered plans $S_r^{\mathrm{D,AI}} = S_r \setminus \cancel{S}_r(D)$.

$$s_p^{*\mathrm{D,AI}} = \arg\max_{s_{p,k} \in S_p^{\mathrm{D,AI}}} u_p(s_{p,k}, \overline{s}_R^{*\mathrm{D,AI}}),$$
$$\text{where } \overline{s}_R^{*\mathrm{D,AI}} = \{ s_r^{*\mathrm{D,AI}} \in S_r^{\mathrm{D,AI}} \mid \overline{s}_p = s_p^{*\mathrm{D,AI}},\ \forall r \in P \setminus \{p\} \}. \tag{3.11}$$

The best considered plan leads to the maximum utility $u_p^{*\mathrm{D,AI}}$ of agent p in this new equilibrium. Due to the decrease of available considered plans, the agents' total utility in this case of "Advance information" is no more than their utility in the normal situation without disruption (Equation 3.12).

$$U^{*\mathrm{D,AI}} = \sum_{p=1}^{|P|} u_p^{*\mathrm{D,AI}} \leq \sum_{p=1}^{|P|} u_p^{*} = U^{*}. \tag{3.12}$$

3.2.5 Timely Information

A relevant case is also the one considering the fact that agents can only know the information about disruptions in a non-anticipatory way, i.e. only after disruptions occur. This is common for all unplanned disruptions. We call this scenario "Timely information" and refer to Figure 3.4 to explain the passengers' adaptations in this scenario. In this case, we assume that passengers know the perfect information of starting time and specific length of disruption, but they know it only after the disruption starts.

Compared to the "Advance information" scenario, passengers' adaptations are much more limited. No change can retroactively take place in the past, i.e. only activities and trips in the future (starting from the start time of the disruption) can be considered. In particular, there cannot be any mode change (i.e. shifting to private car bike or walk) as reaction to the disruption. In other terms, we assume that passengers planning to use public transport do not have an alternative private mode directly available when they realise there is a disruption. This can be the case, for instance, the disruption happens in the afternoon when people already reached their workplace by some means. A different choice of disruption, e.g. in the morning, might oblige people to change their mode for the entire day (i.e. taking their private car to perform all trips). As the former case is more relevant for the information dissemination, we focus on that one. We do not consider taxi alternatives, nor bike or car sharing systems. Passengers planning to use public transport will adapt their plan by choosing the services enabling the best response (Trip leading to the maximum utility) from the previous activity (in this example, Activity 2) to the next one (in this example, Activity 3). We consider the maximum utility of a Trip as a combination of the walking time, waiting time and in-vehicle time, and related penalties with typical parameters of generalized travel time. The information that a disruption occurs is instantaneously transmitted to (and received by) all passengers at the start time.

Passengers that were performing an activity will not change the duration of such activity (i.e. I cannot leave work at Activity 2 earlier, if I know that there is disruption). Passengers that were waiting for a public transport service, or already on board a public transport service will instantaneously re-compute the maximum utility path and implement it at the earliest possible time. If passengers were waiting at a station, this can mean taking a different service; if passengers were on a bus/ train, this can include disembarking the vehicle where they were traveling as a connected service might not be running anymore.

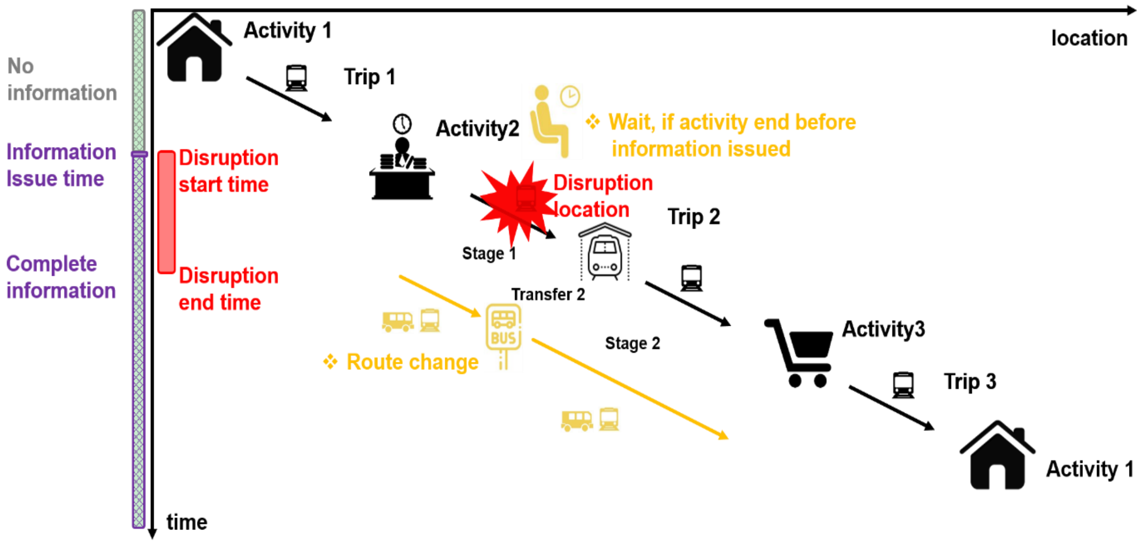

Figure 3.4: The effect of “Timely information”

Formally, this scenario can be modelled as follows. The set $\not{Z}_p(D, s^*_p)$ (adding D and s^*_p as the relevant variables) describes all the considered plans that violate the non-anticipatory condition, i.e. those plans that do not match the normal best considered plan s^*_p before the disruptions’ start time t^D_{start} (Equation 3.13 or 3.14). In other terms, the agents can only consider plans such that all the activities and trips should be the same up and until the start time of the disruption, because of the fact that what has happened in the past cannot be changed any more.

Consider the involved agent $p \in P^D$, then a plan $s_{p,k}$ becomes infeasible under the “Timely information” scenario (i.e. $s_{p,k} \in \not{Z}_p(D, s^*_p)$), if either one of the following conditions is true:

$$\exists \bar{A}_i \in s_{p,k}, t_{start} \geq 0, t_{start} \leq t^D_{start} : \nexists A^*_i \in s^*_p : \bar{A}_i = A^*_i. \tag{3.13}$$

$$\exists \bar{T}_i \in s_{p,k}, t_0 \geq 0, t_0 \leq t_{start}^D : \nexists T_i^* \in s_p^* : \bar{T}_i = T_i^*. \tag{3.14}$$

Equation 3.13 determines that for a considered plan $s_{p,k}$ to become infeasible, there needs to exist an activity $\bar{A}_i$ whose start time t_{start} is no later than the disruption start time t_{start}^D and which is different from all activities A_i^* in the best considered plan in the situation without disruption s_p^*. Equation 3.14 reports the same condition, for trips.

In the case of "Timely information", the number of considered plans further decreases. Equation 3.15 is an example of the decreased considered plans $S_p^{\mathrm{D,TI}} = S_p \setminus (\cancel{S}_p(D) \bigcup \cancel{Z}_p(D, s_p^*))$, further updating Equation 3.10. "TI" is the short hand of "Timely information". Without loss of generality, and for graphical simplicity we delete two considered plans (i.e. $s_{p,k}, s_{p,k+1}$) reported at the bottom rows in Equation 3.15 that are infeasible because of "Timely information" in the non-anticipatory disruptions.

$$S_p = (S_p^{\mathrm{D,TI}} \bigcup \cancel{Z}_p(D, s_p^*) \bigcup \cancel{S}_p(D))$$
$$= \begin{bmatrix} s_{p,1} = \{A_1, T_1, A_2, T_2 \cdots\} \\ s_{p,2} \\ s_{p,3} \\ s_{p,4} \\ \vdots \\ \cancel{s}_{p,k} \\ \cancel{s}_{p,k+1} \\ \vdots \\ \cancel{s}_{p,|S_p|} \end{bmatrix}, \; U_p = \begin{bmatrix} u_p(s_{p,1}, \bar{s}_{R,1}) \\ u_p(s_{p,2}, \bar{s}_{R,2}) \\ u_p(s_{p,3}, \bar{s}_{R,3}) \\ u_p(s_{p,4}, \bar{s}_{R,4}) \\ \vdots \\ \cancel{u}_p(\cancel{s}_{p,k}, \cancel{\bar{s}}_{R,k}) \\ \cancel{u}_p(\cancel{s}_{p,k+1}, \cancel{\bar{s}}_{R,k+1}) \\ \vdots \\ \cancel{u}_p(\cancel{s}_{p,|S_p|}, \cancel{\bar{s}}_{R,|S_p|}) \end{bmatrix} \tag{3.15}$$

In this scenario, the involved agents choose the plan with the maximum utility $u(s_p^{*\mathrm{D,TI}})$ among the limited considered plans. We refer to Equation 3.16, which determines the new actual plan $s_p^{*\mathrm{D,TI}}$ of any involved agent $p \in P^D$ in the condition that all the other involved agents $r \in P^D \setminus \{p\}$ find their best considered plan $s_r^{*\mathrm{D,TI}}$ among the reduced considered plans $S_r^{\mathrm{D,TI}} = S_r \setminus (\cancel{S}_r(D) \bigcup \cancel{Z}_r(D, s_r^*))$. We assume the considered plan of the agents who are not affected by disruption is equal to their choice in the normal situation s_r^*. Note that in general, this is not a user equilibrium solution.

$$s_p^{*\mathrm{D,TI}} = \underset{\forall s_{p,k} \in S_p^{\mathrm{D,TI}}}{\arg\max}\, u_p(s_{p,k}, \overline{s}_R^{*\mathrm{D,TI}}) \ ,$$
$$\text{where } \overline{s}_R^{*\mathrm{D,TI}} = \{s_r^{*\mathrm{D,TI}} \in S_r^{\mathrm{D,TI}},\ \forall\, r \in P^D \setminus \{p\}\} \bigcup \{s_r^{*\mathrm{D,TI}} = s_r^*,\ \forall r \in P \setminus P^D\}. \tag{3.16}$$

In our research, the utility function $u_p^{*\mathrm{D,TI}}$ is calculated by the agent-based simulation model, see more details in Subsection 3.3.3. Due to the further decrease of feasible considered plans, agents' total utility in the case of "Timely information" is no more than their utility in the "Advance information" scenario, and no more than normal situation without disruption (Equation 3.17).

$$U^{*\mathrm{D,TI}} = \sum_{p=1}^{|P|} u_p^{*\mathrm{D,TI}} \le \sum_{p=1}^{|P|} u_p^{*\mathrm{D,AI}} \le \sum_{p=1}^{|P|} u_p^* = U^*. \tag{3.17}$$

3.2.6 No Information

A last relevant scenario is that passengers have no knowledge about the disruption, and the only thing they can do is to wait until the planned service starts running again. This is a rather extreme case, though it is potentially relevant. In particular, some users are routinely in this situation during disruptions: think about tourists (people without familiarity with the network and the alternative choices). Or people without any information available: people without access to a mobile data connection describing alternative choices; stations without real time connection to central command centre; stops without a plan of the services running; outage of a communication network; etc. Figure 3.5 explains passengers' adaptations in the "No information" scenario.

In the "No information" scenario, passengers who were planning to use a public transport service which does not run anymore in the disposition timetable of disruption, they can do nothing else than wait at the station until the disruption recovers. In our case, this happens (see Figure 3.5) at the end of Activity 2, before Transfer 1. To express passengers' adaptations in this scenario, the following behaviour rules are assumed.

Passengers wait at the stations where they were supposed to take a public transport service which is not running (in short, we call it the "affected station") until the end time of the disruption. And then they take the same public transport service as their initial plan (i.e. if they were planning to take bus line 40 in stage 1, they will be taking bus 40 at the end of the disruption) to the same transfer station (Transfer 1) and take the same public transport service, until they finish their trip. For instance, if after Transfer 1 they were planning to take bus 50, they will be taking bus 50 at the end of the disruption, after they reach the transfer point.

These behaviour rules will result in delays for activities following the "Directly affected trip". Moreover, some passengers may face a high risk of failure to finish their whole plan (e.g. because bus line 50 might not run anymore).

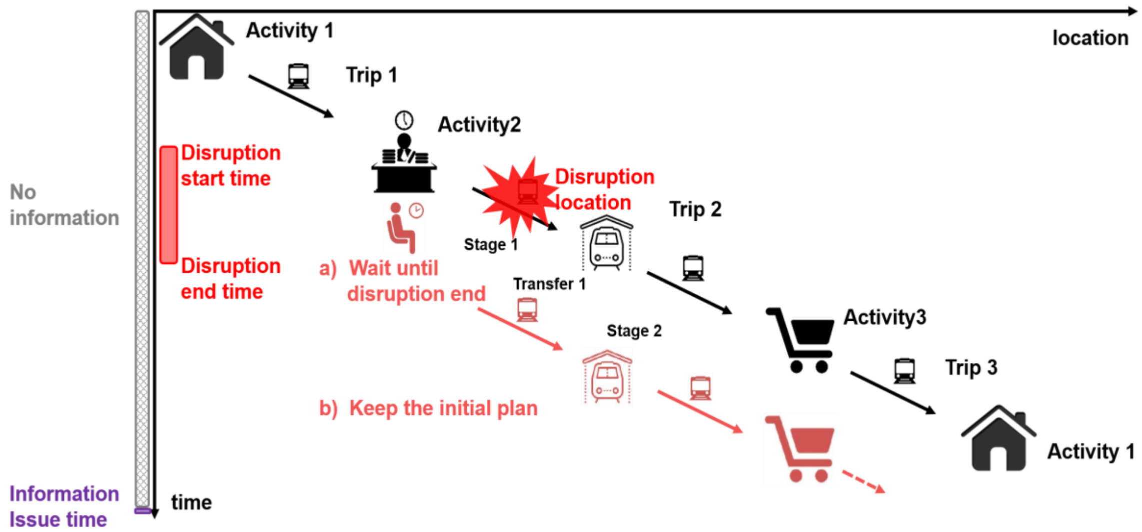

Figure 3.5: The effect of "No information"

We first define the "Directly affected trip" $\mathbf{T}$ as the first trip in the best considered plan s_p^* which matches a disrupted location l_j at the time t_j disruption D takes place. In other terms, this is the first time where the user is affected by the disruption; before this moment his/ her plan is untouched; after this, his/ her plan needs to be updated. Formally,

$$\mathbf{T} = T_h,\ h = \min(i)\{i : T_i^* \in s_p^* \,\big|\, \exists (l_j, t_j) \in T_i^* \text{ with } l_j \in L^D \wedge t_j \in [t_{start}^D, t_{end}^D]\}. \tag{3.18}$$

In detail, we use $(\mathbf{l_h}, \mathbf{t_h})$ to represent the specific location-time pair where and when the agent encounters the disruption in this "Directly affected trip" $\mathbf{T}$.

We model this "No information" scenario as follows. The set $\mathcal{Q}_p(D, s_p^*)$ (adding D and s_p^* as the relevant variables) describes all the agents' considered plans that are different from the normal best considered plan s_p^* starting from the "Directly affected trip" $\mathbf{T}$ (i.e. the considered plans which are not a combination of waiting and postponing the plan s_p^*). The activities and affected trips after $\mathbf{T}$ cannot change to other locations (indicating other transport modes or routes) and also cannot be finished before the end of disruption t_{end}^D.

Consider the involved agent $p \in P^D$, then a plan $s_{p,k}$ becomes infeasible in the "No information" scenario (i.e. $s_{p,k} \in \cancel{Q}_p(D, s_p^*)$), if either one of the following conditions (Equation 3.19 or 3.20) is true:

$$\begin{aligned}
&\exists \overline{T}_i = \{(\overline{t}_j, \overline{l}_j),\ j = 0,1,\cdots,J\} \in s_{p,k}\ , \overline{t}_j \geq \mathbf{t_h} \text{ such that } \exists j \text{ for each:} \\
&\quad \exists T_i^* = \{(t_j^*, l_j^*),\ j = 0,1,\cdots,J\} \in s_p^* \text{ such that } \exists j \text{ for which:} \\
&\qquad \overline{t}_j < t_{end}^D \vee \overline{l}_j \neq l_j^*.
\end{aligned} \tag{3.19}$$

$$\exists \overline{A}_i \in s_{p,k}, t_{end} \geq \mathbf{t_h} \ : \exists A_i^* \in s_p^* : t_{end} < t_{end}^D \vee \overline{l} \neq l^*. \tag{3.20}$$

This can be explained as follows. Equation 3.19 states that a plan $s_{p,k}$ is infeasible, if there is at least one trip $\overline{T}_i$ which is no earlier than "Directly affected trip" $\mathbf{T}$ in the plan $s_{p,k}$, compared with the trip T_i^* in the normally chosen plan s_p^*, such that the two trips $\overline{T}_i$ and T_i^* differ by locations $\overline{l}_j \neq l_j^*$ (i.e. the user would like to go somewhere else) or the trip happens before the disruption ends $\overline{t}_j < t_{end}^D$ (i.e. the users have to wait until the disruption ends, before actually moving forward).

Equation 3.20 reports the similar condition for activities. Plans with activities no earlier than the "Directly affected trip" $\mathbf{T}$ are infeasible under this scenario, if the location $\overline{l}$ of the activity $\overline{A}_i \in s_{p,k}$ is different from the location l^* in the s_p^* (i.e. the agent cannot change the location of their activities) or the activities ends before the end time of disruption $t_{end} < t_{end}^D$ (i.e. the agent has to delay their activities after the direct affected trip).

In the case of "No information", the number of considered plans decreases even further. Equation 3.21 is an example of the decreased considered plans $S_p^{\mathrm{D,NI}} = S_p \setminus (\cancel{S}_p(D) \cup \cancel{Z}_p(D, s_p^*) \cup \cancel{Q}_p(D, s_p^*))$, further updating Equation 3.15. "NI" is the short hand of "No information". Without loss of generality, we delete two considered plans (i.e. $s_{p,3}, s_{p,4}$) in Equation 3.21 that are infeasible in the "No information" scenario, and we put them as last rows for graphical simplicity.

$$
\begin{aligned}
S_p &= (S_p^{\mathrm{D,NI}} \cup \cancel{Q}_p(D, s_p^*) \cup \cancel{Z}_p(D, s_p^*) \cup \cancel{S}_p(D)) \\
&= \begin{bmatrix} s_{p,1} = \{A_1, T_1, A_2, T_2 \cdots\} \\ s_{p,2} \\ \cancel{s}_{p,3} \\ \cancel{s}_{p,4} \\ \vdots \\ \cancel{s}_{p,k} \\ \cancel{s}_{p,k+1} \\ \vdots \\ \cancel{s}_{p,|S_p|} \end{bmatrix}, \; U_p = \begin{bmatrix} u_p(s_{p,1}, \bar{s}_{R,1}) \\ u_p(s_{p,2}, \bar{s}_{R,2}) \\ \cancel{u}_p(\cancel{s}_{p,3}, \cancel{\bar{s}}_{R,3}) \\ \cancel{u}_p(\cancel{s}_{p,4}, \cancel{\bar{s}}_{R,4}) \\ \vdots \\ \cancel{u}_p(\cancel{s}_{p,k}, \cancel{\bar{s}}_{R,k}) \\ \cancel{u}_p(\cancel{s}_{p,k+1}, \cancel{\bar{s}}_{R,k+1}) \\ \vdots \\ \cancel{u}_p(\cancel{s}_{p,|S_p|}, \cancel{\bar{s}}_{R,|S_p|}) \end{bmatrix}
\end{aligned}
\tag{3.21}
$$

The involved agents react by determining the plan with the maximum utility $u(s_p^{*\mathrm{D,NI}})$ among the limited considered plans. In Equation 3.22, we look for such plan $s_p^{*\mathrm{D,NI}}$ of the involved agent $p \in P^D$ in the condition that all the other involved agents $r \in P^D \setminus \{p\}$ find their best considered plan $s_r^{*\mathrm{D,NI}}$ among the reduced considered plans $S_r^{\mathrm{D,NI}} = S_r \setminus (\cancel{S}_r(D) \cup \cancel{Z}_r(D, s_r^*) \cup \cancel{Q}_r(D, s_r^*))$. We assume the considered plans of the agents who are not affected by disruption are equal to their choice in the normal situation s_r^*. Also, this is not a user equilibrium solution. Formally,

$$
\begin{aligned}
s_p^{*\mathrm{D,NI}} &= \underset{s_{p,k} \in S_p^{\mathrm{D,NI}}}{\arg\max}\, u_p(s_{p,k}, \bar{s}_p^{*\mathrm{D,NI}}), \\
&\text{where } \bar{s}_p^{*\mathrm{D,NI}} = \{s_r^{*\mathrm{D,NI}} \in S_r^{\mathrm{D,NI}}, \; \forall\, r \in P^D \setminus \{p\}\} \\
&\qquad \cup \{s_r^{*\mathrm{D,NI}} = s_r^*, \; \forall r \in P \setminus P^D\}.
\end{aligned}
\tag{3.22}
$$

Due to the further decrease of feasible considered plans, agents' total utility in this case of "No information" is no more than that in "Timely information", and further no more than their utility in the "Advance information", and no more than normal situation without disruption (Equation 3.23).

$$
U^{*\mathrm{D,NI}} = \sum_{p=1}^{|P|} u_p^{*\mathrm{D,NI}} \le \sum_{p=1}^{|P|} u_p^{*\mathrm{D,TI}} \le \sum_{p=1}^{|P|} u_p^{*\mathrm{D,AI}} \le \sum_{p=1}^{|P|} u_p^* = U^*. \tag{3.23}
$$

3.3 Agent-based Simulation Approach

The proposed formulations and descriptions of (user equilibrium, or non-equilibrium) solutions are independent of the precise solver used to compute them. We focus on one agent-based simulation environment, specifically MATSim, but our ideas are applicable to any appropriate similar environment. The basic idea of MATSim is that travel demand can be predicted by simulating daily life of persons and particularly the spatial-temporal occurrence of out-of-home activities (see Balmer et al., 2009). Agents in MATSim are the representation of passengers in reality, which will be used the following sections to represent passengers. Three subsections explain the translation of the framework presented in Section 3.2 towards MATSim modules; the day-to-day replanning method used in MATSim; and the novel module able to perform within-day replanning in public transport networks.

3.3.1 Information Availability in MATSim

MATSim is able to describe mobility in a multi-modal network, including private transport and public transport schedules. MATSim is based on scheduled operations, which means the vehicle delay in daily operations is neglected. MATSim can model any public transport disruptions as far as it can be related to an updated disposition timetable (i.e. which public transport services are running from where to where, at which time, with which capacity) regardless of the precise nature and cause of the disruption. These features of MATSim provide the foundation to model the above information availability and the corresponding passenger adaptations.

Figure 3.6 shows the modelling in MATSim of the different information availability. The default MATSim works by reaching a user equilibrium solution by iterations. At each iteration, representing a day of the users, the plans of agents are executed (i.e. performed by the agents) and the choices of the agents are evaluated and changed by a replanning module, if necessary. The basic MATSim loop is shown in “Benchmark” in Figure 3.6, and includes input, execution, scoring, replanning and analysis. More details are briefly summarised in the next Subsection 3.3.2 and available e.g. in (Horni and Nagel, 2016).

First, the situation without disruptions is set as a benchmark to initialize agents and determine a reference case to be used in, and compared with, the simulations including disruptions. This is computed by iteratively simulating the “Benchmark” (left) situation, until a stable solution is found (corresponding to user equilibrium solution in Subsection 3.2.1). The “Benchmark” runs with the default MATSim setting with normal public transport schedule and reflects agents’ behaviours without public transport disruption. The intended demand is consisting of output plans. The output plans resulting from the “Benchmark” simulation are considered as the initial choices (i.e. the ideal situation) of all agents in a normal daily travel.

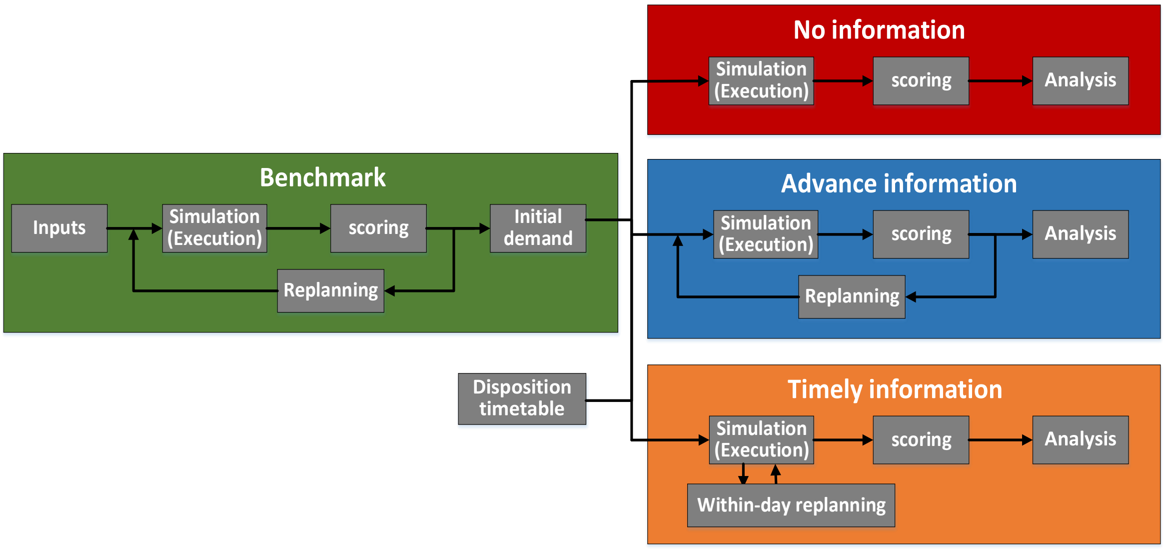

Figure 3.6: The execution in MATSim of different information availability

The initial plans are the basis which used by the passengers, when facing the disruption. In particular the disruption is modelled through a disposition timetable, which makes some of those initial plans infeasible. For the “No information” scenario (top right) in MATSim, the agents’ initial plans are executed on the disposition timetable, for a single iteration (in figure, there is no replanning). During the disruption time, the agent will remain waiting at the stops in case the public transport service is cancelled in the specific disposition timetable implemented. When the disruption is recovered, MATSim will try to execute the initial plans of agents, as far as this is possible and compatible with the public transport services and/ or preferred starting/ ending time of activities.

For the “Advance information” scenario (middle right) in MATSim, the alternative route/ mode/ time/ activity choices are calculated by including them in the iterative process of MATSim (i.e. the blue box contains a replanning feedback mechanism). Agents can rely on their experiences from previous iterations so as to gain the ideally best solutions (i.e. new user equilibrium) which adapt the initial plans, in case of public transport disruptions.

The “Timely information” scenario (bottom right) considers that agents have information, but only after disruption starts. Dobler and Nagel (2016) already point out that using an iterative approach to disseminate information results in problems, like illogical agent behaviour, which would be able to anticipate unforeseeable events. For instance, if a replanning approach is used, agents may start rerouting before disruptions. The key module to solve this approach is a ‘within-day’ replanning module, which is not reaching an equilibrium as in “Advance Information” but rather computing the best response to the disruption, considering the available information, and not learning from experience. This is a key novelty and explained in detail in Subsection 3.3.3.

3.3.2 Day-to-day Replanning

As is described in Subsection 3.3.1, both "Benchmark" and "Advance Information" are calculated based on the day-to-day replanning process approximating the stochastic user equilibrium (SUE) in MATSim. The sets S_p^{new} and S_p^{old} are subsets of the set previously introduced S_p. The overall approach, called a population-based co-evolutionary algorithm (Nagel and Floetteroed, 2016), reads as follows:

Algorithm 3.1 Co-evolutionary, population-based search

1. Initiation: Generate at least one plan $s_{p,k}$ for every agent p.

2. Iterations: Repeat the following until user equilibrium $U^* = \sum_{p=1}^{|P|} u_p^*$.

a) Execution: Select one $s_{p,k}$ of the plans S_p for every agent p.

b) Scoring: Obtain a score $u_{p,k}$ for every agent's selected plan by executing all selected plans simultaneously in a simulation.

c) Replanning: For some of the agents, generate new plans S_p^{new}; for example, as "best replies" or as mutations of existing plans S_p^{old}.

Execution. In the "execution" module, one plan is selected in each iteration. For each agent, select a plan $s_{p,k}$ (which can be possibly be the plan considered at the last iteration $s_{p,j}$), with a convergent switching process (Equation 3.24). $P(s_{p,k})$ is the probability of choosing plan $s_{p,k}$, $T(s_{p,k} \rightarrow s_{p,j})$ is the switching probability from plan $s_{p,k}$ to $s_{p,j}$.

$$P(s_{p,k})T(s_{p,k} \rightarrow s_{p,j}) = P(s_{p,j})T(s_{p,j} \rightarrow s_{p,k}) \tag{3.24}$$

Scoring. Equation 3.25 shows a scoring function determining the utility of a plan for an entire day, formulated by Charypar and Nagel (2005). The utility of a plan $u_{p,k}$ is computed as the sum of all activity utilities u_{A_i} plus the sum of all travel (dis)utilities u_{T_i} for each activity i within the number N of activities, and trip i as the trip that follows activity i.

$$u_{p,k} = \sum_{i=0}^{N-1} u_{A_i} + \sum_{i=0}^{N-1} u_{T_i} \tag{3.25}$$

To ensure the convergence of scores, a learning rate χ is used in Equation 3.26. $u_{p,k}^{\text{new}}$ and $u_{p,k}^{\text{old}}$ are the agents' scores for plan $s_{p,k}$, and $\tilde{u}_{p,k}$ is the most recent actual performance with that plan.

$$u_{p,k}^{\text{new}} = (1-\chi)u_{p,k}^{\text{old}} + \chi\tilde{u}_{p,k} \tag{3.26}$$

Replanning. The replanning module of MATSim works, at each iteration, by generating alternative adjustments of the plan executed (i.e. iteratively considering more plans from S_p). The agents' plans can be changed in terms of routes, transport modes, departure time and activities (Horni and Nagel, 2016); for example, going to work earlier or later, doing an additional activity or not, taking some mode or some other mode to move between activities. To generate new solutions, two operators are often used in evolutionary algorithms: "mutation" (Balmer et al., 2009) takes a candidate solution and performs small modifications to it; and "crossover" (Charypar and Nagel, 2005) takes two candidate solutions and constructs a new one from those.

Iterations. In each iteration, the agents' plans with the best score may be chosen while those with the worst score may be discarded with a higher possibility. After a certain amount of iterations executing different plans, the plan with the highest score (i.e. the best considered plan s_p^*) will be identified. This process mimics the experience of agents from comparable situations to reach ideally a user equilibrium solution of plans. However, the stability of this equilibrium is not perfect, since the simulations are stochastic (see Meister, 2011).

Analysis. MATSim has a complete output of agents' journeys including all activities, trips, detailed departure and arrival time, detailed routes, stops and each agent's score function. Based on this outputs, agents' behaviours and impacts of disruptions and information availability, such as delays, can be analysed.

3.3.3 Within-day Replanning

The concept of within-day replanning is proposed in Dobler and Nagel (2016) for road traffic management in unforeseeable (i.e. subject to non-anticipatory conditions as our "Timely information" scenario) or partially foreseeable events, including road disruptions or accidents. Within-day replanning is fundamentally different from day-to-day replanning, as the simulation is done in a single iteration; there is no equilibrium to be determined, but only a best adaptation, corresponding to a non-equilibrium solution. Moreover, complex detailed behavioural model needs to be described. Due to the very different dynamics of private car users and public transport users, a major improvement to this model has been necessary for application on the public transport disruptions. In fact, car users only choose the physical network route, while agents using public transport have to choose the train/ bus/ tram service, linking the physical network and the service network.

We use the within-day replanning to compute the solution for the "Timely information" scenario explained in previous Figure 3.4. We follow the behavioural assumptions as stated in Subsection 3.2.5. The agents' decision-making process in within-day replanning works as the following Algorithm 3.2.

Algorithm 3.2 Within-day replanning

1. Initiation: Compute the original plans s_p^* in S_p for every agent, regardless of the disruption.

2a. Execution: for every agent $p \in P^D$ affected in disruption, do within-day replanning:

a) Compute the available plans $S_p^{\mathrm{D,TI}}$ from s_p^*.

b) Approximate $s_p^{*\mathrm{D,TI}}$ as the $\underset{\forall s_{p,k} \in S_p^{\mathrm{D,TI}}}{\arg\max}\, u_p(s_{p,k}, \overline{s}_R^*)$ i.e. $\overline{s}_R^*$ approximately equal to $\overline{s}_R^{*\mathrm{D,TI}}$.

c) Execute the new generated plan $s_p^{*\mathrm{D,TI}}$.

2b. Execution: For every agent not affected in disruption $p \in P \setminus P^D$, execute s_p^*.

3. Scoring: Obtain a score $u_p^{\mathrm{D,TI}}$ for every agent's executed plan in a simulation, and related some performance measure.

Without loss of generality, under the assumption of an equilibrium being reached at the initial plans, and to avoid unneeded variability in the execution of travel plans of agents, we focus on replanning only those agents $p \in P^D$, which are directly affected by the disruption.

The agents' plan for the entire day consists of many trips, each trip linking two adjacent activities. In the within-day replanning module, the "Directly affected trip" and all the following activities and trips until the end of the day can be modified. A trip change can influence the start time of the following activities, and a domino effect to next trips and activities. For each selected trip, a possible alternative is sought, which is able to connect the previous activity to the following activity. The plan maximising the utility is sought, but this can be simplified as follows. Any extra delays in starting the disrupted trip will decrease the utility of the trip; any extra delay in starting the disrupted trip, or postponing the activity will decrease the utility of the activity, as well as its cancellation will decrease the utility of the activity. For this reason, under standard MATSim parameters of evaluation of generalized travel time we can directly focus on computing the plan, where the immediate trip to the next activity after the disruption has the maximum utility of the trip. Formally, under the assumptions considered, we can also replace the computation of $\arg\max_{\forall s_{p,k} \in S_p^{\mathrm{D,TI}}} u_p(s_{p,k}, \overline{s}_R^{*\mathrm{D,TI}})$ as the computation of $\arg\max_{\forall s_{p,k} \in S_p^{\mathrm{D,TI}}} u_p(s_{p,k}, \overline{s}_R^{*})$ as $\overline{s}_R^{*}$ will be equal to $\overline{s}_R^{*\mathrm{D,TI}}$.

For trips and activities starting after the disruption, MATSim can execute directly the plan computed by the within-day replanning module without problems. For those trips which were performed at the moment when the disruption begins, in case they happen to be impossible (i.e. the agent is on a bus which breaks), the replanning module will seek for alternative ways of movement.

3.4 Experiments and Results

We perform a large set of experiments, based on calibrated initial demand of Zürich presented in Rieser-Schuessler et al. (2016). The public transport integration is implemented in the Zürich network, in which all public transport is integrated in a single system with a single payment scheme. So the users can use any mode as their choices without extra charges. The total number of agents including both public transport and private users in such Zürich scenario is 15,286, which represents a 1% sampling of the of real Zürich population. Based on the Zürich scenario, we determine a public transport disruption in MATSim and analyse agents' behaviours and satisfaction from the simulation results.

3.4.1 Zürich Scenario

Zürich HB is the central rail station in Zürich, used by almost 400,000 passenger trips per day, and scheduling more than 2,800 trains per day; Zürich Oerlikon is also a major nodal point and junction for Zürich rail network, with almost 80,000 passenger trips per day, and scheduling about 300 trains per day. Physically three railway routes connect the two stations: one passing via Zürich Hardbrücke, one passing via Zürich Wipkingen and one direct tunnel route (DML). The railway route via Zürich Hardbrücke operates six train services: S15, S9, S16, S6, S7, S21; Zürich Wipkingen railway route operates six train services: S24, RE, IC4, IR75, IR37, IR70; the direct tunnel route operates eight train services: S2, S8, S19, S14, IR36, IC8, IC5, IC1. The train frequency on the S-bahn train services (i.e. all those beginning with S) is every half hour, while that on most inter-region (IR) and inter-city (IC) services is every hour, except IC4 with a frequency of every two hours. Each train service stops at Zürich HB while not all train services stop at Zürich Oerlikon, some pass Zürich Oerlikon without stops (i.e. IC4, IR75, IR37, IC8, IC5 and IC1). This situation is graphically represented in Figure 3.7. For the sake of completeness, we include in Figure 3.7 all stations (Zürich Flughafen, Schaffhausen) which are the first/ last stop for train services leaving from/ arriving to the station Zürich Oerlikon, and that do not stop in Zürich Oerlikon.

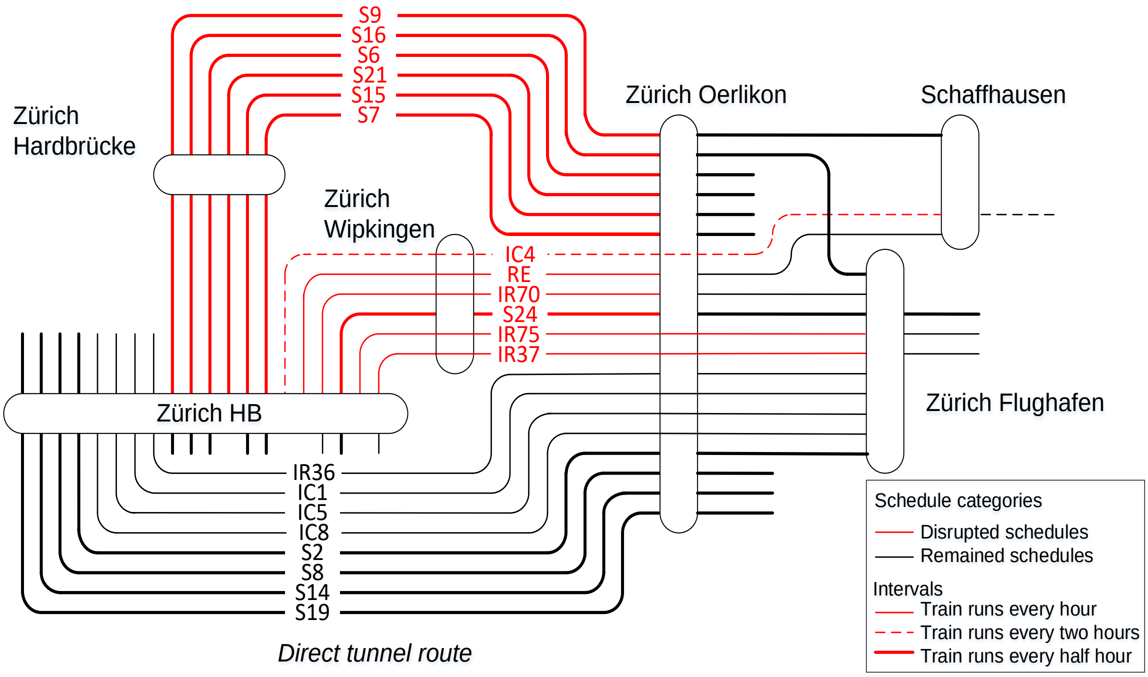

Figure 3.7: Details of rail elements and disposition schedules in Zürich scenario

Each line in Figure 3.7 represents a train service, with the thickness related to the frequency. The travel time between Zürich HB and Zürich Oerlikon on all railway routes is comparable, being between 5 and 7 minutes. The red lines in Figure 3.7 show the assumed rail disruption: two railway routes between Zürich HB and Zürich Oerlikon via both Zürich Hardbrücke and Zürich Wipkingen are disrupted and unavailable during the afternoon peak hours, between 16 and 19 o'clock. One disposition timetable is applied during the disruption time, as follows.

- For the disrupted train services between Zürich HB and Zürich Oerlikon, all the train services are cancelled between 16 and 19 o'clock. The cancellations are extended to the next stop beyond Zürich Oerlikon, in case the train service does not stop there. For instance, train schedules of IR 37 between Zürich HB and Zürich Flughafen are completely cancelled between those two stations.

- For the train services beyond either Zürich HB or Zürich Oerlikon, (or beyond the first/ last stop after/ before Zurich Oerlikon) as well as via the direct tunnel route, the original train schedules are kept.

Outside of the disruption time, the original train schedules are not influenced.

The agents affected by such disruption are those that take any train service passing Zürich HB and Zürich Oerlikon via Zürich Wipkingen and Zürich Hardbrücke between 16 and 19 o'clock. In our test case, 128 agents (representing 12,800 passengers in real world) are involved in this public transport disruption. These agents (we call them "involved agents") are 0.8% of the total population, and more than 2% of the population typically using public transport. In the next sections, we focus on those involved agents, and compare the different behaviours (more details in Appendix B) and satisfaction of these involved agents in the three different scenarios and the benchmark. We first analyse macroscopic features such as the flow over the public transport services. The second part analyses the influence of different information availability on agents' delays and scores.

3.4.2 Agents' Behaviours with Different Information Availability

Figure 3.8 shows the flow of the involved agents on the train services between Zürich HB and Zürich Oerlikon in the benchmark and three scenarios. Each figure shows the time on the x-axis, and the y-axis is the number of involved agents per each hour. The train services are reported in different colours, and grouped per railway route: via Zürich Hardbrücke (the family of blue colours), via Zürich Wipkingen (the family of red colours) and via the DML route (the family of green colours).

In the "Benchmark", top left, the agents are relatively evenly distributed on the trains during the disruption time from 16 to 19 o'clock. The agents distribute themselves in the disrupted railway routes as follows Hardbrücke (87.5%), Wipkingen (12.5%). In the "No information" scenario, top right, a majority of the involved agents can only pass the railway route via Hardbrücke or Wipkingen after 19 o'clock. Some agents cannot finish their trips. In particular, S21 service only operates between 16 to 19 o'clock; those agents, who plan to take this train service in "Benchmark", fail to board in the "No information" scenario and will never reach their final destination within the same day. This is about 15% (see later Figure 3.11). In both the "Advance information" and "Timely information" scenarios, a small share of involved agents shifts from the route via Hardbrücke and Wipkingen, to the route via DML during the disruption time. The rest shifts to bus/ tram or car/ bike (see later Figure 3.9).

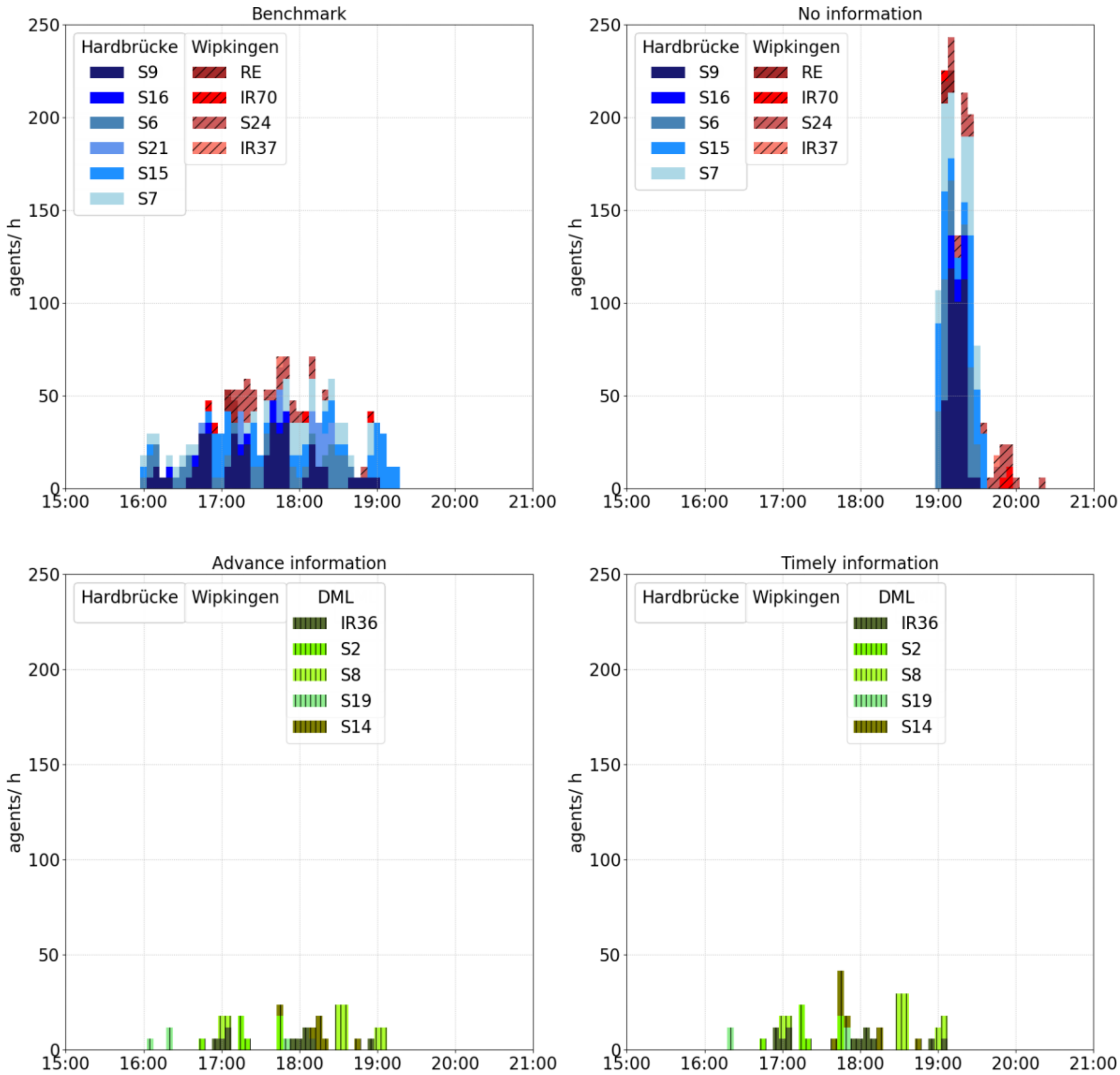

Figure 3.8: Agents' flow distribution per train service and route

The data shown in Figure 3.9 represents the moving average of the involved agents' time spent travelling (on the y-axis, as in Figure 3.8) of the "Directly affected trip" for each route and transport mode, as time goes (x-axis). As is described in the Subsection 3.2.1, one trip is composed of one or more stages. The "Directly affected trip" includes, but is not limited to, the stage that directly passes the defined disruption. It also includes the preceding/ successive stages that may also be indirectly affected by the public transport disruption. In other terms, we are looking at a comprehensive overview over stages of the involved agents, at different moment in time and different stages within the "Directly affected trip" in relation to the disruption. We select five classifications based on alternative route choices (i.e. Wipkingen, Hardbrücke, DML and other rail, respectively red, blue, green and black lines) and transport modes (bus/ tram, car/ bike, respectively purple and yellow lines) in disruptions.

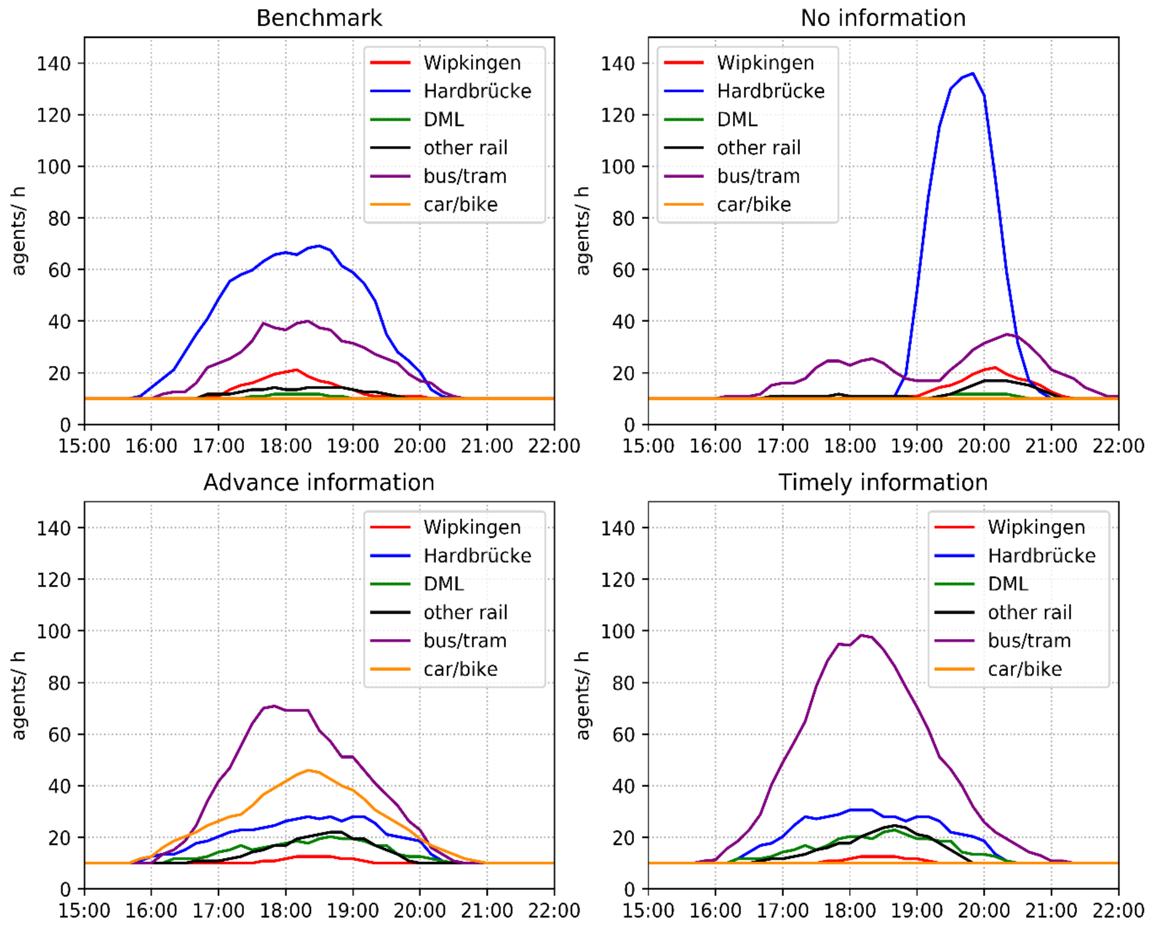

Figure 3.9: Route and mode share of involved agents in the "Directly affected trip"

Within each subfigure, the Wipkingen and Hardbrücke routes (red and blue lines) show similar characteristics, i.e. peak at the same time (for the "Benchmark", this is at 18.30; for the "No information", this is at 20.00), and comparable ratio (the total number of involved agents for Hardbrücke being roughly 4 to 5 times more than the one for Wipkingen). In this sense it is not advantageous for the agents to swap from one of those two routes to the other.

Comparing those two routes across the subfigures, the "No information" scenario compared to "Benchmark", the average agents' proportion decreases from a maximum of around 8% to 0% during the disruption (between 16 and 19 o'clock) while increases dramatically to a maximum of around 16% after 19 o'clock. In other terms, most of the agents are now concentrated moving in a short time horizon, from 19.00 to 20.30. The agents' proportion in both the "Advance information" and "Timely information" scenarios decreases compared to the "Benchmark" between 16 and 19 o'clock but is not reduced to zero. The remaining agents are those who are travelling on the train services beyond either Zürich HB or Zürich Oerlikon rather than between these two stations. This is caused by the fact that agents can still use these running services (see the description of the disposition timetable in Subsection 3.4.1) once they have crossed the disrupted area by using other rail routes or transport modes.

The DML, other rail and bus/ tram (green, black and purple lines) show similar features, in particular a delay between "Benchmark" and "No information"; and an increase of the peak when comparing "Advance information" and "Timely information" to "Benchmark". In the "No information" scenario, the three lines also have a small peak after 19 o'clock. This is caused by the successive delayed stages in the "Directly affected trip".

For the car/ bike (yellow lines), results in the "Benchmark", "No information" and "Timely information" scenarios are zero; i.e. all involved agents are not changing mode as reaction to the disruption and therefore they are not using them. In contrast, an increase of agents' proportion (around 4%) is shown in the "Advance information" scenario between 16 and 19 o'clock. This reflects the fact that agents can successfully change mode to improve their satisfaction, in the "Advance information" scenario.

Table 3.1 summarises the route and mode share (rows: Wipkingen, Hardbrücke and DML and other rail, are the alternative railway routes, while Bus/ tram and Car/ bike represent different modes available) for the involved agents counting all the stages in the "Directly affected trip" (stage-based calculation) in the above scenarios (columns). Comparing the columns, the mode share of the involved agents in "No information" is similar to that in "Benchmark" with slight differences caused by few agents who don't finish their trips. In contrast, in "Advance information" most agents choose alternative transport modes to avoid disruptions: 43.5% agents (i.e. 15.3% more) choose Bus/ tram and 27.1% switch to Car/ bike. The remaining 15.5% agents via Hardbrücke are those who use the undisrupted part of this route. In "Timely information", the mode share of Bus/ tram and other rail increases compared to that in "Advance information" due to the limitation of mode change. Especially the mode share of Bus/ tram increases to 59.9%, approximately equal to the mode share of Hardbrücke in "Benchmark". In fact, agents cannot shift to Car/ bike, so most of them shift to the alternative public transport instead.

Table 3.1: A summary of route and mode share of involved agents in the "Directly affected trip"

Route and mode share	Benchmark	No information	Advance information	Timely information
Wipkingen	6.0%	6.3%	0.9%	1.1%
Hardbrücke	61.5%	62.2%	15.5%	20.4%
DML	0.8%	0.8%	7.0%	10.0%
Other rail	3.6%	4.2%	6.1%	8.6%
Bus/ tram	28.2%	26.5%	43.5%	59.9%
Car/ bike	0	0	27.1%	0

3.4.3 Agents' Benefits with Different Information Availability

The involved agents' delays are an important aspect of passenger satisfaction, focusing only on the direct affected trip. A delay is to this extent, the average time difference between the actual arrival to activities, and the planned arrival to the activities. We discuss the average delay of the involved agents as time goes, to give a feeling of the complexity of the problem. Figure 3.10 (left) reports the average delay (i.e. difference between a scenario and the benchmark, among all involved agents) for the affected trip by the disruption, as the time of the disruption goes by. We report the three scenarios considered (coloured lines) and a simplified calculation (labelled "without agent-based"). All lines show the 15min moving average of the involved agents' average delay over the time (y-axis, in hours).

The simplified calculation symbolically describes the linear decrement (black dotted line) expected to show the relation of agents' average delay and time, under the "No information" scenario. In theory, each agent would have as much delay as the time required to clear the disruption. For this reason, a nicely regular pattern of delay is expected. Compared with the agent-based simulation results of the "No information" scenario (i.e. red line), the differences show the complexity and interaction of choices in a multi-modal network, subject to a disposition timetable unknown to passengers. The two other scenarios differ slightly from the zero delay case; the precise computation of this delay is a major contribution of the present chapter. In fact, only the proposed agent-based simulation is able to reveal the detail and specific behaviours due to the public transport disruption in a microscopic perspective. Overall, the "No information" (red line) results in agents' average delay always larger than the assumed linear decrement (black dotted line). At approximate 15min after disruption starts, the average agents' delay reaches the maximum 3.6 hours. The "Advance information" (blue line) shows agents' average delay varies closely to no delay. Overall, agents always suffer more delay in the "Timely information" (yellow line) compared to the "Advance information". Especially at the beginning of disruption, agents' average delay can reach up to 0.7 hours. The average delay decreases sharply to approximate 0.2 hours after around 30 min after disruption starts. Then, the average delay almost maintains at approximate 0.2 hours and decreases slowly to zero.

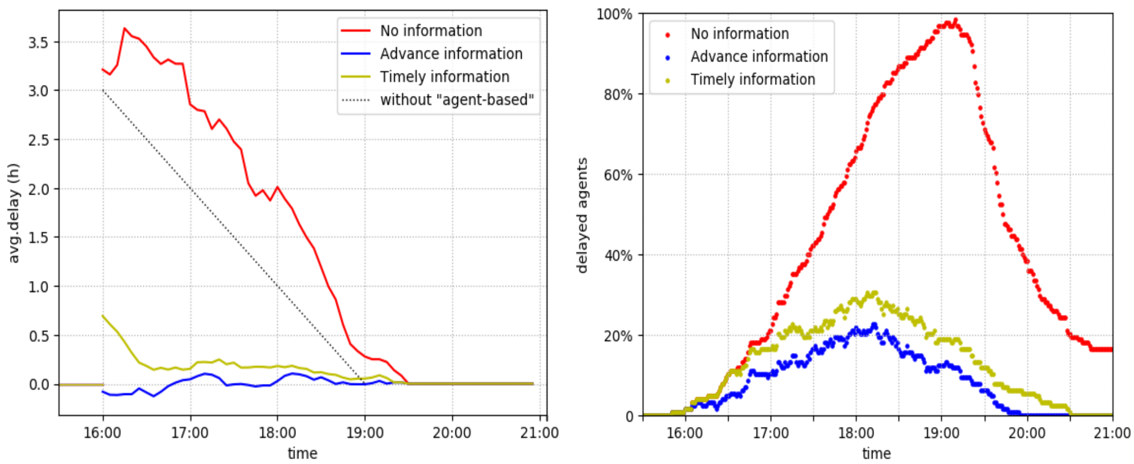

Figure 3.10: Average delay and the number of delayed agents as time goes

Figure 3.10 (right) shows the percentage of the involved agents with positive delay on their "Directly affected trip" at any moment throughout the disruption duration. In other terms, it is the volume of passengers, for which we represent the intensity of delay in Figure 3.10 (left). X-axis and colour scheme are analogous. The red scatters show that 100% agents are delayed in "No information" scenario until the end time of disruption (19 o'clock). After the disruption, delayed agents get less, and then reach their minimum only at almost 21 o'clock. There are still around 20% agents delayed because they cannot find available public transport services any more. The peak of delayed agents are right after 18 o'clock in both "Advance information" (blue line) and "Timely information" (yellow line). This corresponds to the peak hour dynamic in the real life test case considered. Overall, there are more delayed agents in "Timely information" (approximate 30% in the peak) compared to "Advance information" (around 20% in the peak). All delays reduce to zero about 30 min earlier in "Advance information" (at 20 o'clock) than in "Timely information".

In the comparison of agents' delay and score, we need to consider the issue of an imperfect convergence of MATSim (see Subsection 3.3.2). We therefore run MATSim for one more iteration than the "Benchmark" settings (i.e. computing a "Benchmark+1" solution), and then compare this results to "Benchmark" so as to understand the default variability in the scores that MATSim computes. This represents some kind of noise in the evaluations we will perform. We compare the "Benchmark+1" solution to the original "Benchmark"; as we report all scenarios, including this "Benchmark+1" in relative terms with the "Benchmark", we name this as "Benchmark*" in the following figures. The idea is to represent the inherent variability that the Benchmark solution has.

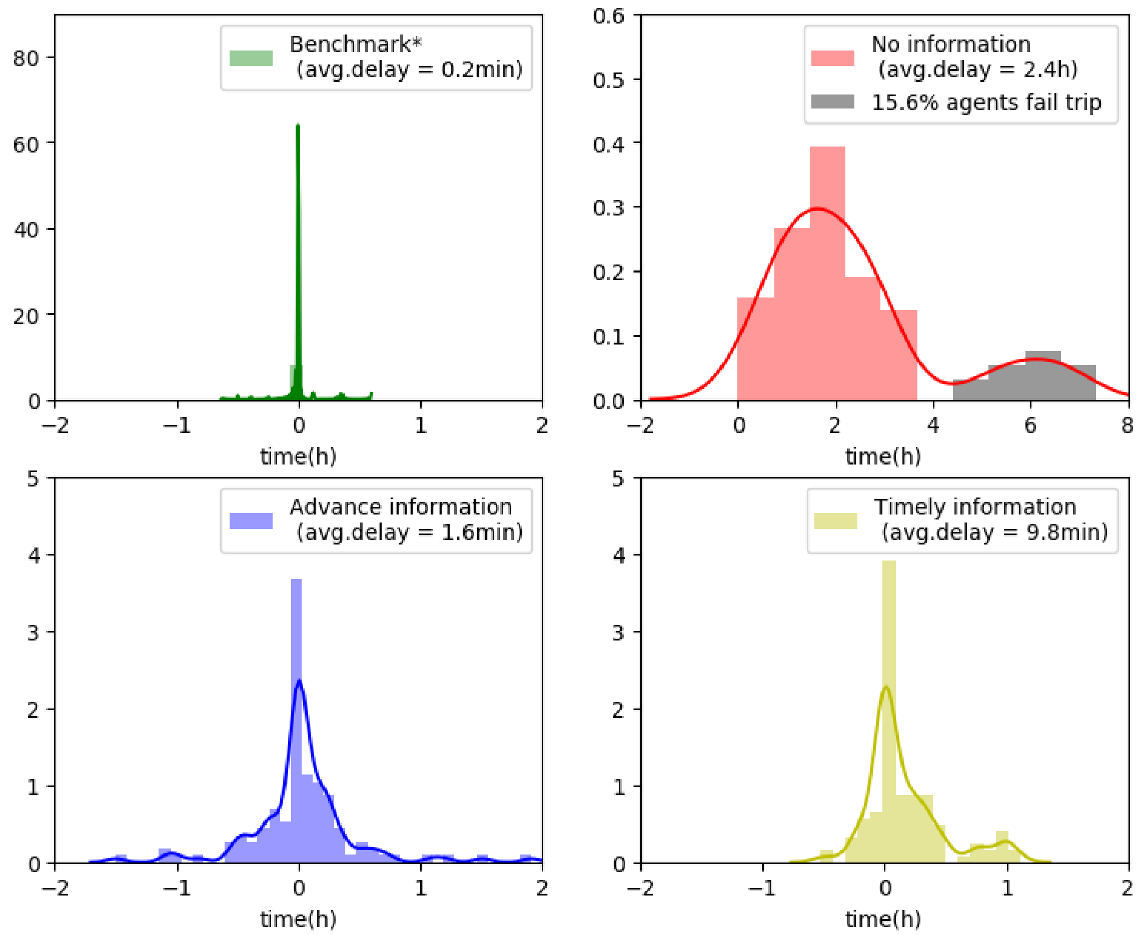

Figure 3.11: Probability density of delays (late arrival to activities) of involved agents in the "Directly affected trip"

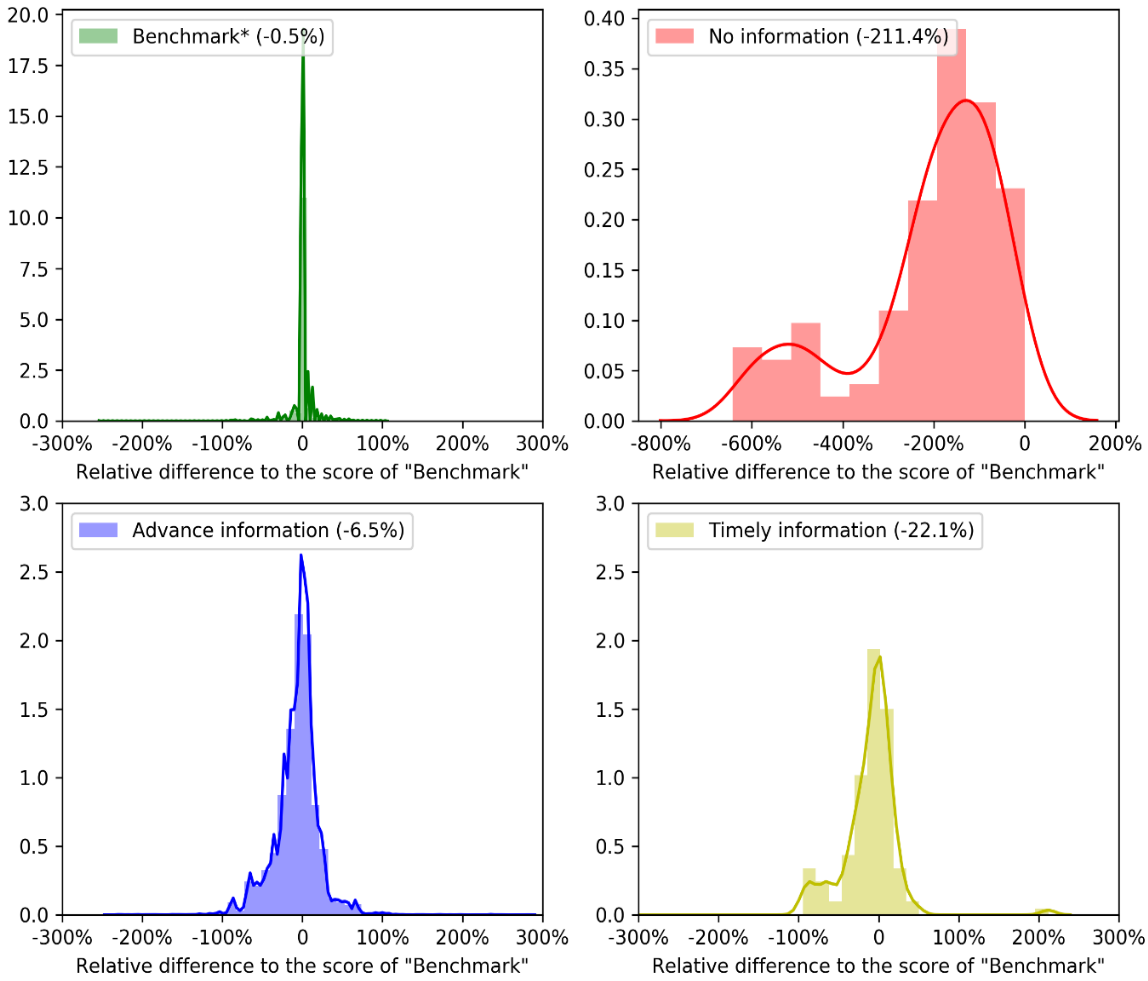

Figure 3.12: Probability density of scores of involved agents

Figure 3.11 displays the comparison results of the probability density of delays in different scenarios. Each subfigure reports the delays (x-axis) and the related probability density (y-axis). The variability of average delays of the agents in the default MATSim is 0.2 min, with a very large amount of agents facing no positive or negative delay. The average delay in the "No information" scenario is 2.4 hours, which includes 15.6% agents who fail to finish their whole-day plan (i.e. both the red and the grey zone in Figure 3.11 top right). In this case, the delay is referred to the end of the day. Focusing only to those agents who are able to complete all activities, the average delay is around 2 hours (i.e. only the red zone in the Figure 3.11 top right). In the "Advance information" scenario, the average delay is 1.6 min, but the variance range of minimum and maximum is up to 2 hours. This reflects major changes to the activity patterns of the agents as a reaction of the "Advance information" on the disruption occurrence. In the "Timely information" scenario, the average delay is 9.8 min, which is larger than that in the "Advance information" scenario. The min-max range is about one hour.

As is described in Section 3.3, the scores calculated by the score function in MATSim express the satisfaction of the agents on the plan of the entire day. The probability density of scores of the involved agents in the considered disruption is showed in Figure 3.12. Each subfigure shows a scenario as in the previous figures; each subfigure reports the relative difference, for each agent, between the score of the "Benchmark" (assumed 100%), and the score of the considered scenario; the y-axis is the associated probability density. The variation of agents' score in "Benchmark*" is minus 0.5% (inherent variability of MATSim). Compared to "Benchmark", the average changes of scores for the three scenarios are: "No information" scenario (-211.4%), "Advance information" scenario (-6.5%), "Timely information" (-22.1%). Of course, all average results are negative, i.e. agents had a higher (better) score without the disruption, but due to the variability of the MATSim computation, some agents might actually have an increase in score. In fact, the variances of scores are large: "Benchmark*" (1.9%), "No information" scenario (265.5%), "Advance information" scenario (7.8%), "Timely information" (68.4%), where the variance is measured based on the value 100% assigned to the "Benchmark". This is an effect of the well-known fact that MATSim cannot always converge to the expected user equilibrium (other papers which discuss convergence of MATSim are for instance Meister, 2011; Fourie et al, 2013).

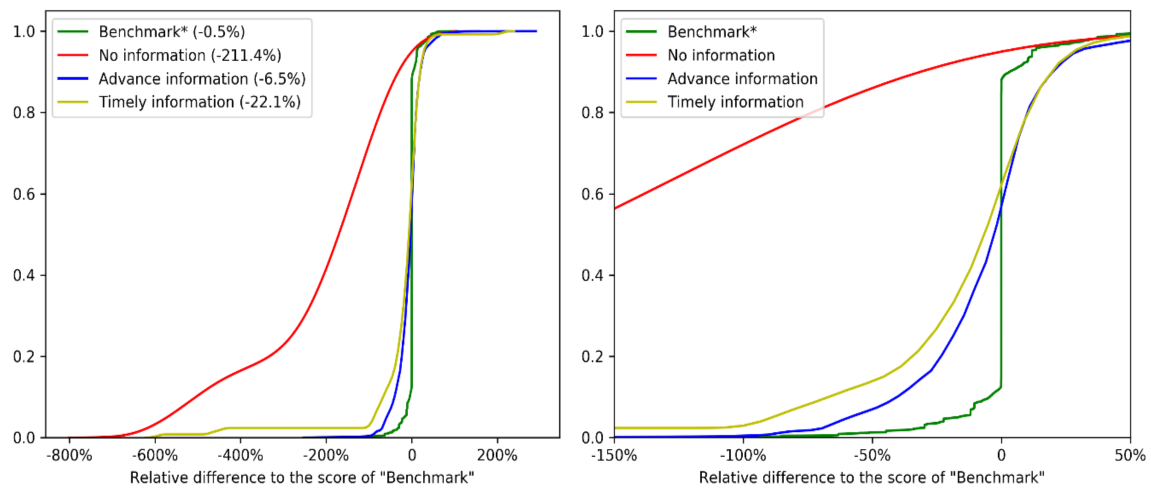

Figure 3.13: Cumulative distribution of scores of involved agents

Figure 3.13 shows the cumulative distribution of the involved agents' scores, i.e. the superimposition of the cumulative densities, associated to the individual subfigures of Figure 3.12. The left plot is the complete result (with an extended x-axis) and the right is the zoomed-in version of the same plot, restrictive to the part where scenario "Benchmark*", "Advance Information", and "Timely information" are most similar.

This figure can express more intuitively that the "Advance information" scenario defines the upper bound and the "No information" scenario shows the lower bound for agents' satisfaction under the same disposition timetable in the public transport disruption management. Within this gap, the "Timely Information" scenario provides an intermediate value. More scenarios, based on different information availability (described in Section 3.2) would result between these two boundaries.

Finally, we report on the detailed statistical results of the involved agents' delays and scores, in Table 3.2. The top rows report on the delays (in minutes; median, 10^{th} and 90^{th} percentile), the bottom rows about the score (reported as variation from the Benchmark value, again as median, 10^{th} and 90^{th} percentile). Columns refer to the scenarios considered.

The median of delay in "Benchmark*" and "Advance information" is zero. The median of delay in "Timely information" is 3 min and that in "No information" is two hours. While almost no agents has delay in "Benchmark*", the score of agents fluctuates in a $\pm 5\%$ range. Most agents' delay in "Advance information" is the range ± 25min, their score because of disruption varies from -40% to 20%. In the "Timely information", most agents (i.e. 90^{th} percentile) have delay less than 40min, while in the "No information" this is larger than 300min. The "Timely information" and "No information" scenarios result in a much skewed distribution, with a stronger tail of very small scores, compared to a few positive scores. In fact the positive scores for the 90^{th} percentile of "Advance Information" and "Timely information" point out the complexity of the effects in which agents change their plans, by which some (few) agents can actually improve their score; this should be compared with the change in percentage from Benchmark*.

Table 3.2: Statistical results of involved agents' delays and scores

Information availability		Benchmark*	No information	Advance information	Timely information
Delay [min]	median	0	120	0	3
	10th percentile	0	30	-24.1	-7.7
	90th percentile	0	333.5	21.9	40.2
Score	median	0	-178.4%	-2.6%	-3.7%
	10th percentile	-4.5%	-505.8%	-40.9%	-60.2%
	90th percentile	3.3%	-44.6%	20.4%	16.7%

3.5 Conclusions

We study passengers' behaviours and satisfaction in public transport disruptions in a large-scale multi-modal network, under the defined information availability on the basis of a novel "who-when-where-what" four-dimensional framework. Compared to a benchmark without disruption, three information availability (scenarios) are defined in public transport disruption: "No information", "Advance information" and "Timely information". Corresponding to each information availability, passengers' behaviours are assumed: waiting and keeping initial plan, multiple choices (e.g. transport mode, route and activity changes), and within-day route choice.

We propose rigorous mathematical descriptions of those cases, and are able to compute performance indicators of user equilibrium and non-equilibrium solutions corresponding to those cases, by means of an agent-based simulation platform (MATSim). MATSim is activity-based and considers comprehensively different transport modes, in which agents' activities, trips and detail choices of users for a whole day can be simulated in detail. Especially for the "Timely information" scenario, we develop the within-day replanning approach in MATSim by enriching the procedure of selecting involved agents and modifying their initial plans in a single iteration/ execution as reaction to public transport disruption.

From the MATSim simulation results of the Zürich scenario, three main conclusions are summarised: First, the "No information" and "Advance information" scenarios are two boundaries and provide the gaps for passenger simulation in public transport disruptions. Second, the average scores of involved passenger behaviours are expected ("Benchmark"> "Advance information"> "Timely information"> "No information"), but the variances are relatively large. Third, the difference of scores between the "Advance information" and "Timely information" scenarios is small, which means agents' satisfaction decreases only slightly when they know of a disruption after its occurrence, as far as they know all details and react immediately in public transport disruption.

For the further research, some more realistic scenarios based on the proposed framework of information availability can be simulated. Some examples are enumerated: one scenario can be that agents know disruptions only when reaching the involved stations otherwise they know nothing about the disruptions; another scenario can be that agents only know the start time of disruptions but they don't know the precise end time; one more scenario can be set based on agents' proportions of diverse information availability; and multiple scenarios can be defined in between those. Moreover, one can play with the size of the user groups having at the same time different information availability. These scenarios will result in different setups and costs for the channels through which information can be disseminated; thus will be crucial in balancing the benefits of the information availability (which we discussed here) with their costs. These scenarios need further development in the within-day replanning module of MATSim.

Moreover, the simulated disposition timetable is just one possible feasible schedule for the defined rail disruption. In reality, public transport operators may apply other schedules which aim to improve passengers' satisfaction in public transport disruptions. So more different disposition timetables (such as retiming, reordering and rerouting) can be tested in MATSim to study which kind of timetable is more passenger-oriented. In addition, the output of agent-based simulations can be used as constraint for optimising a more passenger-oriented disposition timetable.

Chapter 4

Information strategies and timetable, rolling stock rescheduling in public transport disruptions

This chapter is based on the following published article.

Leng, N., Liao, Z. and Corman, F. (2020) Role of timetable, rolling stock rescheduling, and information strategies to passengers in public transport disruptions, *Transportation Research Record*, 1-13.

4.1 Introduction

In public transport operation, disruptions may occur due to multiple potential reasons, such as planned maintenance actions, unexpected events, failures, weather, insufficient resources of tracks, rolling stock, staff and power supply. Typical characteristics of disruptions are for instance public transport malfunctions lasting more than 2-3 hours, where partial technical components are unavailable and the resource allocation plan (drivers, vehicles) might need to be changed, see Pacciarelli (2013). The public transport disruptions can have a significant impact on passengers' travel and lead to critical decisions from passengers' perspective, such as cancelling the trip. In response to disruptions, public transport operators use special alternative plans, called disposition timetables, to keep delivering a service to passengers. Once one disruption occurs, the service levels of public transport decrease, they typically remain stable (at a lower level than original) throughout the disposition timetable, and then increase back to original when the disruption is resolved and the network can operate the original timetable again (so called bathtub model), see Ghaemi (2018). Passenger-oriented disruption management focuses on understanding and adapting the demand of passengers (activities, trips, preferred modes, preferred arrival time), and the supply from operating companies (operating plan, and availability of resources such as vehicles and drivers) to offer better services to passengers. The relation between the two is mediated by some information available about planned and adjusted services; see Leng and Corman (2020).

Generally, modern urban transport is operated in a multi-modal network, including both public and private transport modes. Different operating companies usually manage specific public transport modes (e.g. bus, tram and rail). Each operating company reallocates its internal resources (disposition timetable, rolling stock) to reduce passengers' dissatisfaction in disruptions. In the cities that implement the public transport integration policy, where public transport is integrated in a single system with a single payment scheme, the passengers can use any mode as their choices without extra charges even in disruptions. Therefore, it is of great importance for operating companies to have a comprehensive understanding of the impacts of the specific designed public transport disposition timetable to passengers' reactions in a multi-modal network in case of disruption.

The major goal of this chapter is to study the mutual influences of operation strategies and information to passengers in public transport disruption, i.e. what are passengers' adaptations and satisfaction under different information strategies and disposition timetables (considering different reschedule strategies and the feasibility of rolling stock circulation). We propose to use agent-based micro-simulation (e.g. Balmer et al., 2009), to imitate large-scale passengers' behaviours during public transport disruption. There are two main benefits of such kind of agent-based simulation. The first is the consideration of movement of agents in a multi-modal network, including choices not only within the public transport network, but also including switching to private modes, cancelling trips, and even cancelling or changing activities throughout a daily plan. These agents' movements match the fact that disruption may causes more kind of inconvenience to passengers than just a delay on a trip. The second benefit is the explicit consideration of heterogeneity of users, seen in the activity-based micro-simulation of an entire day, where detailed activities and trips are simulated, so that the specific reaction in disruption can be precisely understood. The trip delays and the total scores of utility for all activities and trips estimate passengers' (dis)satisfaction in disruption.

We focus on railway disruption, since railway usually has limited capacity for extra train services in the alternative train routes. The evaluation of different disposition timetables and information strategies is analysed based on the proposed MATSim implementation, on a realistic case study on a large multi-modal network in Zürich Switzerland under a large railway disruption.

4.2 Information strategies and passengers' adaptation

After disruption, the operating companies apply the optimisation model to produce the disposition timetable considering the details of rescheduling strategies and the feasibility of rolling stock circulation (detail introduction see Section 4.4). Once given a disposition timetable in disruption, passengers' behaviours strongly depend on the information details they know about the disposition timetable. In this chapter, we mainly consider the influence of the "issue time" that information reaches the users to passengers' behaviours. It can be beforehand, for planned disruptions such as planned public transport maintenances, in which the operating companies broadcast the disposition timetable in detail in advance. In case of unexpected unplanned disruptions (like accidents, failures, etc.), the issue time can only be after the start time of the disruption. In the worst case, the information is never issued and passengers know of the disruption only at the moment they try to board a service that is not running. In this chapter, we for instance report three cases, namely the operating companies can issue information about the disruption beforehand; or disseminate information only when they realise that the disruption is going on; or they do not issue any information at all.

Ideal information[1]. In this information strategy, passengers have the perfect information beforehand, which allows them to adapt at best their plan. The following behaviour rules are assumed. Passengers as reaction to the disruption can change services or modes. A mode change means that passengers may leave the public transport system and take private car or bike for the affected trip, or even for the entire day. A service change means that passengers who keep using public transport can change the service they use (i.e. the train service of IC4 instead of IC8), transfer stations (i.e. can be the same physical location or not) or take a completely different sequence of services in the public transport network as far as it enables them to reach their destination. Passengers can depart earlier or later than their planned time, for any trip and activity. In the plan of the entire day, passengers can combine any of those reactions for the maximisation of their satisfaction.

Timely information. In this case, passengers know the perfect information of starting time and specific length of disruption, but they know it only after the disruption starts. Compared to the *Ideal information*, passengers' adaptations are more limited. In

[1] The "Ideal information" in Chapter 4 means the consistent concepts as the "Advance information" in previous Chapter 3. The name "Ideal information" is more from the viewpoint of service providers, who think the complete/ perfect/ advance information is an ideal situation in reality. The name "Advance information" is more from the viewpoint of passengers, who can know the complete/ perfect/ ideal information in advance before they make their daily travel plan.

particular, there cannot be any mode change (i.e. shifting to private car bike or walk) as reaction to the disruption. In other terms, we assume that passengers planning to use of public transport do not have an alternative private mode directly available when they realise there is a disruption. We do not consider taxi alternatives, nor bike or car sharing systems. We consider the shortest path as the fastest path between two activities, including the walking time, waiting time and in-vehicle time, and related penalties with typical parameters of generalized travel time. Further research might also consider more realistic situations, where passengers know only the start time of disruption without knowing the specific end time, until the disruption resolves. In this case, passengers' adaptations will differ, depending on the information they have over time.

No information. To express passengers' adaptations in the case that passengers have no knowledge about the disruption, the following behaviour rules are assumed. Passengers wait at the stations where they were supposed to take a public transport service, which is not running due to the disposition timetable until the end time of the disruption. Then they take the same public transport service as their initial plan (e.g. S16 has a train service every half an hour, if they were planning to take one train service of S16, they will be taking the first train service of S16 at the end of the disruption) to the same transfer station. Then they take the same public transport service until they finish their trip (i.e. if after transfer they were planning to take train the train service of IC4, they will be taking other train service of IC4 at the end of the disruption, after they reach the transfer point). Some passengers may face a high risk of failure to finish their whole plan (e.g. because no train services of IC4 might run anymore).

4.3 Agent-based simulation approach

The present work uses the MATSim platform for agent-based simulation. The basic idea of MATSim is that travel demand can be predicted by simulating daily life of persons and particularly the spatial-temporal occurrence of out-of-home activities, see Horni and Nagel (2016). The following three features of MATSim provide the foundation to model the above information strategies (Section 4.2) and different disposition timetables (Section 4.4), as well as analyse the corresponding passenger adaptations. First, Agents in MATSim are the representation of passengers in reality; their daily movements as successive activities and trips have both a consequence on their utility or score. Second, MATSim is able to describe mobility in a multi-modal network, including private transport and public transport schedules. Third, MATSim is based on scheduled operations, which means the vehicle delay in daily operations is neglected. MATSim can model any public transport disruptions as far as it can be related to an updated disposition timetable (i.e. which public transport services are running from where to where, at which time, with which capacity) regardless of the precise nature and cause of the disruption.

We refer to the specific trip(s) affected by the defined disruption as “Directly affected trip”.

Figure 4.1 shows the modelling in MATSim of the different information strategies and disposition timetables. The default MATSim works by reaching an equilibrium solution by iterations. At each iteration, representing a day of the users, the plans of agents are executed (i.e. performed by the agents) and the choices of the agents are evaluated and changed by a replanning module, if necessary. The basic MATSim loop is shown in “Benchmark” (left), and includes input, execution, scoring, replanning and analysis. More details are available e.g. in Horni and Nagel (2016). The “Benchmark” runs with the default MATSim setting with original public transport schedule and reflects agents’ behaviours without public transport disruption. The output plans resulting from the “Benchmark” simulation are considered as the initial passenger demand (i.e. the ideal situation) of all agents in a normal daily travel.

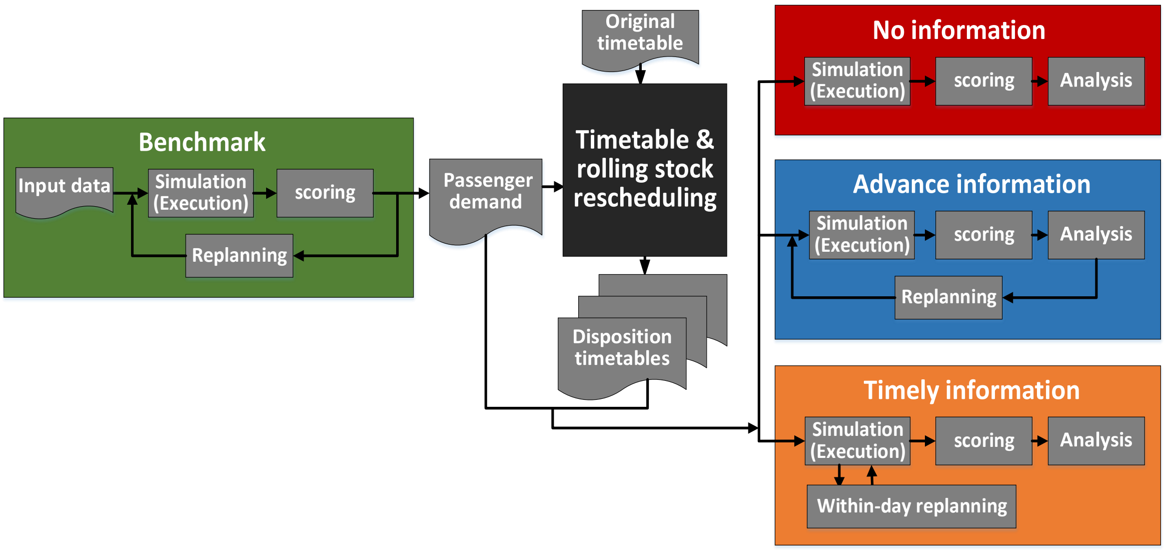

Figure 4.1: MATSim execution of different information strategies and disposition timetables

The initial plans are the basis which used by the passengers, when facing the disruption. The initial plans of all agents and the original railway timetable are the two inputs to the optimisation model (middle). Depending on whether considering retiming, rerouting, with train services fully or partially cancelled and the feasibility of rolling stock circulation, different disposition timetables are generated. Those are completely determined, including possible delays due to extra trains running. More details about timetable and rolling stock rescheduling model are introduced in Section 4.4. Both the initial plans of agents (from “Benchmark”) and the specific disposition timetable are as inputs to MATSim to simulate agents’ behaviours under the three information strategies.

For the *No information* (top-right) in MATSim, the agents' initial plans are executed on the disposition timetable, for a single iteration (in figure, there is no replanning). During the disruption time, the agent will remain waiting at the stops in case the public transport service is cancelled in the specific disposition timetable implemented. When the disruption is recovered, MATSim will try to execute the initial plans of agents, as far as this is possible and compatible with the public transport services and/ or preferred starting/ ending time of activities.

For the *Ideal information* (middle-right) in MATSim, the alternative route/ mode/ time/ activity choices are calculated by including them in the iterative process of MATSim (i.e. the blue box contains a replanning feedback mechanism). Agents can rely on their experiences from previous iterations to gain the ideally best solutions, which adapt the initial plans in case of public transport disruption.

The *Timely information* (bottom-right) considers that agents have information, but only after disruption starts. Dobler and Nagel (2016) already point out that using an iterative approach to disseminate information results in problems, like illogical agent behaviour, which would be able to anticipate unforeseeable events. For instance, if a replanning approach is used, agents may start rerouting before disruption. The key module to solve this approach is a "within-day replanning" module, which is not reaching an equilibrium as in *Ideal Information* but rather computing the best response to the disruption, considering the available information, and not learning from experience.

The utility of a plan for an entire day, and thereby an estimate of agents' satisfaction in different information strategies, is computed by the scoring function Equation 4.1, as in Charypar and Nagel (2005). The score of a plan $u_{p,k}$ is the sum of all activity utilities u_{A_i} plus the sum of all travel (dis)utilities u_{T_i} for all activities and trips:

$$u_{p,k} = \sum_{i=0}^{N-1} u_{A_i} + \sum_{i=0}^{N-1} u_{T_i} \tag{4.1}$$

4.4 Timetable and rolling stock rescheduling

4.4.1 Problem description

Dispatchers usually reschedule the impacted vehicles to decrease the negative impacts of disruption to passengers as much as possible. The most common strategy is timetable rescheduling, including retiming, reordering, rerouting, partial or full cancellation of services, see Cacchiani et al. (2014). In addition, the rolling stock circulation should be checked to ensure the feasibility of the disposition timetable. Feasible rolling stock circulation means that vehicles are available to run the specific services at the right moment and right stations. In this chapter, we consider an optimisation model to solve the timetable rescheduling problem with the feasibility of rolling stock circulation in a railway hub that has alternative train routes to be used in case of disruption.

The optimisation model is to get the disposition timetable, given the input of a railway network, an original timetable, disruption routes and durations, the operation parameters (train running time, minimum headway time) and the origins and destinations of on-board passengers. If some disrupted train services are rerouted to an alternative railway corridor, the original train services on this corridor may also be affected. Especially in the case that this alternative corridor has limited capacity of train services, the optimisation model should decide which train services have the priority to be kept and the order of train services. Because of rerouting, some train services unavoidably suffer delays. Those can be computed on beforehand, by considering the available capacity, headway constraints, and delay propagation phenomena.

The objective of the optimisation model is to minimise the travel time of passengers. We assume that train dispatchers have limited knowledge about passengers' dynamic choices about the disposition timetable in disruption and they expect that passengers will insist to their original choices. In other terms, passengers are assumed to keep using the same train service (i.e. a specific train with defined original, terminal stations and departure time) as their initial plans unless this train service is cancelled. If a train service is rerouted or retimed, passengers will still use this service and may suffer the same delay as this train. Otherwise, passengers on the cancelled train service are considered losing their direct trips with the penalty of unlimited delay. Passengers' transfers and passenger reassignment are not considered in this timetable rescheduling phase since we consider them in more detail in the agent-based simulation model (see Section 4.3).

In a given disruption with fixed time and train route, different disposition timetables can be generated depending on whether rerouting is applied, whether the train cancellation is full or partial and whether rolling stock feasibility are considered. Figure 4.2 shows the examples of the original and possible disrupted train services on the "Route 1" between station A and B during the disruption time. The subfigure (a) shows the original train schedules between these two stations, some train services run on the "Route 1" while the others on the "Route 2". These two train routes can be used as alternative to each other during the time of disruption. Both the two routes can offer train services in two directions (either from left to right or from right to left). The thick line shows the differences of train services compared to the original one, while the thin line means the train services remain the same. The dashed and solid line explains the cancelled and running train services correspondingly.

The subfigures (b) and (c) show the schedules without considering the rerouting strategies. All the disrupted train services between station A and B via "Route 1" are cancelled. As a comparison, the subfigure (d) shows the idea to reroute the disrupted train services from "Route 1" to "Route 2". Especially in case that "Route 2" has limited capacity, the optimisation model is used to calculate which train services can be rerouted and the delays of train services. For instance, the subfigures (e) and (f) show the rerouting schedules. If some trains can be rerouted, the whole train services can be kept from the train's start and end station (thick solid line). If not, at least the train services between station A and B (thick dashed line) will be cancelled.

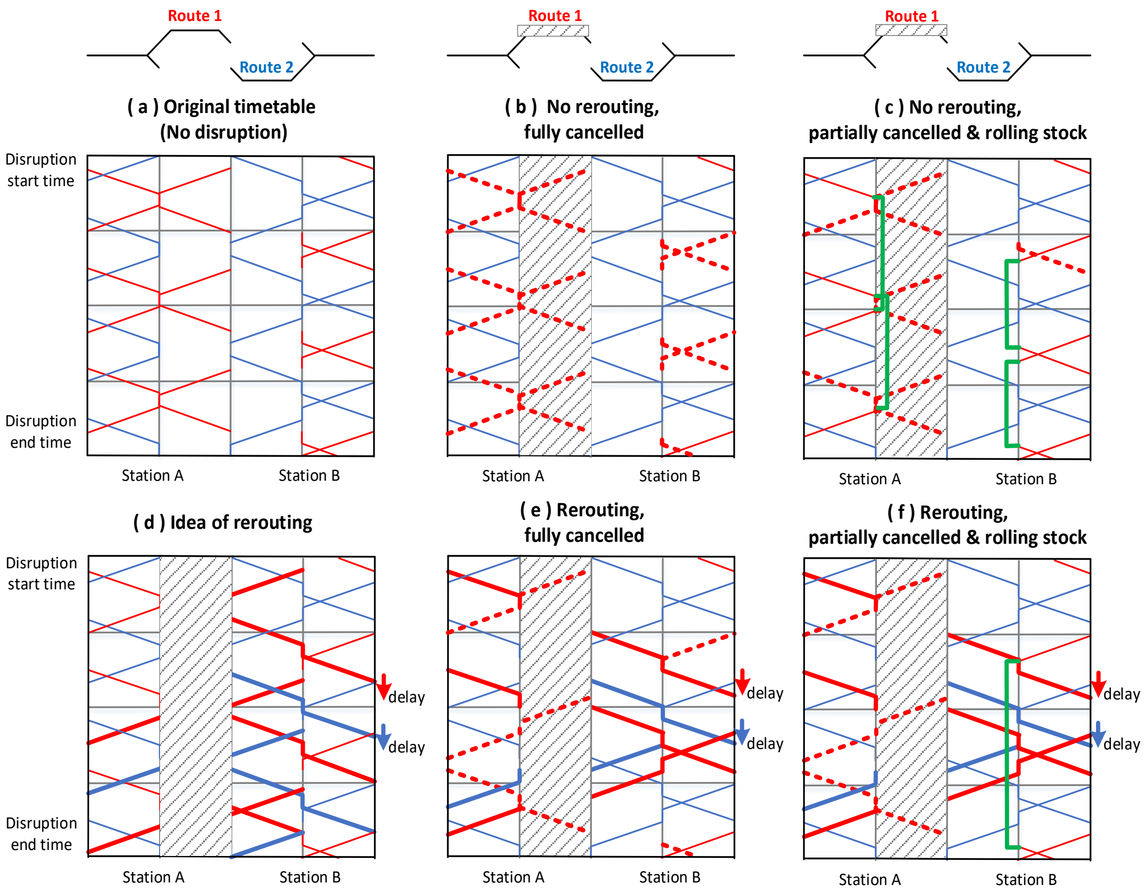

Figure 4.2: Explanations of different schedules

The differences between "full cancellation" and "partial cancellation" depend on whether the trains serving the stations beyond station A or station B are cancelled or not. The subfigures (b) and (e) are examples of the fully cancellation (thick dashed line). If the train services between station A and B are cancelled, the whole train services from origin to destination are completely cancelled. In this case, the rolling stock circulation is relatively simple; the services will wait at the terminal stations, and start running only when the disruption area can be passed. The practitioners often use such an action since it is easy to determine, but it has a large impact to services offered to passengers. The subfigures (c) and (f) illustrate the partial cancellation. The train services beyond either station A or station B will be kept (thin solid line). In particularly, some train services beyond either station A or station B are also cancelled because of considering the feasibility of rolling stock circulation (green line). In such case, the rolling stock circulation must be carefully designed, so that the disposition timetable is feasible in reality, by using vehicles which are available at the stations where they start. Such an approach is much more complex to setup and operationalize, and its evaluation in an agent-based model is a main contribution of the current chapter.

4.4.2 Model formulation

To determine the optimal combination of different rescheduling measurements and strategies, we propose an optimisation model able to compute a new disposition timetable, based on a given planned timetable, and a known disruption. The problem has a disjunctive programming structure, as order of trains on infrastructure elements can be represented by binary decisions (either train A before train B; or vice versa). The mixed integer programming (MIP) optimisation model proposed captures well both binary decisions as well as continuous variables and their interrelation. The key optimisation variable is a binary variable indicating the train sequence; other choices relate to the precise timing, the route chosen, and the possible cancellation of services (as standard, see Pacciarelli, 2013 and Cacchiani et al., 2014).

An overview of all notation used is provided (Table 4.1). We define the direct directed link between two adjacent railway stations as the “segment”. The route of a train is composed of multiple adjacent segments.

Table 4.1: Notation and terminology

Symbol	Explanation
Element and Collection	
$s \in S$	Station/ station set
$k \in K$	Segment/ segment set
$s^+(k), s^-(k)$	Origin/ destination station of segment k
$r \in R$	Route/ route set
K_r	Segment set of route r
f	Train
$\bar{r}_f$	Original route of train f
R_f	Possible alternative route (including the original one) set of train f
p	Passenger

f_p	Boarding train of passenger p
R^p	Alternative route set of passenger p
S^p	Alternative destination station set of passenger p
u	Disruption
k_u	Segment of disruption u
Parameters	
H_k	Minimum headway of segment k
T_f^k	Running time of train f at segment k
$W_f^{k,k'}$	Minimum required dwell time at the station between segment k and k'
$g_r(k,k')$	Binary value, 1 indicates that k' is the successive segment of k, 0 otherwise
θ_f	Binary value, 1 indicates the train f is allowed to be canceled, 0 otherwise
$\overline{e_f^k}, \overline{l_f^k}$	Planned entering/ leaving time of train f at segment k
β_f	Delay tolerance of train f
a_p	Desired arrival time of passenger p
ϕ_p	Cancellation penalty of passenger p
tS_u, tE_u	Starting/ ending time of disruption u
Decision variables	
d_p	Delay time of passenger p
x_f^r	Binary variable, 1 indicates train f selects route r, 0 otherwise
e_f^k, l_f^k	Entering/ leaving time of train f at segment k
b_f^u	Binary variable, 1 indicates train f runs through the segment k_u before disruption u happens, 0 otherwise
$y_{f,f'}^k$	Binary variable, 1 indicates train f runs through segment k earlier than train f', 0 otherwise

The objective function in Equation 4.2 is minimising the total delay d_p of passengers. If a passenger has no available direct trip (the train is cancelled or the rerouted train is no more applicable for the passenger), the corresponding delay will be set to a given penalty value (Equation 4.11). Passengers' transfer penalty is neglected in this model, being only considered in the simulation.

$$\min \sum_p d_p \tag{4.2}$$

The objective is subject to the following constraints. Equation 4.3 describes how each train f can select at most one route in its candidate set R_f; or none, if cancelled.

$$\sum_{r \in R_f} x_f^r \leq 1 \quad \forall f \tag{4.3}$$

Equation 4.4 sets the difference between entering time and leaving time at segment k to be equal to the given running time of train f.

$$l_f^k - e_f^k = T_f^k \quad \forall f, r \in R_f, k \in K_r \tag{4.4}$$

Equation 4.5 models the dwell time of train f at a station (the difference of its entering time and its leaving time) as greater or equal than minimum required dwell time, if the route r is selected, 0 otherwise.

$$e_f^{k'} - l_f^k \geq W_f^{k',k} \times x_f^r \quad \forall f, r \in R_f, k, k' \in K_r : g_r(k,k') = 1 \tag{4.5}$$

Equation 4.6 introduces the train order variable $y_{f,f'}^k$ describing whether train f enters segment k before train f', or vice versa, later used to determine which of the big-M headway constraint (4.7) or (4.8) applies

$$y_{f,f'}^k + y_{f',f}^k = 1 \quad \forall k \in K, f, f' \tag{4.6}$$

Equations 4.7 and 4.8 impose headway constraints when entering and leaving segments, respectively, by means of a standard big-M structure. The headway constraints are valid if (a) the train f enters segment k before train f' and (b) the routes selected by train f and train f' have an overlapped segment k.

$$(3 - y_{f,f'}^k - \sum_{r \in R_f : k \in K_r} x_f^r - \sum_{r' \in R_{f'} : k \in K_{r'}} x_{f'}^{r'}) \times M + e_f^k - e_{f'}^k \geq H_k \quad \forall k \in K, f, f' \tag{4.7}$$

$$(3 - y_{f,f'}^k - \sum_{r \in R_f : k \in K_r} x_f^r - \sum_{r' \in R_{f'} : k \in K_{r'}} x_{f'}^{r'}) \times M + l_f^k - l_{f'}^k \geq H_k \quad \forall k \in K, f, f' \tag{4.8}$$

Equations 4.9 and 4.10 calculate the passenger delay as used in the agent-based simulation. When train f_p, with passenger p, selects route r, the passenger's delay is the difference of actual and desired arrival time .

$$d_p + (1 - x_{f_p}^r) \times M \geq l_{f_p}^k - a_p \quad \forall p, r \in R^p, k \in K_r : s^-(k) \in S^p \tag{4.9}$$

$$d_p - (1 - x_{f_p}^r) \times M \leq l_{f_p}^k - a_p \quad \forall p, r \in R^p, k \in K_r : s^-(k) \in S^p \tag{4.10}$$

Equation 4.11 introduces the passenger cancellation penalty, equal to ϕ_p, in case no candidate routes are selected for a passenger.

$$d_p \geq (1 - \sum_{r \in R^p} x_{f_p}^r) \times \phi_p \quad \forall p \tag{4.11}$$

Equations 4.12 and 4.13 identify the disrupted trains as those (a) selecting any of the route r that contains segment k_u, and (b) running through segment k_u after disruption. Disrupted trains can enter the disrupted segment only after the disruption ends, or before it starts.

$$e_f^{k_u} + (1 + b_f^u - \sum_{r \in R_f : k_u \in K_r} x_f^r) \times M \geq tE_u \quad \forall u, f \tag{4.12}$$

$$l_f^{k_u} \leq (2 - b_f^u - \sum_{r \in R_f : k_u \in K_r} x_f^r) \times M + tS_u \quad \forall u, f \tag{4.13}$$

Equations 4.14 and 4.15 describe the train delay tolerance β_f, providing an upper bound to the admissible delays of trains. A train is cancelled if its delay is more than the delay tolerance.

$$l_f^k - \overline{l_f^k} \leq \beta_f \quad \forall f, r \in R_f, k \in K_r \tag{4.14}$$

$$e_f^k \geq \overline{e_f^k} \quad \forall f, r \in R_f, k \in K_r \tag{4.15}$$

Equation 4.16 forbids the cancellation of train services in specific train routes, indicated by parameter θ_f.

$$\sum_{r \in R_f} x_f^r = 1 \quad \forall f : \theta_f = 0 \tag{4.16}$$

The rolling stock circulation is enforced as post processing to the model. Two trains with compatible destination and origin station (after partial cancellation), identical train type, and sufficient short-turn time can be assigned as consecutive trains in the rolling stock circulation. A first-come-first-served principle constrains further the assignment. A train without available rolling stock assigned is cancelled.

4.5 Test case

We perform a large set of experiments, based on calibrated initial demand of Zürich presented in Rieser-Schuessler et al. (2016). The public transport integration is implemented in the Zürich network, i.e. any multimodal trip between origin and destination is available to public transport users without extra charges. The total number of agents (public transport and private users) is 15,286, i.e. 1% of the real Zürich population. Physically three railway routes, with comparable running time, connect the two major station Zurich HB (400,000 passenger trips/ day) to Zürich Oerlikon (80,000 passenger trips/ day) (Figure 4.3): one passing via Zürich Hardbrücke (green dashed line), one passing via Zürich Wipkingen (red dashed line) and one direct tunnel route (thick blue line). The green and red dashed lines in Figure 4.3 show the assumed rail disruption: two out of three railway routes are disrupted and unavailable during the afternoon peak hours, between 16 and 19 o'clock. All long-distance train service can be rerouted on the available undisrupted route; local S-bahn services are kept if a feasible rolling stock circulation can be found.

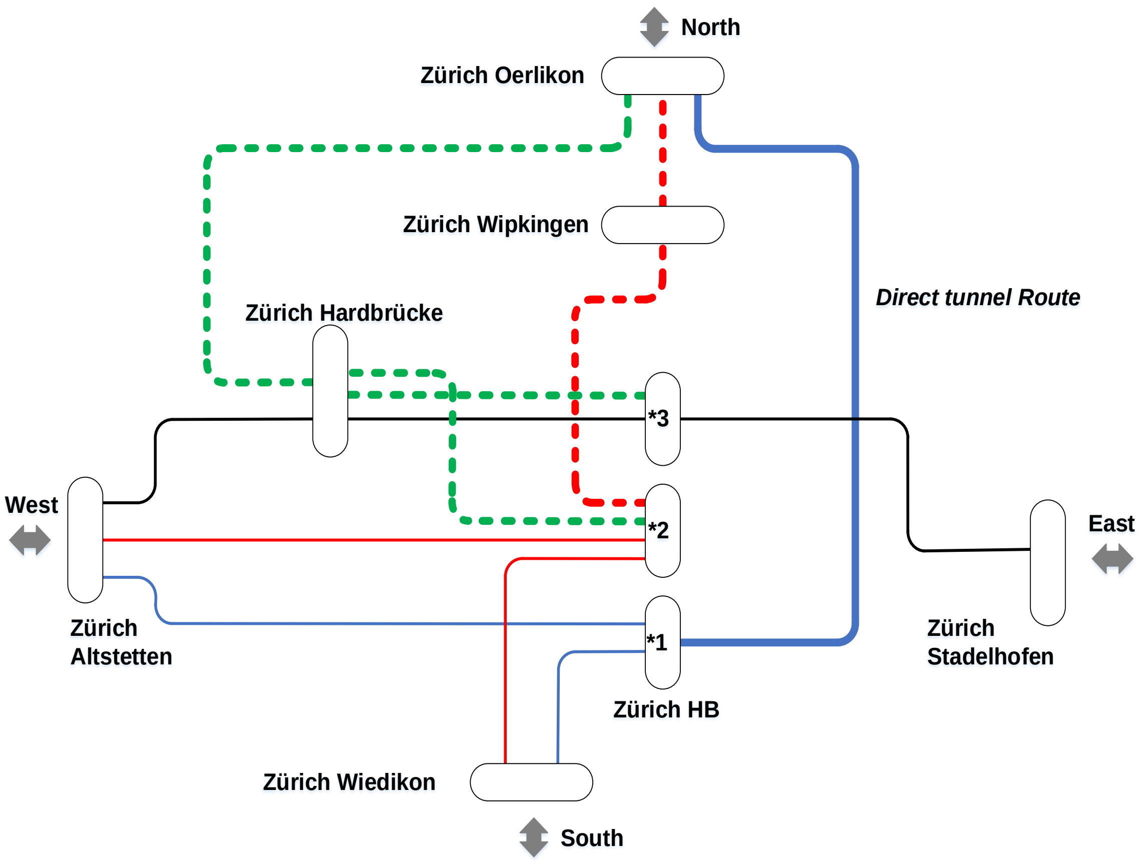

Figure 4.3: Zürich scenario

All instances are solved on a personal computer with Intel Core i7-7700 CPU, 16 GB RAM. The instances are solved as MIP by Gurobi 8.1.1 with default settings. The optimal solution is found within less than 6 seconds. The evaluation of passenger choices in MATSim, for the Zürich multi-modal network, takes less than 60 seconds for *No information* and *Timely information*. The total computation time is thus feasible for real-time reaction to unexpected events. In case of planned disruptions, where much longer time for action is available, the results of *Ideal information* can be simulated in about 6 hours, due to the iterative computation to reach user equilibrium.

4.6 Results and discussion

4.6.1 Schedules

Table 4.2 shows the differences of train services in the different disposition timetables varying with retiming, rerouting, with services fully or partially cancelled, which then refer to an optimised, feasible rolling stock circulation. The percentage shows the proportion of rescheduled train services to the total number of vehicles of each railway route. The average delay refers to the arrival delays on each station of the rescheduled train services of each railway route.

Due to applying the “rerouting” rescheduling strategy, 59.5% of trains can still run on the alternative railway route (the direct tunnel route). This results each train service originally operated on the direct tunnel route suffer the delay (3.3 min on average). With the setting of delay tolerance (30 min) in the optimisation model, some original train services are kept at the end of disruption: 4.4% train services of the railway route via Zürich Hardbrücke and 5.4% of that via Zürich Wipkingen respectively cause 8.7 min and 3.7 min extra delays on average. The average over all traffic is 3.6 minutes of delay.

Considering the feasibility of rolling stock circulation, 1.5% of the train services via Zürich Hardbrücke and 2.7% of that via Zürich Wipkingen must be fully cancelled as no vehicle could be made available in the right moment, at the right place, to enable a partial cancellation.

4.6.2 Passenger delays and scores

We classify the agents into three groups: “disruption affected agents”, “rerouting affected agents” and “multiply affected agents” as they are affected in substantially different way from the disruption, information, reschedule. The “disruption affected agents” are those who wanted to take the (disrupted) train services passing Zürich HB and Zürich Oerlikon via the disrupted railway routes (via either Zürich Wipkingen or Zürich Hardbrücke) between 16 and 19 o’clock. The “rerouting affected agents” are those who intended to take the (rerouted, rescheduled, or cancelled) train services passing Zürich HB and Zürich Oerlikon via the direct tunnel route during the defined disruption time. The “multiply affected agents” aggregate agents using both the disrupted railway routes and the direct tunnel route: either because of multiple trips, or because they need to transfer in one of the two stations to a service using the other line. In our test case, the size of those groups is respectively 125 agents, 56 agents and 30 agents.

Table 4.3 shows the average delay of the directly affected trip and average score of the whole day's trips and activities (based on Equation 4.1) of these three groups of agents (group of columns), with different settings of disposition timetables (rows) and information strategies (columns), compared to "Benchmark" (0 min delay and 100% score) which represents the situation without disruption. For instance, -300% average score means the score is 3 times worse than the "Benchmark" calculated by Equation 4.1. We colour the cells of Table 4.3 for better readability. Here we focus on explaining the delays since the score shows similar trends.

The "disruption affected agents" can substantially decrease their delay, if information will be disseminated, saving on average 93.6 min (*no information* → *timely information*) and further 31.3 min if *ideal information* will be provided. Especially with partial cancellation and rerouting, having *ideal information* reduces delay to a minimal amount of just 2 min. For *ideal information*, partial cancellation brings on average an improvement of 54%, while rerouting 32%; in other terms, having a better rolling stock management can be as important, if not more important than rerouting trains elsewhere in the network. For *timely information*, the benefit of partial cancellation stays well above 50%, while the benefit of rerouting decreases to around 15%. The delay of the agents who have *no information* reports limited improvement from rerouting, and no improvement from partial cancellation, as the agents are unable to find an alternative to bypass for the disrupted area.

The "multiply affected agents" are those getting the largest benefits, if operating companies can keep the services beyond the affected stations in disrupted railway routes, saving up to 110 min in both *no information* and *timely information*. In case of partial cancellation, the benefit of information is rather limited, with 5 minutes between *no information* and *timely information*, and 5 minutes further to *ideal information*. Due to the complexity of their trip, rerouting services does not improve too much their delay.

The "rerouting affected agents" are untouched by the disruption, unless rerouting takes place. In such case, they suffer 2.7 min more delay due to the "rerouting" strategy of the disrupted train services. This result matches the average train delay (3.3 min) of the direct tunnel route's train services; in other terms, the agents' delay is just related to train delay, and information plays a minor role. If they would receive *ideal information*, this minimum delay can be further reduced to a negligible 1.2 minutes. The delay does not depend on the *timely information* because their preferred path remains feasible and available.

Aggregating over all agents, the trade-off arises, if it is preferable to limit the disruption to the "disruption affected agents" and "multiply affected agents", which suffer large delays, or rather reduce their delay at the expense of a small delay for passengers who would be virtually untouched by the disruption, like the “rerouting affected agents”. The net reduction of delay strongly suggests the second choice is better for the entire system provided that the trains can be rerouted, and the circulation is feasible for the operator. Concerning the optimisation of rolling stock circulation, we can see from the table that the impact of a suboptimal, straightforward overreaction in terms of train cancellations, in case of *timely information*, can increase the effect of the disruption by more than three times (i.e. 14.1 minutes to 51.5 minutes on average, 37.5 minutes saving). This gap is larger than what is gained by the availability ahead of operations of complete information (which is in the order of magnitude of 11 minutes).

Regarding scores, a similar trend is found, with a reduction of disutility to a less than a fifth, when changing from no rerouting, full cancellation; to rerouting, partial cancellation, for *timely information*. The availability of *ideal information* is a further reduction to a fifth, but much smaller in absolute improvement (40% against 220% from optimised rolling stock circulation).

Table 4.2: Percentage of rescheduled trains and average train delays in the disposition timetables

Rescheduling strategies	Cancelled, rolling stock	Railway route via Zürich Hardbrücke			Avg. train delay (min)	Railway route via Zürich Wipkingen				Avg. train delay (min)	Direct tunnel route	Avg. train delay (min)
		Fully cancelled	Partially cancelled	Retime		Fully cancelled	Partially cancelled	Rerouted	Retime		Retime	
No rerouting	Fully	100%	0	0	0	100%	0	0	0	0	0	0
	Partially	1.5%	98.5%	0		62.2%	37.8%	0	0		0	
Rerouting	Fully	95.6%	0	4.4%	8.7	35.1%	0	59.5%	5.4%	3.7	100%	3.3
	Partially	1.5%	94.1%	4.4%		2.7%	32.4%	59.5%	5.4%		100%	

Note: Avg. = average.

Table 4.3: Agents' average delay (minutes) and average score (%) due to disposition timetables and information strategies

Rescheduling strategies	Cancelled, rolling stock	Disruption affected agents (125)			Rerouting affected agents (56)			Multiply affected agents (30)			Average, all agents (211)		
		no info	*ideal info*	*timely info*	*no info*	*ideal info*	*timely info*	*no info*	*ideal info*	*timely info*	*no info*	*ideal info*	*timely info*
Agents' average delay of the directly affected trip (minutes)													
No rerouting	Fully	137.2	16.1	59.4	0	0	0	130.3	11.2	114.8	99.8	11.1	51.5
	Partially	137.2	5.4	28.5	0	0	0	19.0	7.1	15.0	84.0	4.2	19.0
Rerouting	Fully	128.8	8.9	49.8	2.7	1.2	2.7	121.0	9.2	108.2	94.2	6.9	45.6
	Partially	128.8	2.1	20.0	2.7	1.2	2.7	12.5	6.4	10.5	78.8	2.5	14.1
Average, all schedules		*133.0*	*8.1*	*39.4*	*1.4*	*0.6*	*1.4*	*70.7*	*8.5*	*62.1*	*89.2*	*6.2*	*32.5*
Agents' average score of the whole day's trips and activities (%)													
No rerouting	Fully	-943.6	-76.8	-337.1	0	0	0	-541.2	-34.3	-528.5	-636.0	-50.4	-274.8
	Partially	-943.6	-32.9	-107.8	0	0	0	-104.5	-18.6	-56.0	-573.9	-22.1	-71.8
Rerouting	Fully	-891.8	-46.8	-297.5	-10.7	-5.8	-10.7	-528.9	-24.0	-524.2	-606.4	-32.7	-253.6
	Partially	-891.8	-14.2	-72.2	-10.7	-5.8	-13.7	-62.5	-12.2	-40.1	-540.0	-11.7	-52.1
Average, all schedules		*-917.7*	*-42.7*	*-203.7*	*-5.4*	*-2.9*	*-6.1*	*-309.3*	*-22.3*	*-287.2*	*-589.1*	*-29.2*	*-163.1*

Note: info = information.

4.7 Conclusions

We consider passengers' delays and scores to quantify and improve their (dis)satisfaction in public transport disruption in a multi-modal network, under different disposition timetables and information strategies. The disposition timetables vary by the actions required by the operating companies: retiming, rerouting, full/ partial cancellation of train services, all based on a feasible and optimised rolling stock circulation. Compared to a benchmark without disruption, three information strategies are defined in public transport disruption: *No information*, *Ideal information* and *Timely information*. In each information strategy, passengers' behaviours are assumed: waiting and keeping initial plan, multiple choices (e.g. transport mode, route and activity changes), and within-day route choice. We use an agent-based simulation platform (MATSim) to model different transport modes, in which agents' activities, trips and detail choices for a whole day are simulated in detail. We optimise the schedule of rolling stock with regards to feasibility and approximated passenger delay. This combination of agent-based simulation and optimisation model is fast enough to be practically applicable, even for a large multi-modal network, for both planned and unplanned disruptions.

From the results of a test case in Zürich, there is capacity for many trains to be kept running despite the disruption on an alternative railway route; this allows running more trains against a minor delay (3.6 min on average, including rerouted and original train services). The challenges related to rolling stock still require a minor amount of train services to be cancelled. Our results show that the information strategy is a major driver of delays: the earlier the agents can receive the disposition timetable, the smaller the delay they will suffer in disruption. Being able to partially cancel trains based on a feasible rolling stock circulation is much better for passengers than full cancellation, especially for passengers crossing the disrupted area multiple times. This might require the possibility to determine automatically optimised circulation plans, and multiple adjustment in the rescheduling process of the company, for additional operation complexity. Last, train rerouting is able to trade-off between a large delay for "disruption affected agents" and a slight delay (2.7 min on average) for agents on the alternative route, assuming agents have enough information to benefit from this change of plans. At system level, the impact of a disruption can be reduced substantially in this way, with a utility impact of the disruption reduced to a fifth only, of the original negative impact, assuming the realistic timely information strategy.

The current assumptions about information strategies might lead to overestimated benefits of information, as all agents have availability of information at the beginning of the disruption, in the most realistic scenario. In reality, other information strategies might disseminate information about the disruption only when reaching affected stations; or the agents would not know at any moment the precise end time of the disruption.

Furthermore, the experiments clarified how different group of agents suffer in different ways from disruption, rescheduling, information; the heterogeneity within each of those groups should be further analysed.

Chapter 5

Incomplete information in public transport delays

This chapter is based on the following article.

Leng, N. and Corman, F. (2020) The role of incomplete information to passengers in public transport delays, *2020 INFORMS Annual Meeting.* (One of winning papers of the 2020 Railway Application Section (RAS) Student Paper Contest)

5.1 Introduction

Delays often occur in the operational business of public transit and usually make the scheduled timetable infeasible due to, e.g. signalling problems, late arrival of crew, and construction work on the tracks (Bauer and Schöbel, 2014). Quality of service in the public transport network requires that situations of delays, disturbances or failures are handled appropriately, trying to reduce the inconvenience caused to passengers despite the emergence of delays (Jespersen-Groth et al., 2009). To improve the quality of service of public transport, operating companies apply traffic management to adjust services to customers in case of delays and disseminate information on the adjusted operations to passengers (Toletti, 2018). This information is the bridge to ensure the individual passengers can cope with public transport delays. In an ideal situation, immediate and complete information (Corman, 2020) refers to a strict assumption that all the delays and the adjusted operations that have occurred and will occur in the network can be disseminated precisely to passengers without any discrepancy. However, the information can be incomplete in reality due to the uncertainty of operation delays, the delay that information dissemination requires, general limitations of information channels, the habits of passengers checking the information about delays only to a limited extent, etc.

The major goal in this chapter is to study the effects of incomplete information to passengers' satisfaction in case of public transport delays, i.e. how to model passengers' behaviours under different incomplete information cases and quantify passengers' satisfaction. This problem is interesting and challenging to solve. First, the incomplete information refers to different aspects: a delayed information availability to passengers, limited information contents about specific public transport services at specific stations within specific time horizon, etc. For instance, Ben-Elia and Avineri (2015) review the literature about inaccurate information under conditions of uncertainty, including information either before departure or once on the move. Second, passengers' belief influences their behaviours in the case of incomplete information. The belief is what passengers' expect about the future unknown operations based on the known information. For instance, Arentze and Timmermans (2005) model passengers' belief about activity locations based on some limited information. Third, passengers' route choices in the case of incomplete information can be different from that with the assumption of complete information. Parvaneh et al. (2014) mention that passengers are not always aware of all available alternatives, i.e. they have the uncertain information and they may update their beliefs.

Passengers' chosen route in case of public transport delays has been studied in literature (e.g. Corman et al., 2017). This is essentially calculated by a kind of graph-based route choice, based on the timetable of adjusted operations (i.e. disposition timetable). We propose that passengers' route choices in case of incomplete information can also be described based on a more complex graph, i.e. so-called multi-layer time-space-event graph. Different layers of this graph are able to depict the details of incomplete information, passengers' belief about future public transport services, and passengers' thinking about their route choices. Passengers' thinking refers to an integral mental model, representing the public transport operations in passengers' mind, composed of both the provided information and their belief. Due to the deviations between incomplete information and passengers' belief, the possible route choices in passengers' thinking can also deviate from the actual alternatives in reality. This matches the typical multi-agent structure Belief-Desire-Intention (BDI), such as Mnif et al., 2017. We show that this proposed multi-layer time-event-graph method provides a valuable understanding of the effects of incomplete information and passengers' belief on their route choices and satisfaction in case of public transport delays.

The major contributions of this chapter are as follows:

(1) We propose a novel multi-layer time-event-graph method to describe the incomplete information (e.g. information issue time, duration, information contents) and belief (internal, own perspective of future operations, based on

e.g. schedule or delay belief) for heterogeneous passengers, to evaluate the effects to passengers' behaviours on public transport network in case of delays.

(2) The proposed multi-layer time-event-graph method and graph-based route choice are described with rigorous mathematical notations and formulas.

(3) The evaluation of different incomplete information cases is on a realistic case study in Dutch railway network.

This chapter is structured as follows. Section 5.2 proposes a new method, named "multi-layer time-space-event graph" to present passengers' information and belief. The graph-based passenger route choice is explained. Section 5.3 explains the set-up of a Dutch railway case study and analyses the results. In Section 5.4, conclusions and future work are presented.

5.2 Incomplete information and passenger route choice

In this section, we discuss the details of incomplete information in the process of managing public transport delays, and explain the main aspects of passengers' belief in case of incomplete information. We also propose a novel method, named multi-layer time-space-event graph, to illustrate passengers' information and belief regarding to the original timetable and disposition timetable. The new graph-based passenger route choice is explained. We apply this to railway, but it is applicable to any public transport network as far as the public transport services can be described as time-space schedules.

5.2.1 Incomplete information and passengers' belief

This subsection introduces concepts relevant to the present research. In general, public transport passengers plan their journeys from origin to destination based on the timetable, a time-space schedule of planned public transport services. The original timetable refers to the long-term planned and published schedule, based on which passengers usually regularly plan their travel. However, delays often occur in daily public transport operation, resulting in deviations of public transport services compared to original timetable, temporally or spatially. Delays can be caused either by external disturbances or by the propagation of delays from one train/ bus to the other, from one station to the other (e.g. the next or connecting) throughout the public transport network. Delay management focuses on the impact of rescheduling decisions on the quality of service perceived by the passengers. A disposition timetable is generated in the process of delay management by operating companies, which is a new updated schedule of public transport services taking into account the delays. This timetable is likely to be different from the original one in the aspects of departure or arrival time at some stations, stops, or even the routes of public transport services.

Passengers' information represents how much they definitely know about the published timetable (e.g. original, disposition); this information generated and disseminated by the operating companies. The information can be complete or incomplete. The completeness is determined by the following factors from passengers' perspective (see the framework of information availability in Leng and Corman, 2020). The first factor is what the information is (i.e. the features of information itself), including information content (e.g. all trains' time at all stations, or one specific train's operation at some stations) and time horizon (the duration of information, e.g. for the whole day, or for the next one hour). Another is when and where passengers receive this information (e.g. before their planned departure, or at the moment they arrive at the departure station). For instance, passengers can have complete information of the original timetable, including all the departure and arrival time at all the stations of all public transport services in the normal operations. In case of public transport delays, passengers might only have incomplete information of the disposition timetable, thus they partially know the operation time of some services at some stations. In some cases, passengers cannot be informed early enough, either the disposition timetable is not disseminated fast enough or passengers do not check the published information in time. In some other cases, the disseminated information only contains limited time horizon of disposition timetable, because the operations may change in the future. These cases are considered as incomplete information in passenger-oriented delay management, in which passengers are not informed fully and timely about the delays that occur and will occur, and the new generated disposition timetable in the network.

In case of incomplete information, passengers have to make an expectation of the public transport operations (e.g. the departing or arrival time of some services at some stations), extending the available information content to future times (beyond the information time horizon). Passengers' belief on delay propagation, shortly called passengers' belief, can be used to define passengers' expectation or inference about the future unknown operations based on information known to them. Passengers' belief might be correct or not. The correctness depends on whether it matches with the actual operations in reality. In general, passengers' belief is based on how passengers interpret the available information, what they expect about the delays and consequences (e.g. propagation of delays or delays fading due to buffer time of the original timetable), as well as how they foresee the possible public transport operations beyond the time horizon in case of a geographical limitation for which they have information.

In summary, the information represents the definite delays or disposition timetable from the information start time (i.e. the moment that passengers know information) within a given information time horizon (i.e. the time length between the start and end of the available information). The belief represents what passengers believe about the delays and the public transport operations from the information end time (i.e. the moment that passengers start to have no available information) to the time passengers might ultimately reach their destination. It is a belief, as those operations did not happen yet, and information is unavailable. Based on both the information and belief, we assume each passenger makes a mental model, representing comprehensively about the public transport operations (especially the possible services related to their journey) in the case of delays, shortly called "passengers' thinking" in this chapter. In each passenger's thinking, his/ her possible route choices are described by a set of "considered paths" (one, or usually more than one) linking the origin to destination, possibly including transfers at intermediate stations. Each "considered path" (Gentile and Noekel, 2016) has an expected utility (e.g. travel time), not definitely known in general, associated with passengers' satisfaction of this specific path. With the assumption that passengers are rational, they choose the path of the maximum utility (e.g. the least travel time) in their thinking/ mental model.

However, due to information's incompleteness and belief's incorrectness, passengers' thinking might deviate from the reality, in the case of delays. In other terms, passengers' incomplete information and passengers' belief on delay propagation might affect their thinking about route choices, and therefore affect their actual route choice in reality. For instance, passengers might not know all the possible alternative paths (i.e. the set of "considered paths" is incomplete and does not include all the possibilities); or the considered paths will result in some misleading deviations (e.g. arrival time) between passengers' thinking and the reality. Especially for passengers who need transfers at intermediate stations, an inaccurate time estimation may mislead passengers missing some feasible connections (i.e. the feeding train/ bus arrives later than the theoretically connected train/ bus departs). Therefore, passengers' chosen route with the "best" utility in their thinking might not always be the optimal one in reality.

5.2.2 Multi-layer time-space-event graph

In this subsection, we propose a novel method, named multi-layer time-space-event graph, to indicate passengers' information of original and disposition timetable, passengers' belief on delay propagation, their thinking of "considered paths" in a time-space network, and the possible deviations between passengers' thinking and reality. We use Figure 5.1 (a railway network) as an example to explain this new method, which can also be applied to other public transport similarly.

There are five layers in the multi-layer time-space-event graph, which can be extended based on the schedule-based structure. The layers are all time-space-event graphs, as follows:

(1) Original timetable: the time and space (or station) of the off-line schedule of train operations;

(2) Disposition timetable: the time and space of on-line train operations;

(3) Information layer: when, where, and which train's operation does the information cover with full precision;

(4) Passengers' thinking layer: generated based on the first three layers, to describe at each time and each station, what is passengers' thinking of each train's operation;

(5) Passengers' actual route choice in reality: based on the forth layer, the shortest path is chosen, which determines the actual travel.

The first two layers are the same for each passenger; but the last three layers are for each passenger depending on their departure time, the time of each train at each station.

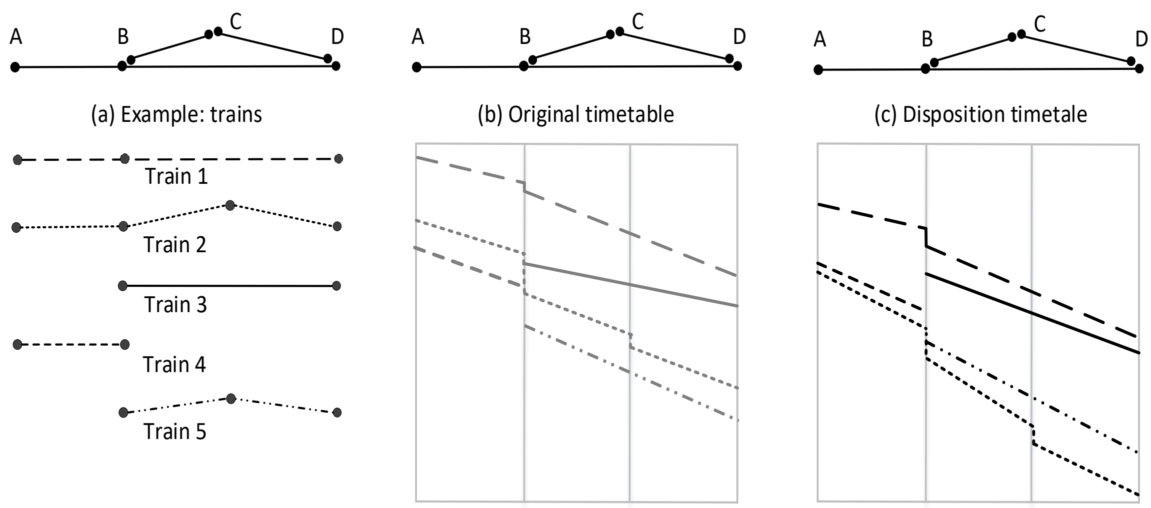

Figure 5.1: Example: railway network, original timetable and disposition timetable

For the details, in Figure 5.1, the example railway network consists of four stations (i.e. station A, B, C, D), connected by two physical routes from station A to station D: one physical route is A-B-D, the other is A-B-C-D. Figure 5.1(a) shows five example trains with different stop patterns, different line styles meaning different trains: Train

1 (loosely dashed line) is A-B-D, Train 2 (dotted line) is A-B-C-D, Train 3 (solid line) is B-D, Train 4 (dashed line) is A-B, and Train 5 (dash-dot line) is B-D.

The graph in the subfigures (b) and (c) in Figure 5.1 reports train operations in a time (y-axis) – space (x-axis) network from station A to station D. The grey lines show the operations of the example five trains in the original timetable, see Figure 5.1(b); while the black lines show the five trains' corresponding operations in an example disposition timetable in the case of delays, see Figure 5.1(c).

We assume one passenger plans to travel from the origin (station A) to destination (station D) with a given planned departure time (the orange node). In the case of "No delay", passengers know all the details of the original timetable and choose the fastest route to reach destination. The red line in the Figure 5.2 shows this passenger's initial plan, choosing Train 2 from station A to station B, and then transferring to Train 3 until station D.

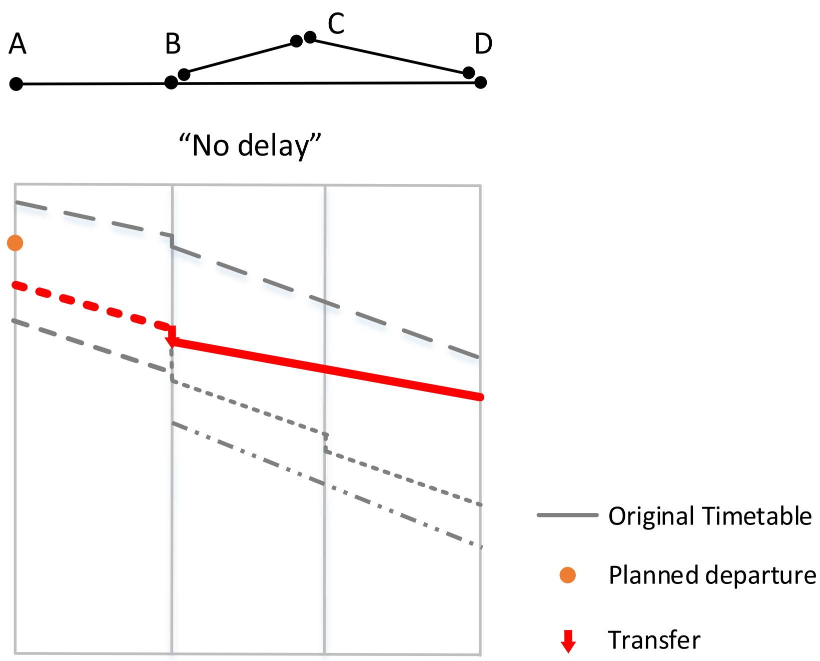

Figure 5.2: Passenger's route choice in case of "No delay"

In the case of delays, the green area in Figure 5.3 indicate the set of events (e.g. trains' departure, arriving) in time and space for which information is fully available to passengers. X-axis describes which stations have available information, while y-axis shows for how long the information is available. The green and red nodes describe the start and end time of available information, respectively. We assume that the operating companies could release the disposition timetable via the media channels (e.g. mobile device or station display) immediately after train delays are detected. That means the start time (the green node) of available information depends on when passengers start to check the information. The time horizon of available information could be shorter or longer because the disposition timetable may change as consequence of successive delays. For instance, Figure 5.3 show the "infinite" available information, while the following Figure 5.6 and Figure 5.7 have a given end time (red node) of information.

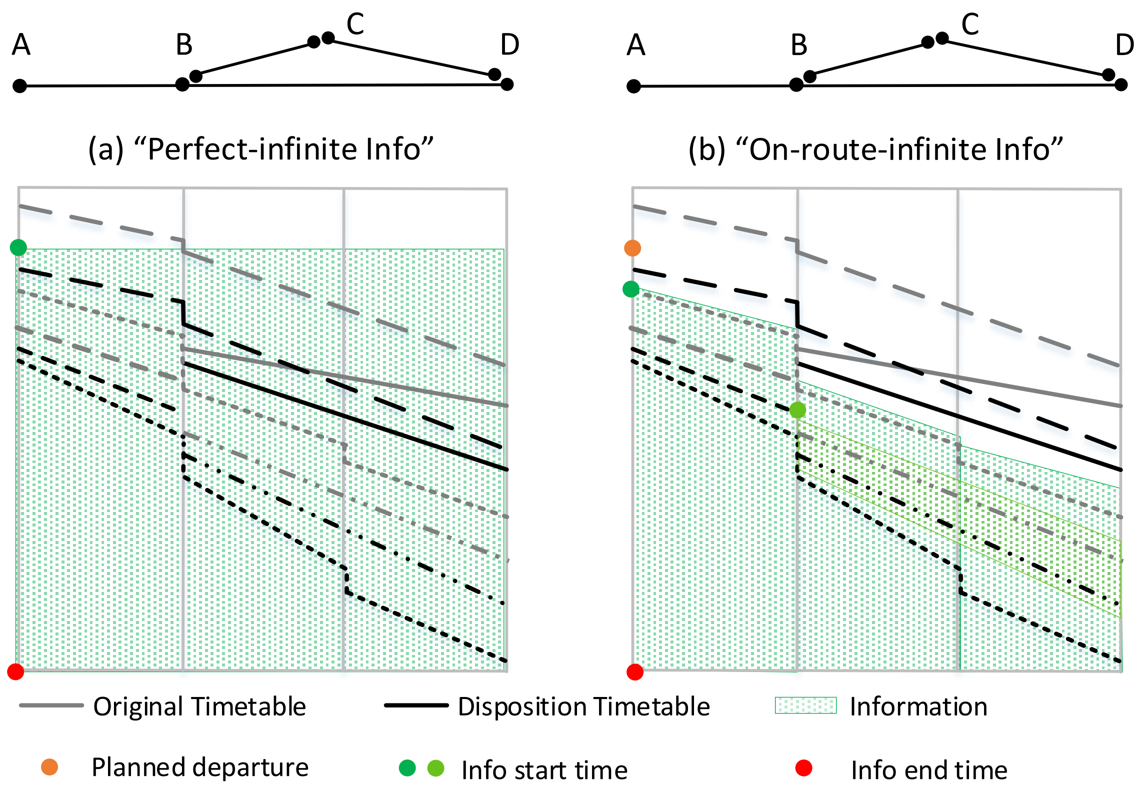

Figure 5.3: Explanation of information layer

The Figure 5.3(a) show the instance of "Perfect information", meaning passengers perfectly know train delays and disposition timetable (i.e. all trains' departure and arrival time at all the stations throughout the whole network) within information's start and end time. This "Perfect information" may happen to the frequent users of mobile channels, who may often check the information about train delays and have a higher chance to know comprehensively the details of disposition timetable (i.e. trains' arrival and departure). Especially, the "Perfect-infinite information", Figure 5.3(a), is the ideal example that passengers are informed of all the train delays that will occur in the network until their destination. With "Perfect information", the green area has always the shape of rectangle within a given time length of the provided information. The start time of information is the same as passengers' planned departure time, meaning the green node overlaps with the orange node.

In contrast, the Figure 5.3(b) show the instance of "On-route information", in which passengers could be aware of delays only at the moment they arrive at specific stations (i.e. their planned departure station and the possible transfer stations) and partially know the rescheduled train services of disposition timetable related to these stations (e.g. depart from, or stop at) within the given information time horizon. This "On-route information" may happen to some passengers who might not check the mobile channels very frequently, and rely on the information displayed at train stations. With "On-route information", the green area are a series of trapezoid shapes within a given time length of the provided information. For each station, the information's start time is the same as the time that passengers arrive at this station. Specifically, passengers start to know the information at the planned departure station (station A in Figure 5.3) at the same time as their initial plan (taking Train 2), meaning the green node is at the same as the departure time of Train 2 (the "No delay" route choice) in the original timetable in Figure 5.2. For the following possible transfer stations (e.g. station B), passengers could know the information about trains departing from these stations after their earliest possible arrival time to these stations (the light green nodes).

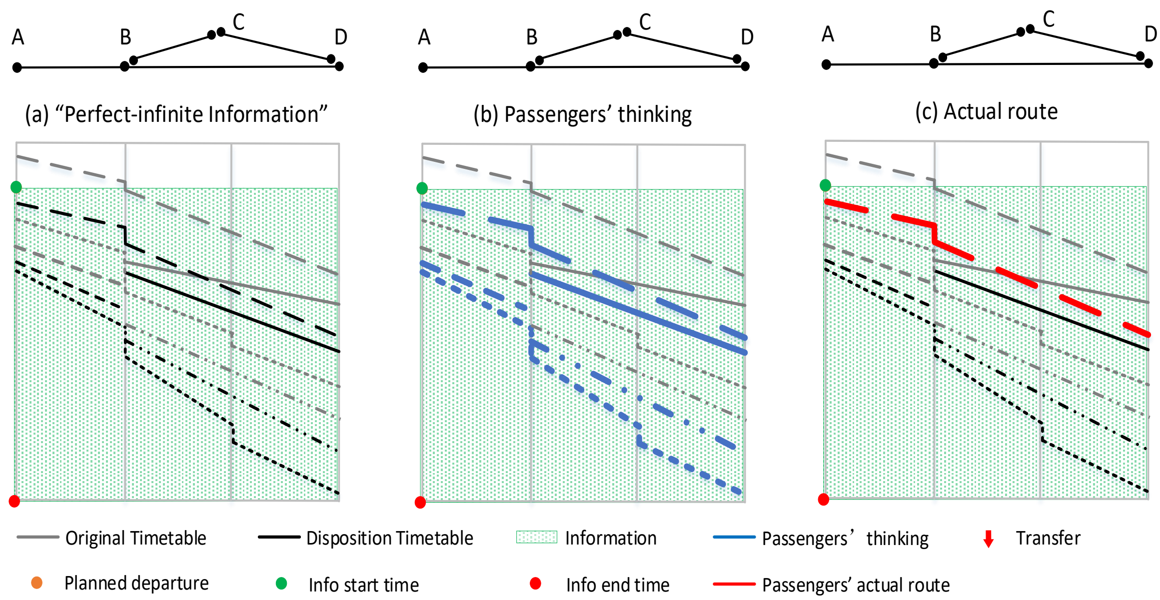

Figure 5.4: Explanation of passengers' thinking and route choice with "Perfect-infinite Information"

In Figure 5.4 and Figure 5.5, the blue lines show the time and space of the possible route between origin to destination in passengers' thinking with the specific information. The red lines show the actual time and space of the chosen route out of the passengers' thinking as it is in reality (as updated/ adjusted in the disposition timetable), which is called "actual route" in this chapter. We assume that at the moment of the information dissemination, passengers immediately start their thinking and make their route choice, with a rational choice process, for minimising travel time among all the "considered paths" in their thinking. As is shown in these figures, within the time horizon of information, passengers' actual routes match with their thinking (i.e. the red lines overlapping with the blue ones), where the time and space are coincident with the disposition timetable.

In addition, the time horizon of information also affects the number of "considered paths". Here are two extreme examples: As the minimum, if passengers have zero information (meaning the green area in Figure 5.4 is negligible or non-existent), their "considered paths" do not include any possible alternatives of disposition timetable at all; while the "Perfect-infinite Information" has the largest set of "considered paths" based on the information of disposition timetable.

Compared to "Perfect Information", the main impact of "On-route Information" on passengers is the smaller set of "considered paths" because of the delayed information at passengers' planned departure station, and the possible transfer stations. At passengers' planned departure station (station A), with "On-route Information", they might miss the trains, which are planned to depart earlier than the passengers' planned departure time (orange node) in the original timetable; but actually are delayed in the disposition timetable (e.g. Train 1), and depart earlier than the moment at which passengers start to receive this information (green node). In a short, the missed trains are called "delayed earlier-departure trains" as they are earlier-departure trains, normally not available for passengers departing at the given time, which are delayed enough; and therefore could enter the set of considered paths. Similarly, "On-route Information" might result in passengers missing some train connections; especially the trains that depart earlier than passengers' arrival time at the possible transfer stations (e.g. station B). For example, in Figure 5.4, passengers' best route choice with the "Perfect-infinite Information" is Train 1. While in Figure 5.5, with the "On-route-infinite Information", passengers miss this direct train (Train 1) due to not including this in their "considered paths"; subsequently they miss the train connection (e.g. Train 3) at the transfer station B because their arrival time with Train 4 is too late.

It has to be mentioned that, with other different delays or disposition timetables, there are also possibilities that either perfect or on-route information does not affect passengers' route choices, either at the planned departure station or the transfer stations. For instance, it can be the case that there is no "delayed earlier-departure trains" (e.g. Train 1) or passengers can arrive at the transfer station early enough to perform their transfer.

There are two tables in Appendix C as explanations of passengers’ route choices. Table C.1 explain the cases of “No delay”, “Perfect-infinite Information” and “On-route-infinite Information”, which are according to Figure 5.2, Figure 5.4 and Figure 5.5, respectively. Table C.2 and Table C.3 explain the cases of incomplete information and passengers’ belief according to the following Figure 5.6 and Figure 5.7.

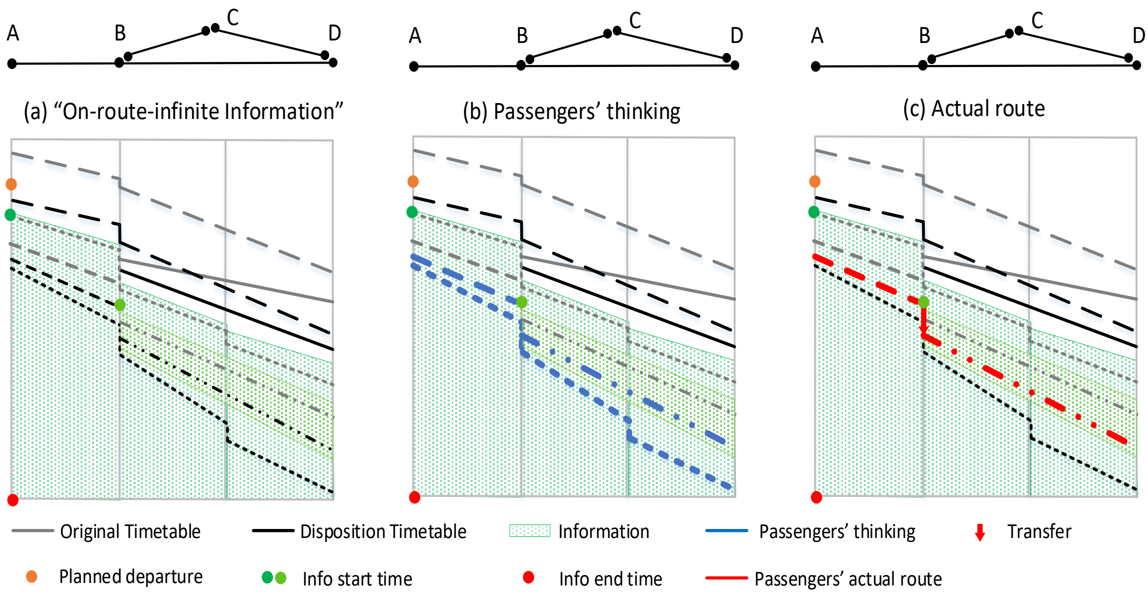

Figure 5.5: Explanation of passengers’ thinking and route choice with “On-route-infinite Information”

Except the infinite information as in Figure 5.3, 5.4 and 5.5, passengers behave in the public transport network based on their belief on delay propagation beyond the information end time, until the end of their journey. Passengers’ belief is an inference about the further delays and network operations, based on their available knowledge of the information they have about the disposition timetable and the original timetable.

Figure 5.6 (a) shows an example of finite “Perfect Information” with a given time horizon of information (the end time of information is marked in red node). Figure 5.6 (b) and (c) show the instances of passengers’ “Schedule-stubborn belief”, in which passengers believe that the train delays for which they have information, will disappear in the subsequent stations and their trains will reach their destinations without any delay. We call it schedule-stubborn because passengers believe that trains will operate as in the original timetable, schedule for those events happening in the future, for which they have no information, no matter how much is the current delay. This assumption often makes sense because the buffer time exists in the original timetable and the trains might catch up their delays. For example, considering the blue lines in Figure 5.6 (b), passengers know Train 1 (loosely dashed line) has delays at station B, but they still believe this train will reach station D on time (the same time as in the original timetable). For small delays and no delay propagation, this is often the case.

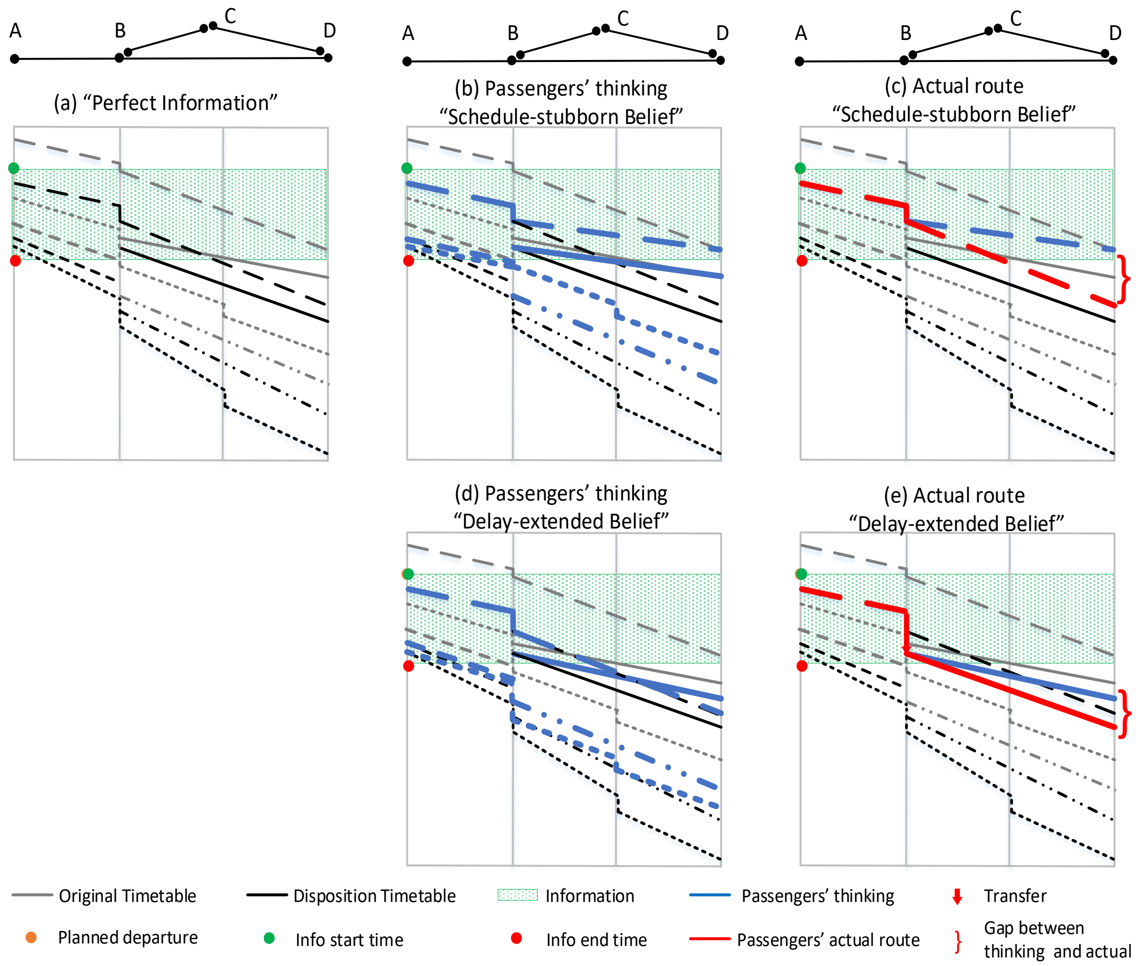

Figure 5.6: Explanation of passengers' thinking and route choice with "Perfect Information" and different beliefs

Figure 5.6 (d) and (e) show the instances of passengers' "Delay-extended belief". We call it delay-extended because passengers believe that the train delays for which they have information will extend along the subsequent stations. As an example, passengers assume the delays constant in time, and with the same amount as the delay at the last station for which they have information. Different, complex mechanisms of delay belief can be applied within such a construction, such as Bayesian belief updating (e.g. Arentze and Timmermans, 2005). As is shown by the blue lines in Figure 5.6 (d), passengers know the delay of Train 1 (9 minutes, solid line) at station

B, and they believe this train will reach station D with the same amount of delay (9 minutes).

We explain the complexity and efficiency of the proposed multi-layer time-space-event graph method with different combinations of incomplete information and passengers' belief as follows.

Limited time horizon of information, together with individual passenger's belief, affects the correctness of the "considered paths". Here we mean the absolute correctness at the level of precise timing, meaning the departure and arrival time at each station of one considered path are exactly the same as in the actual disposition timetable. For instance, the time passengers believe to arrive at station D is incorrect, in Figure 5.6 (b). The arrival time at station D in passengers' thinking (blue lines) differs from that in the actual disposition timetable (black lines), because of the lack of information about station D and their "Schedule-stubborn belief". In general, with the limited information time horizon, it is hard for passengers to have a belief which is absolutely correct about future operations of every single train at each station.

However, this might not affect passengers' final route choice (see red lines in Figure 5.6 (c)) within the "considered paths" if they have appropriate belief. In other terms, the route (either direct train or multiple trains with connections) which passengers believe is the earliest to arrive at the destination, can be indeed the fastest in reality. For instance, in Figure 5.6 (c) considering incomplete information with "Schedule-stubborn belief", passengers can choose the same route, as the "Perfect-infinite Information" in Figure 5.4 (c), i.e. the optimal direct route (Train 1), even if the arrival delay at destination in reality are more than what they think.

Similar results can also be seen in Figure 5.7, as an example of "On-route Information" with two different beliefs: "Schedule-stubborn belief" and "Delay-extended Belief". Figure 5.7 (a) shows an example of finite "On-route Information" with a given time horizon of information (the end time of information is marked in red node). In Figure 5.7 (e), passengers with "Delay-extended Belief" take the best possible route choice: taking Train 4 from station A, transferring at station B to Train 5. This route is the same as the best/ fastest choice in case of "On-route-infinite Information", as shown in Figure 5.5 (c).

In general, limited information results in a gap between passengers' thinking and the reality about the arrival time at the destination. That means, passengers may underestimate or overestimate the delays because of the lack of information, based on their belief. In Figure 5.6 (c) and (e), Figure 5.7 (c) and (e), we can see the gap (curly red braces) between passengers' thinking (blue line) and the actual route (red line).

In case of incomplete information, passengers might choose different routes composed of different transfers or stops, or along different physical routes (such as changing from A-B-C-D to A-B-D). There is the possibility that the incomplete information and passengers' belief mislead their final route choice (red lines in Figure 5.6 and 5.7). We divide this misunderstanding into two categories.

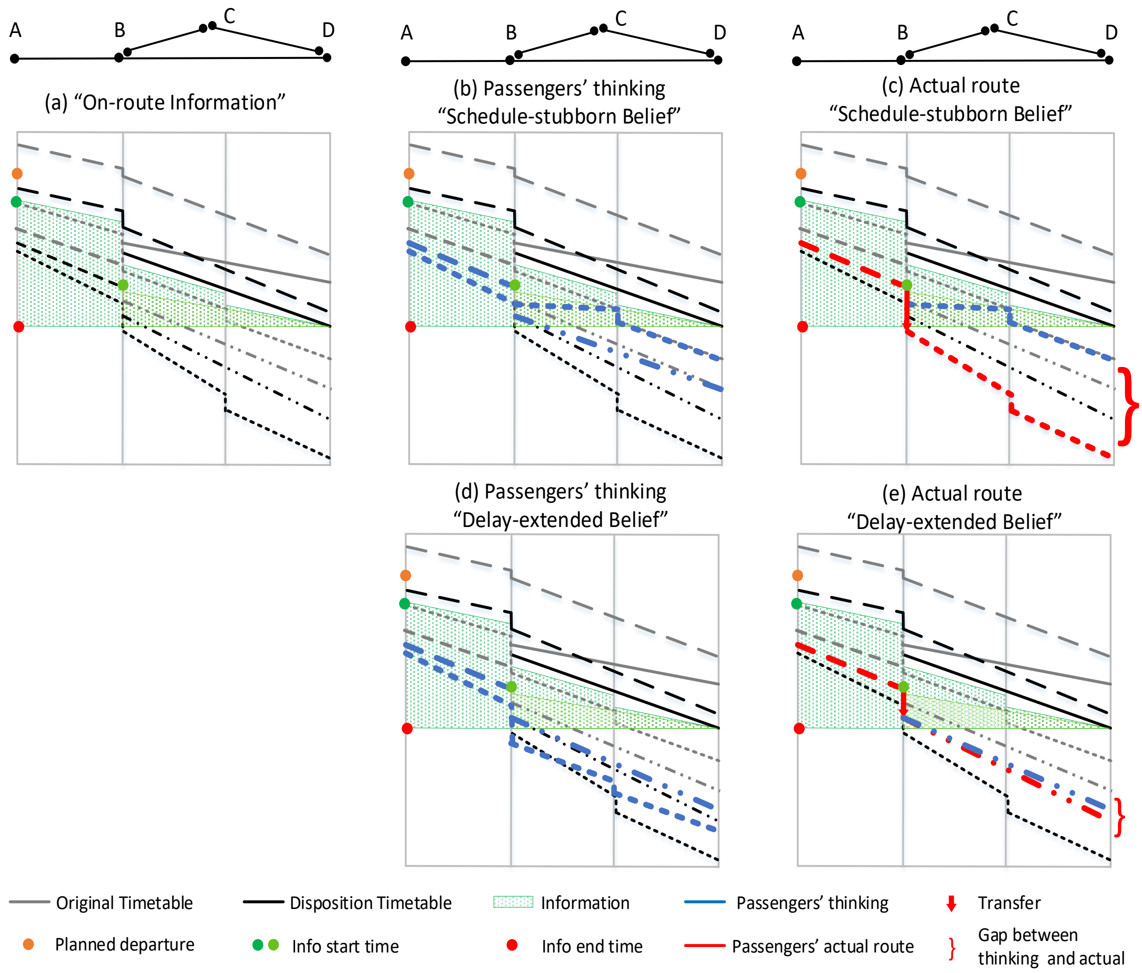

Figure 5.7: Explanation of passengers' thinking and route choice with "On-route Information" and different beliefs

The first category is that the route that passengers believe arriving the earliest at the destination, is indeed not the fastest, but still feasible, in reality. For instance, in Figure 5.6 (e) the incomplete information with "Delay-extended belief", passengers think Train 3 should reach station D earlier than Train 1, and choose the route with transfer from Train 1 to Train 3. In reality this is not the fastest route, instead the direct Train 1 is the fastest one as in Figure 5.4 (c). Similar results can be found with the comparison of Figure 5.7 (c) and Figure 5.5 (c), where “Schedule-stubborn Belief” misleads passengers’ thinking to choose a slower route.

The second category is that the route, feasible according to the passengers’ thinking, is actually infeasible in reality. This infeasibility can be caused by different reasons: some trains are cancelled in the disposition timetable, or some connections, feasible in passengers’ thinking, do not work in reality. For instance, passengers have zero information in the case of delays and they insist on their initial plan as in Figure 5.2 (Train 2 from station A to station B, and then transferring to Train 3 until station D). In reality, because of delays, this connection between Train 2 and Train 3 does not work anymore in the actual disposition timetable.

It has to be mentioned that, this kind of misleading passengers’ thinking might happen to any combinations of the incomplete information and passengers’ belief. It depends on multiple influencing factors: passengers’ origin, destination and planned departure time, the train time deviations between disposition timetable and original timetable, the type and time horizon of incomplete information, as well as the correctness of passengers’ belief. Briefly, this new proposed method, multi-layer time-space-event graph, can sufficiently describe these influencing factors and possible results of route choices.

5.2.3 Graph-based route choices

The proposed method is based on the following assumptions of a given set of passenger groups. In this chapter, we use the following notation. P is the set of all the passenger groups. Each passenger group $p \in P$ includes one or more than one passenger. The total number of passengers in each group is $|p|$. Passengers in the same group p arrive at the same origin o_p at the same time w_p and bound for the same destination d_p. We assume that passengers within the same group p will have the same type of information and belief, resulting in the same “considered paths” in their thinking. Hence, passengers in the same group p move together in the network along the same route (we assume this route as unique, possibly breaking ties arbitrarily), due to the assumptions that each train has infinite capacity and each passenger aims at reaching his/ her destination in the minimum time. Moreover, once the train schedule is fixed, each p moves in the network independently from the others, i.e., the choice of a particular routing for a given passenger group p does not influence the routing of any other passenger groups $r \in P \setminus \{p\}$. The passenger groups can also be generalized, to represent heterogeneous passengers with only one passenger in each group, which demands more detailed passenger data.

As is discussed in Subsection 5.2.2, the multi-layer time-space-event graph is constructed based on both the original (planned) and disposition (actual) timetables. The disposition timetable is generally computed by an optimisation model, managing train rescheduling problem based on the original timetable and train delays. In the present chapter, we chose a microscopic train scheduling model which can check the local microscopic feasibility from an operations-centric view (e.g. D'Ariano et al., 2007), based on the alternative graph model (Mascis and Pacciarelli, 2002). In general, other timetable rescheduling models, with either a macroscopic or a microscopic representation, can be applied to this new proposed method. We apply the iterative model introduced in Corman et al. (2017) composed of train scheduling and passenger routing problems, and apply one heuristic solution approach to generate the disposition timetable in which train retiming, reordering, rerouting and train connections are considered.

The basic time-space graph of the whole network is represented as $G = (N, E)$. Nodes in the set N correspond to operations, each associated with the occupation of a block section by a train. Arcs in the set E model time relations between the starting times of some pairs of operations. For each operation node $i \in N$, we know the time of each operation $\bar{t_i}$ in the disposition timetable; for the same operation, the time t_i is in original timetable. The set F represents all the trains (or buses) running on the entire public transport network. Each train $f \in F$ is composed of a sequence of nodes and arcs. The set S represents all the stations in the public transport network.

Here we define explicitly how to indicate the information, passengers' thinking and route choice based on the original and disposition timetables. For each passenger group $p \in P$, a graph related to passenger routing can be represented as $G_p = (N_p, E_p \bigcup C_p)$. G_p is generated based on G. N_p, E_p and C_p are sets of nodes, fixed arcs and connection arcs that are necessary for passengers to take into account route choices. The set N_p contains the nodes taking into account the origin o_p and destination d_p of the flow associated with p. Each node $i \in N_p$ refers to a specific operation of a train at a specific station. Fixed arcs in E_p link arriving/ departing passengers of p to the first/ last train they may take on their journey. By letting δ_{o_p} be the set of nodes associated with train departures from the origin of p and by letting δ_{d_p} be the set of arrivals at the destination of p, E_p is the set of arcs (o_p, j) with $j \in \delta_{o_p}$ plus the arcs (i, d_p) with $i \in \delta_{d_p}$. C_p is the set of all possible connection arcs, which can be feasible or infeasible. There is an arc $(i, j) \in C_p$ for a pair of nodes i, associated with a train arrival, and j, associated with a train departure, at/ from the same station, for all stations. The set F_p and S_p represent the trains (or buses) and stations related to passengers' route choices.

For each node $i \in N_p$, we use apostrophes and bars to denote the layers of the graph model. $t_i^{'}$ is the time of each operation in passengers' thinking. t_i and $\overline{t_i}$ are respectively the time of the same operation in the original and disposition timetable. Specifically, considering the whole trip of each passenger group p, $t_{o_p}^{'}$ is the starting time at origin o_p and $t_{d_p}^{'}$ is the arrival time at d_p in passengers' thinking. t_{o_p} and t_{d_p} are the planned starting and arrival time based on the original timetable. $\overline{t_{o_p}}$ and $\overline{t_{d_p}}$ represent the actual starting and arrival time according to the disposition timetable in reality.

In case of incomplete information about train delays, G_p can be described as a union of an information graph G_p^{Info} and a graph of passengers' belief G_p^{Belief} for each group p (Equation 5.1). G_p^{Info} includes the nodes and arcs for which there is information available, about the actual train operation in case of delays. G_p^{Belief} represents the remaining nodes and arcs that are necessary for passenger routing but for which there is no information available and passengers need to make an expectation about train operations.

$$G_p = G_p^{Info} \bigcup G_p^{Belief}, \forall p \in P. \tag{5.1}$$

G_p^{Info} represents the available information for each passenger group p. Specifically in this chapter, we discuss two types of information: "Perfect Information" and "On-route Information". The graph of "Perfect Information" for each passenger group p is represented as $G_p^{PI} = (N_p^{PI}, E_p^{PI})$. N_p^{PI}, E_p^{PI} are sets of nodes and arcs for which the "Perfect Information" setup provides information available to passengers in each group p. $t_{start,p}^{PI}$ and $t_{end,p}^{PI}$ represent the start and end time of "Perfect Information", respectively. For all the nodes in the set of N_p^{PI}, the time of each operation $\overline{t_i}$ in the disposition timetable should be between the range of the start and end time of information (Equation 5.2).

$$N_p^{PI} = \{i \in N_p \mid t_{start,p}^{PI} \le \overline{t_i} \le t_{end,p}^{PI}\}, \forall p \in P. \tag{5.2}$$

For "Perfect information", passengers know the details of the disposition timetable for all the nodes $i \in N_p^{PI}$. Their thinking of train time $t_i^{'}$ is equal to the disposition timetable $\overline{t_i}$. Formally,

$$t_i^{'} = \overline{t_i}, \forall i \in N_p^{PI}, \forall p \in P. \tag{5.3}$$

Particularly, with the "Perfect-infinite Information", all the passenger groups P know the information about the time in disposition timetable for their whole trip. Formally, in Equation 5.4, i.e. the information is available earlier than the passengers' starting time at the origin and last until the arrival at the destination.

$$\overline{t_{o_p}} \geq t_{start}^{PI} \wedge \overline{t_{d_p}} \leq t_{end}^{PI}, \forall p \in P. \tag{5.4}$$

The graph of "On-route Information" for each passenger group p is represented as $G_p^{OI} = (N_p^{OI}, E_p^{OI})$. N_p^{OI} , E_p^{OI} are sets of nodes and arcs for which the "On-route Information" setup provides information available to passengers in each passenger group p . The start time of "On-route Information" is station-dependent, represented by $t_{start,s,p}^{OI}$ for each station $s \in S_p$. Passengers can only know the delays after reaching the station and receiving the information. In other terms, $t_{start,s,p}^{OI}$ means the earliest arrival time at each station s . For instance, passengers' arrival time at the origin station s_{o_p} is equal to passengers' departure time t_{o_p} in the original timetable (i.e. planned departure time). Formally:

$$t_{start,s_{o_p}}^{OI} = t_{o_p}, \forall p \in P. \tag{5.5}$$

For each station s_i in the remaining set of nodes $N_p^{OI} \setminus \{o_p\}$, passengers start to know the "On-route Information" at the earliest arrival time of the trains (or buses) which pass this station. Formally:

$$t_{start,s,p}^{OI} = \min_{i \in N_p^{OI} \setminus \{o_p\}: s_i = s} \{\overline{t_i}\}, \forall s \in S_p, \forall p \in P. \tag{5.6}$$

$t_{end,p}^{OI}$ represents the end time of "On-route Information" in the disposition timetable, which is identical for each node i. For each node in the set of N_p^{OI} , the time of each operation $\overline{t_i}$ in the disposition timetable should be between the range of the start and end time of information (Equation 5.7).

$$N_p^{OI} = \{i \in N_p \mid t_{start,s_i,p}^{OI} \leq \overline{t_i} \leq t_{end,p}^{OI}\}, \forall p \in P. \tag{5.7}$$

For all the nodes $i \in N_p^{OI}$ of "On-route Information", passengers' thinking of train time $t_i^{'}$ is equal to the disposition timetable $\overline{t_i}$. Formally,

$$t_i^{'} = \overline{t_i}, \forall i \in N_p^{OI}, \forall p \in P. \tag{5.8}$$

Particularly, with the "On-route-infinite Information", Equation 5.9 is true considering the whole trip of each passenger group p. The actual departure time $\overline{t_{o_p}}$ in case of delays is at the same, time, or later than the planned departure time t_{o_p}; the end time of information is later than the passengers' arrival time at destination.

$$\overline{t_{o_p}} \geq t_{o_p} \wedge \overline{t_{d_p}} \leq t_{end}^{OI}, \forall p \in P. \tag{5.9}$$

G_p^{Belief} represents the graph of passengers' belief for each group p. Specifically in this chapter, we discuss two types of belief: "Schedule-stubborn belief" and "Delay-extended belief". The graph of "Schedule-stubborn belief" is represented as $G_p^{SB} = (N_p^{SB}, E_p^{SB})$. With the "Schedule-stubborn belief", passengers believe that trains will operate as in the original timetable, for those events happening in the future, for which they have no information, no matter how much the current delay is. Formally in Equation 5.10, for the node i in the set N_p^{SB}, passengers' belief time $t_i^{'}$ is equal to the original timetable t_i.

$$t_i^{'} = t_i, \forall i \in N_p^{SB}, \forall p \in P. \tag{5.10}$$

The graph of "Delay-extended belief" is represented as $G_p^{DB} = (N_p^{DB}, E_p^{DB})$. With the "Delay-extended belief", passengers in each group p believe the delays will extend (i.e. keep constant, equal to the last known value) for each train $f \in F_p$. $l_{f,p}$ represents the last node, for which passengers in group p have the information of the delay of train f. The delay at this node $d_{l_{f,p}}$ is computed in Equation 5.11, as the difference between the time at which the event associated to this node occurs, in the original and disposition timetable.

$$d_{l_{f,p}} = \overline{t_{l_{f,p}}} - t_{l_{f,p}}, \forall f \in F_p, \forall p \in P. \tag{5.11}$$

In this case, the nodes in the set N_p^{DB} can be separated into subsets $N_{f,p}^{DB}$ for each train $f \in F$. Passengers in the group p believe that the train delay $d_{l_{f,p}}$ will remain the same for the successive nodes that are related to train f. In other terms, the delay is extended over other events, keeping unchanged its magnitude. As is written in Equation 5.12, their thinking of arrival/ departure time is a constant shift of the time in original timetable t_i plus the believed train delay $d_{l_{f,p}}$.

$$t_i^{'} = t_i + d_{l_{f,p}}, \ \forall i \in N_{f,p}^{DB}, \forall f \in F_p, \forall p \in P. \tag{5.12}$$

In case of public transport delays, due to different combination of passengers' incomplete information and belief of delay propagation, the graph to describe passengers' thinking $G_p = G_p^{Info} \bigcup G_p^{Belief}$ is also different. As is shown in Equations 5.3, 5.8, 5.10 and 5.12, the time of each operation for each node $i \in N_p$ in passengers' thinking $t_i^{'}$ is different according to "Perfect Information", "On-route Information", "Schedule-stubborn belief" and "Delay-extended belief". The different thinking time results in changes of feasibility of connections in the set of connection arcs C_p. For instance, some connections are feasible in the graph $G_p = G_p^{PI} \bigcup G_p^{SB}$ in passengers' thinking, but may be infeasible in other graph such as $G_p = G_p^{OI} \bigcup G_p^{DB}$. The connection is feasible, only if passengers think that the connected train departs sufficiently later than the arrival of the passengers from a feeder service. $C_p^{'}$ shows the set of feasible connection arcs in passengers' thinking of public transport delays. In Equation 5.13, the difference between passengers' thinking time of two nodes of the connection arc $(i, j) \in C_p^{'}$, is larger than the minimum time c_{ij} for transferring passengers from the feeder train to the connected one. $t_i^{'}$ and $t_j^{'}$ differentiate with different combinations of incomplete information, Equation 5.3 and 5.8, as well as passengers' belief, Equation 5.10 and 5.12.

$$C_p^{'} = \{(i, j) \in C_p \mid t_j^{'} \geq t_i^{'} + c_{ij}, \forall i \in N_p, \forall j \in N_p\}, \forall p \in P. \tag{5.13}$$

For $\forall p \in P$, passengers choose the route with the least travel time in their thinking/ mental model in case of public transport delays. The formulation of passengers' best route choice is as follows.

$$\min t_{d_p}^{'} - t_{o_p}^{'} \tag{5.14}$$

$$\sum_{j \in \delta_{o_p}} q_{o_p, j} = 1 \tag{5.15}$$

$$\sum_{i \in \delta_{d_p}} q_{i, d_p} = 1 \tag{5.16}$$

$$\sum_{i \in N_p : (i,j) \in E_p \bigcup C_p^{'}} q_{ij}^p = \sum_{k \in N_p : (j,k) \in E_p \bigcup C_p^{'}} q_{jk}^p \quad \forall j \in N_p \setminus \{o_p, d_p\} \tag{5.17}$$

$$q_{ij}^p \in \{0,1\} \tag{5.18}$$

For each passenger, the objective function is the minimisation of the total travel time in passengers' thinking, as in Equation 5.14. Equation 5.15 to Equation 5.17 define a min-cost flow problem to assign a path to the passengers from origin to destination. q_{ij}^p defined for each passenger group p, is associated with the use of feasible connections $(i,j) \in C_p^{'}$ by the passengers and to the assignment of passengers to arcs in E_p. Specifically, Equation 5.15 and 5.16 describe the departure of passengers from the origin and the arrival at destination, respectively, while Equation 5.17 models the typical flow balance constraints at intermediate nodes. Equation 5.18 defines type and bounds for the optimisation variables used. q_{ij}^p is equal to 1 if arc $(i,j) \in E_p \bigcup C_p^{'}$ belongs to the path of p, and 0 otherwise.

In summary, the graph-based passenger routing is explained in the following Algorithm 5.1.

Algorithm 5.1 Graph-based passenger routing

1. Initialisation: Compute the time t_i in original timetable and $\overline{t_i}$ in disposition timetable for each operation node $i \in N$ in the basic graph $G = (N, E)$.
2. Updating: For each passenger group $p \in P$, generate $G_p = (N_p, E_p \bigcup C_p)$ with a union of two graphs: information G_p^{Info} and belief G_p^{Belief}:
   a) Updating the time $t_i^{'}$ for each node $i \in N_p^{PI}$ with "Perfect Information", or for $i \in N_p^{OI}$ with "On-Route Information".
   b) Updating $t_i^{'}$ for each node $i \in N_p^{SB}$ with "Schedule-stubborn belief", or for $i \in N_p^{DB}$ with "Delay-extended belief".
   c) Compute the feasible connections $(i,j) \in C_p^{'}$ in passengers' thinking via checking the feasibility $t_j^{'} \geq t_i^{'} + c_{ij}$.
3. Passenger routing: For each passenger group $p \in P$, compute the optimal route in passengers' thinking by solving the optimisation problem Equations (5.14) to (5.18).

The time $\overline{t_i}$ in the disposition timetable is computed according to the time t_i the original timetable, based on train rescheduling model (Corman et al., 2017). Each passenger group $p \in P$ has a specific graph $G_p = (N_p, E_p \bigcup C_p)$ in their thinking about train delays and train connections, which is different in the condition of different types of information and belief. On one hand, the time $t_i^{'}$ in passengers' thinking is the same as the time $\bar{t}_i$ in the disposition timetable for each operation node i in the graph of information G_p^{Info}. Different information types determine which nodes have available information: $i \in N_p^{PI}$ with "Perfect Information", or $i \in N_p^{OI}$ with "On-Route Information". On the other hand, the time $t_i^{'}$ in passengers' thinking related to the graph about belief G_p^{Belief} may deviate from the time $\bar{t}_i$ in the disposition timetable. More specifically, the time is updated for $i \in N_p^{SB}$ with "Schedule-stubborn belief", or for $i \in N_p^{DB}$ with "Delay-extended belief". Furthermore, the feasibility of connections $(i, j) \in C_p^{'}$ needs to be checked. Passengers will only choose the connections that they think are feasible $t_j^{'} \geq t_i^{'} + c_{ij}$. According to the graph $G_p = (N_p, E_p \bigcup C_p)$ describing passengers' thinking with the updated time of each node and the check of feasibility of connections, passengers' best/ fastest route is calculated.

As a result, passengers' delay and some related performance measure can be calculated for each passenger group $p \in P$. Due to the deviation between the time $t_i^{'}$ in passengers' thinking and the time $\bar{t}_i$ in reality for some operation nodes, this graph-based passenger routing method may lead to some interesting results. For instance, passengers' route choice based on the graph in their thinking cannot be fulfilled in the disposition timetable. It can be the case that some believed connections from passengers' thinking are infeasible in the reality, or vice versa. It can be also be the case that, passengers may miss the optimal route due to lack of information. This will be evaluated via the experiments and results in Section 5.3.

5.3 Experiments and results

We perform a large set of experiments, based on the initial demand and various train delays of Dutch railway network presented in Corman et al. (2017). We test different cases with including different passengers' origin, destination and planned departure time, different delays, different incomplete information and passengers' belief, as well as different information time horizon. Passengers' behaviours and delays are analysed from the results.

5.3.1 Dutch railway network considered

The network, reported in Figure 5.8, comprises a significant region of the Netherlands, including Amsterdam, Schiphol and Utrecht. The traffic pattern we consider is the real timetable for year 2010, which is schematically reported in Figure 5.8, where every line is a service running twice per hour per direction. The network is highly interconnected and there are several bottlenecks. As a result, there is a need for frequent rescheduling in peak hours in case of disturbances, since any small delay may propagate to other trains with a domino effect.

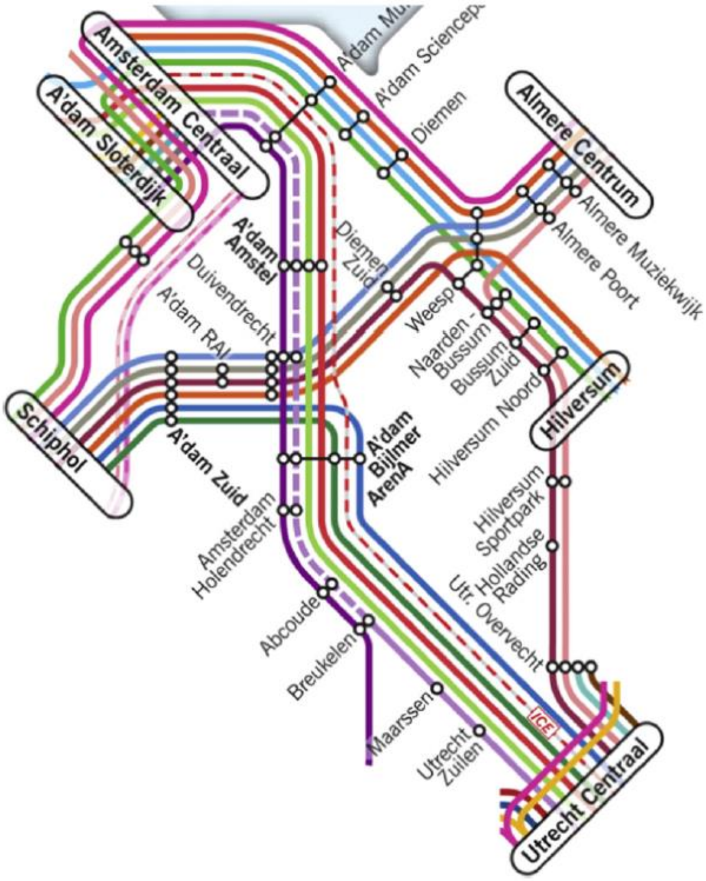

Figure 5.8: Test case infrastructure description (elaboration from sporenplan.nl)

As for the instances evaluated, we consider 20 instances with extended delays, generated with the Weibull distribution, fitted to real data, presented in Corman et al. (2017). Entrance delays, for all trains in the network, are defined based on a three-parameter Weibull distribution. In each instance, train delays are randomly generated according to a typical Monte-Carlo scheme. All computational results are reported as averages over this combination of 20 instances (when not aggregated at higher level).

As presented in Corman et al. (2017), there are 101 trains running on the network, with the average delay of 37 seconds; 52.3% trains have a positive delay at the start of their trip; and 6.4% trains have a delay larger than 5 min at the start of their trip (a typical punctuality measure in railways).

The OD pairs considered in the experiments are based on the average volume of passengers at the considered stations as published by the infrastructure manager, as presented in Corman et al. (2017). Triples odw in ODW are generated by considering the largest 22 OD pairs in the network, for different time windows. Each odw has a number of passengers.

For the 20 delay instances and the mentioned passengers ODW, we test the two types of infinite information (i.e. “Perfect-infinite Information” and “On-route-infinite Information”) as well as the four combinations of passengers’ information and belief mentioned in Subsection 5.2.2. For the incomplete information, different time horizons of information, varying each 5 min from zero to infinite, are tested.

5.3.2 Infeasible routes

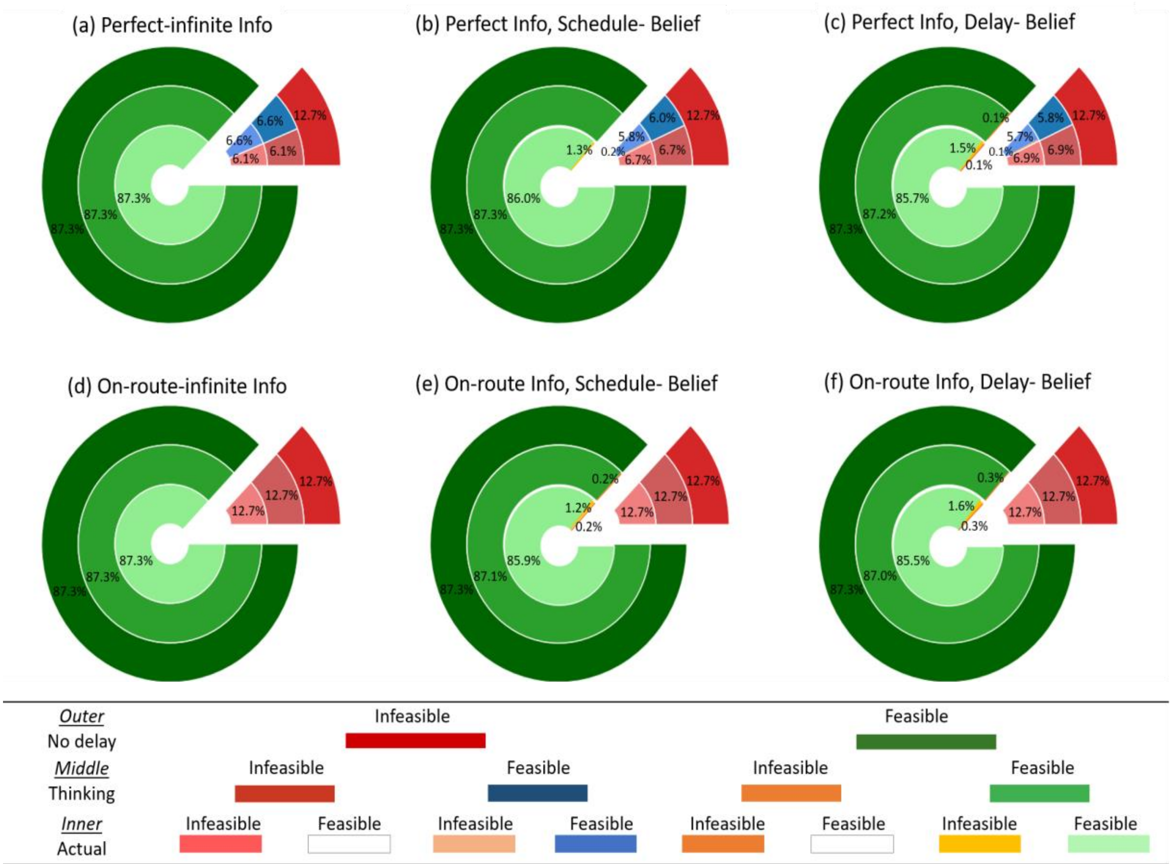

Figure 5.9: The average percentage of feasible/ infeasible routes, comparing different information and belief types (Incomplete information time horizon: average of possibilities from zero to infinite)

Figure 5.9 shows the average percentage of feasible/ infeasible routes in the tested 20 delay instances, comparing different information types (perfect or on-route) which are infinite, or incomplete with different belief types (schedule-stubborn or delay-extended). For the incomplete information, different time horizon of information, varying each 5 min from zero to infinite, are calculated on average.

In each subplot of Figure 5.9, there are three layers to show the percentage of route feasibility: in the case of original timetable i.e. "No delay" (the outer layer), in passengers' thinking (the middle layer) based on defined infinite, complete or incomplete information, and in the actual disposition timetable in reality (the inner layer) due to the corresponding thinking. As is shown in the legend, different families of colours are to mark the changes of route feasibility. The family of green colours means always feasible in the three layers. The family of red colours shows always infeasible in the three layers. The family of blue colours shows the routes which get feasible from infeasible from outer layer to inner, i.e. surprisingly better performance than expected. The family of orange colours shows the routes which get infeasible from feasible from outer layer to inner, i.e. worse performance experienced from plan to reality.

For each layer, the total percentage is 100%. The result of "No delay" (the outer layer) is consistent in each subplot: 87.3% routes (dark green) are feasible; 12.7% (dark red) are infeasible because of the passengers who have a late departure time, wanting to take the last train or missing the connection to their destination.

First, we check the feasible routes of "No delay" (dark green). Thanks to the infinite information of the disposition timetable, i.e. both "Perfect-infinite Information", subfigure (a), and "On-route-infinite Information", subfigure (d), all of these routes are also feasible both in passengers' thinking (green) and in reality (light green) in case of delays. If the information is incomplete (the four subplots on the right: b, c, e and f), most routes (more than 99%) are still feasible in passengers' thinking (green in the middle layer). However, around 2% of these routes, feasible in passengers' thinking, are actually infeasible in reality (orange and yellow in the inner layer) due to the misleading incomplete information plus passengers' wrong belief.

Specifically with the same type of belief, passengers suffer slightly more infeasible routes (less than 1%) in case of "On-route Information", subfigure (e) or (f), compared to "Perfect Information", subfigure (b) or (c). With the same information type, the "Delay-extended Belief", subfigure (c) or (f), causes a bit more infeasible routes (less than 1%) than "Schedule-stubborn Belief", subfigure (b) or (e).

Then, we check the infeasible routes of "No delay" (dark red). With the "On-route Information" (the bottom three subplots: d, e and f), all of these routes are infeasible, either in passengers' thinking or in reality. This is due to the reason that passengers who think they do not have feasible route in “No delay” will not go to the station to check the information of train delays in case of “On-route Information”. In contrast, with the “Perfect Information” (the top three subplots: a, b and c), approximately 50% of these infeasible routes (“No delay”) significantly become feasible (the family of blue colours). That means some train delays together with the “Perfect Information” can result in benefits on route choices, meaning either proper train services or appropriate connection, for passengers who have a late departure time.

Specifically, “Perfect-infinite Information”, subfigure (a), gives the most benefits, 52% infeasible routes in “No delay” get feasible in both passengers’ thinking (blue) and the actual disposition timetable in reality (light blue). If passengers have incomplete “Perfect information” and “Schedule-stubborn Belief”, subfigure (b), results in slight more feasible routes (around 2%) compared to “Delay-extended Belief”, subfigure (c), in passengers’ thinking (blue). In both the two subplots, there are very few routes (around 0.2% of the total amount of routes), which are infeasible (light orange) in the actual disposition timetable in reality.

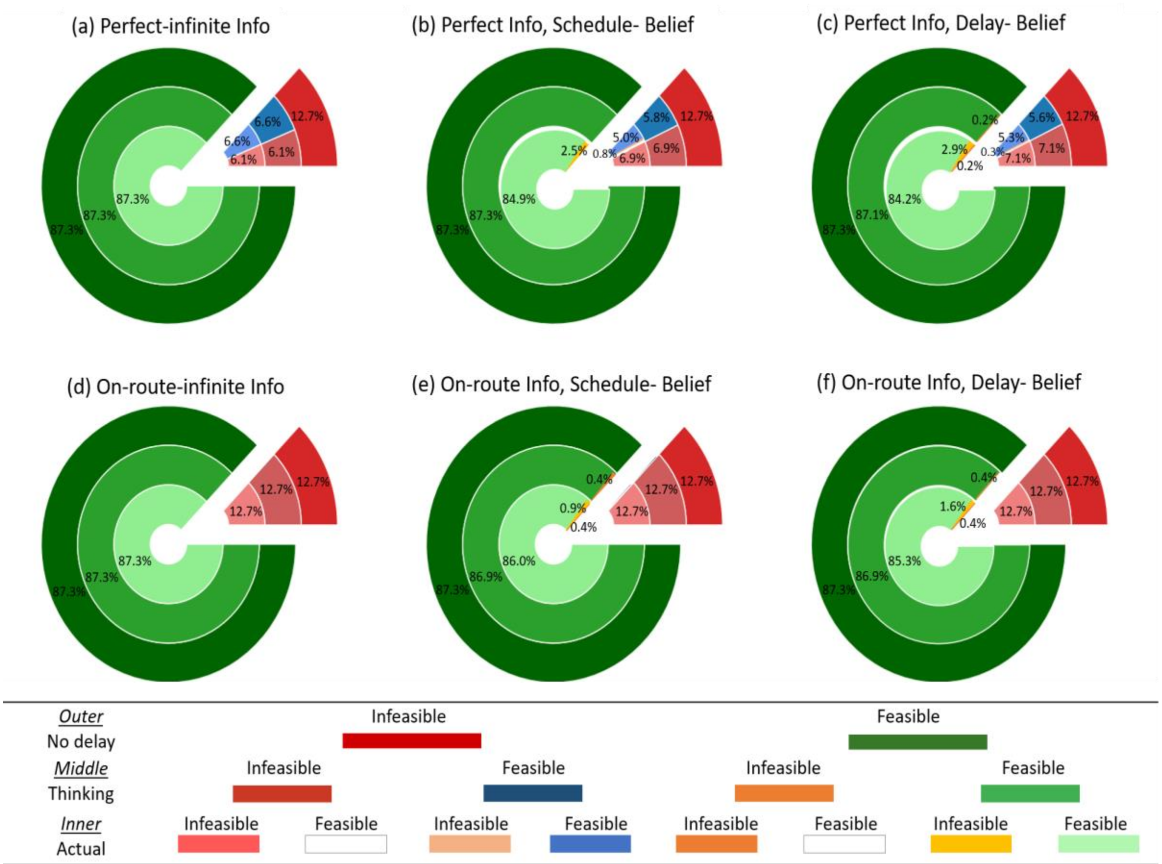

Figure 5.10: The average percentage of feasible/ infeasible routes, comparing different information and belief types (Incomplete information time horizon: 10 min)

Figure 5.10 and Figure 5.11 are two figures with the consistent structure of pie charts as in previous Figure 5.9. Instead of calculating the average of all different time horizon of incomplete information cases, we show two specific examples of information time horizon to show the effects of short or long time horizon to passengers' route choices: 10 min in Figure 5.10, 30 min in Figure 5.11.

Comparing the results of the same type of incomplete information and belief in the Figure 5.10 and Figure 5.11, similar results can be found out, no matter of the belief type. With "Perfect Information", the longer the information time horizon, the more passengers' routes are feasible. For instance, with the "Schedule-stubborn belief", subfigure (b), the 30 min time horizon results in 2.1% more routes feasible in total (the sum of light green and light blue) compared to 10 min information. Similarly, the increased percentage of total feasible routes (from 10 min to 30 min information) are 1.8% with "Delay-extended Belief". For "On-route Information", in case of the "Delay-extended belief", subfigure (f), the 30 min time horizon results in 0.2% more routes feasible (light green) compared to 10 min.

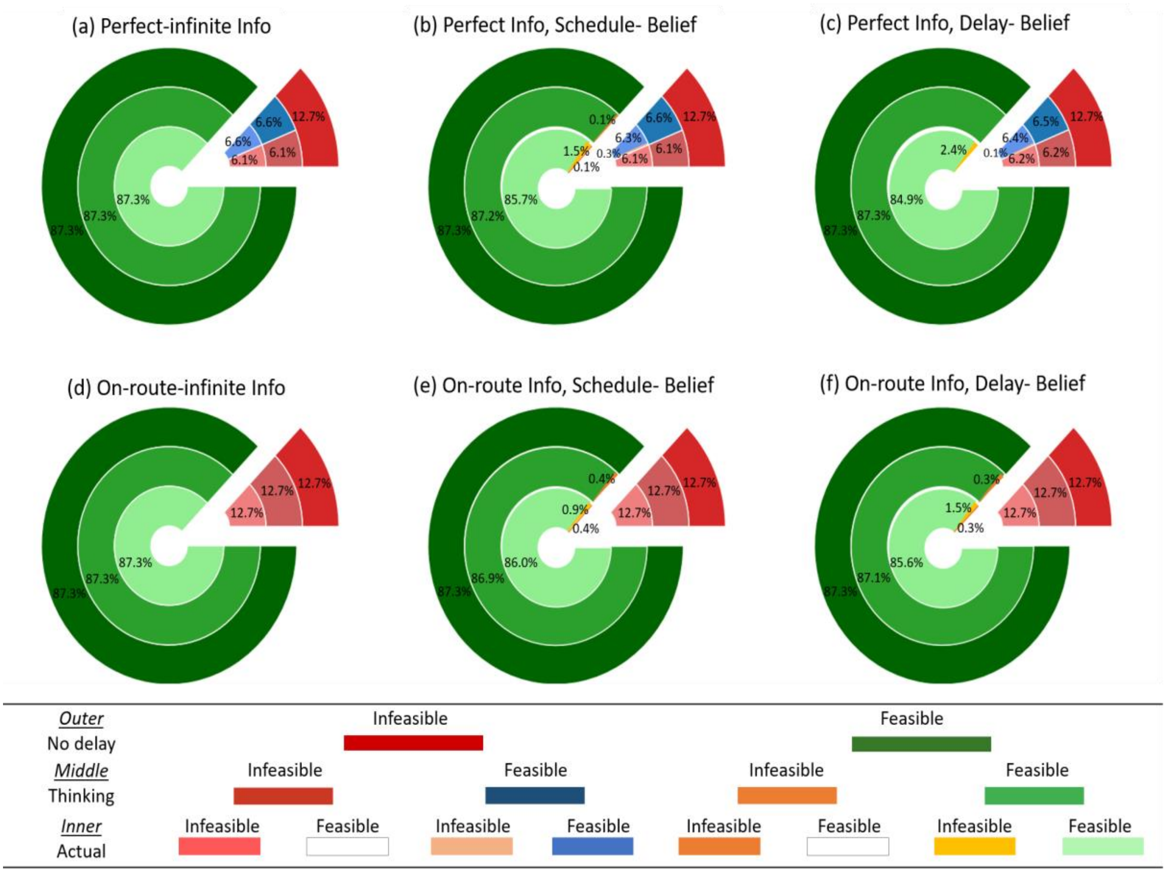

Figure 5.11: The average percentage of feasible/ infeasible routes, comparing different information and belief types (Incomplete information time horizon: 30 min)

Table 5.1 shows the average percentage of passenger numbers on the feasible/ infeasible routes in the tested 20 delay cases with either complete information or incomplete information. The difference from Figure 5.9 is this table counts the number of passengers on each route, and not the amount of groups. We keep the consistency of different families of colours as is explained in Figure 5.9.

By comparing the data in Table 5.1 with Figure 5.9, Figure 5.10 and Figure 5.11, the absolute value is slightly different because of the different/ heterogeneous volume of OD pairs, but the results seem very similar in the sense of comparing different information, belief type, and information time horizon. That means the percentage of passengers' numbers is similar to the percentage of the routes without considering passengers' numbers.

Table 5.1: Average percentage of passenger numbers on the feasible/ infeasible routes, comparing different information and belief types

			Infeasible				Feasible			
No delay			14.6%				85.4%			
			Infeasible		Feasible		Infeasible		Feasible	
Perfect-infinite Info			7.4%		7.2%		0		85.4%	
On-route-infinite Info			14.6%		0		0		85.4%	
			Infeasible	Feasible	Infeasible	Feasible	Infeasible	Feasible	Infeasible	Feasible
All Avg.	Perfect Info, Schedule- Belief	Thinking	8.1%		6.5%		0		85.4%	
		Actual	8.1%	0	0.2%	6.2%	0	0	1.0%	84.4%
	Perfect Info, Delay- Belief	Thinking	8.2%		6.3%		0		85.4%	
		Actual	8.2%	0	0.1%	6.2%	0	0	1.4%	84.0%
	On-route Info, Schedule- Belief	Thinking	14.6%		0		0.1%		85.3%	
		Actual	14.6%	0	0	0	0.1%	0	1.2%	84.1%
	On-route Info, Delay- Belief	Thinking	14.6%		0		0.2%		85.3%	
		Actual	14.6%	0	0	0	0.2%	0	1.6%	83.7%
10 min Info	Perfect Info, Schedule- Belief	Thinking	8.5%		6.1%		0		85.4%	
		Actual	8.5%	0	0.8%	5.3%	0	0	2.2%	83.2%
	Perfect Info, Delay- Belief	Thinking	8.4%		6.1%		0.1%		85.4%	
		Actual	8.4%	0	0.3%	5.9%	0.1%	0	3.1%	82.3%
	On-route Info, Schedule- Belief	Thinking	14.6%		0		0		85.4%	
		Actual	14.6%	0	0	0	0	0	0	85.4%
	On-route Info, Delay- Belief	Thinking	14.6%		0		0.1%		85.3%	
		Actual	14.6%	0	0	0	0.1%	0	0.9%	84.4%
30 min Info	Perfect Info, Schedule- Belief	Thinking	7.4%		7.1%		0.1%		85.4%	
		Actual	7.4%	0	0.3%	6.8%	0.1%	0	1.6%	83.8%
	Perfect Info, Delay- Belief	Thinking	7.5%		7.1%		0		85.4%	
		Actual	7.5%	0	0.2%	6.9%	0	0	2.0%	83.5%
	On-route Info, Schedule- Belief	Thinking	14.6%		0		0.2%		85.2%	
		Actual	14.6%	0	0	0	0.2%	0	1.0%	84.2%
	On-route Info, Delay- Belief	Thinking	14.6%		0		0.2%		85.3%	
		Actual	14.6%	0	0	0	0.2%	0	1.4%	83.9%

5.3.3 Passengers' delays

To study passengers' delays, we consider the passengers whose thinking and actual routes are both feasible, as shown with the family of green colours in Figure 5.9.

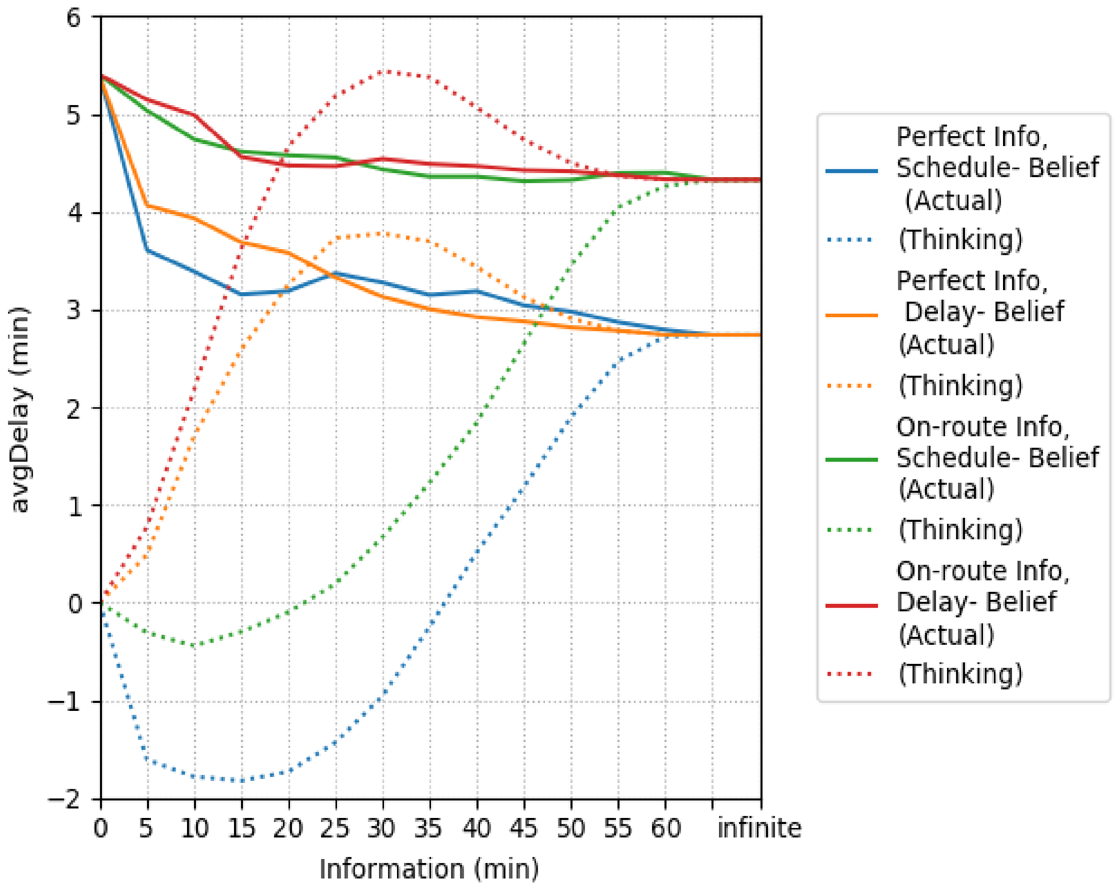

Figure 5.12: The average passengers' thinking delay and actual delay with different information time horizon

Figure 5.12 shows the trend of passengers' average delay (y-axis, min) both in their thinking (dotted line) and in reality (solid line) following the increasing information time horizon (x-axis, min). The four colours report the combinations of two incomplete information types and two belief types.

If passengers have no information of train delays (information is zero), they think they will not have delay (average delay is zero) but they will actually suffer the largest average delay (5.4 min) in actual train operations. Overall, passengers' actual average delay in reality (solid lines) decreases with the increase of the disseminated information. Especially, within approximately 15 min time horizon, the delay decreases in a relatively faster way. More specifically, the “Perfect Information” always leads to less average delay in reality, compared to the “On-route Information”, at any information time horizon no matter of passengers’ beliefs. With the infinite information, the benefit of “Perfect Information” on reducing actual delays gets maximum to 1.6 min.

The gap between the red and green solid lines is small, around 0.1 min, meaning passengers’ belief does not matter too much with “On-route Information” in real life cases. In contrast, the gap between the blue and orange lines is larger, meaning passengers’ beliefs do affect their actual delays in case of “Perfect Information”. Specially, if passengers do not have enough (less than 25 min) information, “Schedule-stubborn belief” leads to smaller delays, around 0.6 min on average; while if they have enough (more than 25 min) information, “Delay-extended Belief” is slightly better to passengers, saving around 0.2 min on average.

With “Schedule-stubborn belief”, passengers could do the optimal choice (blue or green solid lines) with proper information, but they believe they should have smaller delays (blue or green dotted lines). This could lead to annoyance, for instance, according to the “prospect theory” (e.g. Van de Kaa, 2008) which passengers value losses of time and have loss aversion for travel time given a reference value which they know. Passengers actually could choose the fastest route with the limited information in the case of train delays, even though there are losses of time between their thinking assumes (reference value) and reality.

In addition, with “Schedule-stubborn belief”, passengers even think they could have negative delays, compared to their planned arrival time at destination based on original timetable (off-line schedule). For instance, with “Perfect Information” and “On-route Information”, passengers think they will have negative delays within 36 min (blue dotted line) and within 20 min (green dotted line) information, respectively.

In contrast, with “Delay-extended belief”, passengers might be pessimistic about train delays, meaning their thinking is worse than actual delays in reality. For instance, if passengers have “On-route Information” in the range 19 – 55 min, passengers overestimate train delays in their thinking. With “Perfect Information”, the corresponding time range is 22 – 55 min.

With any given time horizon of information, “Perfect Information” always results in less delay in passengers’ thinking than “On-route Information”, in any type of belief. From Figure 5.12, we compare the dotted lines: delay of the red line is always higher than the orange one, and delay of the green line is higher than the blue one.

With the same type of information, with a limited information time horizon, the “Delay-extended Belief” results in a larger average delay in passengers’ thinking than the “Schedule-stubborn Belief”. From Figure 5.12, we compare the dotted lines: delay of the red line is always higher than the green one, and delay of the orange line is higher than the blue one.

Nevertheless, with infinite information, passengers’ thinking delay (the dotted lines) is the same as the actual delay (the solid lines) in reality, which only depends on the types of information.

In Table 5.2, we report on the detailed statistical results of passengers’ thinking and actual delays with different information types, belief types and information time horizon. The columns refer to the statistical results on the delays in minutes: mean, median, 10th and 90th percentile. The top two rows report the two infinite information cases. The following group of rows shows the data of all the possibilities of different information time horizon in the four different information and belief cases; the last two group of rows especially show the data with 10 min and 30 min information time horizon, respectively. For an easier check, we mark the data related to thinking delays in a grey colour.

There is a larger tail of negative delays, about -4 min with “Perfect-infinite Information”, compared to the 10th percentile of “On-route-infinite Information”. That means in case of train delays, some passengers could arrive earlier than their original plan (off-line schedule) with sufficient information about train delays. The 90th percentile of delays in “Perfect-infinite Information” is around 0.5 min less than “On-route-infinite Information”. The benefits of “Perfect-infinite Information” are also reflected in the smaller mean (1.6 min) and smaller median (0.9 min) delays.

With the “Schedule-stubborn Belief”, passengers’ thinking delays has a larger gap to the actual delays, compared to the results with “Delay-extended Belief” in any type of information. Particularly, with “Perfect Information” and “Schedule-stubborn Belief”, passengers suffer the largest gap between their thinking delays and actual delays: the deviation of mean and median delays is around 3 min, the 10th percentile is about 1.4 min, and the 90th percentile is about 4 min.

With the 10 min time horizon of information, most passengers who have the “Schedule-stubborn Belief” think they will not have any delay with any type of information, as is shown in the 90th percentile of thinking delays is zero. However, these passengers can suffer a largest delay of about 10 min in reality.

Table 5.2: Statistical results of passengers' thinking and actual delays (min) with different information

			Mean	Median	10th percentile	90th percentile
	Perfect-infinite Info		2.71	2.8	-4.1	9.52
	On-route-infinite Info		4.33	3.7	-0.18	9.98
All possible Info time horizon	Perfect Info, Schedule- Belief	Thinking	0.33	0	-5.07	5.98
		Actual	3.26	2.98	-3.63	9.88
	Perfect Info, Delay- Belief	Thinking	2.65	1.5	-2.68	9.43
		Actual	3.31	2.87	-3.63	9.98
	On-route Info, Schedule- Belief	Thinking	1.71	0	0	7.25
		Actual	4.55	3.7	-0.12	10.02
	On-route Info, Delay- Belief	Thinking	3.92	2.65	0	10.02
		Actual	4.58	3.7	-0.12	10.2
10 min Info	Perfect Info, Schedule- Belief	Thinking	-1.78	0	-10.8	0
		Actual	3.39	3	-3.62	10.02
	Perfect Info, Delay- Belief	Thinking	1.7	0	-1.22	7.72
		Actual	3.94	3	-3.68	12.75
	On-route Info, Schedule- Belief	Thinking	-0.44	0	0	0
		Actual	4.78	3.88	-0.12	10.18
	On-route Info, Delay- Belief	Thinking	2.18	0.25	0	6.98
		Actual	4.99	3.72	0	11.35
30 min Info	Perfect Info, Schedule- Belief	Thinking	-0.95	0	-9	3.07
		Actual	3.28	2.82	-4.35	10.02
	Perfect Info, Delay- Belief	Thinking	3.78	2.87	-2.5	11.1
		Actual	3.13	2.82	-4.15	9.52
	On-route Info, Schedule- Belief	Thinking	0.67	0	0	4.65
		Actual	4.43	3.7	-0.17	10.13
	On-route Info, Delay- Belief	Thinking	5.44	5.02	0	12.07
		Actual	4.54	3.7	-0.12	10.97

With the 10 min time horizon of "Perfect Information", most passengers think they will have negative delay (i.e. earlier arrival at destination), as the 10th percentile of thinking delays is -10.8 min.

With the 30 min time horizon of information, most passengers who have "Delay-extended Belief" overestimate the delays in a pessimistic way: the thinking delays are larger than the actual delays, more than 1 min in the 90th percentile.

In reality, as expected, passengers' actual delays decrease with the increase of information time horizon (from 10 min to 30 min), especially a decrease of 0.8 min for the "Perfect Information" and "Delay-extended Belief".

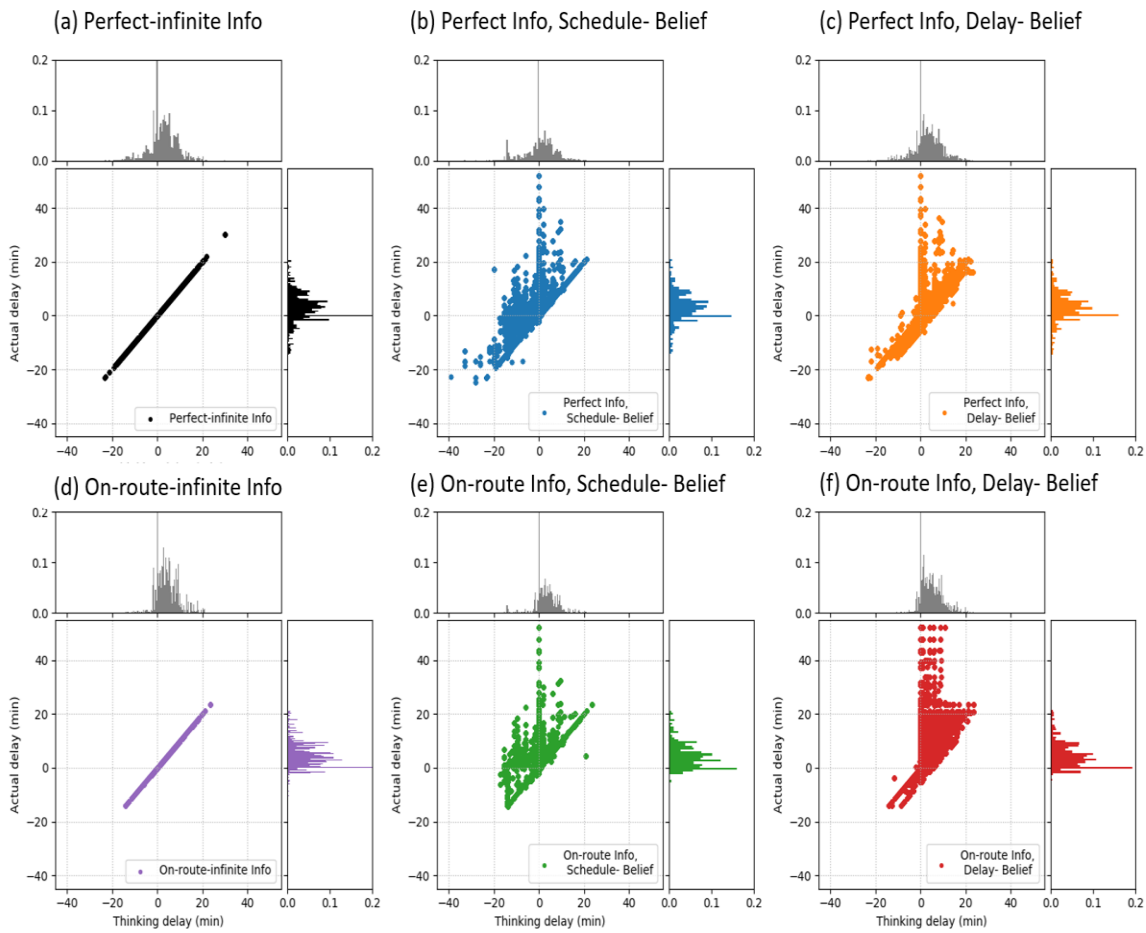

Figure 5.13: Passengers' thinking delays vs. actual delays, comparing different information and belief types (Incomplete information time horizon: each 5 min from zero to infinite)

The bi-axis scatter plots in Figure 5.13 display the thinking delay (x-axis, min) and actual delay (y-axis, min) for each individual passenger in different information cases (in different colours), including the results of different time horizon varying from zero to infinite. The two histograms at the sides of each scatter plot are the probability density of passengers' thinking delays (grey colours) and actual delays (same colour as the scatter) of different information cases.

With the infinite information, a consistent correlation between passengers' thinking delay and actual delay is shown in a diagonal line in the left two scatter plots. The "Perfect-infinite Information", subfigure (a), causes more passengers having the negative delays in reality, compared to "On-route-infinite Information", subfigure (d). One proof is that the least delay, black colour, is less than -20 min, much less than the least delay in purple colour, about -18 min; the other proof is the larger delay distributions between -20 min to zero in the black colour.

With the finite information, as is seen from the four plots with the colour of blue, orange, green and red, there are passengers whose thinking delay is the same as the actual delay, same as the diagonal line in infinite information. However, many other passengers exist whose actual delays (y-axis) are larger than their thinking delays (x-axis), shown in the scatters upper than the diagonal line. Among which, many passengers think they will not have delay (zero, in x-axis), but actually have positive delay (y-axis) in reality. Especially with "Schedule-stubborn Belief" (blue and green), most passengers underestimate the delays in their thinking. With the "Delay-extended Belief", we can identify some scatters under the diagonal line in the orange and red colour, meaning some passengers overestimate the delays in their thinking. The deviations is not too large; the overestimations are not too much away from the diagonal line.

Passengers' thinking delays (x-axis, grey distributions) depend more on passengers' belief based on their known information, usually "Delay-extended Belief" (the right two subplots: c and f) resulting in more thinking delays compared to "Schedule-stubborn Belief" (the middle two subplots: b and e).

However, in reality, passengers' actual delays (y-axis, colourful distributions) depend more on the disseminated information rather than their beliefs. With "Perfect Information", the blue and orange distributions, subfigures (b) and (c), have a longer trail between -20 min to 0, meaning more passengers can have negative actual delays (y-axis), compared to the "On-route Information", subfigures (e) and (f).

Figure 5.14 and Figure 5.15 are the same kind of plots as in previous Figure 5.13. Instead of plotting all different time horizon of incomplete information cases, here gives two specific examples of information time horizon to show the effects of short or long time horizon to passengers: 10 min in Figure 5.14, and 30 min in Figure 5.15.

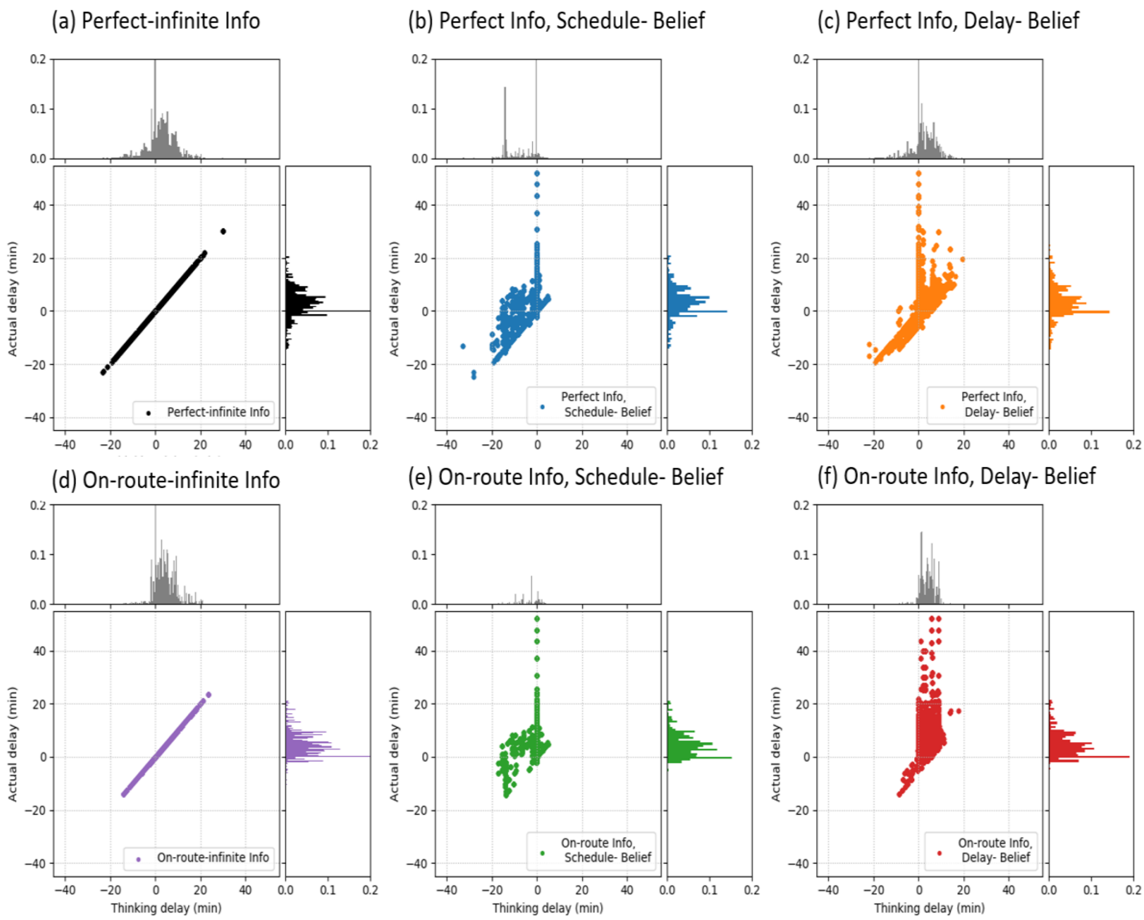

Figure 5.14: Passengers' thinking delays vs. actual delays, comparing different information and belief types (Incomplete information time horizon: 10 min)

In Figure 5.14 and Figure 5.15, the scatters on y-coordinate meaning passengers have delays in reality instead of no-delay as in their thinking. With 10 min information time horizon, compared to 30 min time horizon, we can see that more nodes, subfigures (b) and (e), are accumulated in the part that passengers think the delays are negative for "Schedule-stubborn Belief".

With 30 min information time horizon, compared to 10min time horizon, we can find out there are less scatters on the y-coordinate in all the four incomplete information cases (the four subplots on the right: b, c, e and f). Furthermore, the scatters get more convergent to the diagonal line (i.e. passengers' thinking delay is same as actual delay). In other terms, as expected, with longer information time horizon, passengers' thinking delays get more similar with the actual delays experienced in reality.

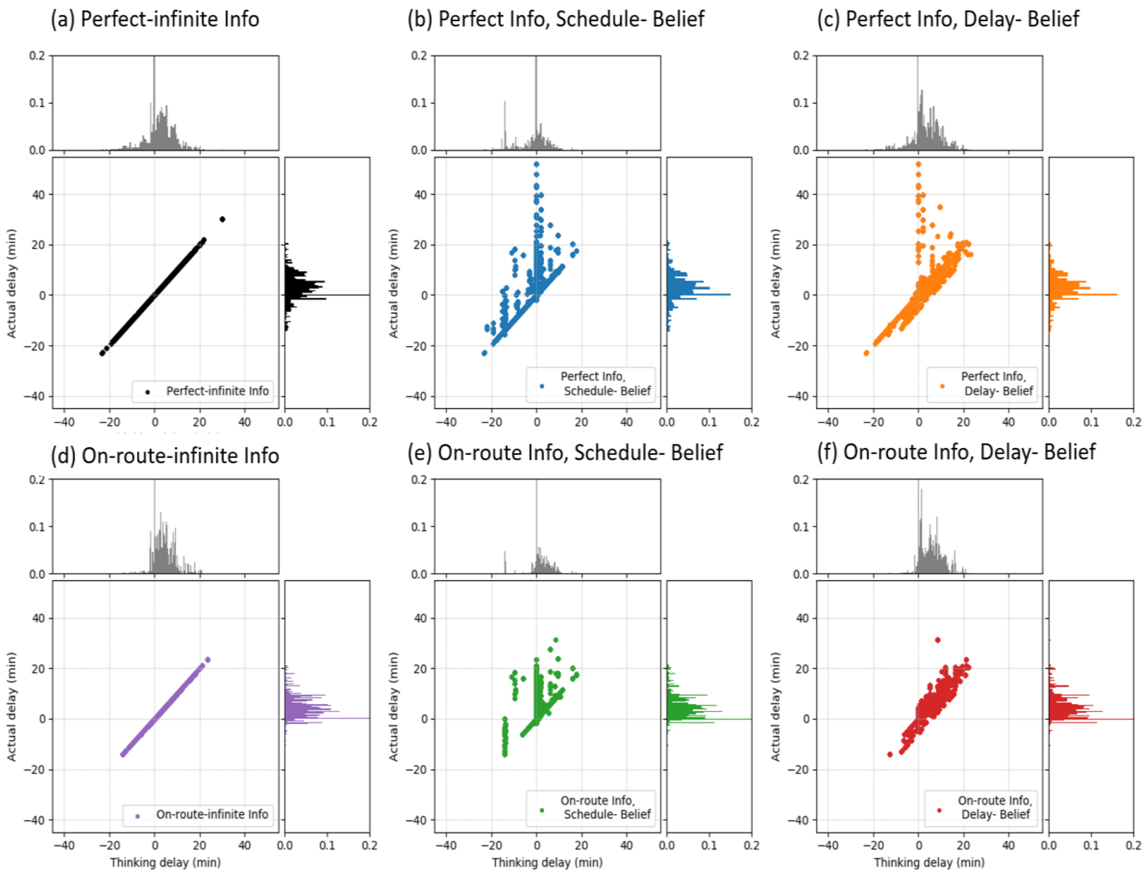

Figure 5.15: Passengers' thinking delays vs. actual delays, comparing different information and belief types (Incomplete information time horizon: 30min)

5.4 Conclusions

We study the problem of incomplete information and its effects to passengers' route choices in case of public transport delays. We propose a new multi-layer time-space-event graph method to describe passengers' behaviours and route choices with the incomplete information and passengers' belief in public transport delays. The graph includes five layers: original timetable, disposition timetable, information, passengers' thinking and passengers' actual route choice. We define and discuss two types of incomplete information, i.e. "Perfect Information" and "On-route Information", and two types of passengers' belief: "Schedule-stubborn Belief" and "Delay-extended Belief". With "Perfect information", passengers perfectly know train delays and disposition timetable within information's start and end time. With "On-route information", passengers could know delays only at the moment they arrive at specific stations and partially know the rescheduled train services of disposition timetable related to these stations (e.g. depart from, or stop at) within the given information time horizon. With “Schedule-stubborn belief”, passengers believe that the train delays, for which they have information, will disappear in the subsequent stations and their trains will reach their destinations without any delay. With “Delay-extended belief”, passengers believe that train delays, for which they have information, will propagate among the subsequent stations. The information time horizon is also considered, from zero (i.e. no information) to infinite. Passengers’ route feasibility and passengers’ delay in both their thinking and in reality are studied to understand the effects of incomplete information.

The results show that the “Perfect Information” helps passengers to have a larger set of considered paths and take the “delayed earlier-departure trains”: the trains plan to depart earlier than passengers’ planned departure time, but actually are delayed in the disposition timetable. “Perfect Information” can offer about 50% more feasible routes and decrease passengers’ delays, compared to “On-route Information”. On a specific case, the largest gap of these two information types is 1.6 min on average when the information is infinite. In case of “On-route Information”, the different effects of passengers’ beliefs on their delays is negligible. However, beliefs indeed affect passengers’ delays depending on the information time horizon. When information is not enough (no more than 25 min), “Schedule-stubborn Belief” cause fewer passengers’ delays (0.6 min on average) in reality. The results has most probably to relate to the rescheduling strategies from operating companies that they prefer to keep the train orders/ sequences in train delays. In other terms, the train that passengers believe to arrive earlier to their destination is indeed arriving earlier, with the efforts of operating companies, in case of delays. Nevertheless, with “Schedule-stubborn Belief”, passengers might not be satisfied with the public transport delays because they believe they will face smaller delays, even zero delay or negative delays in their thinking. Otherwise, when information is enough (more than 25 min), “Delay-extended Belief” causes fewer actual passengers’ delays. With the “Schedule-stubborn Belief”, passengers’ thinking delays has a large gap to the actual delays in reality if the information time horizon is short. The longer the information time horizon, the smaller the gap between passengers’ thinking delays and actual delays. In contrast, passengers can be pessimistic about the delays (i.e. actual delays less than thinking delays) with “Delay-extended Belief”. This effect has most probably to relate to possible transfers in the network.

Based on the proposed multi-layer time-space-event graph method, more research can be performed. For instance, it can be applied to severe public transport disruptions, such as case of physical route infeasible, route blockage for a certain long time or multiple train cancellation, where the incomplete information and passengers’ belief may lead to more missing connections or infeasible routes. For the research field about uncertain delays or disruptions, the information might need to be provided multiple times, resulting in different possibilities of passengers’ thinking, similar to a stochastic programming with recourse; see for instance, Veelenturf, et al. (2016b). This can be studied based on our proposed method.

Moreover, combining the proposed method with timetable or rolling stock rescheduling is able to trade off the benefits and costs of information and public transport operations. This research enriches the passenger heterogeneity on the aspects of their type of belief, which can be applied as one attribute in more complex agent-based simulation, with the efforts of more data collection and calibration and the study about computation efficiency.

Chapter 6

Synthesis

6.1 Main findings

The aim of this dissertation is to quantify the effects of information to passengers' adaptations and satisfaction in public transport disruptions, consequently to improve the service quality of public transport. We recall the overarching question presented in Chapter 1:

What are the influences of information to passengers in case of public transport disruptions on a large-scale multi-modal network, considering the interplay of information availability about the disruption, updated operation strategies, incomplete information about future conditions?

Based on the previous chapters, this main question is answered in summary as follows:

> We identify that the "considered plans" can describe how different factors affect passengers' adaptations in case of public transport disruptions. The "considered plans" represent a set of alternatives of passengers' demand in their daily journey, i.e. a sequence of activities and trips (including alternative paths, transport modes), in a large-scale multi-modal network (see the terminology in Chapter 3). We explain how passengers' "considered plans" are affected jointly by disruption itself, information availability, passengers' belief and the adjusted operation services. The influence of public transport disruptions is to reduce the set of passengers' "considered plans", such as route infeasibility. Providing available information can help passengers to react at best in case of public transport disruptions. A timely/ wide-range/ complete/ precise information availability provides more alternatives in the set "considered plans" for passengers; on the opposite, a delayed/ incomplete/ partial/ imprecise information reduces the set of passengers' "considered plans".

The information availability in disruptions is summarised in our work with a novel "who-when-where-what" four-dimensional framework (Chapter 3). This framework can represent different details about information availability, including incomplete information. Especially with incomplete information, passengers' expectation/ belief on delay propagation may change the details (e.g. time) of some "considered plans" (Chapter 5). Furthermore, the adjusted operation services (disposition timetable) can help some passengers to add more alternatives (e.g. rerouted trains, connections) in their "considered plans", with the condition of available information. (Chapter 4).

We study the interplay of these influencing factors by modelling passengers' adaptations in public transport disruptions as follows. The effects of information availability and disruptions to passengers' adaptations are studied in Chapter 3. We define the mathematical notations and formulas to describe these effects, and apply the agent-based micro-simulation approach (MATSim) to calculate user equilibrium and non-equilibrium solutions. The effects of information availability, disruptions, and adjusted operation services are discussed in Chapter 4, combining MATSim with an optimisation model. The effects of incomplete information about delays and passengers' belief are studied in Chapter 5, with our novel multi-layer time-event-graph method.

Based on these methods, our results quantify passengers' behaviours and their (dis)satisfaction in different settings of information availability, disposition timetables and passengers' belief. We summarise the most significant results, which could be useful for service providers and passengers, as follows:

The adjusted services provided by infrastructure managers and operating companies could substantially benefit passengers in case of public transport disruptions (Chapter 4). First, if the disrupted trains can be partially cancelled (instead of full cancellation), passengers who are directly affected by disruptions can significantly have about 50% smaller delays on average (for both planned and unexpected disruptions). Second, if the disrupted trains can be rerouted, there is a trade-off between passengers who are directly affected (large reduce of delays) and passengers who intended to pass the alternative routes (small increase of delays). For directly affected passengers, rerouting decreases 32% and 15% average delays in planned and unexpected disruptions, respectively. In our results, passengers who pass the alternative routes suffer a small delay (less than 3 min). At system level, these strategies can considerably reduce the impact of especially the unexpected disruptions, with a utility impact reduced to a fifth only, instead of, the original negative impact.

The above benefits of operations can be achieved only on the condition of the best/ perfect information system, both in planned and unexpected disruptions.

That means all the passengers can have available information about all details of the disruptions and the adjusted services, in advance of planned disruptions, or immediately after the unexpected disruptions occur. We summarise the benefits of providing available information and the loss of benefits of incomplete information, based on the research in Chapter 3, 4 and 5. First, providing information, instead of completely no information, is useful for passengers. Without any information, 15.6% passengers fail to find feasible way back to home, and they suffer the maximum delays. Second, the start time of information affects passengers' benefits. The immediately available information in unexpected disruptions, results in approximate 14.1% – 35.8% larger average delays for the directly affected passengers, compared to the beforehand provided information in planned disruptions. The percentage differs in different settings of the adjusted services: the better the adjusted services, the less information' start time affects passengers. Third, if the information is only available at stations, passengers will suffer up to 60% more average delays in our case study, compared to the anywhere-available information. In addition, the station-available information might cause more infeasible routes, especially for the passengers who have a late departure time. Fourth, the more information content (details about adjusted operations) is provided, the more passengers can decrease their delays. In our results, we see a significant reduction of passengers' average delays by providing information from zero to 15 minutes about the further adjusted services.

In different cases of incomplete information, we find out passengers' belief affects their choices to different extents (Chapter 5). The effects of passengers' belief to passengers depend more on the provided information, including information type and the detail contents. If the information is only available at stations, the effects of passengers' belief is negligible. If there is not enough information about adjusted operations can be anywhere available, the schedule belief (train delays will not propagate) brings better approximation and causes up to 22.3% smaller average delays, compared to delay belief (train delays will propagate). In general, passengers' belief could cause approximate 2% infeasible routes, in different cases of incomplete information.

The further details, caring about passengers' heterogeneity, are answered item-by-item, following the structure of sub-questions:

(1) ***How to model passengers' adaptations under different information availability in public transport disruptions and estimate the corresponding passengers' satisfaction?***

We refine the functional requirements of modelling the information availability and heterogonous passengers in a large-scale multi-modal transport network. We propose rigorous mathematical descriptions of how different information availability affects passengers' "considered plans" in public transport disruptions. We also show how to compute performance indicators of user equilibrium and non-equilibrium solutions. The agent-based simulation platform (MATSim) is applied, taking advantage of the detailed descriptions of passengers' entire daily journey (continuous trips and activities). This platform contains also a multi-modal transport network, where passengers' choices of activities and trips can be simulated, including detailed transport modes, routes and time. Especially for unexpected disruptions, we develop the within-day replanning approach in MATSim, by enriching the procedure of selecting the affected agents and modifying their initial plans in a single iteration as reaction to public transport disruption (Chapter 3).

We study two boundaries and provide the gaps for passenger simulation in public transport disruptions. The lower bound is no information at all; the upper bound is a user equilibrium solution with best/ ideal information to simulate the case of the planned disruptions. Besides, we study the non-equilibrium solution with an immediately available information in case of unexpected disruptions. We apply our method to a large-scale multi-modal network of Zürich, Switzerland.

We identify that studying passengers' heterogeneity is helpful to show more details in the simulation results, which can be used to define and evaluate the level of services for passengers in case of public transport disruptions. For instance, with the immediately detailed information in unexpected disruptions, the average delay of passengers is 9.8 min, while the 90th percentile of passengers' delay is 40.2 min. The results can also show heterogeneous passenger's delay as the disruption time goes, in case of different information availability. The mode and route share in different transport modes and routes can be calculated by aggregating the heterogeneous passenger's results, which can useful for the service providers to understand passengers' behaviours. For instance, in our case study, 27.1% passengers leave the public transport system if they have beforehand information in case of planned disruptions.

(2) ***What are passengers' satisfaction under different information strategies and disposition timetables (considering different rescheduling strategies and the feasibility of rolling stock circulation) in public transport disruptions?***

We consider passengers' delays and scores to quantify their satisfaction in public transport disruption in a multi-modal network, under different disposition timetables and information strategies. We apply an optimisation model to calculate the disposition timetables, varying by different rescheduling strategies: retiming, rerouting, full/ partial cancellation of train services, all based on a feasible rolling stock circulation. We use MATSim to simulate passengers' behaviours and their satisfaction in case of these optimised timetables and different information strategies (as in Chapter 3) in case of public transport disruptions. This combination of agent-based simulation and optimisation model is fast enough to be practically applicable, even for a large multi-modal network, for both planned and unplanned disruptions (Chapter 4).

From the results of a test case in Zürich, the information strategy is a major driver of passengers' satisfaction, especially for whom planned to pass the disruptions. The earlier the passengers can receive the disposition timetable, the smaller the delay they will suffer in disruption. The challenges related to rolling stock still require a minor amount of train services to be cancelled. The partial cancellation of trains is much better for passengers than full cancellation, especially for passengers crossing the disrupted area multiple times. This might require the possibility to determine automatically optimised circulation plans, and multiple adjustment in the rescheduling process of the company, for additional operation complexity. There is capacity for many trains to be kept running despite the disruption on an alternative railway route; this allows running more trains against a minor delay (3.6 min on average, including rerouted and original train services). Train rerouting is able to trade-off between a large delay for the passengers who are affected by disruptions and a slight delay (2.7 min on average) for passengers on the alternative route, assuming passengers have enough information to benefit from this change of plans.

(3) ***How to model passengers' behaviours under different incomplete information (Inc. passengers' belief) and quantify passengers' satisfaction?***

We propose a novel multi-layer time-space-event graph method and explain the graph-based route choices in case of incomplete information and passengers' belief in public transport delays. The time-space-event graph can describe five layers: original timetable, disposition timetable, the information, passengers' thinking and passengers' actual route choice. This new method is applicable to study different types of incomplete information and passengers' belief. The incomplete information can be described based on the "who-when-where-what" four-dimensional framework (Chapter 3). Passengers' belief describes their expectations about further train propagations based on their known information. Passengers' route feasibility and passengers' delay in both their thinking and in reality are studied to understand the effects of incomplete information (Chapter 5).

The results show that the information is the major driver of passengers' actual delays in reality. If the information is only available at stations, passengers may miss to take the "delayed earlier-departure trains", where the trains plan to depart earlier than passengers' planned departure time, but actually are delayed in reality. With this on-route information, some passengers have larger delays and fewer feasible routes, compared to the anywhere-available information. As expected, if there is more information about the future operations, passengers will suffer the smaller actual delays and the gap of delays between passengers' thinking and the reality gets smaller. In other terms, if the provided information contains few details of future operations, passengers' belief affects passengers' route choices and their delays. A few passengers choose the route, that they think/ expect is feasible, but is actually infeasible in reality. Passengers, who believe train delays will not propagate, might not be satisfied with their travel because they believe/ expect to face smaller delays, even zero or negative delays in their thinking. Passengers, who believe train delays will propagate, may overestimate the actual train delays.

6.2 Implications to practice

Based on our research, we formulate several implications for the public transport industry.

(1) Managing the planned public transport disruptions

To ensure the public transport services can be provided safely, the infrastructure managers constantly plan and perform the track maintenance, construction or other engineering work. These will disrupt the normal train operations and affect passengers' regular behaviours. To reduce the negative impacts to passengers, different operation strategies can be provided by the infrastructure managers and operating companies. Our methods can help the service providers to quantify the effects of different rescheduling strategies to passengers' satisfaction. The optimisation model is able to calculate different disposition timetables with different timetable and rolling stock strategies (Chapter 4). A user equilibrium solution of passengers can be calculated by the day-to-day replanning approach in MATSim (Chapter 3), because the planned disruptions can be disseminated to passengers beforehand. The calculation time of both the optimisation model and the agent-based simulation is applicable for the planned disruptions. The optimal solution is found within less than 6 seconds. The evaluation of passenger choices in MATSim, for the Zürich multi-modal network, takes about 6 hours. Moreover, multiple simultaneous disruptions can also be evaluated, once the disruptions can be represented as the adjusted schedules. Depending on the requirements of specific cases, many different results can be analysed, such as the number of passengers who leave the public transport system, or passengers' delays and scores with different strategies.

(2) Managing the unexpected public transport disruptions

For the unexpected disruptions, our methods can also provide insights to evaluate different rescheduling strategies, information strategies and the corresponding passengers' satisfaction. One idea is to compute/ evaluate new solutions after other unexpected disruptions. The optimisation model for timetable and rolling stock

(Chapter 4) can be solved fast enough (few seconds). The within-day replanning approach of MATSim (Chapter 3) can be simulated within approximately one minute for the evaluation of passenger choices of the Zürich multi-modal network. The simulation results might overestimate the benefits of information, because we assume passengers could know the details of information immediately after disruptions. To be more realistic, further research needs to be extended in MATSim in the aspects of incomplete information (as in Chapter 5) and the limited capacity of public transport vehicles. Nevertheless, the research findings in Section 6.1 can also provide suggestions to infrastructure managers and operating companies in case of unexpected disruptions. For instance, partially cancelling the disrupted trains, instead of fully cancelling them, is strongly helpful for passengers.

(3) Balancing the benefits and costs of operations

This research focuses on evaluating the benefits of different operation and information strategies to passengers. The results can show the delays and utility of heterogeneous passengers in case of different strategies. The results can also show the aggregate number of passengers on specific stations, trains/ buses, railway routes at specific time or during the whole disruption. Some rescheduling strategies in case of disruptions may need extra operation costs. Based on this research, the operating companies can study the trade-offs of different strategies between passengers' benefits and operation costs. This could even help the long-term investment of public transport operations, such as calculating the number of spare vehicles.

(4) Improving the information system of public transport

This research allows the service providers to evaluate the benefits of improving the information availability, such as station displays, train/ bus information facilities and mobile information to broadcast delays. Based on this, more research can be done at the aspects of information contents, such as train capacity, additional/ alternative services in case of disruptions. At the end, the main goal is to improve the information system so that passengers could receive the information timely, widely and comprehensively.

(5) Passengers' refund in public transport disruptions

The public transport systems around the world start to refund passengers in case of large delays or disruptions. For instance, passengers get refunds from transport for London in a delay of 15 minutes or more, from the Dutch Railways (NS) when a delay exceeds 30 minutes (Yap, 2020). The Swiss Federal Railways (SBB) pays compensation for passengers for the reasons of train delays and train cancellations.

This research can show the delays of heterogeneous passengers, and can further calculate how many refunds that passengers may declare in specific disruptions based on the refund policy.

6.3 Future Research

Given the complexity of public transport system, we recommend several directions to extend and explore in the future research.

Information availability in public transport disruptions. Some more scenarios based on our proposed framework of information availability can be simulated for the further research. Some examples are enumerated as follows. One scenario can be that passengers only know the start time of disruptions but they do not know the precise end time. Another scenario can be that passengers are informed about different aspects of the adjusted services, such as train capacity, additional services (bus bridging, see Liang et al., 2019), the optimal routes (passenger advices, see Van der Hurk et al., 2018). Other scenarios might be to set different stations (e.g. only the affected stations, or only major stations) to have the available information about the disruptions. More scenarios can be set based on different proportions of passengers (e.g. Scherer, 2019) who have diverse information availability; and multiple scenarios can be defined in between those.

Furthermore, the information might need to be provided multiple times, in case of uncertain delays or disruptions. This uncertain information may result in different possibilities of passengers' thinking, similar to a stochastic programming with recourse; see for instance, Veelenturf, et al. (2016b). This can be further studied based on our proposed multi-layer time-space-event graph method.

Passenger heterogeneity. The research in Chapter 5 enriches passenger heterogeneity on the aspects of their type of belief, which can be applied as one attribute in a more complex environment, such as the agent-based simulation. This needs more research about data collection and calibration and the study about computation efficiency. In addition, passengers' choice preferences (e.g. Vij et al., 2013), especially in case of public transport disruptions, can be further modelled in detail. For instance, if there are two choices with the same best utility to passengers, some may prefer the direct train; others may prefer the early departure one. Moreover, it would be interesting to study how the personal attributes (e.g. travel purpose, familiarity of operation schedules, gender, age, profession) affect passengers to realise and react to the information (e.g. Lois et al., 2018) about the disruptions.

Operation strategies in public transport disruptions. Except from what has been studied in this dissertation, other operation strategies can be applied in case of public transport disruptions, such as bus bridging, additional train services between some stations. Moreover, there are four phases to manage disruptions (Ghaemi, 2018): transition phase to disruption, stable disruption situation, transition phase to initial recovered situation. For each phase of disruption management, different rescheduling strategies may have different priorities and benefits. The computation efficiency to produce solutions based on different operation strategies is also one relevant research direction, especially for the large-scale network.

Benefits vs. costs. This dissertation mainly discusses the benefits of different operation and information strategies to passengers in case of public transport disruptions. These strategies will result in different setups and costs for the additional vehicles or for the channels through which information can be disseminated. It will be thus crucial in balancing the benefits of the information availability and operation strategies with their costs.

Bibliography

Adelé, S., Tréfond-Alexandre, S., Dionisio, C. and Hoyau, P. A. (2019) Exploring the behavior of suburban train users in the event of disruptions, *Transportation Research Part F: Traffic Psychology and Behaviour*, **65** 344-362.

Adnan, M., Pereira, F., Lima Azevedo, C., Basak, K., Koh, K., Loganathan, H., Zhang, H. and Ben-Akiva, M. (2017) Evaluating disruption management strategies in rail transit using SimMobility mid-term simulator: A study of singapore MRT north-east line, paper presented at the *96th Annual Meeting of the Transportation Research Board*, Washington, D.C., America.

Albrecht, A. R., Panton, D. M. and Lee, D. H. (2013) Rescheduling rail networks with maintenance disruptions using problem space search, *Computers & Operations Research*, **40** 703–712.

Almodóvar, M. and García-Ródenas, R. (2013) On-line reschedule optimisation for passenger railways in case of emergencies, *Computers & Operations Research*, **40** (3) 725–736.

Anderson, M. K., Nielsen, O. A. and Prato C. G. (2014) Multimodal route choice models of public transport passengers in the greater Copenhagen area, *EURO Journal on Transportation and Logistics*, **6** (3) 1–25.

Andersson, E.V., 2014. Assessment of robustness in railway traffic timetables, Licentiate thesis, Linköping University, Sweden.

Arentze, T. A. and Timmermans H. J. P. (2000) ALBATROSS: A learning-based transportation oriented simulation, EIRASS, Eindhoven.

Arentze, T. A. and Timmermans, H. J. P. (2005) Information gain, novelty seeking and travel: A model of dynamic activity-travel behavior under conditions of uncertainty, *Transportation Research Part A: Policy and Practice*, **39** (2-3) 125-145.

Axhausen, K. W. (2007) Definition of movement and activity for transport modelling, in David A. Hensher , Kenneth J. Button (ed.) Handbook of Transport Modelling (Handbooks in Transport, Volume 1), 329 – 343.

Balmer, M., Rieser, M., Meister, K., Charypar, D., Lefebvre, N., Nagel, K. and Axhausen K.W. (2009) MATSim-T: Architecture and simulation times. In A. L. C. Bazzan and F.

Klügl (eds.) Multi-Agent Systems for Traffic and Transportation Engineering, 57–78, Information Science Reference, Hershey.

Bauer, R. and Schöbel, A. (2014) Rules of thumb: Practical online strategies for delay management, *Public Transportation*, **6** 85–105.

Bender, M., Büttner, S. and Krumke, S. O. (2013) Online delay management on a single line: beyond competitive analysis, *Public Transportation*, **5** 243–266.

Ben-Elia, E. and Avineri, E. (2015) Response to travel information: A behavioural review, *Transport Reviews*, **35** (3) 352-377.

Binder, S., Maknoon, Y. and Bierlaire, M. (2015) Passenger-oriented railway disposition timetables in case of severe disruptions, paper presented at the *15th Swiss Transportation Research Conference*, Ascona, Switzerland.

Binder, S., Maknoon, Y. and Bierlaire, M. (2017) The multi-objective rail timetable rescheduling problem, *Transportation Research Part C: Emerging Technologies*, **78** 78-94.

Bouman, P. (2017) Passengers, crowding and complexity - models for passenger oriented public transport. PhD thesis at Erasmus University Rotterdam.

Brucker, P., Heitmann, S. and Knust, S. (2002) Scheduling railway traffic at a construction site, *OR Spectrum*, **24** (1) 19–30.

Bruglieri, M., Bruschi, F., Colorni, A., Luè, A., Nocerino, R. and Rana, V. (2015) A real-time information system for public transport in case of delays and service disruptions, *Transportation Research Procedia*, **10** 493-502.

Budai, G., Maróti, G., Dekker, R., Huisman, D. and Kroon, L. G. (2010) Rescheduling in passenger railways: The rolling stock rebalancing problem, *Journal of Scheduling*, **13** 281–297.

Büchel, B. and Corman, F. (2020) Meaningful modeling of section bus running times by time varying mixture distributions of fixed components, *Transportation Research Record*, 1-12.

Cacchiani, V., Caprara, A., Galli, L., Kroon, L. G., Maróti, G. and Toth, P. (2012) Railway rolling stock planning: Robustness against large disruptions, *Transportation Science*, **46** 217–232.

Cacchiani, V., Huisman, D., Kidd, M., Kroon, L. G., Toth, P., Veelenturf, L. and Wagenaar, J. (2014) An overview of recovery models and algorithms for real-time railway rescheduling, *Transportation Research Part B: Methodological*, **63** 15-37.

Cadarso, L., Maroti, G. and Marin, A. (2013) Document recovery of disruptions in rapid transit networks, *Transportation Research Part E: Logistics and Transportation Review*, **53** (1) 15-33.

Cadarso, L., Maroti, G. and Marin, A. (2015) Smooth and controlled recovery planning of disruptions in rapid transit networks, *IEEE Transactions on Intelligent Transportation Systems*, **16** (4) 2192–2202.

Carrel, A., Halvorsen, A. and Walker, J. L. (2013) Passengers’ perception of and behavioral adaptation to unreliability in public transportation, *Transportation Research Record*, **2351** (1) 153-162.

Cats, O., Koutsopoulos, H. N., Burghout, W. and Toledo, T. (2011) Effect of real-time transit information on dynamic path choice of passengers, *Transportation Research Record*, **2217** (1) 46–54.

Cats, O., Yap, M. and van Oort, N. (2016) Exposing the role of exposure: Public transport network risk analysis, *Transportation Research Part A: Policy and Practice*, **88** 1–14.

Charypar, D. and Nagel, K. (2005) Generating complete all-day activity plans with genetic algorithms, *Transportation*, **32** (4) 369–397.

Cheng, Y. and Tsai, Y. (2014) Train delay and perceived-wait time: passengers’ perspective. *Transport Reviews*, 710-729.

Chiu, C. K., Chou, C. M., Lee, J. H. M., Leung, H. and Leung, Y. W. (2002) A constraint-based interactive train rescheduling tool, *Constraints*, **7** (2) 167–198.

Chorus, C. G., Arentze, T. A., Timmermans, H., Molin, E. J. E. and van Wee, B. (2007) Travelers’ need for information in traffic and transit: Results from a Web survey, *Journal of Intelligent Transportation Systems*, **11** (2) 57-67.

Corman, F. (2020) Interactions and equilibrium between rescheduling train traffic and routing passengers in microscopic delay management: A game theoretical study, *Transportation Science*, articles in advance, 1-38.

Corman, F. and D’Ariano, A. (2012) Assessment of advanced dispatching measures for recovering disrupted railway situations, *Transportation Research Record*, **2289** 1-9.

Corman, F., D’Ariano, A., Hansen, I. A., and Pacciarelli, D. (2011) Optimal multiclass rescheduling of railway traffic, *Journal of Rail Transport Planning & Management*, **1** (1) 14–24.

Corman, F., D’Ariano, A., Marra, A. D., Pacciarelli, D. and Samà, M. (2017) Integrating train scheduling and delay management in real-time railway traffic control, *Transportation Research Part E: Logistics and Transportation Review*, **105** 213-239.

Corman, F., D’Ariano, A., Pacciarelli, D. and Pranzo, M. (2014) Dispatching and coordination in multi-area railway management, *Computers & Operations Research*, **44** 146–160.

Corman, F. and Meng, L. (2015) A review of online dynamic models and algorithms for railway traffic control, *IEEE Transactions on Intelligent Transportation Systems*, **16** (3) 1274 – 1284.

Cottrill, C., Gault, P., Yeboah, G., Nelson, J. D., Anable, J. and Budd, T. (2016) Tweeting transit: An examination of social media strategies for transport information management during a large event, *Transportation Research Part C: Emerging Technologies*, **77** 421-432.

D'Ariano, A., Pacciarelli, D. and Pranzo, M. (2007) A branch and bound algorithm for scheduling trains in a railway network, *European Journal of Operational Research*, **183** (2) 643–657.

Dobler, C. and Nagel, K. (2016) Within-Day replanning. In: Horni, A, Nagel, K and Axhausen, K W. (eds.) The Multi-Agent Transport Simulation MATSim, 187–200. London: Ubiquity Press.

Dollevoet, T., Huisman, D., Schmidt, M. and Schöbel, A. (2012) Delay management with rerouting of passengers, *Transportation Science*, **46** 74–89.

Dorbritz, R. (2012) Methodology for assessing the structural and operational robustness of railway networks, Dissertation no. 20250, ETH Zürich, Institut für Verkehrsplanung und Transportsysteme.

Durand, A. L. (2017). Managing disruptions in public transport from the passenger perspective: A study to assess and improve operational strategies for the benefit of passengers in rail-bound urban transport systems. Master thesis at Delft University of Technology.

Dziekan, K. and Kottenhoff, K. (2007) Dynamic at-stop real-time information displays for public transport: effects on customers, *Transportation Research Part A: Policy and Practice*, **41** (6) 489–501.

European Rail Research Advisory Council (2012) Rail Route 2050: *The Sustainable Backbone of the Single European Transport Area* (European Rail Research Advisory Council, Brussels).

Federal Council, the portal of the Swiss government. (2009) Art. 64 Abs. 1 EBG. Railway Act. (In German) www.admin.ch/opc/de/classified-compilation/19570252/index.html.

Federal office for Spatial Development (2016) Perspektiven des Schweizerischen Personen- und Güterverkehrs bis 2040-Synthesebericht. (In German) Bern: Bundesamt für Raumentwicklung. www.are.admin.ch.

Fink, O. (2014) Failure and degradation prediction by artificial neural networks: applications to railway systems, Dissertation no. 21648, ETH Zürich, Institut für Verkehrsplanung und Transportsysteme.

Fioole, P. J., Kroon, L. G., Maróti, G. and Schrijver, A. (2006) A rolling stock circulation model for combining and splitting of passenger trains, *European Journal of Operational Research*, **174** 1281–1297.

Foell, S., Kortuem, G., Rawassizadeh, R., Phithakkitnukoon, S., Veloso, M. and Bento, C. (2013) Mining temporal patterns of transport behaviour for predicting future transport usage, paper presented at the *2013 ACM Conference on Ubiquitous Computing*, Zurich, Switzerland.

Fourie, P. J., Illenberger, J. and Nagel, K. (2013) Increased convergence rates in multi-agent transport simulations with pseudo-simulation, *Transportation Research Record*, **2343** 68–76.

Fuchsberger, M. (2012) Algorithms for railway traffic management in complex central station areas, Dissertation no. 20398, ETH Zürich, Institut für Operations Research.

Gentile, G. and Noekel, K. (2016) Modelling public transport passenger flows in the era of intelligent transport systems: COST Action TU1004 (TransITS). **1** (10). Cham: Springer International. Print. Springer Tracts on Transportation and Traffic.

Ghaemi, N. (2018). Short-turning trains during full blockages in railway disruption management. PhD thesis at Delft University of Technology.

Goerigk, M., Schmidt, M., Schöbel, A., Knoth, M. and Müller-Hannemann, M. (2014) The price of strict and light robustness in timetable information, *Transportation Science*, **48** 225–242.

Golledge, R. G. (2002) Dynamics and ITS: Behavioral responses to information available from ATIS. In H. S. Mahmassani, ed. In perpetual Motion Travel behaviour research opportunities and application challenges. Pergamon, 81-126.

Graffagnino, T. and Labermeier, H. (2016) A definition of timetable stability for a long-term timetable, *WIT Transactions on The Built Environment*, **162** 91-100.

Han, Q., Arentze, T. A., Timmermans, H. J. P., Janssens, D. and Wets, G. (2011) The effects of social networks on choice set dynamics: Results of numerical simulations using an agent-based approach, *Transportation Research Part A: Policy and Practice*, **45** (4) 310–322.

Hensher, D. A., Greene, W. H. and Li, Z. (2011). Embedding risk attitude and decision weights in non- linear logit to accommodate time variability in the value of expected travel time savings, *Transportation Research Part B: Methodological*, **45** (7) 954–972.

Herrigel, S. (2015). Algorithmic decision support for the construction of periodic railway timetables, Dissertation no. 22548, ETH Zürich, Institut für Verkehrsplanung und Transportsysteme.

Heyndrickx, C., Frederix, R., Bosch, P. and Ciari, F. (2016) Benefits of informing travellers in case of extreme precipitation events: A model based case study for Zürich using MATSim, paper presented at the *95th Annual Meeting of the Transportation Research Board*, Washington, D.C., America.

Hickman, M. D. and Bernstein, D. H. (1997) Transit service and path choice models in stochastic and time-dependent networks, *Transportation Science*, **31** (2) 129–146.

Hirai, C., Kunimatsu, T., Tomii, N., Kondou, S. and Takaba, M. (2009) A train stop deployment planning algorithm using a petri-net-based modelling approach, *Quarterly Report of RTRI (Railway Technical Research Institute) (Japan)*, **50** (1) 8–13.

Horni, A and Nagel, K. (2016) More about configuring MATSim. In: Horni, A, Nagel, K andAxhausen, K W. (eds.) The Multi-Agent Transport Simulation MATSim, 35–44. London: Ubiquity Press.

Jespersen-Groth, J., Potthoff, D., Clausen, J., Huisman, D., Kroon, L. G., Maróti, G. and Nielsen, M. (2009) Disruption management in passenger railway transportation. In: Ahuja, R., Möhring, R., Zaroliagis, C., (Eds.), *Robust and Online Large-Scale Optimisation*, **5868** 399–421.

Kanai, S., Shiina, K., Harada, S. and Tomii, N. (2011) An optimal delay management algorithm from passengers' viewpoints considering the whole railway network, *Journal of Rail Transport Planning & Management*, **1** (1) 25-37.

Kroon, L., Maróti, G. and Nielsen, L. (2015) Rescheduling of railway rolling stock with dynamic passenger flows, *Transportation Science,* **49** (2) 165-184.

Kumazawa, K., Hara, K. and Koseki, T. (2010) A novel train rescheduling algorithm for correcting disrupted train operations in a dense urban environment, *WIT Transactions on the Built Environment*, **103** 565-574.

Kunimatsu, T., Hirai, C. and Tomii, N. (2012) Train timetable evaluation from the viewpoint of passengers by microsimulation of train operation and passenger flow, *Electrical Engineering in Japan*, **181** (4) 51-62.

Lamorgese, L. and Mannino, C. (2015) An exact decomposition approach for the real-time train dispatching problem, *Operations Research*, **63** (1) 48-64.

Leng, N. and Corman, F. (2020) The role of information availability to passengers in public transport disruptions: An agent-based simulation approach, *Transportation Research Part A: Policy and Practice*, **133** 214-236.

Leng, N., Liao, Z. and Corman, F. (2020) Role of timetable, rolling stock rescheduling, and information strategies to passengers in public transport disruptions, *Transportation Research Record*, 1-13.

Leng, N., De Martinis, V. and Corman, F. (2018) Agent-based simulation approach for disruption management in rail schedule, paper presented at the *14th International Conference on Advanced Systems in Public Transport*, Brisbane, Australia.

Leng, N. and Weidmann, U. (2017a) Discussions of the reschedule process of passengers, train operators and infrastructure managers in railway disruptions, *Transportation Research Procedia*, **27** 538-544.

Leng, N. and Weidmann, U. (2017b) Multi-objectives of the passenger oriented disruption management problem, paper presented at the *7th International Conference on Railway Operations Modelling and Analysis*, Lille, France.

Liang, J., Wu, J., Qu, Y., Yin, H., Qu, X. and Gao, Z. (2019) Robust bus bridging service design under rail transit system disruptions, *Transportation Research Part E: Logistics and Transportation Review*, **132** 97-116.

Lois, D., Monzón, A. and Hernández, S. (2018) Analysis of satisfaction factors at urban transport interchanges: Measuring travellers' attitudes to information, security and waiting, *Transport Policy*, **67** 49-56.

Loo, P. Y. and Leung, Y. K. (2017) Transport resilience: The Occupy Central Movement in Hong Kong from another perspective, *Transportation Research Part A: Policy and Practice*, **106** 100–115.

Lorek, M., Fekete, S. and Pfetsch, M. E. (2011) Disruption management with rescheduling of trips and vehicle circulations, *Joint Rail Conference*, 395-404.

Louwerse, I. and Huisman, D. (2014) Adjusting a railway timetable in case of partial or complete blockades, *European Journal of Operational Research*, **235** (3) 583–593.

Lu, Y., Adnan, M., Basak, K., Pereira, F. C., Carrion, C., Saber, V. H., Loganathan, H. and Ben-Akiva, M. E. (2015) SimMobility mid-term simulator: A state of the art integrated agent based demand and supply model, paper presented at the *94th Annual Meeting of the Transportation Research Board*, Washington, D.C., America.

Lüthi, M. (2009) Improving the efficiency of heavily used railway networks through integrated real-time rescheduling, Dissertation no. 18615, ETH Zürich, Institut für Verkehrsplanung und Transportsysteme.

Malandri, C., Fonzone, A. and Cats, O. (2018) Recovery time and propagation effects of passenger transport disruption, *Physica A*, **505** 7-17.

Marra, A. D., Becker, H., Axhausen, K. W. and Corman, F. (2019) Developing a passive GPS tracking system to study long-term travel behaviour, *Transportation Research Part C: Emerging Technologies*, **104** 348–368.

Marra, A. D. and Corman, F. (2020) From delay to disruption: the impact of service degradation on public transport networks, paper presented at the *99th Annual Meeting of the Transportation Research Board*, Washington, D.C., America.

Mascis, A. and Pacciarelli, D. (2002) Job shop scheduling with blocking and no-wait constraints, *European Journal of Operational Research*, **143** (3) 498–517.

Meng, L. and Zhou, X. (2014) Simultaneous train rerouting and rescheduling on an N-track network: A model reformulation with network-based cumulative flow variables, *Transportation Research Part B: Methodological*, **67** (0) 208–234.

Meister, K. (2011) Contribution to agent-based demand optimisation in a multi-agent transport simulation, Ph.D. Thesis, ETH Zürich.

Mnif, S., Darmoul, S., Elkosantini, S. and Ben Said, L. (2017) Integration of immune features into a belief-desire-intention model for multi-agent control of public transportation systems, Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), **10334** 459-470.

Nagel, K. and Floetteroed, G. (2016) Agent-based traffic assignment. In: Horni, A, Nagel, K and Axhausen, KW. (eds.) The Multi-Agent Transport Simulation MATSim, 315–326. London: Ubiquity Press.

Narayanaswami, S. and Rangaraj, N. (2013) Modelling disruptions and resolving conflicts optimally in a railway schedule, *Computers & Industrial Engineering*, **64** (1) 469–481.

Nielsen, O. A., Landex, A. and Frederiksen, R. D. (2008). Passenger delay models for rail networks, *Schedule-Based Modeling of Transportation Networks: Theory and applications*, **46** 27–49.

Nielsen, L. K., Kroon, L. G. and Maróti, G. (2012) A rolling horizon approach for disruption management of railway rolling stock, *European Journal of Operational Research*, **220** (2) 496–509.

Ojo, T. K. (2019) Quality of public transport service: an integrative review and research agenda, *Transportation Letters*, **11** (2) 104-116.

Pacciarelli, D. (2013) Introduction and classification of existing rescheduling literature, paper presented at the *RailCopenhagen 2013*, Copenhagen, Denmark.

Padgham, L., Nagel, K., Singh, D. and Chen, Q. (2014) Integrating BDI agents into a MATSim simulation, *Frontiers in Artificial Intelligence and Applications*, **263** 681–686.

Papangelis, K., Velaga, N., Sripada, S., Beecroft, M., Nelson, J. D., Anable, J. and Farrington, J. F. (2013). Supporting rural public transport users during disruption: The role of real-time information, paper presented at the *92nd Annual Meeting of the Transportation Research Board*, Washington, D.C., America.

Parbo, J., Nielsen, O. A. and Prato, C. G. (2014) User perspectives in public transport timetable optimisation, *Transportation Research Part C: Emerging Technologies*, **48** 269–284.

Parbo, J., Nielsen, O. A. and Prato, C. G. (2015) Passenger perspectives in railway timetabling: A literature review, *Transport Reviews*, 1–27.

Parvaneh, Z., Liao, F., Arentze, T. and Timmermans, H. (2014) A micro-simulation model of updating expected travel time in provision of travel information: A bayesian belief approach implemented in a multi-state supernetwork, *Procedia Computer Science*, **32** 796-801.

Paulsen, M., Rasmussen, K. T. and Nielsen, O. A. (2018) Modelling railway-induced passenger delays in multi-modal public transport networks: An agent-based Copenhagen case study using empirical train delay data, paper presented at the *14th International Conference on Advanced Systems in Public Transport*, Brisbane, Australia.

Pender, B., Currie, G., Delbosc, A. and Shiwakoti, N. (2014) Social media use during unplanned transit network disruptions: A review of literature, *Transport Reviews*, **34** (4) 501–521.

Poulopoulou, M. and Spyropoulou, L. (2019) Active traffic management in urban areas: Is it effective for professional drivers? The case of variable message signs, *Transportation Research Part A: Policy and Practice*, **1300** 412-423.

Rieser-Schuessler, N., Boesch, P. M., Horni, A. and Balmer, M. (2016) Zürich. In: Horni, A, Nagel, K. and Axhausen, K. W. (eds.) The Multi-Agent Transport Simulation MATSim, London: Ubiquity Press, 375–378.

Rao, X. (2015). Holistic rail network operation by integration of train automation and traffic management, Dissertation no. 22706, ETH Zürich, Institut für Verkehrsplanung und Transportsysteme.

Sato, K. and Fukumura, N. (2012) Real-time freight locomotive rescheduling and uncovered train detection during disruption, *European Journal of Operational Research*, **221** 636–648.

Schachtebeck, M. and Schöbel, A. (2010) To wait or not to wait and who goes first? Delay management with priority decisions, *Transportation Science*, **44** 307–321.

Scherer, A. (2019) Information to passengers as enabler of demand management and delay reduction, Master Thesis, ETH Zürich, Institut für Verkehrsplanung und Transportsysteme.

Schmidt, M., Kroon, L., Schöbel, A. and Bouman, P. (2017) The travelers route choice problem under uncertainty: Dominance relations between strategies, *Operation Research*, **65** (1) 184–199.

Schranil, S. (2013) Prognose der Dauer von Störungen des Bahnbetriebs, Dissertation no. 21473, ETH Zürich, Institut für Verkehrsplanung und Transportsysteme. (In German)

Schöbel, A. (2007) Integer programming approaches for solving the delay management problem, *Algorithmic Methods for Railway Optimisation, Lecture Notes in Computer Science*, **4359** 145–170.

Schöbel, A. (2009) Capacity constraints in delay management, *Public Transport*, **1** (2) 135–154.

Shimizu, H., Tanabe, H. and Yamamoto, M. (2008) The proposal system for Shinkansen using constraint programming, paper presented at the *8th World Congress of Railway Research*, Seoul, Korea.

Shires, J., Ojeda-Cabral, M. and Wardman, M. (2019) The impact of planned disruptions on rail passenger demand, *Transportation*, **46** 1807-1837.

Smith, L., Beckman, R., Anson, D., Nagel, K. and Williams, M. (1995) TRANSIMS: Transportation analysis and simulation system, paper presented at the *5th National Transportation Planning Methods Applications Conference*, Seattle, America.

Stahel, A., Ciari, F. and Axhausen, K. W. (2014) Modeling impacts of weather conditions in agent-based transport microsimulations, paper presented at the *93th Annual Meeting of the Transportation Research Board*, Washington, D.C., America.

Strässle, S. and Schneeberger, T. (2017) CUS, the central customer information system for Swiss public transport, *SIGNAL + DRAHT*, **3** 40-44. (In German)

Suhl, L. Biederbick, C. and Kliewer, N. (2001) Design of customer-oriented dispatching support for railways, *Computer-Aided Scheduling of Public Transport*, **505** 365-386.

Sun, L., Jin, J. G., Lee, D. H., Axhausen, K. W. and Erath, A. (2014). Demand-driven timetable design for metro services, *Transportation Research Part C: Emerging Technologies*, **46** 284–299.

Toletti, A. (2018). Automated railway traffic rescheduling and customer information, Dissertation no. 25111, ETH Zürich, Institut für Verkehrsplanung und Transportsysteme.

Tomii, N., Tashiro, Y., Tanabe, N., Hirai, C. and Muraki, K. (2005) Train operation rescheduling algorithm based on passenger satisfaction, *Quarterly Report of RTRI (Railway Technical Research Institute) (Japan)*, **46** (3) 167-172.

Törnquist, J. and Persson, J. A. (2007) N-tracked railway traffic re-scheduling during disturbances, *Transportation Research Part B: Methodological*, **41** (3) 342–362.

Transport for London (2019). Underground service performance: Latest performance figures (from 10 November to 7 December 2019). tfl.gov.uk/corporate/publications-and-reports/underground-services-performance.

Tsuchiya, R., Sugiyama, Y., Yamauchi, K., Fujinami, K., Arisawa, R. and Nakagawa, T. (2006). Route-choice support system for passengers in the face of unexpected disturbance of train operations, *Computers in Railways*, **88** 189-197.

Van de Kaa, E. J. (2008) Extended prospect theory: Findings on choice behaviour from economics and the behavioural sciences and their relevance for travel behaviour. PhD thesis at Delft University of Technology.

Van der Hurk, E. (2015) Passengers, information, and disruptions. PhD thesis at Erasmus University Rotterdam.

Van der Hurk, E., Kroon L. G. and Maróti G. (2018) Passenger advice and rolling stock rescheduling under uncertainty for disruption management, *Transportation Science*, **52**(6) 1391-1411.

Veelenturf, L. P., Kidd, M. P., Cacchiani, V., Kroon, L. G. and Toth, P. (2016a) A railway timetable rescheduling approach for handling large-scale disruptions, *Transportation Science*, **50** (3) 841-862.

Veelenturf, L. P., Potthoff, D., Huisman, D., Kroon, L. G., Maróti, G. and Wagelmans, A. (2016b) A quasi-robust optimisation approach for crew rescheduling, *Transportation Science*, **50** (1) 204-215.

Veelenturf, L. P., Kroon, L. G. and Maroti, G. (2017) Passenger oriented rail disruption management by adapting timetables and rolling stock schedules, *Transportation Research Part C: Emerging Technologies*, **80** 133-147.

Vij, A., Carrel, A. and Walker, J. L. (2013) Incorporating the influence of latent modal preferences on travel mode choice behavior, *Transportation Research Part A: Policy and Practice*, **54** 164–178.

Vromans, M. J., Dekker, R. and Kroon, L. G. (2006) Reliability and heterogeneity of railway services, *European Journal of Operational Research*, **172** (2) 647–665.

Wardman, M., Chintakayala, P., de Jong, G. and Ferrer, D. (2012). European wide meta-analysis of values of travel time, report prepared for the European Investment Bank.

Wang, J., Yuan, Z. and Yin, Y. (2019) Optimisation of bus bridging service under unexpected metro disruptions with dynamic passenger flows, *Journal of Advanced Transportation*, **12** 1-13.

Watkins, K. E., Ferris, B., Borning, A., Rutherford, G. S. and Layton, D. (2011) Where is my bus? Impact of mobile real-time information on the perceived and actual wait time of transit riders, *Transportation Research Part A: Policy and Practice*, **45** (8) 839–848.

Weidmann, U., Laumanns M., Montigel, M. and Rao, X. (2015) Dynamic capacity optimisation by fully automated rail operation, *Railway Update*, **10** 58–63.

Weston, P., Goodman, C., Takagi, R., Bouch, C., Armstrong, J. and Preston, J. (2006) Minimising train delays in a mixed traffic railway network with consideration of passenger delay, paper presented at the *7th World Congress on Railway Research*, Montréal, Canada.

Wiklund, M. (2007) Serious breakdowns in the track infrastructure – calculation of the effects on rail traffic, paper presented at the *2nd International Seminar on Railway Operations Modelling and Analysis – RailHannover 2007*, Hannover, Germany.

Yu, G. and Qi, X. (2004) Disruption management: Framework, models and applications, *World Scientific*, Singapore.

Yap, M. (2020) Measuring, predicting and controlling disruption impacts for urban public transport. PhD thesis at Delft University of Technology.

Zanni, A. M. and Ryley, T. J. (2015) The impact of extreme weather conditions on long distance travel behaviour, *Transportation Research Part A: Policy and Practice*, **77** 305–319.

Zhan, S., Kroon L. G., Veelenturf, L. P. and Wagenaar, J. C. (2015) Real-time high-speed train rescheduling in case of a complete blockage, *Transportation Research Part B: Methodological*, **78** 182-201.

Zhang, S. and Lo, H. K. (2020) Metro disruption management: Contracting substitute bus service under uncertain system recovery time, *Transportation Research Part C: Emerging Technologies*, **110** 98-122.

Zhu, Y. (2019). Passenger-oriented timetable rescheduling in railway disruption management. PhD thesis at Delft University of Technology.

Appendices

Appendix A

With the classifications by the proposed “Who-When-Where-What” four-dimension framework, more examples of scenarios can be extended as in Figure A.1 to define diverse information availability based on passengers’ different level of knowledge for the public transport disruptions. The differences depend on the proportion of agents who know the information, the locations and time they receive, and the contents of the information.

The dimension “who” refers to which passengers can receive the information, such as frequent users of public transport or not. The green and blue lines in Figure A.1 give examples about the studies that information is only available to some passengers. The dimension “when” means the time passengers start to know the information. The available information can be in advance of disruption (planned maintenance) (Chapter 3, 4) or after disruption (unexpected events) (Chapter 3, 4, 5). Passengers may know this information before their departure time or afterwards (Chapter 3, 4, 5). The dimension “where” shows the locations passengers start to know the information, such as anywhere (Chapter 3, 4, 5) or only at station (Chapter 5). The dimension “what” means the content of the available information. It can be only the news about disruption itself, such as the start/ end time of disruption or the reasons of disruption. The pink and blue lines in Figure A.1 give examples of the study about the uncertain disruption end time. It can also include the details of the adjusted operations in disruptions, such as the train delays or cancellation (Chapter 3, 4, 5).

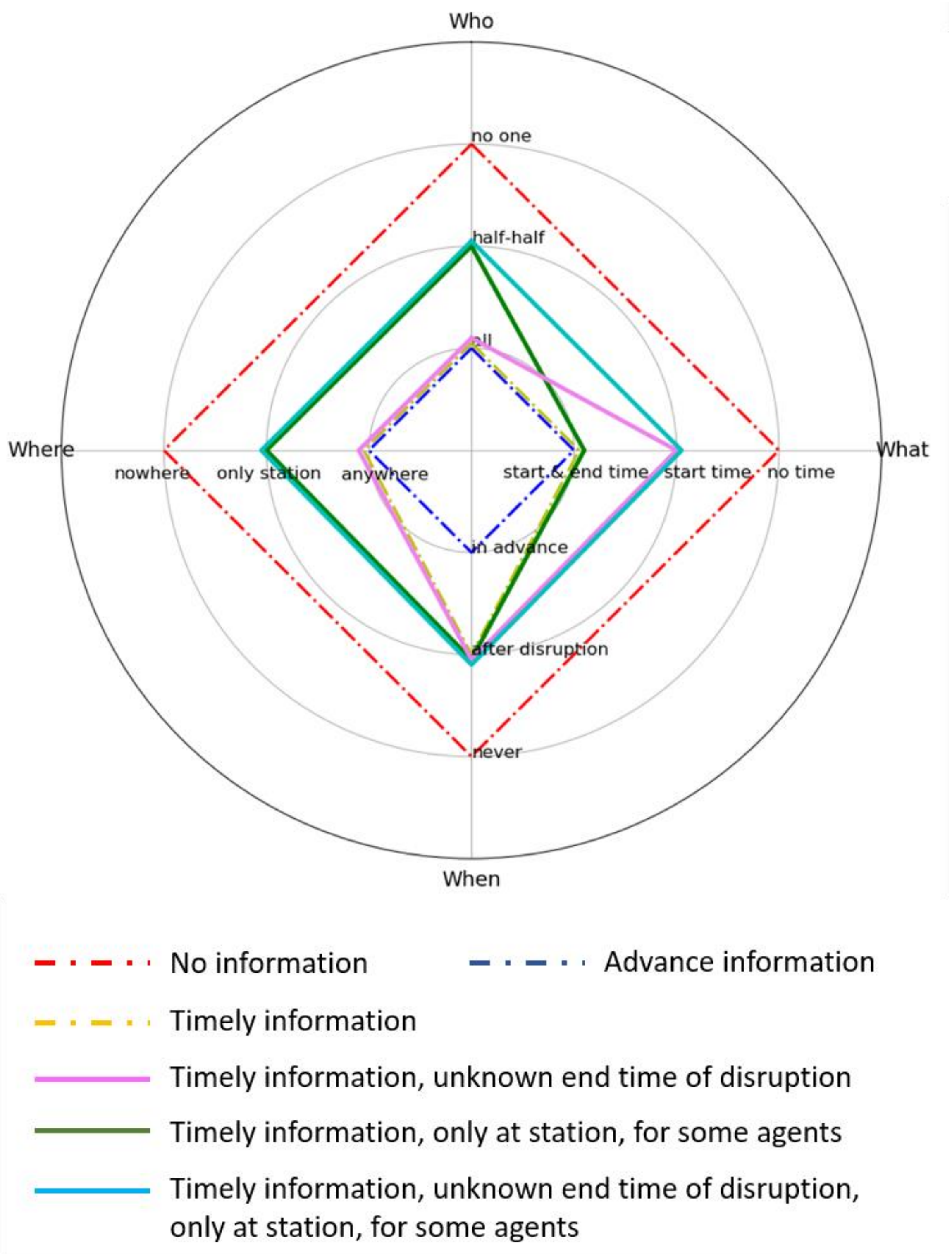

Figure A.1: More scenarios with the information framework

Appendix B

The detailed agents’ behaviours of the case study in Section 3.4 are shown in the results of Appendix B. The figures from B.1 to B.4 represent the detailed travel chain of the involved agents (y-axis) for each route and transport mode, as time goes (x-axis). We select five classifications based on alternative route choices (i.e. Wipkingen, Hardbrücke, DML and other rail, respectively red, blue, green and black lines) and transport modes (bus/ tram, car/ bike, respectively yellow and pink lines) in disruptions.

Figure B.1 shows agents’ behaviours in case of “Benchmark” (without disruptions). With the “Advance Information” in Figure B.2, the agents have different behaviours: choosing the alternative rail routes (green and black lines), other public transport modes (bus/ tram in yellow lines), and even the private transport modes (pink lines).

The agents’ proportion via the Wipkingen and Hardbrücke routes in the “Timely information” scenario in Figure B.3 decreases between 16 and 19 o’clock but is not reduced to zero. The remaining agents are those who are travelling on the train services beyond either Zürich HB or Zürich Oerlikon rather than between these two stations. This is caused by the fact that agents can still use these running services once they have crossed the disrupted area by using other rail routes or transport modes. Instead, more agents in “Timely information” choose The DML, other rail and bus/ tram (green, black and yellow lines).

In the “No information” scenario in Figure B.4, agents wait during the disruption (between 16 and 19 o’clock) while the number of agents increases dramatically to a maximum after 19 o’clock. In other terms, most of the agents are now concentrated moving in a short time horizon, from 19.00 to 20.30.

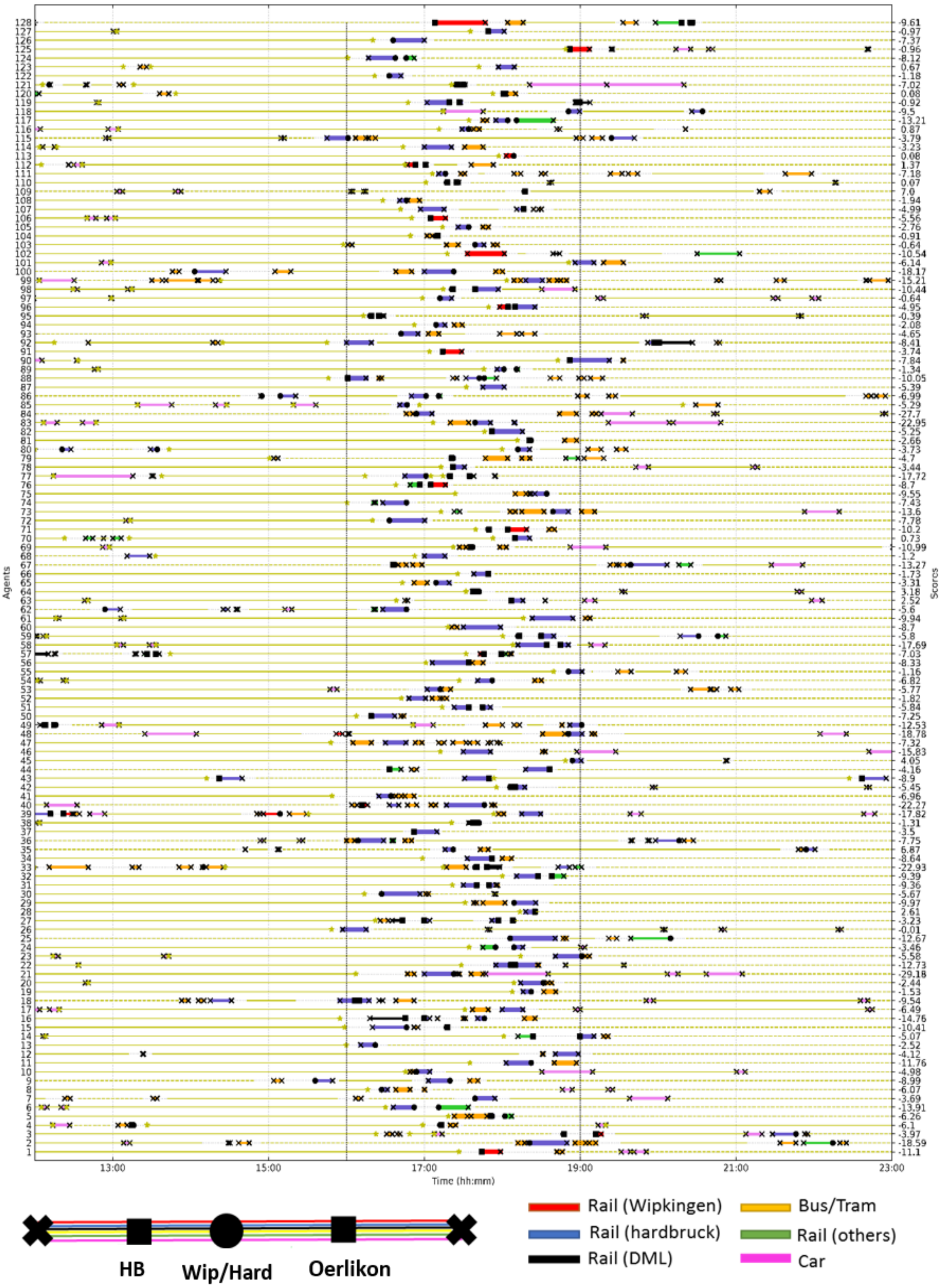

Figure B.1: The detailed travel chain of involved agents in “Benchmark”

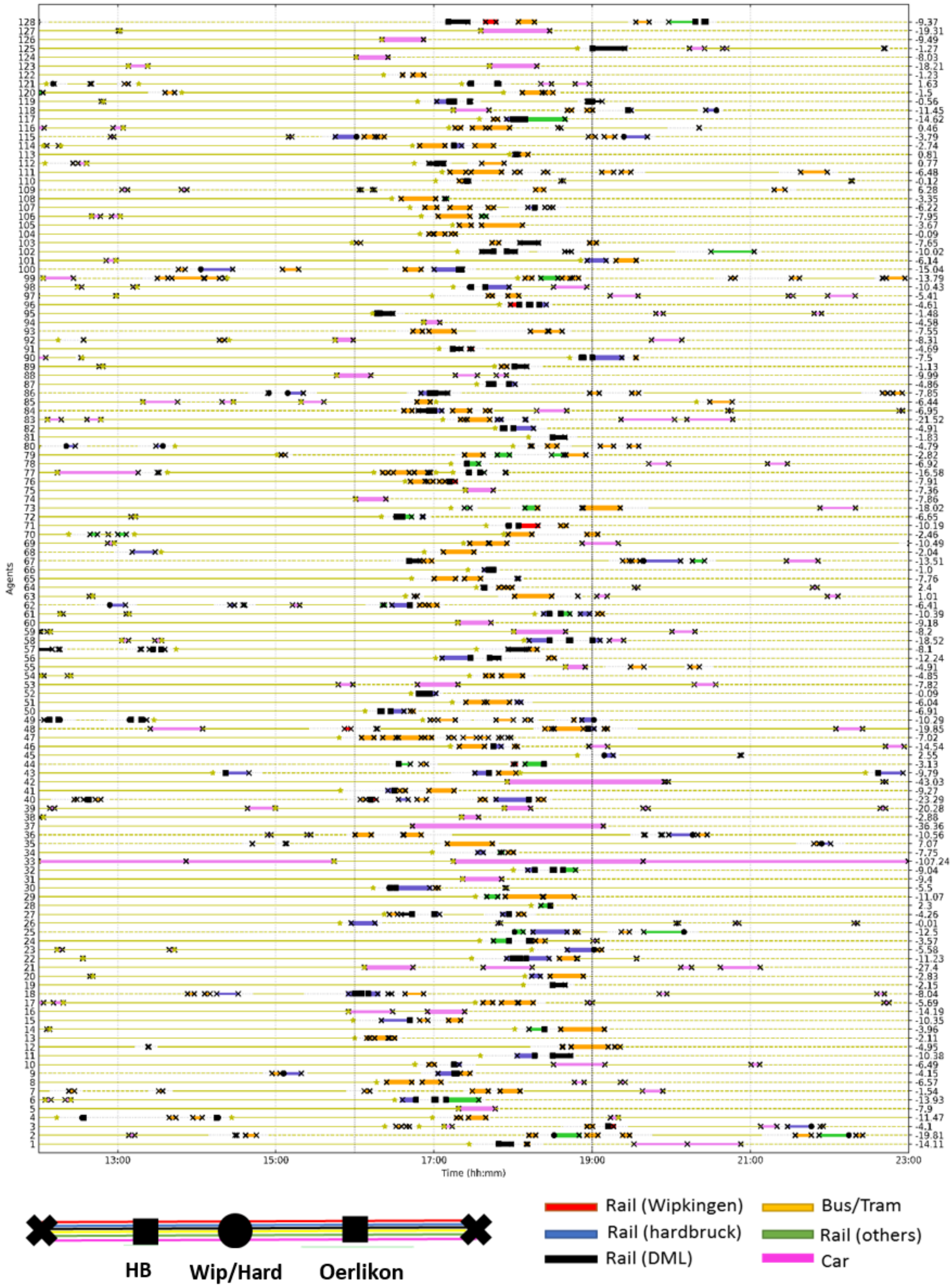

Figure B.2: The detailed travel chain of involved agents in “Advance Information”

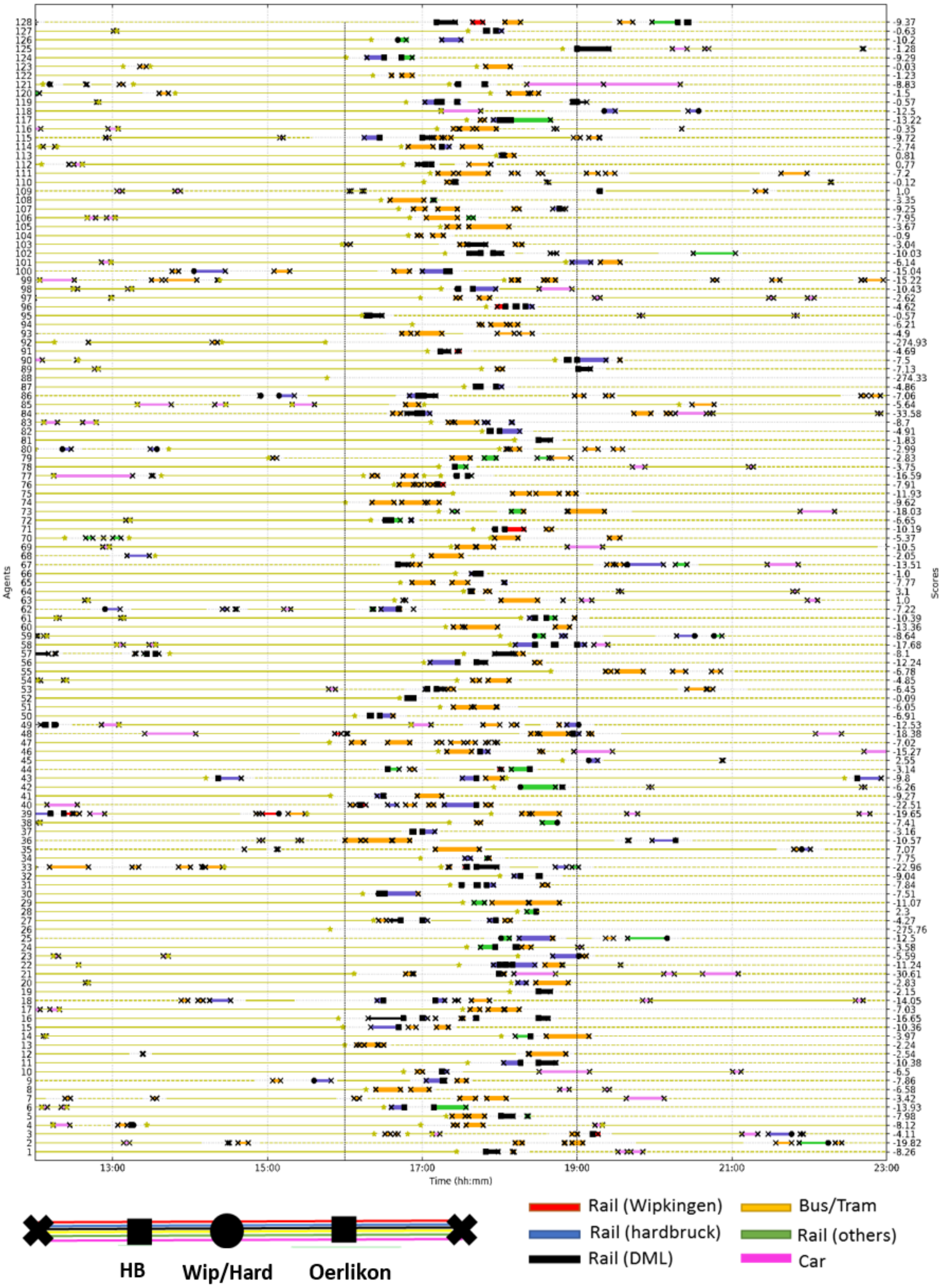

Figure B.3: The detailed travel chain of involved agents in “Timely Information”

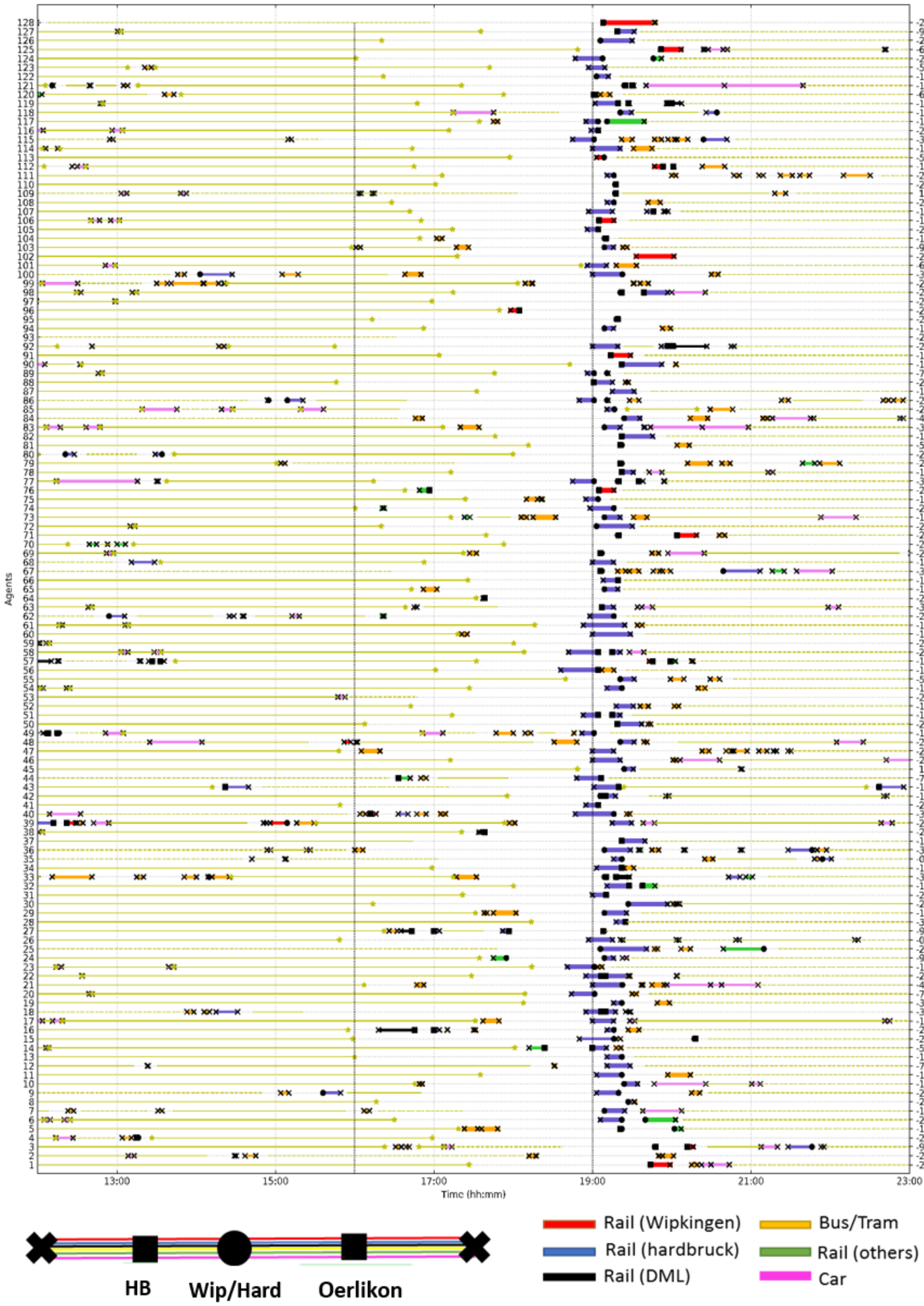

Figure B.4: The detailed travel chain of involved agents in “No Information”

Appendix C

Appendix C explains passengers' route choices based on their thinking, referring to Section 5.2. Table C.1 explain the cases of "No delay", "Perfect-infinite Information" and "On-route-infinite Information", which are according to Figure 5.2, Figure 5.4 and Figure 5.5, respectively. Table C.2 and Table C.3 explain the cases of incomplete information and passengers' belief according to the following Figure 5.6 and Figure 5.7.

All tables have the same structure. The column labelled "Considered paths" in passengers' thinking, enumerates the possibilities of route choices. "->" means transfer from previous train to the next one. For each train, a series of train ID, station ID, time is reported. For instance, "Train 2 (A, 120 - B, 180) -> Train 3 (B, 190 - D, 220)" means that, passengers take the Train 2 at station A at the time 120, and then arrive at station B at 180, then they can transfer to Train 3 which departs from station B at 190 and arrives at station D at the time 220. The numbers in black is the time in original timetable; the numbers in bold black is the time in disposition timetable; the numbers in red is the time of passengers' belief. The yellow mark is the best/ fastest route for passengers in their mental model among all the "considered paths". The column labelled "No." counts the total number of "considered paths" in each case. "Thinking arrival time" and "Thinking delay" are the arrival time and delay in passengers' thinking in each case. "Actual arrival time" and "Actual delay" are the time and delay according the disposition timetable if passengers choose the fastest route based on the "considered paths" in their thinking. The column labelled "Deviations: think vs. act" shows the deviations of delay between passengers' thinking and the reality.

With the given examples of passengers' route choices, the comparison of different cases shows the following the effects of information in case of train delays:

(1) The delays may provide more route choices for passengers with sufficient information.

    The total number of "considered paths" in case of "No delay" is five, while in case of train delays, with "Perfect-infinite Information", the total number is seven. The increased number of route choices is due to the "delayed earlier-departure trains": the routes related to "Train 1" in this specific case. In the original timetable, "Train 1" departs earlier than this passengers' planned departure time, but it has delay and passengers can take "Train 1" thanks to the "Perfect-infinite Information".

(2) "Perfect Information" may provide more route choices and cause smaller passenger delays, compared to "On- route Information".

For instance, with the comparison of "On-route-infinite Information", passengers could take the "delayed earlier-departure trains" in case of "Perfect-infinite Information" and get more route choices: the routes related to "Train 1" in this specific case. As a result, passengers suffer smaller delays in case of "Perfect-infinite information".

(3) Passengers' connections may change with information in case of delays.

The "Train 2" can connect with "Train 3" in case of "No delay", but this connection becomes infeasible in case of "Perfect-infinite Information". The reason is "Train 2" arrive at station B too late, and "Train 3" has already departed from station B.

(4) Passengers may choose the "best" route in case of incomplete information.

The route choice with "Perfect-infinite Information" is the best one among all the possible options for passengers in case of delays, in reality. The best route is "Train 1 (A, **100** - B, **150** - B, **160** - D, **290**)". As is shown in the result of "Perfect Information" and "Schedule-stubborn Belief", passengers will choose "Train 1" based on their thinking. Even if passengers think, they can arrive at station D at the time 200. Similarly, passengers with "On-route Information" and "Delay-extended Belief" can choose the best route, same as the route choice with "On-route-infinite Information".

(5) Deviations exist between passengers' thinking and reality in case of incomplete information.

In table C.2 and Table C.3, we can see the results that the delays are different in passengers' thinking and in reality. For instance, in case of "Perfect Information" and "Delay-extended Belief", passengers think they will suffer the delay of 10, but in the reality, the actual delay is 90. These deviations are because passengers' belief about delay propagation is not consistent to the actual delays in reality.

Table C.1: Example of passengers' route choices in case of "No delay" or infinite information of delays

	Figure	"Considered paths" in passengers' thinking	No.	Thinking arrival time	Actual arrival time	Thinking delay	Actual delay	Deviations: think vs. act
No delay	5.2	Train 2 (A, 120 - B, 180) -> Train 3 (B, 190 - D, 220) Train 2 (A, 120 - B, 180 - B, 220 - C, 290 - C, 300 -D, 390) Train 2 (A, 120 - B, 180) -> Train 5 (B, 290 - D, 410) Train 4 (A, 170 - B, 210) -> Train 2 (B, 220 - C, 290 - C, 300 - D, 390) Train 4 (A, 170 - B, 210) -> Train 5 (B, 290 - D, 410)	5	220	220	0	0	0
Perfect-infinite Info	5.4	Train 1 (A, **100** - B, **150** - B, **160** - D, **290**) Train 1 (A, **100** - B, **150**) -> Train 3 (B, **200** - D, **310**) Train 1 (A, **100** - B, **150**) -> Train 5 (B, **300** - D, **470**) Train 1 (A, **100** - B, **150**) -> Train 2 (B, **310** - C, **420** - C, **430** - D, **520**) Train 4 (A, **190** - B, **250**) -> Train 5 (B, **300** - D, **470**) Train 4 (A, **190** - B, **250**) -> Train 2 (B, **310** - C, **420** - C, **430** - D, **520**) Train 2 (A, **200** - B, **290** - B, **310** - C, **420** - C, **430** -D, **520**)	7	290	290	70	70	0
On-route-infinite Info	5.5	Train 4 (A, **190** - B, **250**) -> Train 5 (B, **300** - D, **470**) Train 4 (A, **190** - B, **250**) -> Train 2 (B, **310** - C, **420** - C, **430** - D, **520**) Train 2 (A, **200** - B, **290** - B, **310** - C, **420** - C, **430** -D, **520**)	3	470	470	250	250	0

Table C.2: Example of passengers' route choices in case of incomplete "Perfect Information"

	Figure	"Considered paths" in passengers' thinking	No.	Thinking arrival time	Actual arrival time	Thinking delay	Actual delay	Deviations: think vs. act
Perfect Info, Schedule-Belief	5.6(b) 5.6(c)	Train 1 (A, **100** - B, **150** - B, **160** - D, 200) Train 1 (A, **100** - B, **150**) -> Train 3 (B, **200** - D, 220) Train 1 (A, **100** - B, **150**) -> Train 5 (B, 290 - D, 410) Train 1 (A, **100** - B, **150**) -> Train 2 (B, 220 - C, 290 - C, 300 - D, 390) Train 4 (A, **190** - B, 210) -> Train 5 (B, 290 - D, 410) Train 4 (A, **190** - B, 210) -> Train 2 (B, 220 - C, 290 - C, 300 - D, 390) Train 2 (A, **200** - B, 180 - B, 220 - C, 290 - C, 300 -D, 390)	7	200	290	-20	70	90
Perfect Info, Delay-Belief	5.6(d) 5.6(e)	Train 1 (A, **100** - B, **150** - B, **160** - D, 290) Train 1 (A, **100** - B, **150**) -> Train 3 (B, **200** - D, 230) Train 1 (A, **100** - B, **150**) -> Train 5 (B, 290 - D, 410) Train 1 (A, **100** - B, **150**) -> Train 2 (B, 300 - C, 370 - C, 380 - D, 470) Train 4 (A, **190** - B, **250**) -> Train 5 (B, 290 - D, 410) Train 4 (A, **190** - B, **250**) -> Train 2 (B, 300 - C, 370 - C, 380 - D, 470) Train 2 (A, **200** - B, 260 - B, 300 - C, 370 - C, 380 -D, 470)	7	230	310	10	90	80

Table C.3: Example of passengers' route choices in case of incomplete "On-route Information"

	Figure	"Considered paths" in passengers' thinking	No.	Thinking arrival time	Actual arrival time	Thinking delay	Actual delay	Deviations: think vs. act
On-route Info, Schedule-Belief	5.7(b) 5.7(c)	Train 4 (A, **190** - B, **250**) -> Train 5 (B, **300** - D, 410) Train 4 (A, **190** - B, **250**) -> Train 2 (B, 290 - C, 290 - C, 300 - D, 390) Train 2 (A, **200** - B, **290** - B, 290 - C, 290 - C, 300 -D, 390)	3	390	520	170	300	130
On-route Info, Delay- Belief	5.7(d) 5.7(e)	Train 4 (A, **190** - B, **250**) -> Train 5 (B, **300** - D, 420) Train 4 (A, **190** - B, **250**) -> Train 2 (B, 330 - C, 400 - C, 410 - D, 500) Train 2 (A, **200** - B, **290** - B, 330 - C, 400 - C, 410 -D, 500)	3	420	470	200	250	50

Curriculum Vitae

NUANNUAN LENG

Date of birth:	November 24, 1989
Place of birth:	Shandong, China
Nationality:	China

Education

Doctor of Sciences in Civil Engineering, 2020

ETH Zurich, Switzerland

Focus:	Disruption management, information availability, passenger heterogeneity, public transport, large-scale multi-modal network, agent-based simulation, railway operations
Dissertation:	"The role of information to passengers in public transport disruptions"
Advisors:	Prof. Dr. Francesco Corman, Prof. Dr. Ulrich Weidmann, Prof. Dr. Anita Schöbel (TU Kaiserslautern), Dr. Paul Bouman (Erasmus University Rotterdam)

Master of Engineering in Transportation Planning and Management, 2015

Beijing Jiaotong University, Beijing, China

Focus:	Passenger flow forecasting, railway traffic management
Master thesis:	"Passenger flow forecasting and analysis for High-speed railway based on analogy method" (Advisor: Prof. Dr. Lei Nie)

Bachelor of Engineering in Traffic and Transportation, 2012

Beijing Jiaotong University, Beijing, China

Focus:	Transportation planning, railway simulation
Bachelor thesis:	"The layout plan of passenger transport hubs of Chinese High-speed railway" (Advisor: Prof. Dr. Lei Nie)

Experience

Doctoral student at ETH Zurich

- Project member: Technological Development of the Rail System (Technologische Weiterentwicklung des Bahnsystems)
- Teaching assistent: Logistik und Gueterverkehr

Master student at Beijing Jiaotong University

- Multiple projects about High-speed railway: Passenger Flow Forecasting, Transfer Hub Location Selection, Train Connection Scheme, Railway Operations

Publications

Journal Articles

- Leng, N. and Corman, F. (2020) The role of information availability to passengers in public transport disruptions: An agent-based simulation approach. *Transportation Research Part A: Policy and Practice*, **133** 214-236.
- Leng, N., Liao, Z. and Corman, F. (2020) Role of timetable, rolling stock rescheduling, and information strategies to passengers in public transport disruptions, *Transportation Research Record*, 1-13.
- Leng, N. and Corman, F. (2020) How the issue time of information affects passengers in public transport disruptions: an agent-based simulation approach. *Procedia Computer Science*, **170** 382-389.
- Leng, N. and Weidmann, U. (2017) Discussions of the reschedule process of passengers, train operators and infrastructure managers in railway disruptions, *Transportation Research Procedia*, **27** 538-544.
- Leng, N. and Corman, F. (under review) A multi-layer time-space-event-graph to model the effects of incomplete information to passengers in public transport delays.

Peer-reviewed conference contributions

- Leng, N. and Corman, F. (2020) The role of incomplete information to passengers in railway delays, *2020 INFORMS Annual Meeting.* (One of winning papers of the 2020 Railway Application Section (RAS) Student Paper Contest)
- Leng, N., Liao, Z. and Corman, F. (2020) Role of timetable, rolling stock rescheduling, and information strategies to passengers in public transport disruptions, paper presented at the *99th Annual Meeting of the Transportation Research Board*, Washington, D.C., America.
- Leng, N., De Martinis, V. and Corman, F. (2018) Agent-based simulation approach for disruption management in rail schedule, paper presented at the *14th International Conference on Advanced Systems in Public Transport*, Brisbane, Australia.
- Leng, N. and Weidmann, U. (2017) Multi-objectives of the passenger oriented disruption management problem, paper presented at the *7th International Conference on Railway Operations Modelling and Analysis*, Lille, France.
- Leng, N. and Weidmann, U. (2016) Design of passenger-oriented timetable rescheduling in railway disruptions, paper presented at the *16th Swiss Transportation Research Conference*, Ascona, Switzerland.