Assessing Traffic Network Resilience Using Agent-Based Modeling and Simulation

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Assessing Traffic Network Resilience Using Agent-based Modeling and Simulation

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Executive Summary

Urban areas are seeing influx of population and therefore are experiencing increasing stress on the systems currently in place. With that in mind, some policy makers are turning towards the idea of resilient cities in order to cope with the larger population. It is fair to say that the specifics of resilience in terms of meaning are in contention even today, but nonetheless it is clear that traffic and transport systems are a crucial element to resilient cities. Resilience in this thesis means the ability for a system to quickly return to normal operating conditions after some disturbance. In traffic networks, a larger population means that their are inevitably a short term increase in mobility demands. To accommodate this, governments and and the private sector are proposing new solutions for mobility. One such focus is the introduction of new transport modes. A common classification for these modes is Mobility-as-a-Service (MaaS), which includes modes such as carsharing, shared last-mile transportation like bicycles, and ridesharing. MaaS also overlaps with other new modes such as autonomous and electric vehicles. Modeling these types of modes and their subsequent interactions with each other and traditional modes requires more complex modeling techniques than have been traditionally used in transport modeling.

The purpose of this thesis is split into two main components. First, an academic research gap exists in using modeling and simulation to assess traffic network resilience. This gap is especially prevalent when considering novel modes of transport, such as ridesharing. Second, there is motivation specific to TNO, as the research was part of an internship with the Dutch research organization. This aspect of the purpose is specific to incorporating data from the metropolitan region of Rotterdam and The Hague (Metropoolregio Rotterdam Den Haag or MRDH) into an agent-based traffic model. These two purposes are brought together in the form of a case study of the MRDH traffic network in order to prove feasibility of a method for assessing resilience in traffic networks using agent based-modeling and simulation (ABMS). ABMS has the dynamic qualities that match well with the time variant nature resilience.

A resilience framework for urban mobility is proposed that uses six categories to characterize resilience: (1) *reflective*, *redundant*, *flexible*, *resourceful*, *inclusive*, and *integrated*. Using this framework as a guide, three metrics are proposed for measuring resilience using agent-based simulation: origin-destination (OD) travel time, link travel time, and link volume. These metrics are used to compare scenarios that either include a disturbance in the network or do not, which in this case occurs for a 30 minute period on the A4 roadway between Rotterdam and The Hague. The OD travel time metric is tested on trips that either originate in Rotterdam and end in The Hague or

vice versa. The different characteristics of ridesharing trips, namely the inclusion of walking time and waiting time at pickup points, means that these trips are longer on average than car trips and therefore not comparable in this setting. The OD travel time metric is ultimately not useful when comparing different modes like this. The two link-related metrics, though, show promise in measuring resilience. The link travel time metric makes apparent the the recovery time to achieve normal operating conditions after a disturbance. In the presented case study, scenarios that included ridesharing had worse recovery time then the car only scenario, as well as a higher maximum travel time across the disturbed link. The link volume metric contextualizes these results, showing that while the overall volume throughout the simulation is lower for the ridesharing cases, the volume during the disturbance across the disrupted portion of the A4 roadway is higher. The higher volume shows why the travel time is higher with the presence of ridesharing in the disturbance scenario. These results are subject to the limitations of the model, though, which include dynamic routing that may not avoid the disturbed portion of the network when the disturbance occurs.

Other limitations come to light with regards to modeling for the purpose of resilience measurement. Dynamic routing is an important behavior in models that wish to model resilience. The drawback to this, though, is that there are high computation times associated with the dynamic vehicle routing problem, especially for realistically large simulations. This is an important consideration for policy advice as it makes the models less accessible and less useful in time critical situations. For TNO, this means that the application of models should be carefully taken into account. There is additional risk involved with higher computation times as when things go wrong, they take much longer to fix. Incorporating agent-based models as well as adding more within day dynamics to traffic models should be a long term goal, but avoided if the given project is time sensitive.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Resilience is a measure of a systems ability to recover from a shock in a short period of time; the quicker the recovery to equilibrium, the better. Urban traffic networks are a major component of resilient urban systems. With the increasing demand for mobility in ever-growing urban regions, new transport modes are entering into the market and becoming more popular. Considering new transport modes in the context of resilience is therefore important not only today, but in the future as well. The remainder of this chapter includes a motivation for this particular topic; additional information on TNO, whom is a partner in the thesis; the research gap; research questions; approach; and a conclusion with an overview of the structure of the rest of the report.

1.1 Problem definition

1.1.1 Motivation

A majority of the world population lives in urban areas (World Bank, 2018a) and in the Netherlands, the percentage of the population living in urban areas in 2018 is 91% (World Bank, 2018b). The 11th goal of the United Nations Sustainable Development Goals highlights that cities should be inclusive, safe, resilient, and sustainable, and mobility is a major factor in this (United Nations, 2019). The global trend towards urbanization indicates that the future of urban transport and mobility must be understood in order for policies to be conceived proactively. Passenger transport is also very location dependent; for example, the public transport systems in major US cities are often quite different from their European counterparts. In some cities, public transport and other sustainable transport modes, such as biking, take a back seat to personal vehicles. When compared to the most sustainable forms of personal transit (e.g. walking and biking), a personal vehicle with one passenger is immensely wasteful and results in poor air quality, especially in urban areas (European Environmental Agency, 2016). The traffic networks of each city are unique, so local solutions that accommodate all travellers are mandatory; there is no one-size-fits-all policy, making this a wicked problem according to Rittel & Webber (1973).

If the 2050 emission targets envisaged by the European Commission are to be met for any given country, the traffic network of that country ought to be a primary concern as transport accounted for 30% of CO_2 emissions in Europe in 2019 (*CO2 emissions from cars: facts and figures*, 2019). That being said, new solutions to mobility that are accessible, safe, and sustainable are being explored. Regardless of the transport mode, it is important to consider the impacts that its introduction may have on the resilience (defined in section 2.2.4) of traffic networks. This thesis aims to present a method for assessing network resilience when new modes of transport are introduced into the system by using an agent-based modeling method. To show feasibility of the method, this research will use a case study on ridesharing in the metropolitan region of Rotterdam and The Hague (Metropoolregio Rotterdam Den Haag or MRDH). In this thesis, ridesharing is the shared use of a vehicle in the form of a ride, in this case a car, where the rider is picked up at an origin and delivered to their destination. The difference betwen this and a conventional taxi is that ridesharing taxis may pick-up multiple passengers at once and are scheduled on-demand as part of a fleet. This is also similar to automated taxi services. Policies that are conducive to the adoption of both the vehicles and essential infrastructure need to be examined now so that decision makers are not caught off guard by the introduction of new transportation modes such as ridesharing. A key tool to aid decision making on this subject is simulation.

The motivation for the thesis is heavily focused on The Netherlands. This is partly because the research is carried out with TU Delft, but also due to the additional partnership with the Dutch research organization TNO. Thus, the case study uses data from the MRDH, however the techniques used in the thesis are meant to also be broadly applicable to other regions.

1.1.2 More about TNO

TNO is a scientific research organization whose scope as a knowledge institution is to use this knowledge to "to create innovations that boost the competitive strength of industry and the well-being of society in a sustainable way" (*Mission and Strategy*, n.d.). TNO works closely with Dutch governmental bodies on a variety of projects, among other clients. Some of the fields of work include infrastructure, the circular economy, energy, ICT, and strategic analysis and policy, however this research is in cooperation with the Sustainable Urban Mobility and Safety (SUMS) department within TNO, whom have their own research goals. This section provides a high level overview of the ambitions of SUMS and how they relate to this project, without going into too much detail to maintain appropriate confidentiality.

SUMS aims to contribute to research on new developments in urban mobility which includes the introduction of new modes. Their goal is to improve the knowledge base for new mobility and analytical tools with regard to autonomous vehicles and Mobility-as-a-Service. Traditionally aggregated traffic models fail to answer many policy questions that are relevant for governments and private interests in the mobility sector, so SUMS wishes to improve upon their own models by incorporating new techniques. This is where the present research contributes to SUMS' goals. The development of an agent-based traffic model applied to a local case study (MRDH) is one component of this broader goal.

1.1.3 Research gap

Two opportunities present themselves from a research perspective. The first has to do with how well traffic systems, especially urban ones, are represented in models. Increasing mobility demands by urban populations drive innovation that leads to new transport modes (van Eck et al., 2014). In the continued presence of traditional modes of transport, new modes increase the system complexity. This gap concerning the introduction of new modes of person transport into traffic models exists because this complexity is not readily captured by traditional traffic models. In literature, these new modes are often studied using optimization methods. However, overhauling a transport system is not as simple as optimizing for supply and demand because implementation takes time and there are intermediate effects to be considered.

The second gap involves the integration of urban resilience into these models. In the context of this thesis, urban resilience (see Section 2.2.4 for more detail) is the ability of a system to recover to equilibrium, in a short period of time, after a shock. By integration of urban resilience into models, it is not meant that resilience should be a component of the model itself. Rather, it is in the assessment and conceptualization of traffic models where resilience can be taken into account, as it is typically not. Ribeiro & Gonçalves (2019) discuss the evaluation of urban resilience and the shortage of tools available, showing that the gap extends beyond just traffic networks as well.

As was mentioned previously, the introduction of new transport modes into an existing traffic network is not as simple as determining the optimum supply of that mode. Though this provides an idea for a goal to aim for, considering the intermediate effects as new transport modes are actively being adopted is important as well. This is where the idea of resilience and new transport modes intersect. Understanding the effect of a new mode on the traffic system as it is incrementally adopted allows for more informed decisions on the process incorporating that mode. Optimization of supply shows the promise of the new mode, while looking at a metric such as resilience gives insight into the effects of implementation on the current system.

1.2 Research questions

The main research question is given below.

> *How can resilience in urban traffic networks be measured using agent-based modeling and simulation?*

Given this main research question, sub-questions have been formulated to guide the proposed research and motivate a research methodology. The sub-questions are ordered to reflect the general flow of research.

1. *What does resilience mean when considering urban traffic?*

The concept of resilience is applied to many different domains with each one presenting a possibly different interpretation of its meaning. Therefore, resilience should be defined in this specific setting to avoid confusion. Given the definition for resilience in urban traffic networks, the next important consideration is how it can be measured, leading to the second sub question.

2. Which metric(s) should be used to assess traffic network resilience given the modeling context?

Resilience can be assessed with different techniques that are often application specific. In this thesis, the traffic dynamics of the system and resulting model are to be taken into account, so these techniques should be differentiated between. Finally, the outputs of these measuring techniques must be made sense of in a 'real' way. This means framing the results in the arena of transportation policy as shown in the following question.

3. How can measuring resilience in this context be used for transportation policy advice regarding ridesharing?

The focus on policy is derived from not only the overarching teaching goals of the Engineering and Policy Analysis masters degree, but also the role of TNO in governance in The Netherlands, recalling that this thesis is in partnership with the research organization. With these sub-questions, a few key elements arise that expand on the main research question. Firstly, resilience should be given a definition that is specific to studying urban traffic networks. Second, resilience must be measured in the modeling and simulation context. Finally, the results are given meaning in the form of model-based policy advice.

1.3 Approach

The research will primarily follow a modeling approach with some elements of an exploratory approach to answer key sub-questions. The exploratory approach addresses the first three sub-questions, which are ultimately used in the modeling process to answer questions on resilience. Questions one and two concern the theory behind setting up and assessing the experiments while question three concerns the experimental setup. These three questions are setup for questions four and five, which are answered using the modeling approach. These questions answer the heart of the main research question regarding the effect of ridesharing on resilience and additionally provide advice on potential policy measures.

1.4 Thesis structure

Chapter 2 consists of a literature review on the key terms and concepts used throughout the research. Chapter 3 presents the method used for the modeling process. This begins with conceptual modeling and carries through to the implementation in MATSim. In Chapter 4, the case study used for analysis is discussed including the data for the networks and the population as well as the specific setup for MATSim. Chapter 5 explains the scenario analysis done on the model. The results of these experiments are then presented in Chapter 6 and then discussed in Chapter 7. Finally, Chapter 8 gives conclusions on the research questions, along with recommendations for TNO and for future research.

Chapter 2

Literature Review

The literature review begins with outlining the method of finding papers and is followed by an overview of key terms. Then, a review of resilience and its meaning in urban traffic networks produces a framework that is later used to guide discussion of resilience assessment. The remainder of the review consists of background literature on transport modeling and examples of use cases that are relevant to this thesis along with some relevant examples of transport policy. Finally a conclusion is drawn from the presented literature.

2.1 Method

The main key words that guided the literature search included multimodality, resilience, urban traffic, ridesharing, MaaS, and traffic network. The initial scope of the search includes general traffic modeling research on methodologies to become more familiar with the topic. Then, the search is narrowed to focus on modeling methods for the given contexts of new transport modes and multimodality, as these are important to the research goals of TNO. A second main area of research is resilience. This too begins with a broad search of resilience in general to gain understanding of its meaning in different applications. This too is narrowed to be specific to urban areas and then again to urban traffic networks. This way, a definition for resilience is provided that is specific to the problem at hand.

A preliminary literature list is also provided by TNO, who are collaborators for the thesis. Google Scholar is the primary search engine used for finding new articles. Once a suitable article related to the topic was found, the literature from that paper was then explored. This leads to additional, more specific keywords such as super-networks, dynamic activity assignment, and mode chains. The 'snowball effect' of searching for literature within other literature is the main strategy for finding further papers.

2.2 Key terms

The following section brings forward key terms and their respective definitions for this paper. These terms are **agent-based modeling and simulation**; **mircro-** and **macro-simulation**; **new transport modes** and **ridesharing**; and **resilience**, **robustness**, **recovery**, and **criticality**.

2.2.1 Agent-based modeling and simulation

Agent-based modeling and simulation (**ABMS**) provides a specific way for defining agents in a model. In **ABMS**, agents have properties that include *autonomy*, *self-containment*, and *interaction* (Macal & North, 2009). An *autonomous* agent acts on its own given the sensory input it obtains from its surroundings (other agents) and environment (2009). A *self-contained* agent is discrete and has it's own attributes and decision making capability (2009). An *interacting* agent has protocols that describe its interactions with other agents (2009). Macal & North provide additional optional attributes for agents in **ABMS** but these three make up the core.

2.2.2 Micro- vs macro-simulation

Micro-simulation and **macro-simulation** are two different aggregation levels in modeling. In traffic modeling, the former focuses on individual vehicles and their interactions while the latter considers general motion constraints like roads and traffic lights (Härri et al., 2009). **Micro-simulation** goes hand in hand with ABMS and is thus the aggregation level used in this thesis.

2.2.3 New transport modes and ridesharing

The broader application for this thesis work is on the introduction of **new transport modes** into existing traffic systems. This includes but is not limited to modes such as electric vehicles, autonomous vehicles, and shared vehicles. Considering all **new transport modes** is not within scope of this thesis however, so a smaller sub-category is considered. That category is shared mobility, defined as the shared use of a vehicle, bicycle, or other mode. Even more specifically, the case study in this paper looks into **ridesharing**, which is the shared use of a vehicle, in this case a car, where the rider is picked up at an origin and delivered to their destination (Shaheen et al., 2015). For this thesis, only sharing of a vehicle through means of a shared ride as a passenger is considered, not shared use of a vehicle in terms of a short-term rental. The user is therefore never in control of the vehicle itself.

2.2.4 Resilience, robustness, recovery, and criticality

Resilience and **robustness** are loosely defined and vary by application (Ribeiro & Gonçalves, 2019). For this research, **resilience** is defined as the ability of a system to recover to normal operating conditions in a short period of time after a shock and **robustness** is defined as the ability of a system to resist a shock and maintain its equilibrium. Taylor (2017) provides a visual representation of resilience and robustness in the form of the "resilience triangle," an adaptation of which can be

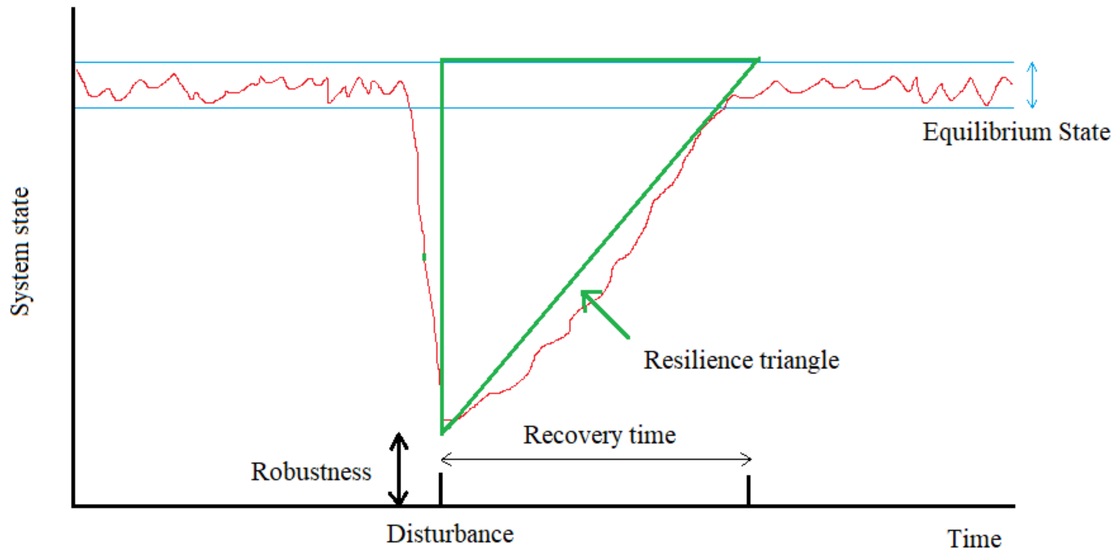

Figure 2.2.1: Resilience triangle adapted from Taylor (2017).

seen in Figure 2.2.1. **Recovery**, according to the resilience triangle, is the time it takes for a system to return to equilibrium and is a major component of resilience. **Criticality** is also disputed in literature (Jafino et al., 2020), but is defined here as the importance of a link or node in a network. Expanding on this, a link or node is of high importance if it has a high expected absolute flow during peak conditions, a high expected flow relative to its capacity, and there are few alternative links with similarly high capacity. The final criteria of few alternative links is case specific, but in general this means that there are 1 or 2 major links with high capacity in the network that can reasonably used in alternative routes when rerouting traffic away from the disrupted link. Section 5.3 goes into more detail on how a critical link is chosen. Here, the A4 roadway is a primary route for vehicle traffic between Rotterdam and The Hague, and the other major link between the cities is the A13.

2.3 Resilience in urban transportation

Resilience has been defined in Section 2.2 and it should be noted that the following literature may define this term differently, but the general meaning is similar. This section aims to further contribute to the first research sub-question on defining resilience in the context of urban traffic networks. Martins et al. (2019) discuss how different indicators may be used to estimate the resilience of urban traffic networks. This method works well when data is limited (Martins et al., 2019), however it does not seek to further understand the underlying system behavior as a modeling and simulation method would. Scheurer (2016) studies how resilience in transit networks may be improved when there exist intermediate capacity modes of transport. The research was carried out using the Spatial Network Analysis for Multimodal Urban Transport Systems (SNAMUTS) tool (Curtis et al., 2012) which uses indicators and graph theory to make judgment on accessibility within traffic networks. Scheurer (2016) also do not use a simulation approach which may lead to the interaction effects of the system to be overlooked. Aydin et al. (2017) use betweenness centrality to compare node criticality before and after an earthquake. Accessibility to hospitals is used as a measure of network resilience (Aydin et al., 2017). In the proposed research, measuring resilience will require careful consideration of which KPIs are most useful. The provided papers use data-driven and graph-theory approaches whereas the proposed research aims to use modeling and simulation to better capture the impact of new transport modes.

2.3.1 Traffic network performance indicators

Litman (2003) provides a starting point for transportation measurements. Three major approaches are provided, each dealing with different aspects of transportation (2003). These approaches are traffic, mobility, and access. For the scope of this project, the second approach of mobility is most useful. The modes considered for traffic are too narrow, while the modes considered for access are too broad (2003). This is due to the inclusion of ridesharing in the model, which can be viewed as a form of public transit. The mobility approach proposed by Litman cites common performance indicators such as person-trip volumes and speeds and cost per person-trip. These three indicators are used to further define the resilience framework proposed in the following section.

Gu et al. (2020) observe that previous quantitative studies of traffic network resilience failed to capture resilience more generally. Two categories of indices are considered by Gu et al., those that consider congestion effects and those that do not. The latter include connectivity-based indices using graph theory methods such as betweenness centrality whereas the former include the dynamics of the system (2020). As this thesis has a strong modeling focus, the proposed indices fall under the category that considers congestion effects. The following are examples of such indices. Cox et al. (2011) measure transport resilience in the context of a targeted attack on a specific mode of transport. The volume of journeys taken with the attacked modes as well as alternative modes is used to estimate the recovery time (2011). Ip & Wang (2011) use volume at nodes in an undirected graph representing a traffic network to measure the resilience at these nodes; the sum of the values for resilience at every node represents the network resilience. Other metrics focus on measuring the recovery of the system by comparing the proportion of recovered performance to the loss of performance (Henry & Ramirez-Marquez, 2012). Henry & Ramirez-Marquez describe this as a generic metric and assume that system performance can be measured for the given system. Finally, Omer et al. (2011) use the ratio of travel time in a non-disrupted scenario to the travel time in the presence of a disruption to measure resilience.

2.3.2 A resilience framework

In order to further characterize resilience in the context of urban transportation, a resilience framework is proposed. ARUP (2014) give a "city resilience framework" made up of four categories, twelve indicators, and seven qualities. In this framework, "reliable mobility and communication" is considered as an indicator that measures a city's resilience in the category of infrastructure and

Table 2.3.1: Paraphrased definitions for the qualities of urban mobility as found in the City Resilience Framework (ARUP, 2014).

Quality	Definition
Reflective	Systems that are accepting to uncertainty, with mechanisms to continuously evolve and learn from past experience.
Redundant	Spare capacity within systems such that they can accomodate a disruption. This includes diversity as well, or the prescence of multiple ways to achieve a goal.
Flexible	Implies that systems can change, evolve, and adapt to changing circumstances.
Resourceful	People and institutions are able to rapidly find different ways to achieve goals when the system is under stress.
Inclusive	Emphasizes the need for broad consultation and community engagement. Addressing shocks to one location is done inclusively rather than in isolation
Integrated	Consistency in decision making ensures that investments support a common outcoume. Information exchange between subsystems enables collective functioning.

environment 2014. Rather than use this framework as is, the mobility portion will be broken down and further defined in a similar fashion. In the framework presented in this thesis, urban mobility becomes the focus and the category which is further explained through indicators and qualities. Table 2.3.1 provides definitions for these qualities.

The category of urban mobility is broken down into indicators that can be used to assess the qualities that characterize resilience according to ARUP (2014). The indicators come from the discussion in the previous section on traffic network KPIs and metrics for measuring resilience and are used to motivate outputs of interest from the model and case study that are specific to this thesis. In this way, the indicators contribute to the second research sub-question on resilience measurement. Table 2.3.2 gives an overview of the relationships between indicators and qualities. The reasoning behind these relationships is as follows, where the indicators are given in bold and the qualities they measure are italicized.

1. **Person-trip volumes and link volumes**: *Redundancy* concerns spare capacity in systems. These indicators show how that capacity is being used. Person-trips and links offer two different aggregation levels where person-trips consider the traveler more closely while links considers the network itself, regardless of who travels where.

2. **Person-trip speeds and link travel times**: *Flexibility* in a system means that it is adaptable. If person-trip speeds, or times, are maintained under stress, it shows the system is flexible to possible changes in capacity in the network via a disruption.

Table 2.3.2: Resilience framework table. The category of urban mobility can be broken down further according to indicators. These indicators assess the qualities of resilience in urban mobility from ARUP (2014) which in turn measure estimates traffic network resilience. The check marks indicate that some indicator is linked to that quality.

Category	Indicator	Quality					
		Reflective	Redundant	Flexible	Resourceful	Inclusive	Integrated
Urban Mobility	Person-trip volumes		✓				
	Link volumes		✓				
	Person-trip speeds			✓			
	Link travel times			✓			
	Cost per person-trip				✓	✓	

3. **Cost per person-trip**: The more cost efficient options there are for trips, the more *resourceful* the system is, as there are different alternatives for a similar cost. An *inclusive* system will have cost effective options that are broadly applicable to the whole system, rather than to specific locations or groups.

Two of the qualities are not represented in the indicators as seen in Table 2.3.2. The reflective quality is not captured in the indicators, however it is captured in the model. For example, the learning aspect of a reflective system is captured in the models ability to learn from previous agent plans including its routing and mode choice decisions. This is a qualitative aspect of the model that should be representative of agents ability to evolve their plans. The integrated quality is not captured in either the model output or the model itself. Instead, this thesis addresses consistency in decision making in the form of policy advice which is seen as more of a goal rather than a measurable outcome or trait of the model.

2.4 Introduction of new transport modes

An evolving transport industry means that there are always new modes to be considered when modeling. Boesch et al. (2016) discuss a need for future work to address dynamic traffic demand that comes as a result of new transport offerings. In the context of autonomous vehicles, the distinction between connectivity and autonomy is infrequently discussed in the literature (Talebpour & Mahmassani, 2016), leading to models that do not account for connected, non-autonomous vehicles. Calvert et al. (2017) find that with increasing penetration rates of autonomous vehicles comes an increased network capacity. This in turn reduces network congestion (Fagnant et al., 2015). Other considerations for new transport modes also include Mobility-as-a-Service. Fagnant et al. (2015) performed simulation experiments on an Austin, Texas based model showing that shared autonomous vehicles have a substantial positive impact on parking and emissions. Narayan et al.

(2019) study the effects of ride-sourcing (ridesharing) on the demand for other modes of transport in Amsterdam, finding that increased fleet size of ride-sourcing vehicles led to a decrease in the number of trips in personal vehicles. These papers do not consider the impacts of the new mode when the network is under unexpected stress from, for example, an accident that closes part of the network. Research into optimization of ridesharing is present in the literature (Agatz et al., 2011); (Fagnant & Kockelman, 2016); (Alonso-Mora et al., 2017). Luo et al. (2019) present an optimization model for determining bus-bridging routes in the event of a disruption to a mass rapid transit network. This research gives an example of how optimization techniques may also be used in urban resilience and is motivation for the use of modeling. Finally, there is motivation to study the effects of shared vehicles in combination with other new modes, as this is seldom studied (Alazzawi et al., 2018; Bradley et al., 2018; Snelder et al., 2019).

2.5 Transport modeling paradigms

The aptly named four-step transport model consists of the following steps: trip generation, trip distribution, mode choice, and route assignment (McNally, 2007). Trip generation establishes how many origins or destinations occur in the pre-defined zones while trip distribution matches the origins with destinations (2007). The transportation mode of trips is selected in the mode choice step, typically using a logit model, followed by the route assignment step, which chooses a shortest time path for each traveler (2007). Mladenovic & Trifunovic (2014) point out some shortcomings to the four-step model. Some general shortcomings include lack of behavioral considerations, a deterministic nature, aggregation of behavior that does not represent individual travelers, and limited modeling of congestion effects (2014). These shortcomings motivate the use of agent-based modeling techniques, especially in the case of assessing a dynamic aspect such as resilience. Activity-based models are demand-based models that aims to predict the choices at various aggregation levels including persons and households (Transportation Research Board and National Academies of Sciences, Engineering, and Medicine, 2014). Travel decisions such as mode choice and departure time choice, are estimated by utility maximization accoriding to joint and conditional probability trees (2014). Activity-based models only consider the demand side but are more disaggregated than traditional four step models, therefore better capturing individual behavior. Because of this disaggregation, the activity schedules produced from activity-based models may also be incorporated into agent-based models to define the initial trip schedules for agents.

2.6 Multimodality in modeling

Models that include multimodality are part of the broader research goals of TNO, so while it may not be included in the model in this thesis, outside of walking trips to and from ridesharing vehicles, it is important that it be considered when selecting software and methods for modeling and simulation.

Multimodality in modeling and simulation constitutes agents that use one or more modes of transport chained together in a single trip to reach their destination (van Nes, 2002). In Europe, multimodality is becoming increasingly emphasized. Violeta Bulc, the EU Transport Commissioner, went as far as to deem 2018 the "Year of Multimodality" (ec.europa.eu, 2018). van Eck et al. (2014) show that network demand predictions are systematically incorrect and decision makers may make choices using this information. As such, they argue for more multimodal complexity in models. Finally, van Eck et al. (2014) point out that multimodality facilitates a shift to more sustainable transport modes and alleviates congestion in urban areas.

van Eck et al. (2014) discuss classical modeling that is insufficient in modeling multimodality due to its separation of private and public transportation. Building on the classical model, they provide an overview of two other approaches. The first, referred to as the state-of-the-practice model, uses pre-specified mode chains that describe which mode transfers are possible in the model. An example sequence that van Eck et al. provide is car-transit-walk. The second method outlined by van Eck et al. is the use of super-networks, which define layers for available modes of transport that allow for transfer between layers.

Two examples of state-of-the-practice models are provided. Verbas et al. (2015) present a simulation tool which dynamically assigns travellers to the optimal hyperpaths. The multimodality is implemented by modeling the links and nodes of the Chicago Transit Authority network. The computational speed of the optimization algorithm proposed by Verbas et al. (2015) is improved by defining the mode transfers within the links. Abdelghany & Mahmassani (2001) provide a model with pre-specified modal combinations including bus to bus transfer and car to bus transfer. In addition, the model uses dynamic trip assignment to overcome some of the shortfalls of static tools. The mode combinations are limited compared to the real world and also exclude all of the recent, new forms of transportation.

Super-networks are discussed often in the literature. Thses are layers of networks each representing a mode of transport, for which there are connecting nodes to model transfer between nodes. Lozano & Storchi (2002) study the impact of user preferences on the transport modes used, explaining that the optimal paths provided by search algorithms often give hyperpaths that are not realistic for travellers to use. There is a focus by Lozano & Storchi on the viability and realism of optimal paths chosen by search algorithms. Lozano & Storchi give an algorithm to find Pareto optimal and viable hyperpaths, but only give an example on a relatively small network. Liu et al. (2015) provide an algorithm for formulation of dynamic activity-travel assignment to tackle the issue of integration structure in super-networks. However, the algorithm does not consider capacity constraints for public transport nor has it been tested on full-scale super-networks. Carlier et al. (2003) implement a super-network of the Rotterdam/Dordrecht corridor using stochastic travel assignment as it is considered feasible at this scale. Arentze & Timmermans (2004) describe a network representation for multimodal systems by using copies of super-networks with state transition links between. For each transport mode there is a super-network that defines it. The research by Arentze & Timmermans (2004) excludes the viability of the transitions between modes. Super-networks, though more descriptive than state-of-the-practice models, are held back by these limitations that relate mostly to computational scalability.

Ziemke et al. (2019) give an example of a multimodal traffic simulation done in MATSim based on open data from Berlin. The technique used by Ziemke et al. (2019) is also applicable to creating agent-based traffic simulations of other regions using similar open data. Snelder et al. (2019) presents a model which contains 12 different transport modes. The ultimate goal of this model is to be allow for quicker incorporation of new modes into the model.

2.7 Agent-based approach in traffic simulation

ABMS (Agent-based modeling and simulation) is used to address complex systems and is has recently gained popularity today due to availability of more granular data and greater computational power (Macal & North, 2009). Balmer et al. (2004) recognize that the traditional four-step process of transport modeling does not capture the essence of individual travelers. Weiss et al. (2014) explore the need for dynamic agent-based traffic assignment. Balmer et al. propose a formulation for ABMS that distinguishes between the physical (network) and mental (choice behaviour) layers, where the latter is a motivating factor for using ABMS. The feedback mechanisms in traffic systems are also represented more realistically in ABMS (2004). Yuhara & Tajima (2006) state that "the micro-simulation used in traffic engineering community is not effective for traffic safety issues" (p. 284), which motivates their use of ABMS. Bekhor et al. (2011) integrate a demand defined by activity schedules with an agent-based supply definition to model Tel Aviv. ABMS can also be used to model demand, and is specifically useful when considering shared mobility (Franco et al., 2020); (Narayan et al., 2019); (Maciejewski et al., 2016). Considered together, these papers show that the need for ABMS in traffic and transport modeling is still expanding today due to greater need to model human behavior. As such research is continuing in this direction.

2.8 Dynamic vehicle routing problem (DVRP)

The introduction of ridesharing, and more generally any mode of transport that is dynamic in nature, calls for dynamic routing capability in the simulation engine. With ridesharing specifically, there is a limited supply determined by the vehicle fleet size and capacity of the vehicles and each of these vehicles is scheduled for various pick-ups and drop-offs as the demand dictates. This leads to the dynamic vehicle routing problem (DVRP). Two aspects make up the definition of the DVRP according to Larsen & Madsen (2000, p. 5):

"1. *Not all information relevant to the planning of the routes is known by the planner when the routing process begins.*

2. *Information can change after the initial routes have been constructed.*"

In practice, Maciejewski & Nagel (2012) propose a method for simulating the DVRP in MATSim using the DVRP Optimizer. Maciejewski & Nagel also point out that that rule-based dispatching used is simple and efficient but does not consider planning horizons longer than just a single choice. This gives an indication that increasingly realistic modeling comes at the cost of computation time.

2.9 Policy in transportation

Ridesharing is typically discussed in the context of Mobility-as-a-Service (MaaS) and therefore policies surrounding MaaS give a good indication of potential hurdles in ridesharing policy initiatives. Liljamo et al. (2020) present results of a survey of Finnish residents willingness to adopt MaaS offerings. In their study, Liljamo et al. find that respondents who are willing to use a MaaS offering were on average willing to pay 64% of their current estimated mobility costs. However, in a study of German citizens, Andor et al. (2020) estimate that people tend to underestimate the cost of owning a vehicle by 52% on average. Pairing the information from both these articles together gives insight into one of the difficulties in getting MaaS offerings to be widely used and successful; users may be incorrectly assessing the relative price of MaaS in comparison to personal vehicle use. Hamre & Buehler (2014) discuss the impacts of commuter benefits such as free parking, public transportation benefits, and walking and biking benefits. An important conclusion of Hamre & Buehler is that providing free parking significantly decreases travelers likelihood of walking, biking, or using public transportation. While this article does not directly address MaaS, it can be said that a reduction in personal car usage may have a negative correlation with MaaS usage. Therefore, policies that do not directly impact MaaS or ridesharing are also worth considering. Hamre & Buehler also point out that providing direct benefits to public transportation rather intuitively promotes the use of public transportation, but also encourages walking.

2.10 Conclusion

The presented literature shows two main research gaps. First, new modes of transportation are becoming prevalent which should be integrated into traffic models (van Eck et al., 2014) and second, Ribeiro & Gonçalves (2019) mention a "lack of tools and methods to evaluate resilience" which is also not studied in relation to novel forms of mobility. Concerning the first point, Weiss et al. (2014) explore the need for dynamic agent-based traffic assignment. Boesch et al. (2016) discuss future work needed in addressing dynamic traffic demand that comes as a result of new transport offerings. In addition, few studies consider the effects of shared vehicles in combination with other new modes (Alazzawi et al., 2018; Bradley et al., 2018; Snelder et al., 2019). Snelder et al. (2019) presents a model which contains 12 different transport modes. A desired extension to this model is the addition of the ability to process new mobility concepts and the incorporation of an agent-based methodology. This a large part of the motivation from TNO's perspective as well.

Resilience, on the other hand, is often studied in a static way (e.g. graph theory), but transportation modes, such as ridesharing, should also be studied dynamically in time-dependent networks as it is important to capture their interaction with other, traditional modes of transport. Ridesharing is often modeled and simulated from an optimization perspective, but the same techniques are not applied to urban resilience. Data-driven techniques for estimating resilience are prevalent, but introducing simulation and scenarios may provide additional insight, especially when considering future events. Because of the dynamic nature of resilience, agent-based modeling is a prime candidate for assessing it as opposed to other more traditional transport modeling methods like the four-step model and activity-based models. Narayan et al. (2019), in their study of ride-sourcing in Amsterdam, state that “a future direction of research includes assessing the impact of a shared service (where passengers share a ride) on the mobility of users...” (found in the conclusion section). This shows a desire to incorporate new transport modes with the idea of resilience. To address this gap, a resilience framework is given that serves as an aid to discussion of resilience in urban traffic networks.

With regards to the research questions, this literature review produced a resilience framework to address sub-question 1, allowing for resilience to be discussed in the context of urban traffic networks. Performance indicators are also outlined, contributing to the second research question on measuring resilience. This will be expanded upon further to be made more specific to the case study at hand as well as the modeling software used.

In addition to the academic research gap, TNO has an internal gap; to date, there is no connection between existing activity schedules and agent-based assignment models. In the future, it is also important that the agent-based models support multimodal trips. This research aims to address this gap while also contributing to the academic field.

Chapter 3

Method

This chapter outlines the method with which the model is designed and implemented. First, the model conceptualization aims to give a high level overview of the model requirements. Second, the role that resilience plays in this model is discussed. Third, the details of the modeling itself are given, including a deeper dive into the software used and the process undertaken for implementing the model in that software. Finally, the specifics of the case study are laid out which then give context for a brief discussion of the scenarios for experimentation.

3.1 Conceptualization

This section provides a high level overview of the model and its requirements given the research question and sub-questions. The section is split into three parts. The first subsection goes into more detail on why it is important to make a conceptual model. The second subsection details how the model for this project was conceptualized using a series of general questions about the intended purpose and layout of the model. The final subsection discusses the answers to the previously mentioned questioned and how that all comes together into a conceptual model.

3.1.1 Why model conceptually?

The purpose of making a conceptual model prior to the final, implemented version of the model is to anticipate model requirements and potential hurdles before getting deep into the implementation. This anticipation is important as it becomes increasingly difficult to make large changes to a model the further into the process one is. Ultimately, conceptual modeling is not an end result, but rather a step in a process (Fettke, 2009). The requirements set out by a conceptual model also give a basis for making a decision on a suitable modeling formalism and thus on a suitable software package for the task. Finally, model conceptualization allows for early engagement with stakeholders who are involved in the project.

3.1.2 How this model is conceptualized

For this project, the model conceptualization begins by asking questions about the problem and then going deeper to discover specific requirements for the model. Ultimately, the aim of these questions is to produce more actionable items that can be translated from ideas into model elements. Guiding questions for the development of this conceptual model and their associated answers are given in the following subsection.

3.1.3 The conceptual model

As is discussed above, the questions below guide the process of conceptual modeling. The answers for each of these questions serve as a basis for the diagram presented in Figure 3.1.1.

What is the problem?

The problem the model aims to address features two parts. First, traffic network resilience is not often studied quantitatively using models, so this particular model should be able to achieve that. Second, more specific to TNO, the effects of ridesharing, and ultimately other new forms of transport, wish to be studied in more detail using an agent-based model. The research gap presented in Section 1.1.3 provides more detail on this.

What needs to be modeled?

The model should include (1) traditional car traffic, (2) ridesharing vehicles, (3) the ability for a network disruption, (4) real network data, (5) real population data, (6) route and mode choice algorithms, and (7) queuing behavior for traffic.

What kind of input and output is needed?

The simplest form of output is the events that take place to dictate traffic flow of the system. This is inherent to any traffic-based simulation software and can be aggregated to many different metrics, such as modal split and other typical traffic-based indicators. To be more specific, the primary goal of the model is to measure resilience with the introduction of ridesharing. The model should contain an element that records a time-dependent metric because of the dynamic nature of resilience. Ultimately, some change in the system should be measured over time, preferably during the simulation run.

How can the validity of the output be checked?

The typical outputs involving traffic flow can be checked for validity in a variety of ways. One strategy is to use output flows across certain links and compare them to real data. Another is to compare travel times between two points in the model with expected travel times between the same points in the real network at a similar time of day as the corresponding simulation time. The output for the resilience measurement is much more difficult to validate. This is primarily because the network disturbance that is simulated has an effectively zero percent chance of happening in real life, so there is no situation to compare it to. In the end, it makes sense to use the validity assessment of the underlying traffic model as a proxy to make an assertion on the validity of the output metric for resilience.

What is the initial state of the system?

Suh (2016) discuss the importance of accounting for initialization bias in traffic simulations. The start-up problem for this model is specifically important when considering the route choice behavior of agents. In the initial stages of the simulation, agents will calculate routes based solely on a least cost algorithm. In an empty traffic network, this leads to agents being greedy in their choices without considering other agents in the system. This problem is mitigated through using multiple iterations during the simulation and learning across these iterations during a single simulation run. Agents should be able to choose from multiple different routes from their "memory" that allows for variation in the links they travel on. This prevents certain links from being overcrowded if they are favorable in low traffic situations.

What do the agents do?

Their are two types of agents in the simulation: people and ridesharing taxis. People are defined by the input population file and have attributes that include their activity end times, activity locations, and preferred mode choice. Additionally, they may have attributes that define them demographically such as age, sex, and occupation. People take trips between locations in the model and spend some amount of time in these locations based on their expected activity duration derived from the activities end time. Ridesharing taxis have attributes including starting location and capacity. These taxis remain idle until called upon by an event handler to retrieve a passenger. Upon this event, the taxi determines its route dynamically and picks up the passenger, reroutes to the destination, and drives towards the destination. Occupied taxis can also be called upon by the event handler to pick up multiple passengers up to its capacity and reroute accordingly.

What are the model components?

First, the model should have the ability to accept external data sources for the network and population inputs. Therefore, an initial data cleaning step is required to prep the external data for use in the simulation environment. Internal components include

- the links and nodes that make up the network,
- the agents that compose the population,
- the activity schedules associated with these agents,
- the vehicles that the agents use which include cars and ridesharing taxis,
- the routing algorithm that directs the vehicles,

- trip scoring functions,
- and the strategies that agents use to adjust their route and mode choice, and components for calculating output metrics.

What methods will be used?

Routing can be achieved through a shortest-path-finding algorithm. Some examples of these are Dijkstra's algorithm or the A* search method Yin Chao & Wang Hongxia (2010), but this is ultimately dependent on the offerings of the selected software for modeling. Mode choice occurs in two instances. First, there is the selection of which agents in the population will switch to ridesharing in the initial population input file. Given the size of the full agent set is approximately 600,000 agents, it is most feasible to do this randomly. Between iterations, agents can be allowed to switch their mode either randomly or using the previous score achieved for that mode. In either case, agents tend towards routes and modes with better payoff. The available modes must have their own scoring equations.

What experiments will be done?

The first factor in the experiments is the inclusion or exclusion of ridesharing taxis. The second is the inclusion or exclusion of a network disruption. Third, there is the number of taxis available in the network. Finally, the number of ridesharing trips per simulation run can be adjusted. Each of these factors has levels and all the various combinations of these factors make up the experiment scenarios. Section 5.3 discusses these experiments in more detail.

Diagram of the conceptual model

A diagram of the conceptual model is given in Figure 3.1.1. The diagram shows the main components that are to be incorporated into the final model. This model assumes that agents who do not use ridesharing do not require an additional module to take their trip and thus cars are not included in the diagram. Also of note is that the ridesharing vehicles have an internal router, as they should have the ability to route dynamically.

3.2 The link between resilience and modeling

A core aspect of this thesis is analyzing resilience using agent-based modeling and simulation. The outputs of the simulation need to be considered given the resilience framework discussed in Section 2.3.2. It has been shown that resilience is linked with recovery time, so therefore the model should contain a network disruption event during the simulation run which the effects of can be measured with a time-dependent metric. It is this ability to change the traffic dynamics during simulation that gives power to using modeling and simulation to measure resilience. Rather than use static techniques, such as graph theory (Dunn & Wilkinson, 2016), using agent-based modeling techniques

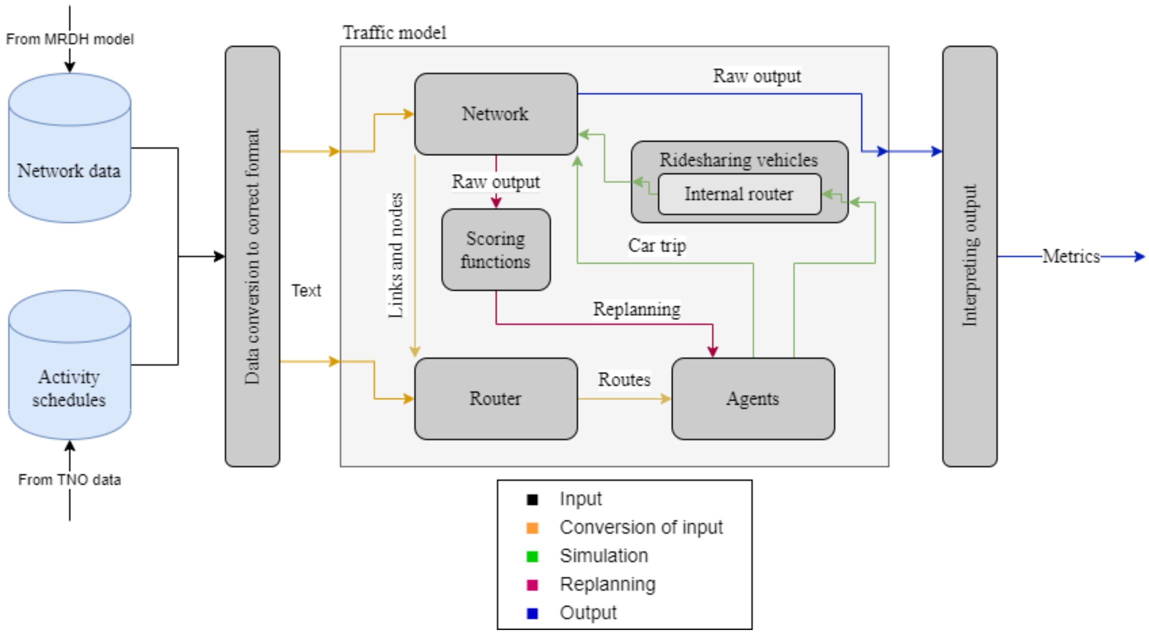

Figure 3.1.1: Diagram of the conceptual model.

presents greater opportunity to realistically assess resilience. In short, modeling and simulation is linked with resilience by virtue of the ability to represent change over time.

3.3 Simulation environment

Selecting the appropriate simulation environment allows for as many of the model requirements to be met as possible. This section provides an analysis of potential software packages that offer agent-based traffic modeling. After this selection is narrowed down to a single candidate, in this case MATSim, inner workings of the environment are discussed.

3.3.1 Software selection

A preliminary list of software packages provided by TNO was expanded on to create a list of software packages. Additionally, Franco et al. (2020) present seven alternatives for agent-based modeling approaches. An initial search also reveals that there are many other software options for transport modeling ranging from Python packages to fully-fledged commercial offerings. A compilation of these packages is shown in Table A.1.1 in Appendix Section A.1. To speed up the process of software selection, a quick pass is performed to determine which of these packages can be omitted for any reason, which is also shown in Table A.1.1. This resulted in four software packages worthy of additional consideration for this project.

These four packages are MATSim, SUMO, AIMSUN, and AgentPolis. Each of are ranked based on seven dimensions that are important for the research of this thesis as well as the continuation of research at TNO. These dimensions are multimodal capability, accessibility, documentation, output metrics, evidence of ridesharing, input compatibility, and dynamic network capability.

Multimodal capability

The software should be able to handle multimodal trips. This is not necessary for this thesis, however it is applicable to TNO's broader research goals so it is included.

Accessibility

This pertains to the ease with which the software can be downloaded and installed. Open source packages score highly here.

Documentation

Software that has associated tutorials, user guides, and example models rank better in this category. Due to the time limitations of a master thesis, it is important to have access to the information needed to get started.

Output metrics

The number of output metrics that come as default should be relatively high. Additionally, the ability to make custom metrics is favorable as well as the ease with which this is done.

Evidence of ridesharing

Whether in documentation or in literature, there must be an indication that the software is capable of modeling ridesharing trips.

Input compatibility

The provided input from TNO should either be accepted natively or intuitively converted to the correct format. Widely excepted standards for network and activity schedule formats are preferred.

Dynamic network capability

The software should be able to simulate a network disturbance via a dynamic change in the network during the simulation.

Table 3.3.1 shows how each software ranks on these dimensions. The blank entries indicate that information on the dimension was not found. Ultimately, MATSim was chosen based on the further research conducted here. It should also be noted that MATSim was considered a frontrunner for TNO prior to the start of this thesis project and internship. This analysis, however, aimed to ensure that the final decision was well informed given the goals of the thesis as well as the goals of TNO.

Table 3.3.1: Software scoring (higher is better).

Dimension	MATSim	SUMO	AIMSUN	AgentPolis
Multimodal capability	2	3	-	-
Accessibility	3	3	1	3
Documentation	3	3	1	1
Output metrics	1	-	-	-
Evidence of ride-sharing	3	1	-	3
Input compatibility	2	0	-	-
Dynamic network capability	3	-	-	-
Total	17	10	2	7

3.3.2 How MATSim works

MATSim (Horni et al., 2016) is an agent-based, open-source, traffic modeling and simulation tool. The remainder of this section provides an overview of the main components in MATSim and how they work together to simulate traffic dynamics.

Network input and agent-based population

The network and population input types are both XML documents. The network is broken down into elements for nodes and links. Nodes provide the location data while the links provide the remaining data on the network such as speeds, capacities, length, and , among other optional parameters. As is previously mentioned, MATSim importantly has the ability to change the network dynamically during a simulation iteration by changing the capacity or speed of given links, thus being capable of simulating network disruptions.

The population data is incorporated as activity schedules for each of the agents in the population. These activities are defined by a start and (or) end time and a location. Typical activities include "home", "work", and "shopping", but any number of user-defined activities are allowed as well. Each activity, other from the final one, has a leg element which defines the mode of transport used to travel between activity locations. A simple example activity schedule is provided in Figure B.2.1 in Appendix B.2.

Traffic flow model

MATSim uses a queuing system to model traffic flow. Each time a vehicle enters a link it is added to the end of the waiting queue for that link. The vehicle waits for at least the minimum time that it takes for the vehicle to travel the link at the prescribed free speed and then waits additional time if it is either not at the head of the queue or the next link in its route does not have free capacity. This is shown visually in Figure 3.3.1. This level of granularity in traffic flow modeling misses out on inter-vehicle interactions within links but is computationally efficient.

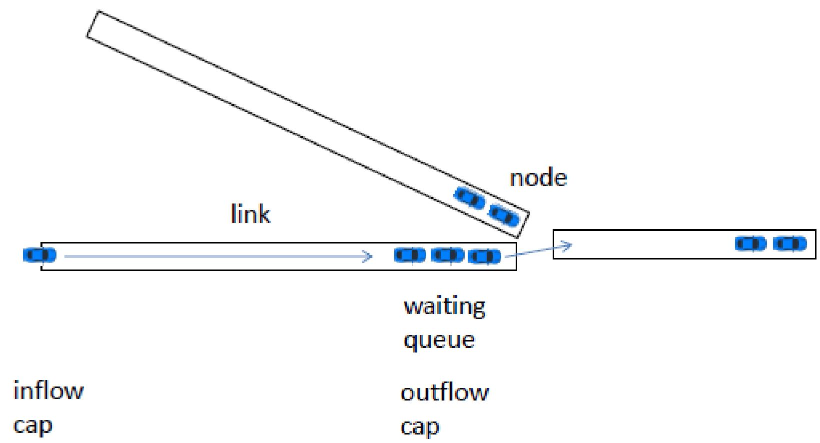

Figure 3.3.1: MATSim's traffic flow model (Horni et al., 2016).

Static vs. dynamic routing

Static routing in MATSim is performed by either Dijkstra's algorithm or the A* search method. Each of these also have "fast" versions that make use of heuristics to plan routes more quickly, but at the risk of missing global optima (Horni et al., 2016). Static routing is done prior to the start of an iteration and rerouting is performed between iterations based on the weight that is given to this replanning strategy. Dynamic routing is important for taxis, autonomous vehicles, and ridesharing vehicles. This routing is done via the dvrp module in MATSim (Maciejewski & Nagel, 2012). A major disadvantage to dynamic routing is that is significantly increases computation time (2012). This is why it is typically used sparingly in agent-based traffic models.

Simulating with the Mobsim

Simulation generally consists of multiple iterations of a single day of activities. In Figure 3.3.2 the loop consisting of the Mobsim (Mobility Simulation), scoring, and replanning shows the process of a single iteration. The Mobsim defaults to Queue Simulation (QSIM), however Java Discrete Event Queue Simulation is available as well. The QSIM component of MATSim implements the traffic flow model as described above in an agent-based manner. After an iteration of the simulation is complete, the plans used by the agents in that iteration are scored according to their utility. Replanning takes place on a prescribed subset of agents between iterations to add variation to mode, route, and departure choices. The plans and their respective scores are saved in the agents memory and ultimately used for optimization. These scoring functions and their optimization are discussed in more detail below.

Scoring functions

Scoring in MATSim is done using the Charypar-Nagel Utility Function (Horni et al., 2016; Charypar & Nagel, 2005). An agents plan is scored based on the summation of the utilities for each of its

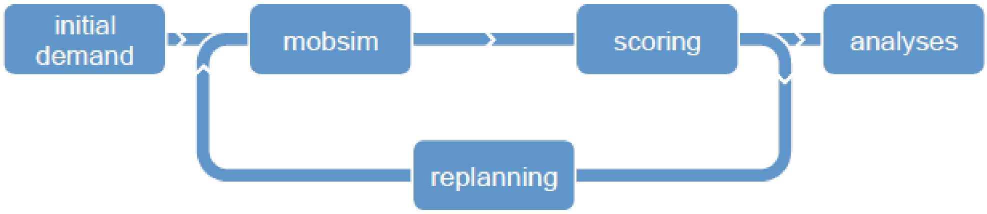

Figure 3.3.2: The MATSim loop for simulation (Horni et al., 2016).

activities and legs. The equation is written as follows:

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{1=0}^{N-1} S_{trav,mode(q)} \tag{3.3.1}$$

where S represents the utility, q indicating the leg, and N giving the total number of activities for a given agent's plan. Activities are scored using the following function (Horni et al., 2016):

$$S_{act,q} = S_{dur,q} + S_{wait,q} + S_{late.ar,q} + S_{early.dep,q} + S_{short.dur,q} \tag{3.3.2}$$

where the individual component utilities from right to left are performing the activity, waiting, late arrival, early departure, and short activity duration.

The function for travel utility is as follows (Horni et al., 2016):

$$\begin{aligned} S_{trav,q} = {} & C_{mode(q)} + \beta_{trav,mode(q)} * t_{trav,q} + \beta_m * \Delta m_q \\ & + (\beta_{d,mode(q)} + \beta_m * \gamma_{d,mode(q)}) * d_{trav,q} + \beta_{transfer} * x_{transfer,q} \end{aligned} \tag{3.3.3}$$

where $C_{mode(q)}$ is a constant specified per mode, $\beta_{trav,mode(q)}$ is direct marginal utility of time spent traveling by a mode, $t_{trav,q}$ is travel time, β_m is marginal utility of money, Δm_q is change in monetary budget, $\beta_{d,mode(q)}$ is marginal utility of distance, $\gamma_{d,mode(q)}$ is is the monetary distance rate per mode, $d_{trav,q}$ is is distance traveled, $\beta_{transfer}$ is public transport costs, and $x_{transfer,q}$ is an integer Boolean signifying a transfer (Horni et al., 2016). More information on the individual breakdown of utilities can be found in Horni et al. (2016, p. 24) and on the implementation in MATSim in Horni et al. (2016, p. 29).

Replanning

Optimization of agents plans in MATSim is done using a co-evolutionary algorithm. This means that agents co-evolve via the competition for achieving higher utilities. A high level interpretation of the process can be broken down into three key stages: initial routing, mode choice, and departure times; replanning of route choice, mode choice, and departure time; and final plan selection. The initial plans are defined by the input activity schedule data and serve as a starting point for the simulation. In the first simulation iteration, the input plans are executed and scored. Between iterations, the routing, mode choice, and departure times may all be replanned according to user defined preferences. The main preference is the percentage of plans that go through the replanning phase. The remaining plans are unchanged for the very next iteration. This process then repeats after each iteration until a stopping criteria is met. This criteria is the percentage of iterations that go through replanning. For example, if the stopping criteria is 85% and the total number of iterations is 10, then replanning will only take place before the 9^{th} and 10^{th} iterations. In these 9^{th} and 10^{th} iterations, the final stage of optimization takes place in which the highest scoring plans in each of the agents memory is used for simulation.

3.4 Modeling

This section is split into two subsections on the process of modeling and an overview of the choice models used. The process by which the model was iterated on to achieve the end result is discussed, followed by a summary of the route and mode choice models as implemented by MATSim.

3.4.1 Process

The approach for the implementation of the model is akin to the Agile method. That is primarily to say that a working model is iterated upon to incorporate new elements in each iteration. The reasoning behind this process is to mitigate the risk of running out of time while having produced no complete model versions. The first step in this process is to create a basic working version of a model in MATSim. This model is as simple as it gets, comprised of a small, grid-shaped network with only a handful of agents taking car trips. The first expansion to this model is incorporating an additional mode, followed by incorporating a more sophisticated mode, in this case ridesharing. Then, a network disturbance is introduced in the form of a time variant network. At this point, the model has its fundamental basis given the research objective of measuring system resilience. The next step is incorporating the data for the case study. It is important to start with the network data as this defines where the population may travel to and from; the population data is meaningless without the network to travel on. Next, the population data is incrementally incorporated into the model starting with a small subset so that potential errors are easier to find and fix. Finally, the population data can be expanded on and altered such that it includes the ability for agents to take ridesharing trips. At this stage, experiments can be set up that alter the number of ridesharing vehicles in the system as well as the number of ridesharing users.

3.4.2 Choice models

The three distinct choices made by agents in this model are for route, mode, and departure time. The route choice is decided by MATSim on the initialization of the simulation and updates between iterations unless the trip is taken by a ridesharing vehicle, in which case the routing is done dynamically. The mode choice, on the other hand, behaves in two separate ways depending on the scenario. In the case where ridesharing is not included in the model, mode choice does not occur as agents only have cars to choose from. In the case where ridesharing is included, the mode choice is initialized in the input population file and is altered between iterations in an exploratory manner.

Table 3.4.1: Strategy settings. The first two columns are general settings and the last four dictate how the innovation behaves. In this case the weights sum to 1, but this does not need to be the case.

Stategy setting		Value (or) Weight	
Name in MATSim	Meaning		
fractionOfIterationsToDisableInnovation	Disable learning after 80% of iterations	0.8	
maxAgentPlanMemorySize	# of performed plans agents may store	5	
SelectExpeBeta	Use best stored plan		0.675
ReRoute	Change route		0.1
SubtourModeChoice	Change mode		0.075
TimeAllocationMutator	Change departure time		0.15

Finally, departure time is initialized in the input population file and also changes in order to explore different possibilities that may result in higher utility scores. These choice models are part of a larger module in MATSim called “strategy”. The remainder of this section gives an overview of how this is used in this specific model and more detail on strategies in MATSim is provided by Horni et al. (2016, p. 38). The core of the choice strategy consists of selecting actions based on weights. These actions include selecting the best plan so far (“SelectExpBeta”), changing the route (“ReRoute”), changing mode (“SubtourModeChoice”), and changing departure time (“TimeAllocationMutator”). The parameters for this model are chosen based on parameters of similar models (Fagnant et al., 2015; Maciejewski et al., 2016) combined with trial and error through model revisions. They can be found in Table 3.4.1 and further explanation is provided on each of the choice models below.

Route choice

Route choice is done differently depending on the type of trip being taken. For car trips, a static form of routing is done prior to the beginning of an iteration. The algorithm used is MATSim’s implementation of Dijkstra’s algorithm. As per the “ReRoute” strategy in MATSim, agents with car trips may reroute by testing alternative routes between iterations at a rate of 10% of agents per iteration, as per the weight of 0.1. The remaining travelers maintain the route from their currently most favored plan, unless they switch mode.

Ridesharing vehicles are implemented in the drt (demand responsive transport) module in MATSim. These vehicles are dynamically routed using the dvrp module from MATSim (Maciejewski & Nagel, 2012). The routing is performed as-needed, when an agent requests a ride. Not only may ridesharing agents route during the simulation from a waiting position, but they may also reroute in order to pick up additional passengers if they are already driving to a destination. Ridesharing vehicles, though, do not partake in the co-evolutionary optimization of plans. It is only the agents who may “decide” to take a ridesharing trip in the event that they are replanning or if it is part of that agents best plan.

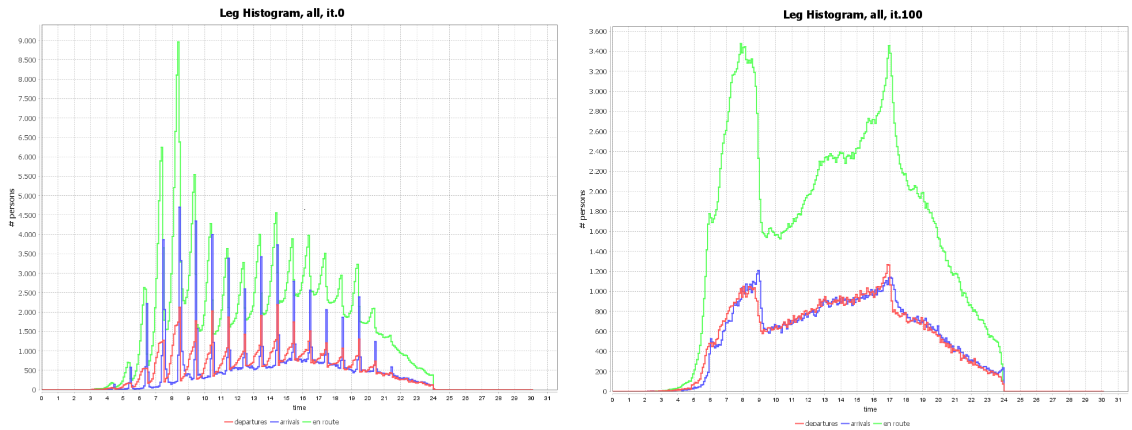

Figure 3.4.1: On the left is the trip departure, trip arrivals, and en-route trips for the 0^{th} iteration and on the right is the same but for the 100^{th} iteration.

Mode choice

Mode choice is only implemented in the case where ridesharing is included in the model, as otherwise there are only cars in the model. In early iterations of the model, ridesharing was prescribed to agents at random prior to simulation initialization. However, this resulted in many "bad" ridesharing trips being taken; a "bad" trip means that their were trips being assigned for agents who may have had origin points that were far away from any of the ridesharing vehicles, such as trips that may be returning to the MRDH after earlier going to a city outside the MRDH, such as Amsterdam. In order to remedy this, ridesharing trips are included in the mode choice selection of the "SubtourModeChoice" strategy. With a weight of 0.075, this strategy allows for a random sample of 7.5% of agents to adjust there mode selection for their entire trip-set from car to ridesharing or vice versa. Each iteration, a new, randomly selected 7.5% of agents is chosen for mode choice replanning. Using the strategy in this way allows for the number of agents using ridesharing services to be optimized for given the fleet size and also limits the number of poorly selected ridesharing trips, as agents will ultimately choose the plan with the mode that gave the best utility score.

Departure time

The provided data for the departure time is cyclical at the beginning of the simulation, however this is adjusted for by optimization during the simulation. This development of departure time is shown in Figure 3.4.1. The inter-iteration variation in departure times is dictated by the strategy in MATSim called "TimeAllocationMutator". As this is all part of the same strategy module, it works similarly to the strategies for mode and route choice. 15% of users will adjust their activity end times which in turn changes their trip departure times. Because the utility scoring functions includes the sum of both activity and trip utilities, the end time with the best score is ranked on both the amount of time saved on traveling as well as maintaining an expected duration for the activity.

Final plan selection

The final plan selection occurs after 80% of the iterations have completed, according to the "fractionOfIterationsToDisableInnovation" strategy setting in MATSim. At this stage, the best stored plan for each agent is selected according to the utility scoring function, which is discussed in more detail in Section 3.3.2. These plans are used to simulate the final 20% of iterations.

3.4.3 Assumptions

Many of the modeling assumptions concern the way in which car trips are switched to ridesharing trips for experimentation. These and other assumptions are listed below.

- Traffic passing through the MRDH that originates in other regions may be ignored. Only traffic of travelers who live in the MRDH is considered. This is a characteristic of the provided data.
- Population demographics do not play a role in who switches to ridesharing. MATSim optimizes the selection of ridesharing trips based on utility scores.
- Location does not directly play a role in who switches to ridesharing. MATSim may optimize this in some way, however the initial placement of ridesharing vehicles is random.
- An agent may take a car to a destination but does not need return in that same car, as they may take a shared ride instead.
- Ridesharing vehicle start locations may be randomized if ridesharing trip start locations are also randomized due to the assumptions on the demographics above.
- Ridesharing vehicles may remain active through an entire simulated day. The vehicles do not need to manage resources such as fuel.
- Vehicles do not need to adhere to traffic lights, stop signs, etc. They are only concerned with traversing to the next link.

Chapter 4

Case study

The case study for this project is the MRDH and was chosen for its importance to the research goals of TNO as well as being the region that TU Delft is situated in. Further, the specific mode of transport that is being studied is ridesharing, as new modes of transport are also important to the research goals of TNO. The case study is further discussed in the remainder of this section in three parts: the MRDH network, the MRDH population, and finally an overview of the scenarios used for experimentation.

4.1 The network

The data for the network comes from version V-MRDH 2.0 of the traffic model from the MRDH (Metropoolregio Rotterdam Den Haag, 2018). For this study, only the links from the car network are included, ignoring the additional layer of the public transport and cycling network. Rotterdam, The Hague, and their immediate surroundings are fully modeled comprising the MRDH. This means that all of the links in the real traffic network in these cities are included. The other regions in The Netherlands are modeled as well, but only major roads are included. Figure 4.1.1 shows the MRDH as well as Amsterdam. In this figure, the high density of links in the MRDH show how how it is fully modeled, while Amsterdam, a similarly sized area, has much fewer of its links represented.

Also included in the network data from MRDH are centroid locations. Centroids represent the areas where agents live and work, similar to a neighborhood. They are travelled to by specific links that are not present in the real network. Additionally, these centroid links have infinite capacity so as to not influence the dynamics of traffic flow. The centroids are required to match the locations of agents to their approximated locations in the population data.

In MATSim, networks are defined in XML files with separate elements for links and nodes. The key elements of nodes are an identifier, x location, and y location. The main elements of links are an identifier, start node, end node, length, freespeed, flow capacity, and number of lanes. Links in MATSim are unidirectional, unlike the data given by the MRDH model. This is accounted for in the conversion from the shape file data to XML format by splitting the bidirectional link into two, the second of which uses the same numbered identifier but adds 0.5 to it (e.g. a bidirectional link

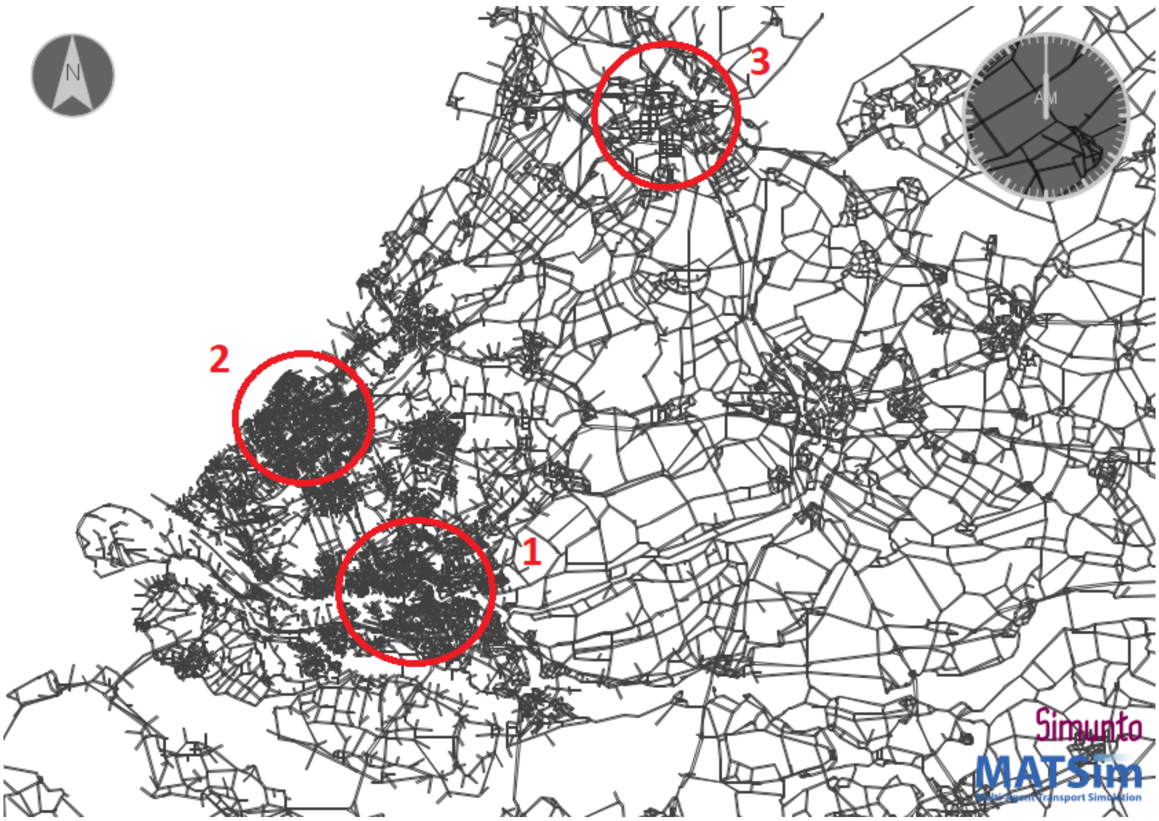

Figure 4.1.1: A network visualization from Simunto's Via software. The circles labeled 1 and 2 are Rotterdam and The Hague, respectively, and circle 3 is Amsterdam. Via additionally allows for replaying of simulations, hence the clock in the upper right for showing simulation time.

Table 4.3.1: Activity parameters for use in utility scoring functions by MATSim.

Activity type	Units of [hh:mm:ss]			
	Typical duration	Opening time	Latest start time	Closing time
Work	08:00:00	06:00:00	09:00:00	17:00:00
Business	03:00:00			
Education	06:00:00			
Home	12:00:00			
Shopping	01:30:00			
Pick-up	01:00:00			
Other	01:00:00			

in the data with an id equal to 3 would be represented by two links in the XML file, 3 and 3.5). As MATSim identifiers are stored as strings, adding a ".5" to the end causes no issue. Figure B.2.2 in Appendix B.2 shows an example of a bidirectional link represented as two unidirectional links in XML using MATSim's standards.

4.2 The population

Population data for this thesis originates from a project using OVIN data and activity-based modeling software FEATHERS to generate activity schedules (de Romph et al., 2018). The original data is aggregated to ensure anonymity, and then subsequently dis-aggregated to get estimated activity schedules for the population of the MRDH. The population does not include travelers from outside of the MRDH. The data comes in the form of a tab-separated text file with all the necessary information to create XML files for input into MATSim. The starting locations of trips, departure times, activity types (e.g. home or work), and mode of transport for legs in between activities are used to create the activity schedules for initial input into MATSim. The final size of the population after keeping only car trips is approximately 620,000 agents.

4.3 MATSim setup

The replanning strategy is previously discussed in Table 3.4.1. Table 4.3.1 contains the activity parameters for the model which the help to define how the activities are scored. Note that not all of the parameters are required. These additional parameters are included for the work activity because it has a more predictable schedule than any of the other activities. The typical activity durations are used in the calculation of utility and impact the scores given to plans.

Ridesharing taxis are initialized in an XML file that defines the starting location of all taxis. The two fleet sizes are 500 and 1000 taxis, where each of the taxis is assigned to a start link at random which is restricted to be in either Rotterdam or The Hague.

Chapter 5

Scenario Analysis

It is important to consider multiple scenarios for ridesharing fleet sizes because it is still a fledgling technology in the MRDH. Therefore, little is known about how the technology might be used in the future. These scenarios are not only meant to be used to assess resilience with the introduction of ridesharing, but also to gain insight into the behavior of different ridesharing scenarios. The remainder of this chapter contains a hypothesis using the main research question as a guide, a discussion on experimental design, an overview of the scenarios, and concludes on the topic of measuring resilience.

5.1 Hypothesis

To reiterate, the main research question is as follows.

> *How can resilience in urban traffic networks be measured using agent-based modeling and simulation?*

The hypothesis is constructed with consideration of the possible use case of the proposed method for measuring resilience. If the effects of ridesharing on network resilience are to be studied, then it is hypothesized that introducing ridesharing vehicles will result in improved resilience in said network. Diving deeper into this hypothesis requires recalling that resilience is defined as the ability for a system to recover from a shock. It can be said that a system with ridesharing will recover more quickly to equilibrium after a disturbance. One reason that this may be the case is that the routing of a ridesharing taxi is different than its traditional alternative, personal vehicles or cars. Because a shared taxi can pick up multiple passengers, it is more likely that parts of its route are in neighborhoods while they pick up additional passengers, thus diverting them from the main roads and freeing up capacity. This in particular relates to the *redundancy* of the system, as the freed up capacity can be viewed as spare capacity for disruptions. In addition, a shared taxi at full capacity simply takes up less space on the road as opposed to the situation where each of the passengers is instead driving a personal vehicle. This of course requires that the number of ridesharing vehicles be well optimized for the user demand. The ridesharing vehicles can be seen as an additional *resource* for travelers to use in the event of a disturbance. This *resourcefulness* might mean that a larger fleet size allows for the ridesharing vehicles to absorb some of the capacity that is lost in the form of a reduced throughput on a disturbed link.

It is important to also consider why the opposite of what is hypothesized might happen because of the complex nature of traffic dynamics. One reason that there might be a negligible difference in resilience, or even a decrease in resilience, is if the number of taxis is either too low or too high. For example, if too many taxis are available, then it is effectively the same as if passengers were simply using there own vehicles, as the average capacity of each vehicle may go down. On the other hand, if there are too few taxis, then agents who wish to take a shared taxi trip will have to wait much longer to be serviced, thus leading to higher travel times across for these travelers. Another possible situation is that shared taxis may favor certain routes and thus clog these routes, leading to increased traffic. This would indicate a lack of *flexibility* in the system, meaning the ridesharing taxis might be unwilling to change routes after a disturbance. In MATSim, this is dependent on the routing algorithms of the DVRP contribution.

5.2 Experimental design

Tolk et al. (2014) explain different approaches for experimental design. For the purpose of this thesis, the 2^{k} factorial method is used as a starting point. The 2^{k} factorial method involves selecting a set of factors that can each have two different levels, for example a fleet size factor with two different levels of small and large. These the experiments are then all of the combinations of the factors and there associated levels. A key difference in the method of this thesis is that rather than restrict each factor to two levels as Tolk et al. point out, these experiments allow for factors with three levels. Therefore this design is not strictly a 2^{k} method, however it is otherwise the same. Ultimately, this does not pose an issue as the number of factors is low (3), so the total number of experiments also remains low and therefore within scope. These factors are vehicle type, presence of a disturbance, and ridesharing fleet size. The way in which these factors manifest themselves in the scenarios used for analysis is described in the following section.

5.3 Scenarios

In total, six scenarios are used to evaluate the proposed resilience metrics. The parameters of each of these scenarios are shown in Table 5.3.1.

In addition, each of the scenarios is run with the general parameters shown in Table 5.3.2. The number of iterations is set to 100 because at this number the convergence is stable and adequate for the purpose of this thesis. In this case convergence is assessed by the change in agent scores over time. This is determined by assessing the score progression across 500 iterations of a simulation with a population of 1% the original size. Additionally, there are diminishing returns to adding more iterations beyond 100. The score progression of this test simulation can be seen in Figure A.2.1 in Appendix A.2. Ultimately, the difference between running 100 versus 200 iterations, for example, is marginal in comparison to the doubling of computation time. The percentage of car trips used is

Table 5.3.1: The scenarios with their associated levels for the factors.

Scenario	Disturbance?	Vehicle types	Ridesharing fleet size (# of vehicles)
1	Without disturbance	Cars only	0
2		Cars and RS vehicles	500
3		Cars and RS vehicles	1000
4	With disturbance	Cars only	0
5		Cars and RS vehicles	500
6		Cars and RS vehicles	1000

Table 5.3.2: General parameters used for all of the scenarios.

Parameter	Value
# of iterations per scenario	100
% of car trips simulated	10
Approximate # of agents	62,000

10% of those provided in the initial population file. This is also due to the computation time and the general time constraints of the thesis. At 10% population size, each ridesharing scenario takes approximately 2 days to run on 8 of the cores on the server provided by TNO. This ends up being over a week in computation time to complete all scenarios. In the best case where computation time scales linearly with the number of agents in the simulation, this amounts to over two months of computation time to complete the 100 iterations needed to reach meaningful convergence for each scenario. It is fair to assume that the computation time scales worse than linearly with population size and therefore it is unrealistic to run the full population. Along with this reduced population size, the capacity of all the links in the network need to be adjusted proportionately such that the traffic flow dynamics are maintained as best as possible. As a result of this, all the links in the network are reduced in capacity by a factor of 0.1 to match the 10% population size. The number of agents per simulation ends up being approximately 62,000.

The disturbance used in these experiments is targeted to intensify the effects of the disturbance. Alternatively, these disruptions could be random, however, this makes the resilience measurement more difficult as the whole system must be considered, rather than two bounding boxes as is presented in this thesis.The network disruption occurs at 8:15 in the morning, and ultimately persists for 30 minutes in the simulation. The reason that this particular disturbance duration and time of day is chosen is because it is at the morning peak and therefore exacerbates the effects of the disturbance. Figure 5.3.1 gives the concurrent trips in a simulation iteration where it is shown that the morning peak occurs at approximately 8:15.

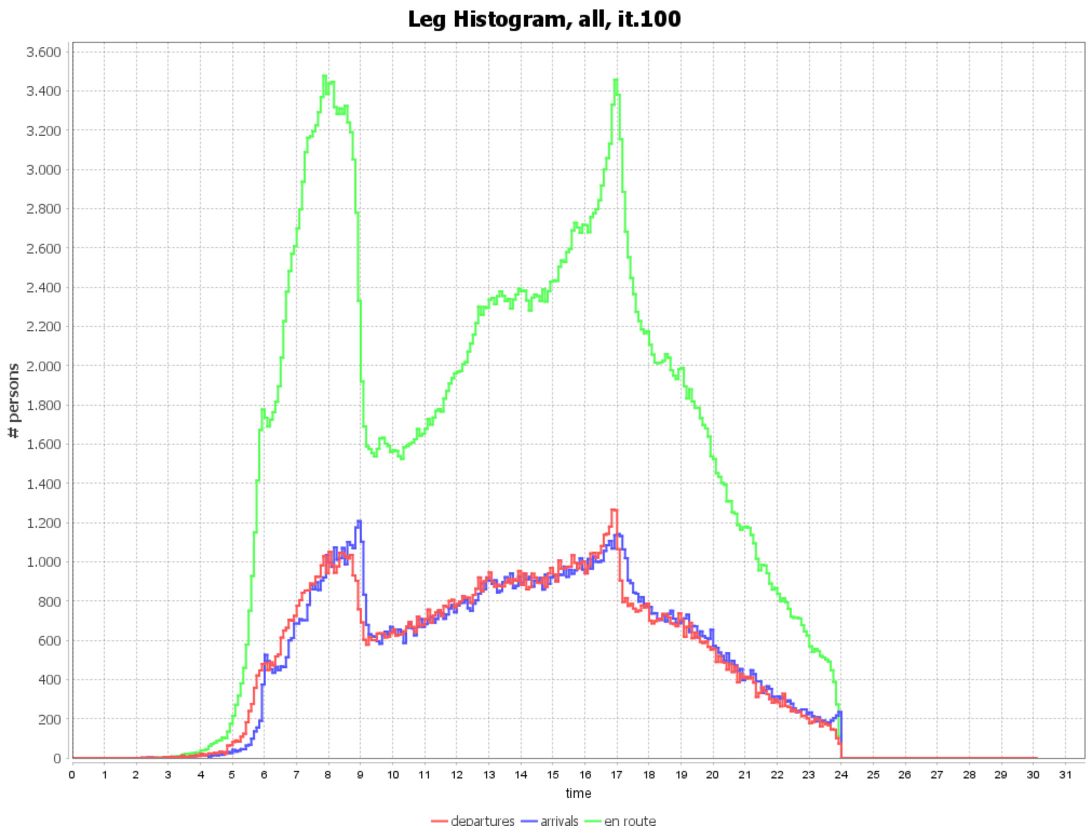

Figure 5.3.1: An example histogram showing the number of en-route trips in green, departing trips in red, and arriving trips in blue. These are counted in 5 minute bin periods.

Figure 5.3.2: The portion of the A4 roadway which is perturbed.

The disturbed portion of the roadway is shown on a map in Figure 5.3.2. This particular portion of the A4 is chosen because it matches the desired characteristics for a critical link in the network. A critical link is previously defined to be of high importance if it has a high expected absolute flow during peak conditions, a high expected flow relative to its capacity, and there are few alternative links with similarly high capacity. The A4 roadway is one of two major roadways between Rotterdam and The Hague and its alternative, the A13, is of a similar size or capacity. In MATSim, the disturbance comes in the form of scaling the flow capacity by a factor of 0.05 in both directions. This disturbance is than reverted to normal after 30 minutes as can be seen in the XML input file shown in Figure B.2.3 in Appendix B.2.

This form of disturbance was chosen to accentuate its effects and make the measurement of resilience more meaningful. In the situation where a disturbance on a less relevant link is looked at, the sheer size of the whole system may overshadow any negative effects that can be measured. The A4 is a major roadway and one of few routes between Rotterdam and The Hague, so it is a prime candidate for this study. The reason the disturbance occurs at 8:15 in the morning is that this represents a peak time in number of travelers. This is important as it provides more data points for measurement but also represents a worst case scenario, which is imperative to consider when drafting preventative policy measures. If, for instance, the study focused on solely the city of Rotterdam, then a different link or links should be selected for study, as the A4 and A13 are not critical to the dynamics within the city itself.

Ideally, a variety of disturbances should be studied to get a better view of the system as a whole. However, the time constraints of the project allow for either one disturbance to be studied more thoroughly, or multiple disturbances to be studied at a lower level of fidelity with fewer experiments for each disturbance.

5.4 Measuring resilience

Section 2.3.2 gives a resilience framework which proposes possible quantitative metrics for measuring different aspects of resilience. In addition to certain metrics measuring specific characteristics of resilience, Gu et al. (2020) discuss that many quantitative indices are region specific. This is certainly difficult to deal with, as no two traffic networks are alike. As such, the proposed method for measuring resilience incorporates the following quantitative metrics which are henceforth referred to by their italicized names below. These metrics focus on the corridor between Rotterdam and The Hague because it reduces the scope of the problem to be more manageable, otherwise, the number of links that would need to be studied would not be feasible.

1. *average_OD_TT*: the average travel time in 2 minute intervals for trips taken from Rotterdam to The Hague, or vice versa. The interval of 2 minutes is chosen as it allows for enough trips to occur to reliably compute an average, but also is a short enough period to capture rapid changes in system performance.

2. *link_TT*: the travel time across the disturbed link in the model. This includes the links immediately before and after the disturbed portion and in both directions.

3. *link_volume*: the accumulation of vehicles leaving the disturbed link.

Each of the proposed metrics can be related back to the resilience framework in the following ways. *Average_OD_TT* and *link_TT* pertain to the person-trip speeds and link travel times indicators from the framework. This means that these two metrics are best used to assess the *flexibility* of the system. The difference between the two is that on the one hand, *average_OD_TT* considers the aggregate of all trips between Rotterdam and The Hague, regardless of route, while on the other hand, *link_tt* considers all trips across just the disturbed link without considering origin and destination. The combination of these two metrics aims to give more context to the assessment of resilience. In the proposed resilience framework, *Link_volume* relates to the *redundancy* quality of resilience. *Redundancy* in this case refers to both the link capacity as well as the supply of vehicles in the system, which varies depending on the inclusion of ridesharing.

The use of these metrics is not meant to be an all-purpose method, but rather is most appropriately applied to situations that are similar to that in the MRDH. That is, situations in which there are two distinct locations separated by at least one major road. In the MRDH case that would be either the A4 or A13 roadways between Rotterdam and The Hague. This is not limited to intercity travel either, as can also be seen in Rotterdam, which is split by the Nieuwe Maas river with several bridges crossing it. These bridges can be considered critical to the network.

5.4.1 Data collection and event handlers

The fundamental output from a simulation in MATSim is the events file. This file contains every event that occurred throughout an iteration of the simulation, where each iteration has its own events file. Post-processing this data can be cumbersome, though, especially in the simulations with a large population sizes in the tens to hundreds of thousands. Event handlers, which are written in Java, allow for this data to be processed during simulation iterations without significant effect on computation time so long as the function of the script is reasonable. The output of these event handlers is typically orders of magnitude smaller than the events file and is much easier to interpret. MATSim provides a base set of analysis metrics in the form of event handlers, however as the proposed metrics are more specifically applied to resilience, they must be custom built into MATSim. In particular, the proposed metrics implement the pre-built handlers PersonDepartureEventHandler, PersonArrivalEventHandler, LinkEnterEventHandler, and LinkLeaveEventHandler. Two event handlers collect and save the data for the four metrics; one for the two link metrics and another for the origin-destination travel time and person trips metrics. The associated code for these processes is located in Appendix B.1.

Chapter 6

Results

The results are broken down into four sections. The first section provides the relevant results to understand the baseline scenario without ridesharing or a disturbance. Second, the same will be done for the baseline ridesharing scenario without a disturbance. The third section gives similar results for the disturbance scenarios and finally in the fourth section the disturbance scenarios will be compared to these reference scenarios by showing the results for the proposed resilience metrics. Unless otherwise specified, all results given are taken from the final iteration of the corresponding experiment as this is the most optimized iteration. Also note that the first three sections are included to give some background on the performance of the model in order to contextualize the results in the discussion in Chapter 8.

6.1 Baseline scenario

The baseline scenario without a disturbance nor the presence of ridesharing (referred to as "baseline scenario" for the remainder of this section) incorporates all car trips taken by a subset of 10% of the population given in the activity schedules in the provided data. This equates to approximately 62,000 total agents combining for just over 200,000 trips. As all scenarios incorporate this same 10% subset of the population data, the network capacity is adjusted to also be 10% of its original capacity on all links. Figure 6.1.1 shows the number of departures, arrivals, and en-route trips in 5 minute bins for the baseline scenario. Here we can see the two major peaks for morning and afternoon rush hour.

Figure 6.1.2 shows the score progression across iterations for the baseline scenario.

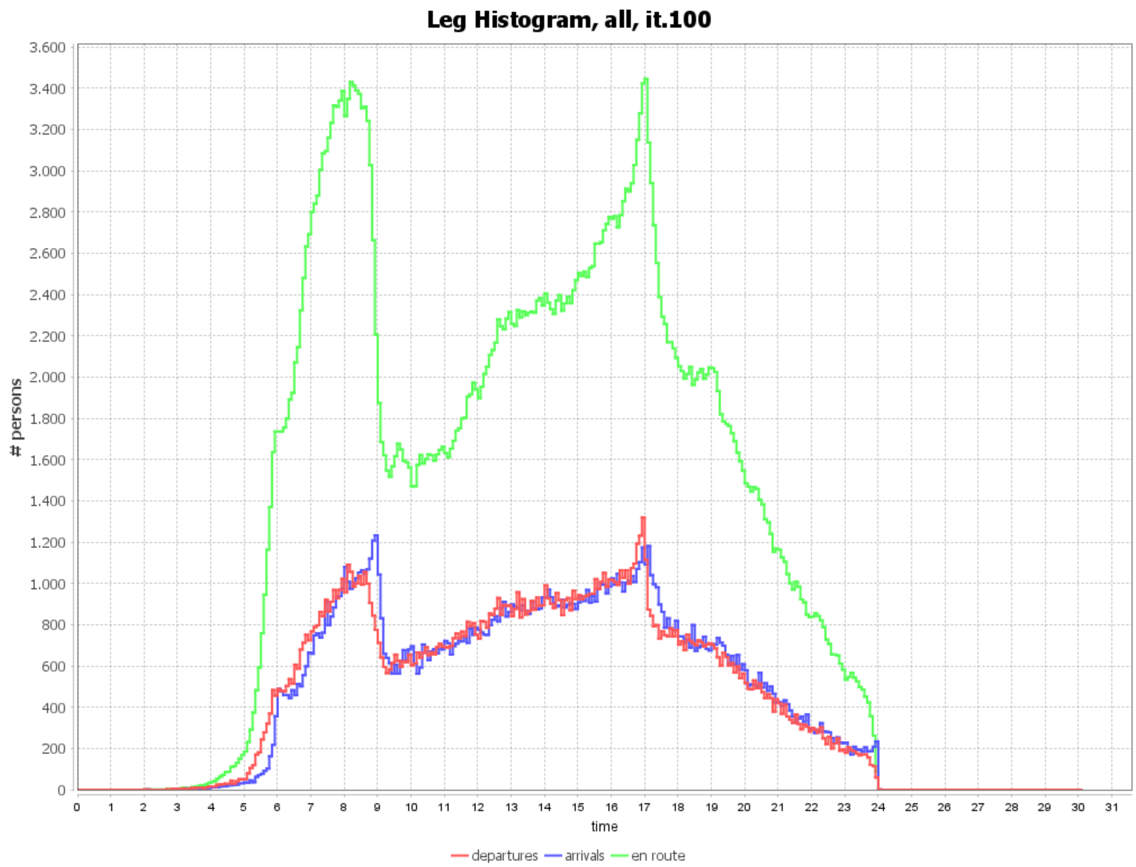

Figure 6.1.1: Histogram for the baseline scenario without ridehsharing nor a disturbance showing the number of leg departures in red, leg arrivals in blue, and legs of agents currently en-route to their destination in green.

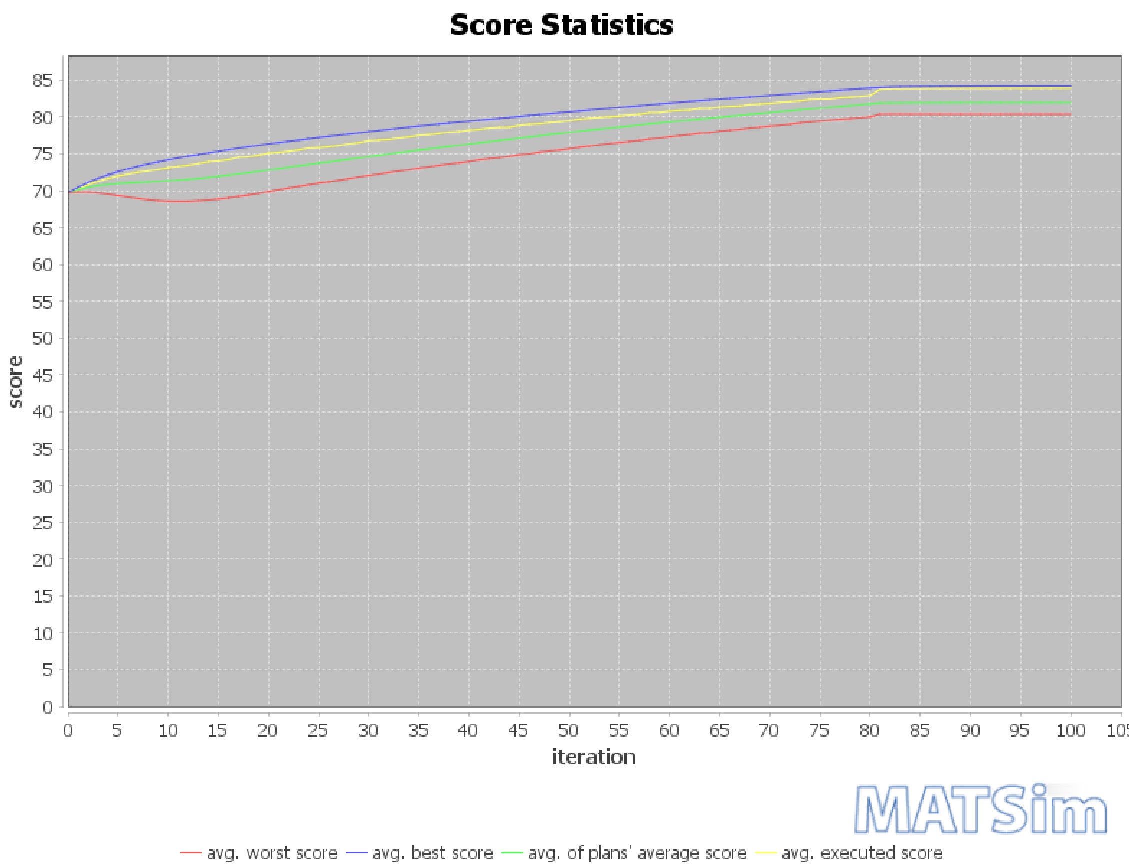

Figure 6.1.2: Score statistics for the car only scenario without a disturbance.

6.2 Introducing ridesharing

The results for the introduction of ridesharing in the model are first presented without the inclusion of a network disturbance to see how it performs isolated from that situation. Two baseline ridesharing scenarios are presented: one with a fleet size of 500 vehicles and the other with a fleet size of 1,000 vehicles. Figure 6.2.1 shows the histogram of departures, arrivals, and en-route trips for the 500 vehicle ridesharing scenario. Note that the green line showing en-route trips is much higher than that of the car only scenario. This is due to the way in which MATSim 'double-counts' ridesharing trips by counting the walking and waiting times. The histogram for the larger fleet size scenario is included in Appendix C.1. The inclusion of these histograms acts as a sanity check to ensure that the simulations are behaving as expected.

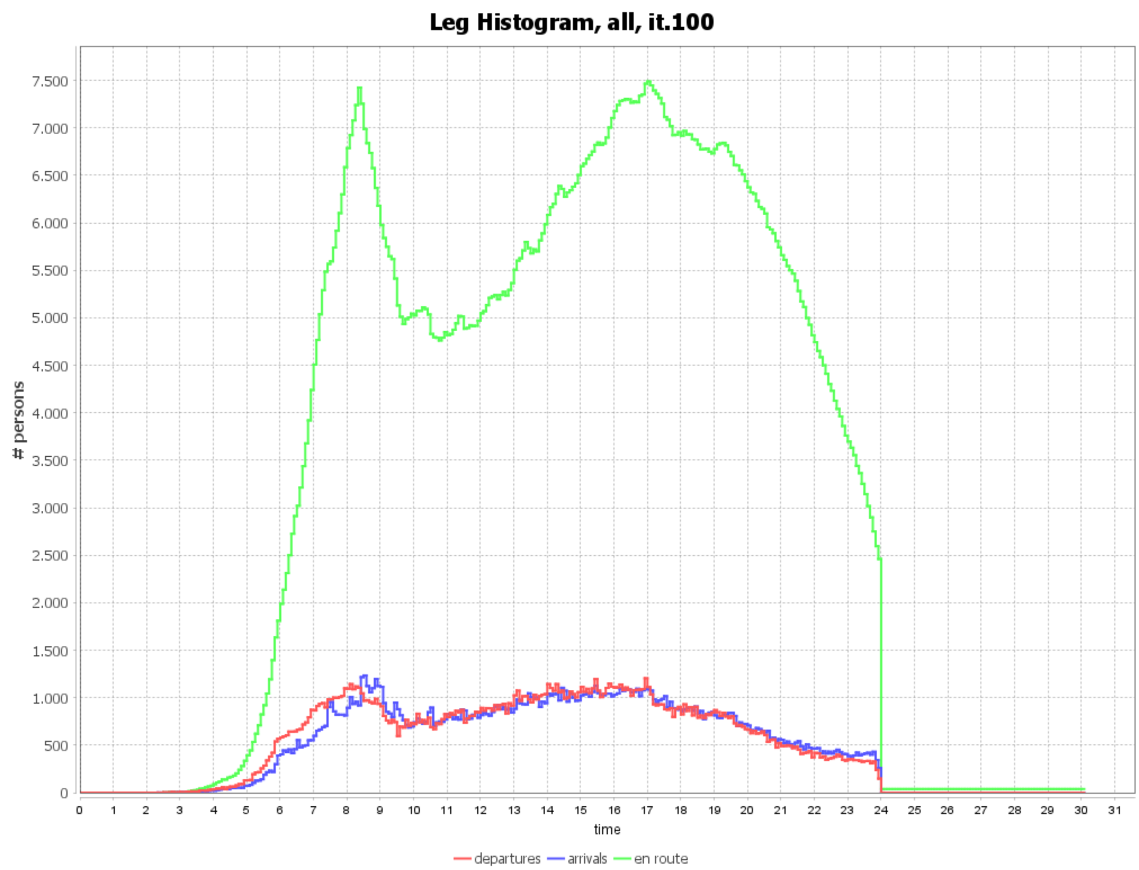

Figure 6.2.1: Histogram for the baseline ridesharing scenario without a disturbance (500 vehicle fleet size) showing the number of leg departures in red, leg arrivals in blue, and legs of agents currently en-route to their destination in green.

Figure 6.2.2 shows the utility score progression over 100 iterations for the 500 fleet size ridesharing scenario with no disturbance. These scores are derived from the utilities of the activities and travel plans of each of the agents. In this graph, it is clear that the scores are much lower when compared to the car only scenario. Possible reasons for this are discussed in the next chapter, but it is clear that the inclusion of ridesharing alters the way in which MATSim optimizes plans.

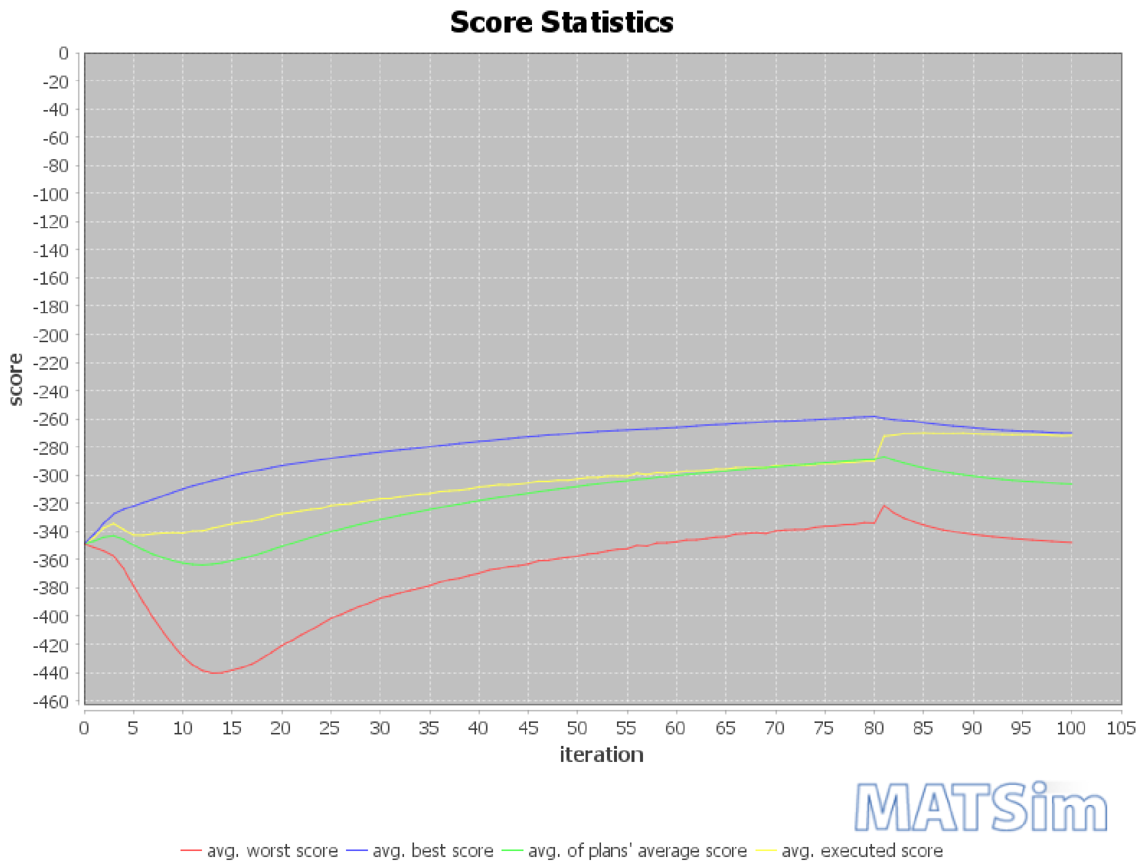

Figure 6.2.2: Score statistics for the baseline ridesharing scenario without a disturbance (500 vehicle fleet size).

The stacked profile in Figure 6.2.3 shows how the capacity of the ridesharing vehicles is being used. The 'pax' in the legend of the graph means 'passenger', so the red region indicates the portion of ridesharing vehicles at full capacity at some point in time. It is desirable in this model to have taxis at capacity in at least some cases because that allows for additional car traffic to be removed from the road.

The wait times for ridesharing vehicles are given for the 500 fleet size scenario in Figure 6.2.4. These substantial wait times come as a result of the intention of having some ridesharing vehicles be at capacity. This stresses the supply of ridesharing vehicles. For more information on this refer to the request statistics given in Appendix C.5. The effect of this on the conclusions is discussed in the next chapter.

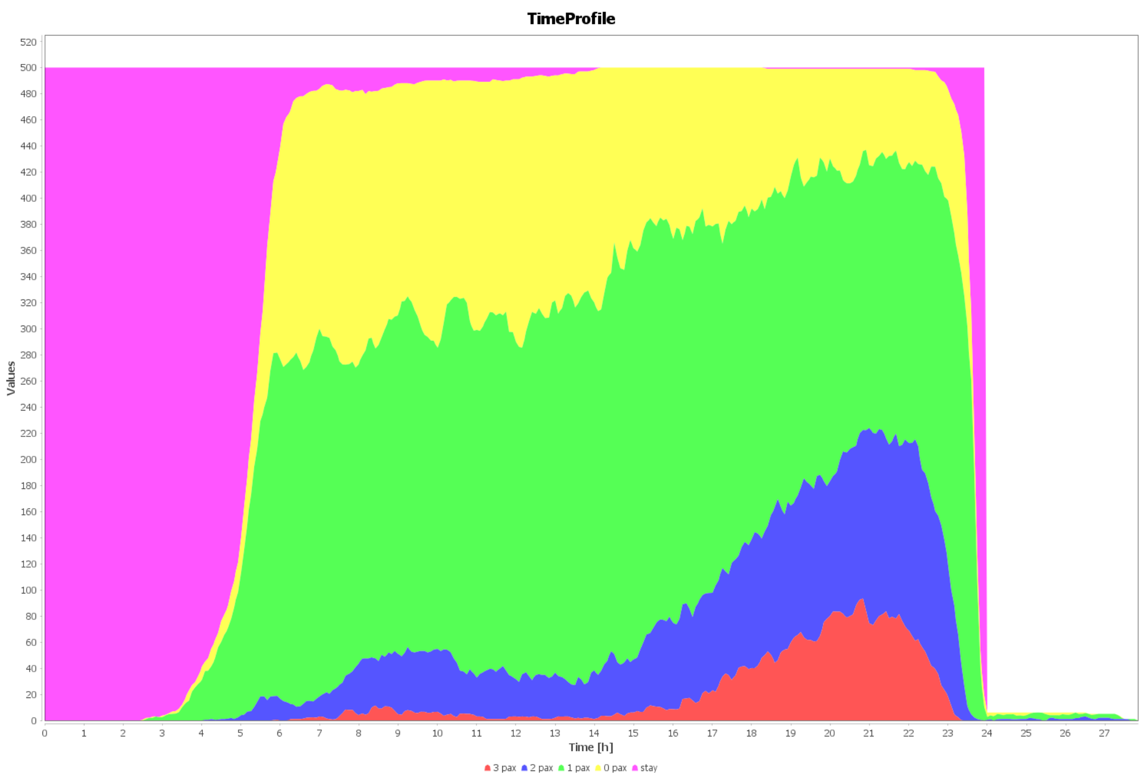

Figure 6.2.3: A stacked profile of the breakdown of passengers in ridesharing vehicles for the baseline ridesharing scenario without a disturbance (500 vehicle fleet size). Here, "pax" means passenger, so the read profile indicates the number of ridesharing vehicles with 3 concurrent passengers at the associated time.

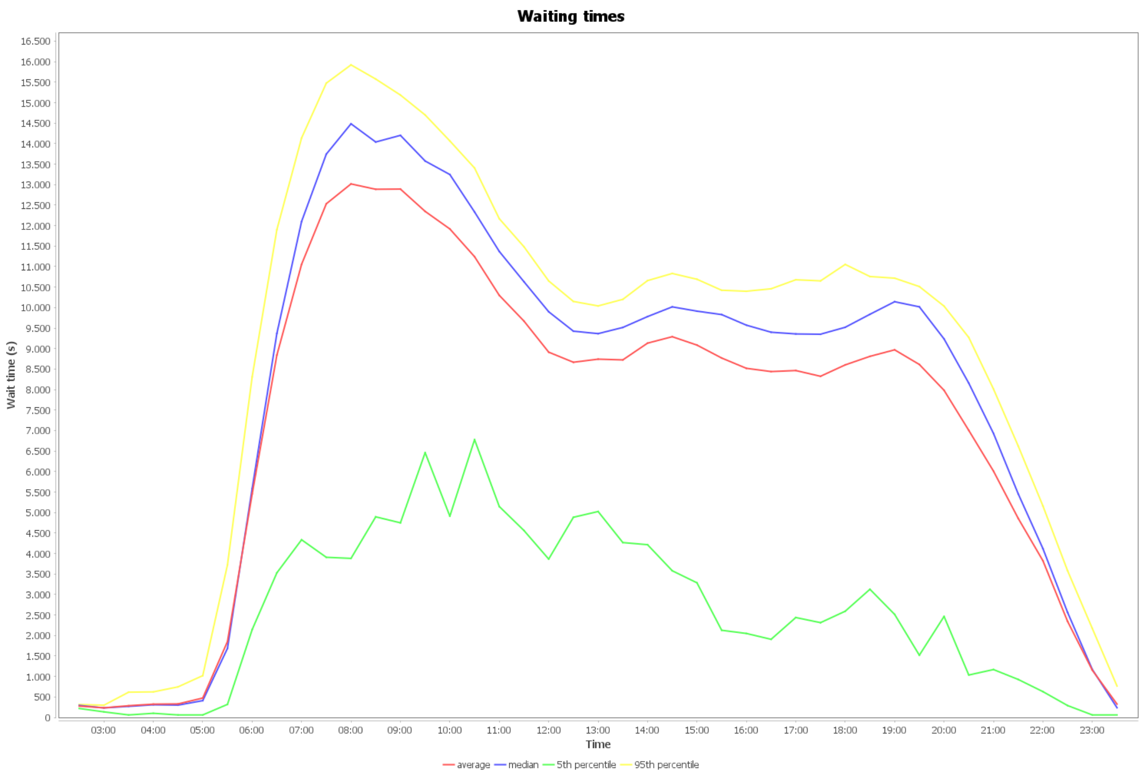

Figure 6.2.4: Waiting times for the baseline ridesharing scenario without a disturbance (500 vehicle fleet size).

6.3 Introducing a disturbance

With the introduction of a disturbance, the graphs showing departures, arrivals, and en-route trips indicated no discernible difference when compared to the non-disturbance scenarios. This is desirable because it means that the agents are not entirely disrupting their behavior in anticipation of the disturbance as a result of MATSim's optimization. If there were a major shift in peak morning departure times, for example, then it would be clear that the agents are predicting the disturbance event. The graphs are shown in Appendix C.1. The same goes for the scoring progression, the graphs for which are given in Appendix C.2. Comparing the two counterpart scenarios in terms of disturbance shows that there is not a significant difference between the two. This shows that the disturbance is not changing the underlying utilities, which is expected behavior. The main effects of introducing a disturbance will be shown in the resilience metrics.

6.4 Resilience metrics

The resilience metrics are each presented separately starting with the origin-destination travel time, then the link travel time, and finally the link volume.

Origin-destination travel time

The first metric proposed is the origin-destination travel time for trips that either start in Rotterdam and end in The Hague or vice versa. The figures discussed here show the link that is in the direction of Rotterdam. Figure 6.4.1 shows the progression of this metric for the cars only baseline case and the ridesharing baseline case with a 500 vehicle fleet. Recall that the travel time depicted here is an average of across two minute intervals in simulation time. Here it is shown that the trip times for ridesharing trips are significantly higher. A more thorough discussion of why this behavior exists is provided in the next chapter but in short it is due to high wait times for ridesharing trips, which are included in the total trip time for ridesharing trips. Because wait times are highly variable, there is significant noise for the ridesharing scenario as well.

Figure 6.4.2 shows the same metric, but for both of the 500 fleet size ridesharing scenarios; one with a disturbance and the other without. The graph shows that there is no discernible difference in the the travel times in either of these scenarios. The existence of a disturbance also seems to have little to no effect on the OD travel time.

Finally, Figure 6.4.3 gives a comparison of the two disturbance scenarios of each of the fleet sizes. Although the graph shows little difference between the two, there is notably a consistently lower travel time in the later hours of the day. This is also the case in the non-disturbance scenarios.

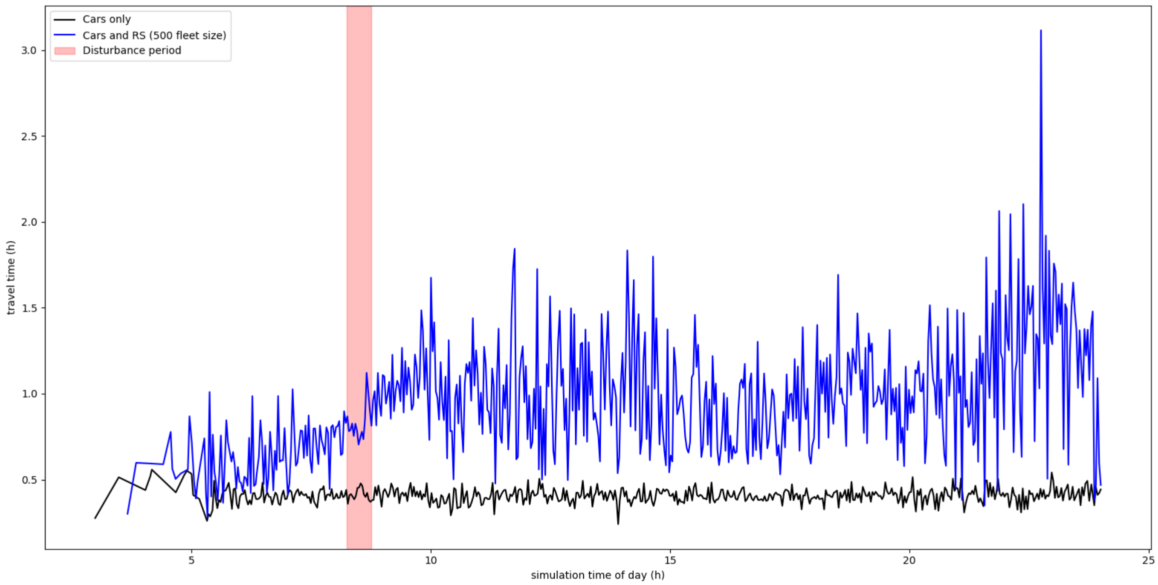

Figure 6.4.1: Travel time for all trips that either start in Rotterdam and end in The Hague or vice versa. The scenarios shown are the car only scenario and the 500 fleet size scenario, both without a disturbance.

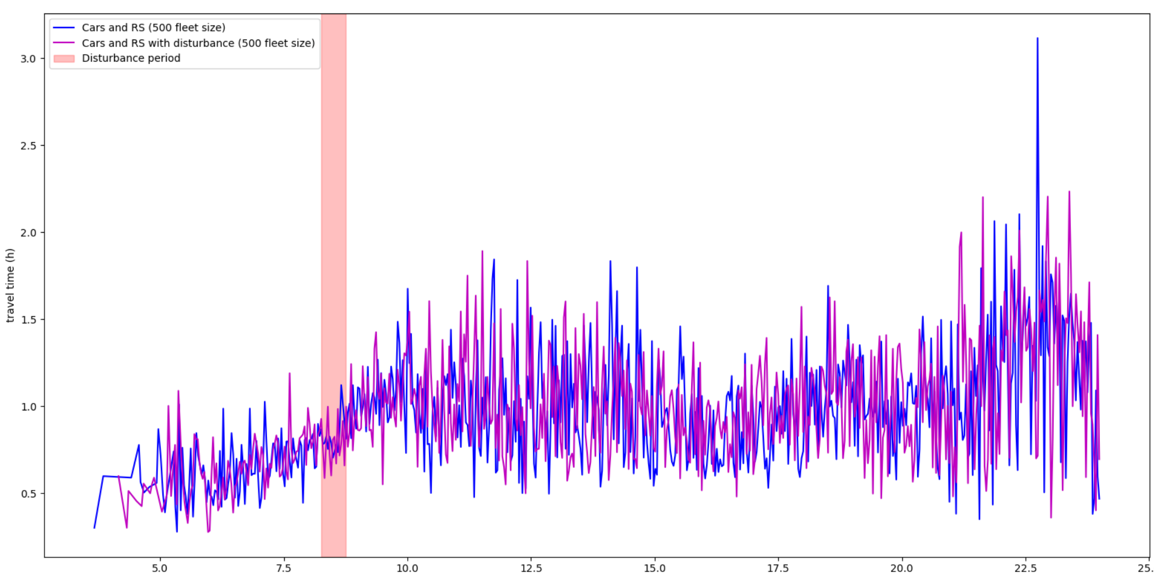

Figure 6.4.2: Travel time for all trips that either start in Rotterdam and end in The Hague or vice versa. The scenarios shown are the non-disturbed and disturbed ridesharing scenarios with a fleet size of 500.

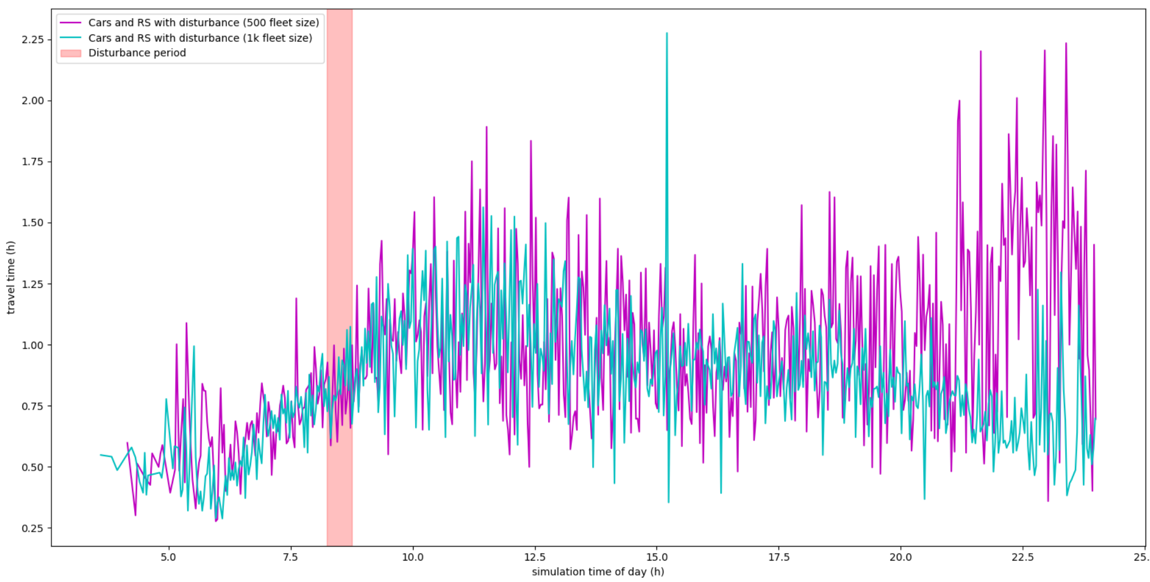

Figure 6.4.3: Travel time for all trips that either start in Rotterdam and end in The Hague or vice versa. The scenarios shown are the disturbed scenarios for both fleet sizes.

Link travel time

The second of the resilience metrics is the link travel time and more specifically the link in question is along the A4 roadway where the disturbance also occurs in the simulation. Again, the figures introduced here are for the direction towards Rotterdam. Figure 6.4.4 shows the link travel time comparison between the cars only scenarios with and without a disturbance. Of note is the significant increase in travel time during the disturbance time as well as the uptick in travel time in the second afternoon rush hour.

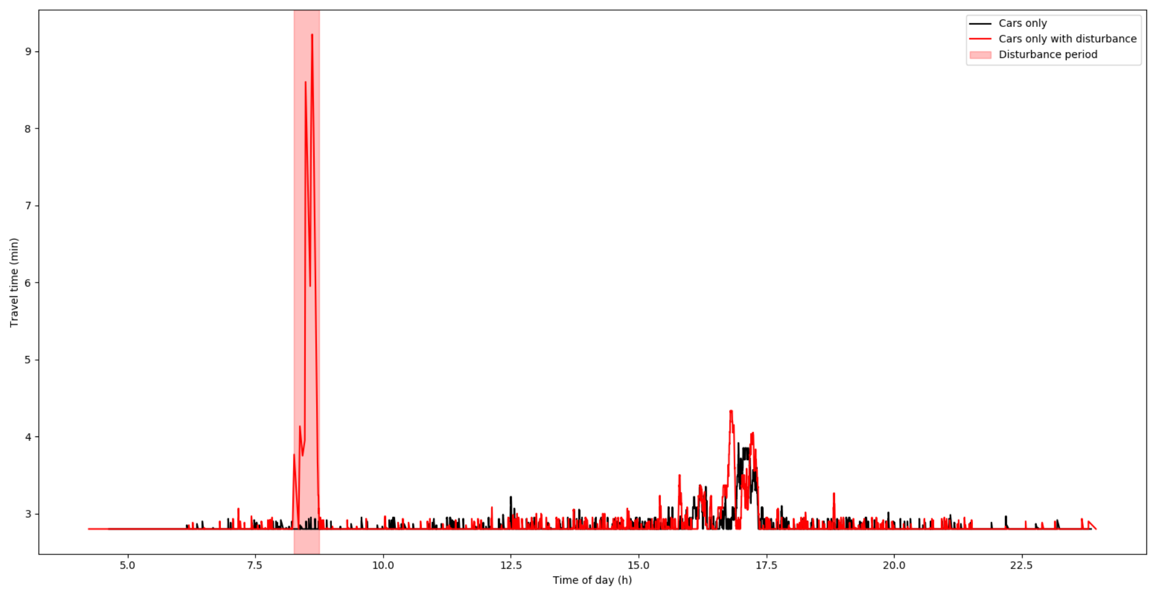

Figure 6.4.4: The travel time across the disturbed portion of the A4 comparing the car only scenarios.

Figure 6.4.5 gives a comparison between the three disturbance scenarios. What is interesting to note initially from here is the absence of a peak in link travel time in the afternoon rush hour for the ridesharing scenarios, which is otherwise present in the cars only scenario. Additionally, it is apparent that the extent of the increase in link travel time during the disturbance period is much greater for the ridesharing scenarios, prompting a closer look at this period of time.

Figure 6.4.6 shows a zoomed in look at the disturbance period for the previously discussed three scenarios. Here it is observed that not only is the extent of the effect of the disturbance on travel time larger in the ridesharing scenarios, but the recovery time to expected travel times occurs later. Forgoing the initial spike in travel time for the car only scenario, the small fleet size scenario and car only scenario both seem to incur the initial spikes in travel time at the same time. The larger fleet size scenario, though, has not only a significantly higher peak, but also begins sooner.

The travel time on the A13 link has also been looked into, however there is no indication of negative effects on travel time in any of the disturbance scenarios. This is not expected, however is likely a result of the lack of traffic from regions outside of the MRDH, resulting in lower overall traffic. Travelers may also be taking a different alternative route. Appendix C.6 shows a graph of

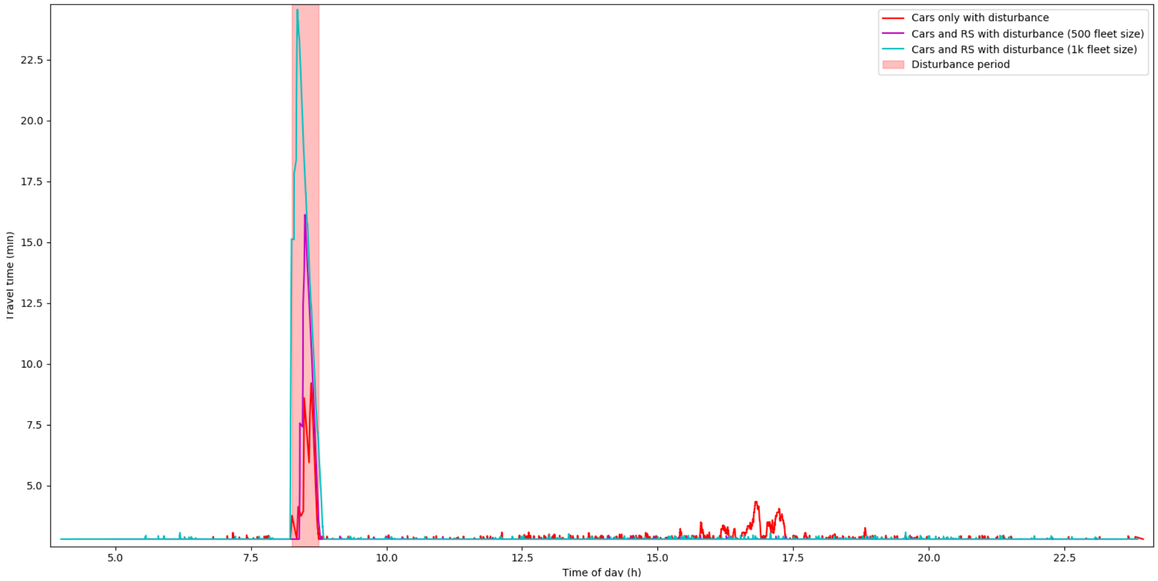

Figure 6.4.5: The travel time across the disturbed portion of the A4 comparing the disturbance scenarios.

the link travel time for a portion of the A13 towards Rotterdam.

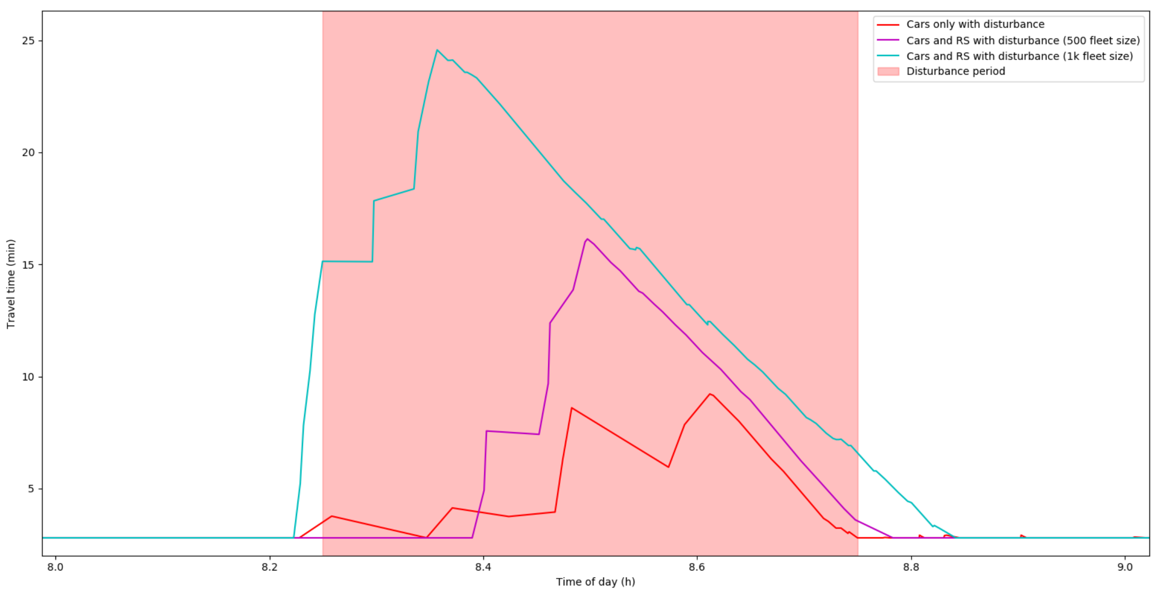

Figure 6.4.6: Magnified version of the travel time across the disturbed portion of the A4 comparing the disturbance scenarios.

Link volume

The final metric proposed for measuring resilience is link volume, which, just as the link travel time is measured across the disturbed portion of the A4 roadway. Figure 6.4.7 shows the accumulation of volume that has traveled across the link in the direction of Rotterdam for all scenarios. The accumulation is much greater in general for the car only scenarios. This means that more vehicles are passing over the link over time. There are two reasons for this. First the ridesharing vehicles have additional capacity and each passenger in these vehicles is not double-counted. Second, the waiting times in the ridesharing models incurs a constant delay on many trips. This also explains why the larger fleet size has greater volume, despite having more total ridesharing capacity. This is discussed further in the next chapter. It can also be seen that during the disturbance period, there is less volume traversing the link when comparing the disturbed scenarios with their undisturbed counterparts.

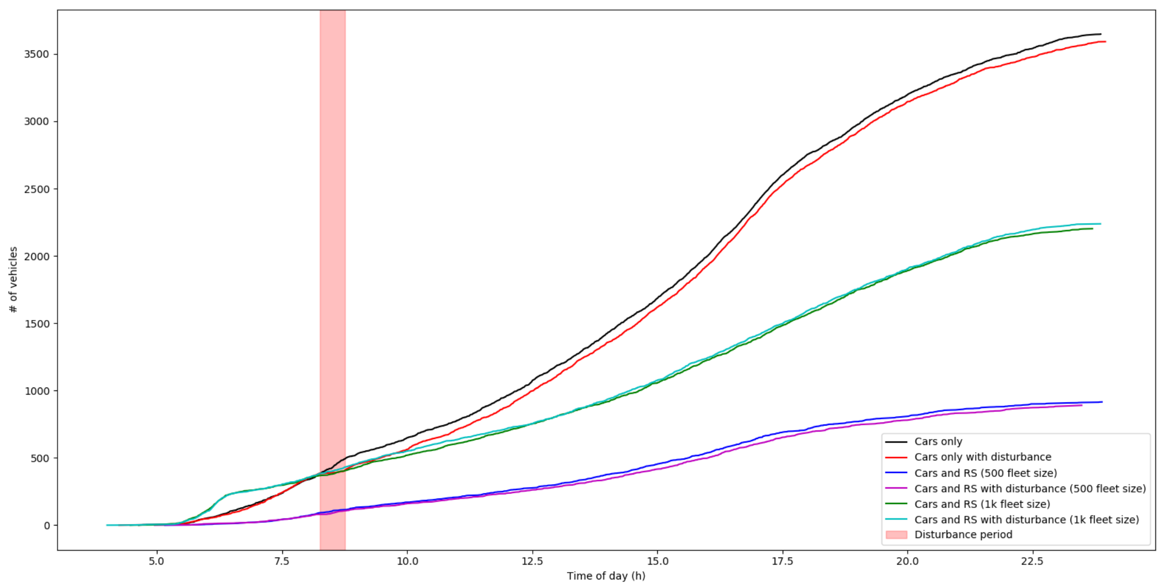

Figure 6.4.7: Cumulative volume across the disturbed portion of the A4 link comparing all scenarios.

Figure 6.4.8 gives a zoomed in look at the previously introduced figure to address the lower volume for the disturbance period. In this figure, the disturbed scenarios are compared in isolation from their undisturbed counterparts. What is most noteworthy here is that the number of cars that cross the link in the duration of the disturbance is higher for the ridesharing scenarios, despite the overall volume for the duration of the entire simulation being much smaller. This points to a meaningful difference in the behavior of static versus dynamic routing, which is discussed in more detail in the next chapter.

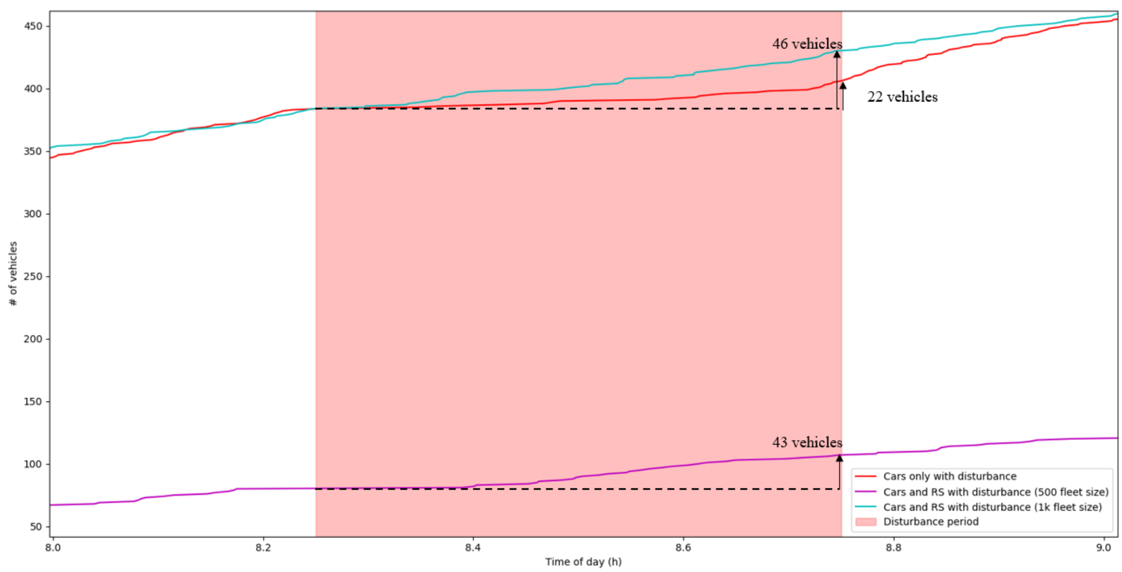

Figure 6.4.8: Magnified version of the cumulative volume across the disturbed portion of the A4 link focusing on the disturbance scenarios.

Chapter 7

Discussion of Results

The previous chapter presented results from 6 different simulation experiments performed in MATSim on a model of the MRDH network. These results are discussed further here in the following categories: (1) general model performance, (2) OD travel time metric, (3) link travel time metrics, (4) link volume metric, (5) other metrics, (6) the relation to resilience, (7) hypothesis, and (8) notes on statistical significance.

7.1 General model performance

The implementation of ridesharing proves to be a considerable drawback to the performance of the model, especially when comparing to what may be expected from the real world. First, refer back to Figures 6.1.2 and 6.2.2 which showed the scoring progression for agents plans across every iteration of the cars only scenario and the ridesharing scenario with a 500 vehicle fleet size (both with no disturbance). These figures show a stark difference between the scores of each of these scenarios, the former having scores in the range of 75 to 85 and the latter ranging in the -360 to -280 region. It is clear that the system changes quite drastically with the introduction of ridesharing, with not only car trips having lower scores, but also ridesharing trips having substantially lower scores. One reason this may be occurring is sensitivity to initial conditions of the model. Additionally, offering more modes means that there is a larger set of possible plans to explore. This means that it is entirely possible the ridesharing model requires many more iterations to reach convergence, and because the 100 iteration target is derived from the car only model, it may be the case that the ridesharing model suffers from lack of convergence.

Additionally, Figure 6.2.4 shows how unreasonable the wait times are for ridesharing trips. This is the result of a sacrifice being made to ensure that some ridesharing vehicles hit their passenger limit of 3 by encouraging ridesharing. Though this is achieved, as shown by Figure 6.2.3, it is at a cost which is also displayed in Figure 6.4.1 through a consistently much higher trip time in the non-disturbed, 500 vehicle ridesharing scenario. It is also worth mentioning that it is expected that the OD trip times be higher with the introduction of ridesharing, however this is discussed further in the next subsection on the OD travel time metric. Figure 6.2.3 also shows a peak in ridesharing in the evening. The most logical reason for this is that at this point, most travelers are going home, meaning that there is no incurred penalty for arriving 'late' according to MATSim's scoring criteria for the 'home' activity, which has no preferred start time, end time, nor duration. Finally, the histograms presented in Figures 6.1.1 and 6.2.1 show a discrepancy in the way that MATSim is counting en-route trips. Essentially, MATSim is counting multiple times for ridesharing trips, including the walking to pick-up points and associated waiting. These trip histograms instead give an indication of whether or not a simulation is behaving unexpectedly.

7.2 OD travel time metric

The OD travel times proved to be incomparable when considering car only scenarios vs. ridesharing scenarios. While it is expected that the travel times for ridesharing and car trips be different, the problem is accentuated by the excessive wait times for ridesharing trips mentioned earlier. Ridesharing trips include the time to walk to a pick-up point and subsequently wait for the vehicle to arrive. The wait time is the real core of the issue in this model, but in any case, the added walking and wait time make it such that the total OD travel time for ridesharing trips is not comparable to car trips. It is also not recommended to exclude the walking and waiting time from the calculation of OD travel time, as this is ultimately time spent by the traveler on their trip. Ultimately, the main takeaway from this metric is that it is very important to consider the different behavior inherent to different modes. Some modes can not be compared directly with each other, at least when the desire is to observe recovery time in a large system.

The next question is can ridesharing simulations be compared relative to other ridesharing simulations? Unfortunately in this model, the answer is rather unclear. Again, the wait times caused significant noise in the data because of the wide range of wait times experienced, as shown in Figure 6.2.4. This noise means that only very large changes in the OD travel time are visible between simulations, as is shown in Figure 6.4.3, where the scenario with a larger fleet size experienced lower OD travel times in the late hours of the simulation when compared to the smaller fleet size. Though this is not at the time of the disturbance, it does point to a larger fleet size being more able to handle demand buildup, which in this case is an artifact of long wait times. At the time of the disturbance on the other hand, there is no indication of any significant difference in OD travel times. It is likely that this can be attributed to trips that are arriving during the disturbance period, but were not affected by the disturbance itself as they are already in the destination city of either Rotterdam or The Hague. There is also no delayed effect.

The main takeaway from the OD travel time metric is that it is unfit for assessing resilience in the current setup of the simulation. The different behavior and expectations of travel times for the two modes means that the OD travel times are incomparable between the two modes.

7.3 Link travel time metric

The link travel time metric confines the problem to the location of the disturbance and, if desired, its nearby surroundings. The major drawback to looking specifically at the disturbed area is that

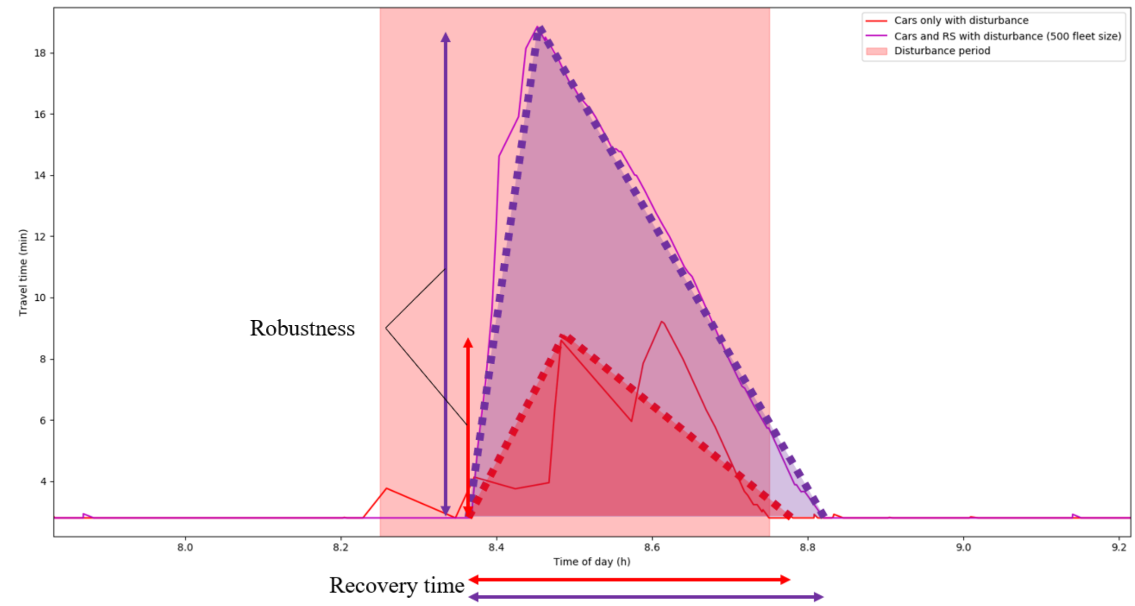

Figure 7.3.1: SOME CAPTION.

it does not necessarily say anything about the resilience of the system as a whole. This, however, may be of no issue depending on the use case. For example, some projects may be focused entirely on intercity roads, or possibly just on roads in city centers, in which case a magnified viewpoint is useful. With that in mind, link travel time certainly shows the most promise.

If, for a moment, we ignore the shortcomings of the ridesharing model, conclusions can be made on the effectiveness on resilience of introducing ridesharing. Figure **??** shows the progression of travel time across the disturbed portion of the A4 roadway. Looking closely and considering an idealized interpretation, it becomes apparent that an inverted resilience triangle appears. This is illustrated in Figure 7.3.1 where it can be seen that the recovery time for the ridesharing scenario is longer and the extent of the effect of the disturbance on link travel time is larger. Once again ignoring the limitations of the model, it can be concluded from this that the introduction of ridesharing does not improve the resilience of the network. Of course this conclusion should not be made without consideration of the model limitations, but this is the type of conclusion that can be drawn depending on how confident we are in a given model. With this model and case study, this particular conclusion can not be held to be accurate, but rather this is a proof of concept on how the metric is intended to be used.

In addition to this, the 1000 vehicle fleet size scenario performed significantly worse than the smaller fleet size in terms robustness and recovery time. This points again to the possibility that MATSim's dynamic routing does not encourage ridesharing vehicles to avoid the disturbed link, and since there are more vehicles there is a larger travel time increase. Finally, the lack of any change in travel time on the A13 does not have one definitive conclusion to be drawn. A possible reason may be that the lower volume of travelers caused by a lack of traffic originating from outside of the MRDH is resulting in insufficient buildup to see any affect from the disturbance. Alternatively, traffic may be rerouting onto other links that are not the A13. In the future, it would be useful to look into more alternative links than the A13, including even the minor links in the Rotterdam and The Hague corridor.

7.4 Link volume metric

The link volume metric may not be able to say as much about the *redundancy* of the network, but this is down to the limited links that are studied. In this case, the local volume across the A4 link is used to corroborate what is observed in the link travel time metric. Figure **??** shows the difference in vehicle volume across the disturbed link over the course of the disturbance. The larger volume in the ridesharing case is in line with the increased travel time; more traffic is causing the extra travel time. The routing of additional traffic to the A4 roadway during the disturbance can likely be attributed to the way in which MATSim routes cars versus ridesharing vehicles. The static routing of cars occurs between iterations and is evolved through exploration of other plans, ultimately resulting in car trips tending to avoid the A4 during the disturbance. Ridesharing vehicles, though, are routed dynamically during the simulation. This poses a problem as the online routing uses the original, undisturbed network to determine the fastest route. This means that ridesharing vehicles are are not seeing the disturbance in the same way and thus are not avoiding the A4 at this time. Ideally, studying as many links as is possible would result in a broader picture that gives an indication of whether the rest of the network has the capacity to handle traffic that is dispersed from a disturbed portion of the network. This is the ultimate goal of this metric; to judge if the network has redundant capacity to support a disrupted link. In this study, there was no discernible increase in volume on the alternative A13 roadway, nor was there an increase in travel time. This is down to the overall volume of traffic being lower than expected because traffic originating outside of the MRDH is not incorporated.

7.5 Other metrics

The percentage of the population affected by the disturbance could be measured by looking at the number of agents whose OD travel time was increased by various levels. For instance, the percentage of travelers whose OD travel times increased by 30% or more could give an indication of who is experiencing delays and why. This would give insight into the *inclusiveness* of the traffic network, meaning it may show if there are any disproportionately negatively affected populations or locations. However there is one glaring problem with a metric such as this. The plans of different scenarios may be completely different. This means that an agent may be taking a different route or using a different mode of transport in different experiments due to how each of the experiments was optimized differently. This type of a situation would result in a different travel time regardless of the disturbance, yielding unreliable results as it is unclear what the cause of the increase is.

7.6 Relation to resilience

The most clear association to resilience is in the link travel time. Figure 7.3.1 shows how this relates back to the idea of the resilience triangle. As is mentioned before, the important takeaway is not that ridesharing has a negative impact on local resilience, but instead that the robustness of the area near the disturbance and the recovery time after a disturbance can be measured. The quality of *flexibility* is most easily assessed by using this metric, which is most closely related to the recovery time. It can be argued that the robustness seen in the inverted resilience triangle can be related back to the *redundancy* of the system as well because with more *redundancy* in the system comes a lesser negative affect on link travel time as capacity is more easily offloaded. There is also some potential in using the link volume to assess the *redundancy* of the system, however this is held back by the fact that many links would need to be assessed, which can be time-consuming. Finally, there is potential in addressing some of the other qualities in the resilience framework, namely *resourcefulness* and *inclusivity*. *Resourcefulness* characterizes the rapidity with which the agents in the system adapt to a changing environment. It is feasible that the delay between the onset of a disturbance and the time at which the peak negative affect occurs (e.g. largest increase in travel time) can give an indication of how rapidly the system adjusts. A system that adjusts slowly will have a sooner peak and one that adjusts quickly will experience the peak later as agents have begun to adjust more quickly. *Inclusivity* would require an additional metric that considers the demographics of the travelers in order to see if any particular group experiences disproportionate adverse effects.

7.7 Hypothesis

The original hypothesis had to do with the effect that ridesharing might have on the resilience of traffic networks. It was proposed that ridesharing would provide not only an additional option for travelers, but would also decrease the number of vehicles on the road and stress the system less. While it is true that fewer vehicles on the road, it is not the case that the introduction of ridesharing made the resilience appear any better, and in fact seemed to perform worse. Even though this may be the case, it can not be definitively said that ridesharing improves or worsens resilience. Instead, the way in which resilience is measured becomes more important because the model limitations do not justify the results.

7.8 Notes on statistical significance

The limitations of the model and the time constraints of the thesis mean that measuring the statistical significance of the results is moot. While the aim of this thesis was not to have the most realistic simulation that stands up to tests of significance, it is important to still consider how the statistical significance of the simulation results can be improved. One way of doing this is to rerun using the plans of the final iteration of the simulation many times and to average all of these results. The resulting confidence intervals will give an indication of how stable the final set of plans is in producing consistent results. Another way to assess the significance is to compare the final iterations of the simulation after the replanning phase. The plans of the agents will be slightly different in each iteration, but ultimately this would demonstrate whether or not slight variations in plans significantly impact the performance of the model. If the variance is high in this case, then the model can likely be said to be sensitive to initial conditions.

Chapter 8

Conclusions and Recommendations

The structure of this chapter begins with concluding on the research questions presented in Section 1.2. Then, future work that may contribute to furthering of the presented research is discussed. This is split into future work on modeling, resilience assessment, and that which is specific to TNO and SUMS.

8.1 Concluding on research questions

Drawing conclusions on the remaining sub-questions sheds light on the overall conclusion on the main question. As such, each of the sub-questions is concluded on below followed by an overall conclusion of on the main research question.

The first research question aimed to define resilience in the setting of urban traffic networks. First, resilience, robustness and criticality are defined. **Resilience** is defined as the ability of a system to recover to normal operating conditions in a short period of time after a shock and **robustness** is defined as the ability of a system to resist a shock and maintain its equilibrium. **Criticality** is also disputed in literature (Jafino et al., 2020) is defined specifically for links and nodes where a link or node is critical if it has a high expected absolute flow during peak conditions, a high expected flow relative to its capacity, and there are few alternative links with similarly high capacity. Additionally, this thesis proposes an adapted version of the City Resilience Framework presented by ARUP (2014). The adapted resilience framework of this thesis specifically considers the category of urban mobility. This category is further described by six qualities: reflectiveness, redundancy, flexibility, resourcefulness, inclusivity, and integration. Indicators are proposed that can then be used to measure these qualities of resilience in urban mobility. All of this combines to allow a structured way in discussing resilience in this thesis.

The second sub-question concerns the metrics that may be able to assess resilience given that the aim is to use agent-based modeling and simulation. Using the indicators proposed in the resilience framework as a starting point, three metrics are introduced. The first is origin-destination travel times, which for this thesis specifically refers to trips with origins in The Hague and destinations in Rotterdam or vice versa. The second and third metrics are link travel time and link volume.

These are both measured across a given road segment. This thesis looked at two of the main road segments in the corridor between Rotterdam and The Hague. An isolated look such as this gives a better indication of local resilience while looking into more links around the network will push closer to assessing the network as a whole. Ultimately, the link travel time is the most telling metric for measuring resilience. Figure 7.3.1 shows how the travel time across the disturbed link spikes and settles back down to expected values, much like the resilience triangle of Figure 2.2.1. The ridesharing scenarios have higher maximum travel times during the disturbance and this is only made worse by the addition of more ridesharing vehicles. It is suspected that the implementation of dynamic routing of ridesharing vehicles in MATSim does not take into consideration the disturbance right away, and thus ridesharing vehicles on-route to destination do not adjust their route, whereas ridesharing trips that are newly departing during the disturbance avoid the area. The link volume metric across the same link confirms that the volume change in the ridesharing scenarios is higher during the disturbance than the car only scenario. The OD travel time metric is not as telling as initially speculated. This is because of the difference in behavior of a ridesharing trip versus a car trip. On the one hand, car trips incur no extra waiting time in this model as parking is not considered, and on the other hand, ridesharing trips have additional walking time to pick-up points as well as wait times for the vehicle to reach the pick-up point. This model experienced some extreme wait times, but the two modes should still not be compared with each other in this way.

The final sub-question gives purpose to this method of resilience measurement by situating the results of the resilience metrics in the environment of transportation policy. One consideration for using the proposed method for measuring resilience is the scope of the problem the policy aims to contribute to. Policy makers should first ask how large of an area needs to be studied. The case study in this thesis focuses on the corridor between Rotterdam and The Hague which limits the number of links that should be studied. If the area of study is larger, then it must be considered how much time is available for the study. For instance, if the inner city of Rotterdam was to be studied, then a plethora of link would likely have to be included in the study, which in turn takes a lot of time to analyze. Additionally, the number of different disturbance cases that should be included is higher. This is when a quicker alternative should be acknowledged, namely the use of graph theory techniques to study network resilience. Another consideration is the readiness of the model used for analysis. In this thesis, the model is made from scratch and thus is not developed to a standard that may be seen in the policy arena. If the model is not already developed and considered a sufficiently valid representation of real life, then possibly other solutions than an agent-based approach should be used. These are general ideas to consider prior to using the proposed method, but how can the results of the method be used by policy makers to inform their decisions?

First, let us ignore any model limitations for a moment and assume that the results presented in this thesis are to be used as part of a policy recommendation. First, it may be hypothesized that the introduction of ridesharing in the MRDH will reduce the number of vehicles on the road by replacing personal vehicles. After running the simulations, we see that ridesharing, while reducing total volume as expected, does not always perform better. The larger spike in travel time and slower recovery time from a disturbance show that ridesharing is vulnerable to a disturbance. Next, it can be asked why these results are being seen. In this case, it is the dynamic routing of ridesharing vehicles that is the suspected culprit. Now there is an additional development for the decision maker to examine, namely the effect that the scheduling of ridesharing vehicles have on their performance. In this way, the proposed method for measuring resilience leads to a point of further investigation that may not have been arrived at using a graph theory method which does not consider this dynamic routing. In the end, it is also worth noting that modeling and simulation is not just useful for the quantitative results it gives. The process of modeling ridesharing on the agent-based level teaches those involved about the underlying nature of the mode of transport.

Before bringing the ideas presented on the three sub-questions together, recall that the main research question is

> *How can resilience in urban traffic networks be measured using agent-based modeling and simulation?*

The first sub-question provided a way in which resilience could be discussed in the context of urban mobility. This is paramount as resilience has different interpretations depending on the application. Using the terminology here, the second sub-question leads to metrics that can be obtained from the simulation to address the categories that describe resilience in the proposed framework. After simulation, sub-question three motivates for the results to be analyzed with respect to policy advice on ridesharing and the impact that resilience may play in decision making. Two out of the three proposed metrics are directly useful for measuring resilience. First and foremost is the link travel time. The link volume is supplementary because it may give insight into the progression of the link travel times. The presented case study looked into a disturbance on the A4 between Rotterdam and The Hague. This is a focused look at the corridor between the two cities, meaning that there are fewer links to be studied. Given the scope of the thesis, this worked out well, but other problems may require a larger scope of study, in which case the number of studied links should also increase. Ultimately, it is recommended that an area of interest in the network be strictly defined such that the study does not become too large and therefore time consuming.

8.2 Future work

The limitations of this thesis and the proposed future work is discussed in three categories: (1) modeling, (2) resilience assessment, and (3) specific to TNO. The order is meant to reflect that modeling limitations are highly influential on the other two categories and is thus discussed first.

Modeling

The model for this thesis has been produced from scratch in MATSim and therefore has its limitations but also plenty of room for improvements to be made. The limitations can be split into improvements on existing elements and new elements that can be added in. The most important of the existing elements to improve upon is ridesharing. Some of the drawbacks are more difficult to handle such as the scheduling of pick-ups, which is an entire area of research in and of itself. Using a simplified scheduling regime can lead to unrealistic wait times caused by assignment of sub-optimal taxis to riders. For instance, if a taxi becomes empty and is the only empty taxi, it may be routed to the next passenger request, regardless of distance away from the passenger, whereas a better taxi may become available soon after the request, but no adjustment is made even though the newly available taxi is a better candidate for the request. This improvement is perhaps more in the hands of the developers of MATSim and less so the modeler. The calibration of scoring for ridesharing, as well as all other modes in the model, can be improved as well. In the presented model, the scoring parameters are based on example models in MATSim and trial and error to produce more expected behavior, but they can be further based on real pricing models for existing ridesharing services or similar services. Related to the scoring parameters, the strategy settings can also be improved further. This would require running many simulations with various settings and assessing the performance and behavior produced by these settings. As ABMS is often sensitive to initial conditions, this would require extensive computation time more so than additional desk research.

An important addition to the model is the introduction of additional modes of transport. These include the traditional modes like public transport, walking, and biking as well as freight and commercial traffic. Including these would allow for a larger set of the population to be included in the model and therefore more realistically model the traffic dynamics. Along the same line, introducing multimodality in the model would improve the realism of the model and make it more future-proof. Another limitation to the model is the absence of traffic that originates outside of the MRDH. Not incorporating this external traffic poses a problem of insufficient volume, especially on major roads that are used by through traffic originating and ending their trips outside of the MRDH. The reason that this cannot be solved by a simple adjustment of the capcity of the network is because it is variable on the road location; inner city roads will not see as much external traffic as intercity highways and freeways, so a blanket adjustment of road capacity is unrealistic. This can be improved in a few ways. First, faux trips can be added into the model to artificially simulate a more realistic volume. This requires data on the expected volumes both within and outside of the city. Second, incorporating a more full data set of trips originating in nearby regions to the MRDH would also contribute to more realistic traffic volumes. In either of these cases, it is recommended that external trips be prohibited from using ridesharing, as this may disrupt the ridesharing fleet. This would require another model addition of ridesharing service zones that would restrict ridesharing vehicles from operating outside the MRDH. It is a realistic expectation that ridesharing trips would not be used for distance trips in the first place. The role of external traffic is especially important in the case of The Netherlands because of its compact geography.

Finally, there is something to be said about the convergence rates of models with different parameters and characteristics. In this case, the ability for a simulation to reach stable operating conditions, measured through an observed equilibrium state of scoring, is affected by the introduction of ridesharing in the model. The original estimation for number of iterations to achieve meaningful convergence is taken from a simulation of the cars only scenario. However, the introduction of ridesharing in later scenarios means that there is a larger set of possible selections for plans because of the additional mode. Ultimately, this scenario requires additional iterations to sufficiently explore possible plans. In the future, convergence should be considered depending on the scenario.

Resilience assessment

The model improvements above are important because they would produce more realistic results when compared to real world traffic dynamics. It should be noted though, that the methodology itself does not improve because of model improvements, but rather the results are more reliable because of the more accurate model. One limitation to the resilience assessment as presented in this thesis is the limited number of scenarios that are run. Including other scenarios that look into, for instance, a wider range of fleet sizes would lead to the results being more statistically significant, regardless of whether or not the underlying model changes. Other improvements include looking at link travel times and volumes for other links in the region near the disturbed section of road as well as near the alternative routes. In this case that would be along the A4 and A13 roadways. This would give additional insight into the resilience of the traffic network as a whole under the specified disturbance. In addition to this, considering more disturbance scenarios would allow for a more thorough analysis of the network as a whole. This however is not necessary, as it may be desirable to consider a targeted portion of road depending on the application. For instance, one might wish to focus on intercity transportation and therefore only need to consider a few critical links for disturbance. Studies of larger areas should also consider different ways to visualize and interpret the data from a large number of links in order to speed up the analysis process.

Another limitation has to do with the resilience framework and the proposed metrics not addressing each of the qualities of. This primarily affects the *integration* and *inclusivity* qualities. These qualities tend to be more quantitative and thus are difficult to capture in an agent-based model. A large part of *inclusivity* is the community engagement. While this can be incorporated into models, it is arguably dissociated with the broader problem presented in this thesis, which is the incorporation of new modes into traffic networks. One way that inclusivity can be measured is through location-based metrics. This would be metrics that compare areas, like neighborhoods, to determine if any one is disproportionately affected in a negative way. Insight such as this may point to underlying issues in specific communities. *Integration* is about consistency of decision making across subsystems. In the policy arena this is at a much higher level than the model-based analysis proposed in this thesis. The onus is on leaders in the political arena to align their decision making, so a specific metric may not be feasbile.

Specific to TNO

A large part of TNO's work consists of advising governmental agencies in The Netherlands. Specifically at SUMS, the desire is to move away from traditional traffic models towards more representative models that consider interactions on the individual level by incorporating agent-based modeling and simulation into their simulation architecture. This includes multiple different components that interact with each other in various ways, for example, the output of an activity-based model may provide the input data for the population in a MATSim model. Ultimately, TNO wish to give advice that considers system optimums rather than user optimums as may be the case in the private sector. In the future, SUMS should take into account two key things: the importance of dynamic routing for certain tasks and the computation time that dynamic routing incurs. Dynamic routing is important for measuring resilience because of how disruptions occur at random. In order to properly measure this, the affected agents should have the ability to route online during the simulation. However, dynamic routing is computationally heavy, so it should not necessarily be used in just any case. The time sensitivity of a project should also play a role in the decision to incorporate dynamic routing or not. Ultimately, dynamic routing should remain on the radar for the SUMS department at TNO.

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Appendix A

Supplemental Materials

A.1 Software packages

Table A.1.1: Full list of software packages initially considered.

Software	Reason for omitting (N/A means further research needed)	Source
Repast Simphony	General purpose ABM, not specific to T&T	https://repast.github.io/
NetLogo	General purpose ABM, not specific to T&T	https://ccl.northwestern.edu/netlogo/
AirSim	Meant more for AV research and not traffic flow research	https://github.com/microsoft/AirSim
Janus	General purpose ABM, not specific to T&T	http://www.sarl.io/runtime/janus/
MATSim	N/A	MATSim book
Gazebo	3D robotics simulator, very few agents only	http://gazebosim.org/
SUMO	N/A	http://sumo.sourceforge.net/ (see citation on website)
GAMA	General purpose	https://gama-platform.github.io/wiki/Home
Polaris	No indication of external use	https://www.anl.gov/es/polaris-transportation-system-simulation-tool
SimMobility	Public code based not updated in 3 years	https://its.mit.edu/software/simmobility https://github.com/smart-fm/simmobility-prod
EMME	Commercial software	https://www.inrosoftware.com/en/products/emme/
UrbanSim	Commercial software	https://urbansim.com/
TRANUS	Focus on land use	http://www.tranus.com/tranus-english/general-description
AequilibraE	Not present in literature, only a python package	http://aequilibrae.com/python/V.0.6.3/overview.html
Stplanr	R package, no focus on motorized transport	https://cran.r-project.org/web/packages/stplanr/index.html
TRANSIMS	No longer active since 2013	https://code.google.com/archive/p/transims/source/default/commits
ActivitySim	Not agent-based, used for different purpose by TNO	https://activitysim.github.io/activitysim/index.html
PARAMICS	Free trial but not student friendly, 3D simulation will be slow and not suited for purpose	https://www.paramics.co.uk/en/
VISSIM	Student version, but limited. Commercial software	https://www.ptvgroup.com/en/solutions/products/ptv-vissim/
AIMSUN	N/A	https://www.aimsun.com/
AgentPolis	N/A	http://sum.fel.cvut.cz/mod.html
Brutus	Sparsely documented	N/A
LITRES-2	Not clear where to find it	N/A

A.2 Simulation convergence

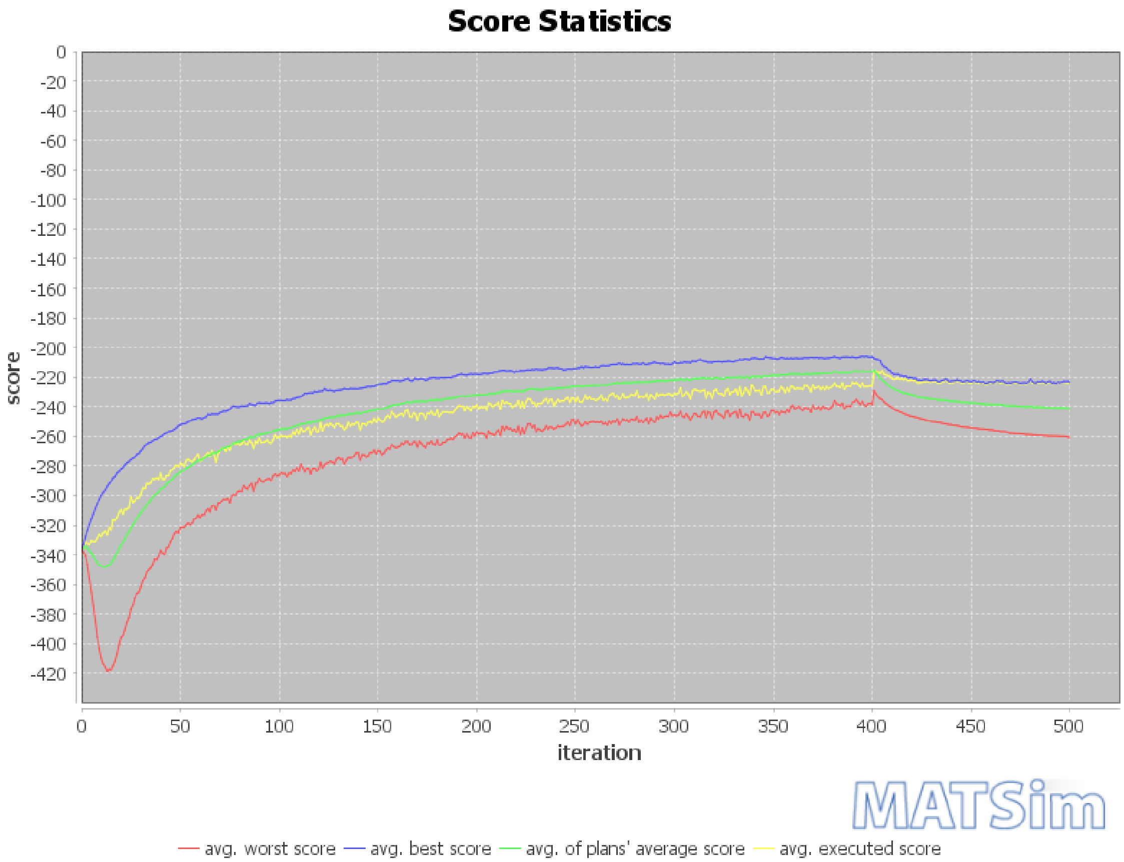

Figure A.2.1: Score progression of a simulation of 500 iterations and a 1% population size. Note that the jolt in the data seen at iteration 400 is because this is the stage where the simulation stops optimizing scores and begins running the plans with the best scores for all agents; this does not have to do with the convergence.

Appendix B

Code

B.1 Event handlers

B.1.1 Travel time

```
public class TravelTimeEventsHandler implements PersonDepartureEventHandler,
    PersonArrivalEventHandler, LinkEnterEventHandler {
  private Map<Id<Person>, Double> departureTimes = new HashMap<>();
  private double travelTimeSum = 0.0;
  private int travelTimeCount = 0;
  private double totalElapsed = 0.0;
  private double prevTotalElapsed = 0.0;
  private double timeCount = 0.0;
  private Map<Double, Double> averageTimes = new HashMap<>();
  private ArrayList<String> rotterdamLinks =
      parseTextFile(System.getProperty("user.dir")+"\\data_analysis\\rotterdam_links.txt");
      // NOTE: This can be generalized to any 2 bounding boxes
  private ArrayList<String> theHagueLinks =
      parseTextFile(System.getProperty("user.dir")+"\\data_analysis\\the_hague_links.txt");
  private Map<Id<Person>, String> startingLocations = new HashMap<>();
  private Map<Id<Person>, ArrayList<String>> startLinks = new HashMap<>();
  private Map<Id<Person>, ArrayList<String>> endLinks = new HashMap<>();
  private Map<Id<Person>, ArrayList<Double>> individualTravTimes = new HashMap<>();
  private Map<Id<Person>, ArrayList<Double>> individualDepartureTimes = new HashMap<>();

  public static final String delimiter = "\t";
  public static final String rotterdam = "Rotterdam";
  public static final String theHague = "The Hague";
  public static final String neither = "Neither";
  public static final Integer interval = 120; // Amount of time between average
      calculations
```

```java
@Override
public void reset(int iteration) {
   this.departureTimes = new HashMap<>();
   this.travelTimeSum = 0.0;
   this.travelTimeCount = 0;
   this.totalElapsed = 0.0;
   this.prevTotalElapsed = 0.0;
   this.timeCount = 0.0;
   this.averageTimes = new HashMap<>();
   this.startingLocations = new HashMap<>();
   this.startLinks = new HashMap<>();
   this.endLinks = new HashMap<>();
   this.individualTravTimes = new HashMap<>();
   this.individualDepartureTimes = new HashMap<>();

}

@Override
public void handleEvent(PersonDepartureEvent event) {
   Id<Person> personID = event.getPersonId();
   this.departureTimes.put(personID, event.getTime());
   String linkID = event.getLinkId().toString();
   if (linkID.contains(".5")) {
      linkID = linkID.substring(0, linkID.length() - 2);
   }

   if (this.startLinks.get(personID) == null) {
       this.startLinks.put(personID, new ArrayList<String>());
   }
   this.startLinks.get(personID).add(linkID);

   // Check where the starting link is ("Rotterdam", "The Hague", "Neither")
   if (this.rotterdamLinks.contains(linkID)) {
      this.startingLocations.put(personID, rotterdam);
   } else if (this.theHagueLinks.contains(linkID)) {
      this.startingLocations.put(personID, theHague);
   } else {
      this.startingLocations.put(personID, neither);
   }
}

@Override
public void handleEvent(PersonArrivalEvent event) {
```

```java
// Get location of the arrival (Rotterdam, The Hague, or Neither)
Id<Person> personID = event.getPersonId();
String linkID = event.getLinkId().toString();
String loc = "";
if (this.rotterdamLinks.contains(linkID)) {
  loc = rotterdam;
} else if (this.theHagueLinks.contains(linkID)) {
  loc = theHague;
} else {
  loc = neither;
}

if (this.startingLocations.get(personID) == rotterdam && loc == theHague) { // Check
    if trip was from rotterdam to the hague
  double departureTime = this.departureTimes.get(personID);
  double travelTime = event.getTime() - departureTime;

  if (this.endLinks.get(personID) == null) {
     this.endLinks.put(personID, new ArrayList<String>());
  }
  this.endLinks.get(personID).add(linkID);

  if (this.individualTravTimes.get(personID) == null) {
    this.individualTravTimes.put(personID, new ArrayList<Double>());
  }
  this.individualTravTimes.get(personID).add(travelTime);

  if (this.individualDepartureTimes.get(personID) == null) {
    this.individualDepartureTimes.put(personID, new ArrayList<Double>());
  }
  this.individualDepartureTimes.get(personID).add(departureTime);

  this.travelTimeSum += travelTime;
  this.travelTimeCount++;

} else if (this.startingLocations.get(personID) == theHague && loc == rotterdam) { //
    Check if trip was from the hague to rotterdam
  double departureTime2 = this.departureTimes.get(personID);
  double travelTime2 = event.getTime() - departureTime2;

  if (this.endLinks.get(personID) == null) {
    this.endLinks.put(personID, new ArrayList<String>());
  }
  this.endLinks.get(personID).add(linkID);
```

```
            if (this.individualTravTimes.get(personID) == null) {
                this.individualTravTimes.put(personID, new ArrayList<Double>());
            }
            this.individualTravTimes.get(personID).add(travelTime2);

            if (this.individualDepartureTimes.get(personID) == null) {
                this.individualDepartureTimes.put(personID, new ArrayList<Double>());
            }
            this.individualDepartureTimes.get(personID).add(departureTime2);

            this.travelTimeSum += travelTime2;
            this.travelTimeCount++;

        } else {
            // Remove start links with no end link
              int index = this.startLinks.get(personID).size() - 1;
              this.startLinks.get(personID).remove(index);
        }
    }

    @Override
    public void handleEvent(LinkEnterEvent event) {
        this.totalElapsed = event.getTime();
        this.timeCount += this.totalElapsed - this.prevTotalElapsed;
        this.prevTotalElapsed = this.totalElapsed;

        if (this.timeCount > interval && travelTimeCount > 0) { // Calculate the average
             every ten minutes (NOTE: This won't always be exactly
                                          // 2 minutes because events happen as scheduled
            this.averageTimes.put(this.totalElapsed, this.getAverageTravelTime());
            // Reset time counter and travel time summer / counter
            this.timeCount = 0.0;
            this.travelTimeSum = 0.0;
            this.travelTimeCount = 0;
        }
    }

    public double getAverageTravelTime() {
        return this.travelTimeSum / this.travelTimeCount;
    }

    public ArrayList<String> parseTextFile(final String inputFile) {
        ArrayList<String> arrayList = new ArrayList<String>();
```

```java
    try {
        Scanner s = new Scanner(new File(inputFile));
        while (s.hasNextLine()){
            arrayList.add(s.nextLine());
        }
        s.close();
    } catch (FileNotFoundException fe) {
         fe.printStackTrace();
    }
    return arrayList;
}

public void writeHeader(BufferedWriter timeWriter, int writeCase) throws IOException {
    switch (writeCase) {
    case 1:
        timeWriter.write("time");
        timeWriter.write(delimiter);
        timeWriter.write("periodAvgTravTime");
        timeWriter.write("\n");
        break;
    case 2:
        timeWriter.write("personID");
        timeWriter.write(delimiter);
        timeWriter.write("startLink");
        timeWriter.write(delimiter);
        timeWriter.write("endLink");
        timeWriter.write(delimiter);
        timeWriter.write("travelTime");
        timeWriter.write(delimiter);
        timeWriter.write("departureTime");
        timeWriter.write("\n");
        break;
    }
}

public void writeRows(BufferedWriter timeWriter, int writeCase) throws IOException {
    switch (writeCase) {
    case 1:
        for (Map.Entry<Double, Double> entry : this.averageTimes.entrySet()) {
            timeWriter.write(String.valueOf(entry.getKey()));
            timeWriter.write(delimiter);
            timeWriter.write(String.valueOf(entry.getValue()));
            timeWriter.write("\n");
        }
```

```
          break;
        case 2:
          for (Id<Person> personID : this.endLinks.keySet()) {
              for (int i = 0; i < this.endLinks.get(personID).size(); i++) {
                timeWriter.write(personID.toString());
                timeWriter.write(delimiter);
                timeWriter.write(this.startLinks.get(personID).get(i));
                timeWriter.write(delimiter);
                timeWriter.write(this.endLinks.get(personID).get(i));
                timeWriter.write(delimiter);
                timeWriter.write(String.valueOf(this.individualTravTimes.get(personID).get(i)));
                timeWriter.write(delimiter);
                timeWriter.write(String.valueOf(this.individualDepartureTimes.get(personID).get(i)));
                timeWriter.write("\n");
              }
          }
          break;
      }
  }

  public void writeStats(final String myFilename, int writeCase) {
      Log.info("writing stats to " + myFilename + "...");

      try {
          BufferedWriter timeWriter = IOUtils.getBufferedWriter(myFilename);

          this.writeHeader(timeWriter, writeCase);
          this.writeRows(timeWriter, writeCase);

          timeWriter.flush();
          timeWriter.close();

      } catch (IOException e) {
          throw new RuntimeException(e);
      }
  }
}
```

B.1.2 Link stats

```
public class LinkTravelTimeEventsHandler implements LinkEnterEventHandler,
    LinkLeaveEventHandler {
  private static final Id<Link> a4R = Id.createLinkId("31517");
```

```
private static final Id<Link> a4DH = Id.createLinkId("31518");
private static final Id<Link> a4RBefore = Id.createLinkId("668780");
private static final Id<Link> a4DHBefore = Id.createLinkId("31500.5");
private static final Id<Link> a4RAfter = Id.createLinkId("668771.5");
private static final Id<Link> a4DHAfter = Id.createLinkId("668781.5");
// ADDING IN A13 Links
private static final Id<Link> a13R = Id.createLinkId("26077.5");
private static final Id<Link> a13DH = Id.createLinkId("26076");

private static final List<Id<Link>> linksOfInterest = Arrays.asList(a4R, a4DH,
    a4RBefore, a4DHBefore, a4RAfter
     , a4DHAfter, a13R, a13DH); // ADDING IN A13 links

private List<LinkEnterEvent> linkEnterEvents = new ArrayList<>();
private List<LinkLeaveEvent> linkLeaveEvents = new ArrayList<>();

public static final String delimiter = "\t";

@Override
public void reset(int iteration) {
   this.linkEnterEvents = new ArrayList<>();
   this.linkLeaveEvents = new ArrayList<>();
}

@Override
public void handleEvent(LinkEnterEvent event) {

   Id<Link> linkID = event.getLinkId();

   if (linksOfInterest.contains(linkID)) {
      this.linkEnterEvents.add(event);
   }
}

@Override
public void handleEvent(LinkLeaveEvent event) {
   Id<Link> linkID = event.getLinkId();
   if (linksOfInterest.contains(linkID)) {
      this.linkLeaveEvents.add(event);
   }
}

public void writeHeader(BufferedWriter timeWriter) throws IOException {
   timeWriter.write("vehicleID");
```

```
    timeWriter.write(delimiter);
    timeWriter.write("link");
    timeWriter.write(delimiter);
    timeWriter.write("eventTime");
    timeWriter.write(delimiter);
    timeWriter.write("eventType");
    timeWriter.write("\n");
}

public void writeRows(BufferedWriter timeWriter) throws IOException {
    for (LinkEnterEvent event : this.linkEnterEvents) {
        timeWriter.write(event.getVehicleId().toString());
        timeWriter.write(delimiter);
        timeWriter.write(event.getLinkId().toString());
        timeWriter.write(delimiter);
        timeWriter.write(Double.toString(event.getTime()));
        timeWriter.write(delimiter);
        timeWriter.write("linkEnter");
        timeWriter.write("\n");
    }

    for (LinkLeaveEvent event : this.linkLeaveEvents) {
        timeWriter.write(event.getVehicleId().toString());
        timeWriter.write(delimiter);
        timeWriter.write(event.getLinkId().toString());
        timeWriter.write(delimiter);
        timeWriter.write(Double.toString(event.getTime()));
        timeWriter.write(delimiter);
        timeWriter.write("linkLeave");
        timeWriter.write("\n");
    }
}

public void writeStats(final String myFilename) {
    Log.info("writing stats to " + myFilename + "...");

    try {
        BufferedWriter timeWriter = IOUtils.getBufferedWriter(myFilename);

        this.writeHeader(timeWriter);
        this.writeRows(timeWriter);

        timeWriter.flush();
        timeWriter.close();
```

```java
        } catch (IOException e) {
            throw new RuntimeException(e);
        }
    }
}
```

B.2 XML inputs

```xml
<person id="42">
    <plan selected="yes">
        <act end_time="06:09:00" type="home" x="1000" y="2000"/>
        <leg mode="car"/>
        <act end_time="14:26:00" type="work" x="4500" y="600"/>
        <leg mode="car"/>
        <act type="home" x="1000" y="2000"/>
    </plan>
</person>
```

Figure B.2.1: Example activity schedule. Note that the activities do not contain an start time as this is not required by MATSim. Additionally, the final activity in a schedule does not need a start nor end time defined.

```xml
<network>

    <nodes>
        <node id="1" x="0" y="0"/>
        <node id="2" x="400" y="500"/>
    </nodes>

    <links>
        <link id="12" from="1" to="2" length="700" freespeed="15" capacity="100" permlanes="2"/>
        <link id="21" from="2" to="1" length="750" freespeed="15" capacity="100" permlanes="2"/>
    </links>

</network>
```

Figure B.2.2: A simple network of two unidirectional links given in MATSim's XML format.

```xml
    <networkChangeEvent startTime="08:15:00">
        <!-- Making it easier to choose one or both directions -->
        <!-- Portion of A4 towards Rotterdam -->
        <link refId="31517"/>
        <!-- Portion of A4 towards The Hague -->
        <link refId="31518"/>
        <flowCapacity type="scaleFactor" value="0.05"/>
        <!-- <freespeed type="absolute" value="2.77777"/> -->
    </networkChangeEvent>

    <!-- change network back to normal -->
    <networkChangeEvent startTime="08:45:00">
        <!-- Portion of 4 towards Rotterdam -->
        <link refId="31517"/>
        <!-- Portion of A4 towards The Hague -->
        <link refId="31518"/>
        <flowCapacity type="scaleFactor" value="20"/>
        <!-- <freespeed type="absolute" value="27.7777"/> -->
    </networkChangeEvent>
```

Figure B.2.3: XML representation of a network disturbance on a portion of the A4 roadway between Rotterdam and The Hague.

Appendix C

Additional Results

C.1 Histograms

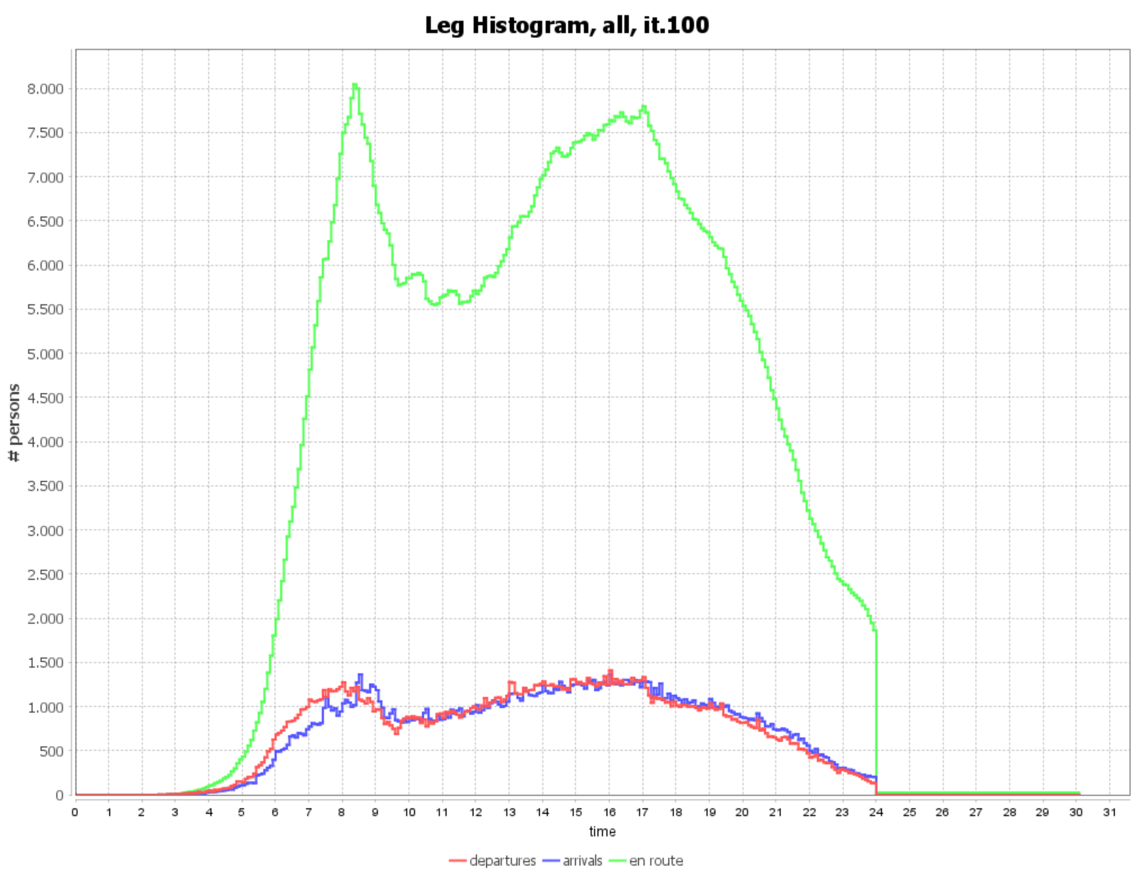

Figure C.1.1: Histogram of the ridesharing scenario with large fleet size and no disturbance showing the number of en-route trips in green, departing trips in red, and arriving trips in blue. These are counted in 5 minute bin periods.

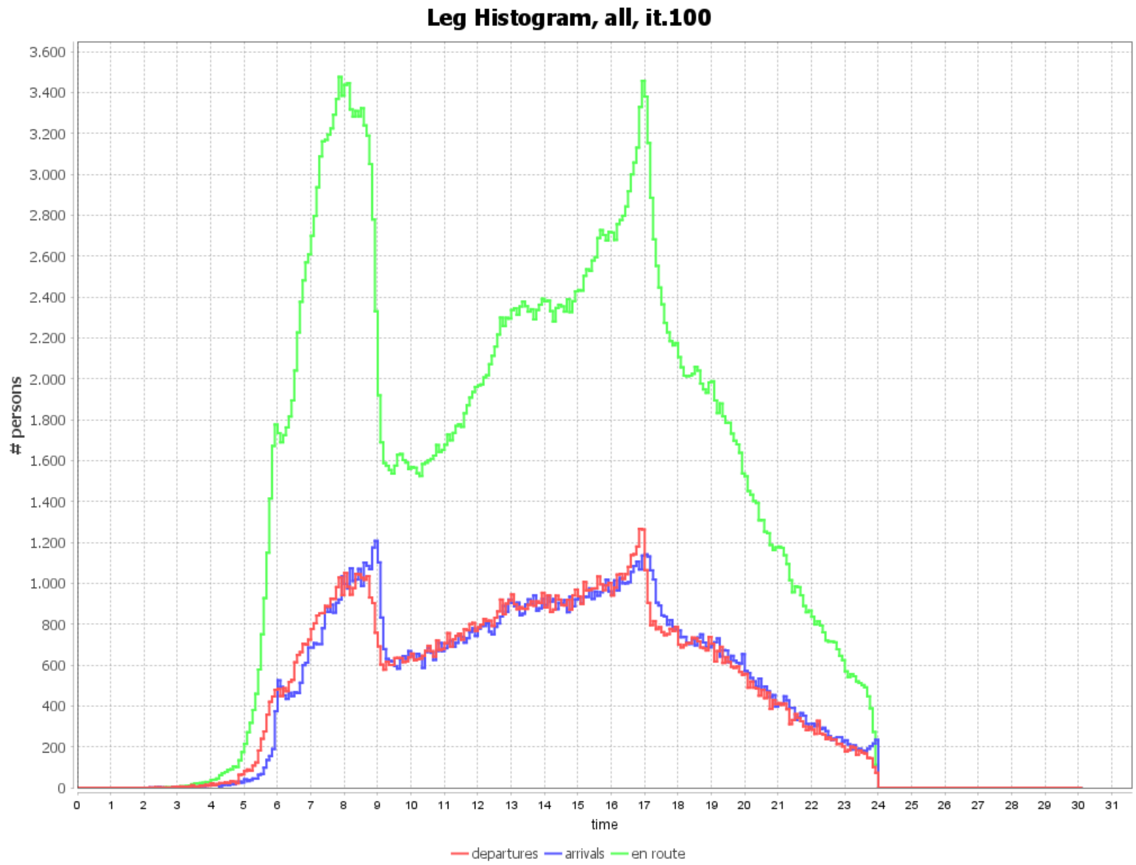

Figure C.1.2: Histogram of the car only disturbance scenario showing the number of en-route trips in green, departing trips in red, and arriving trips in blue. These are counted in 5 minute bin periods.

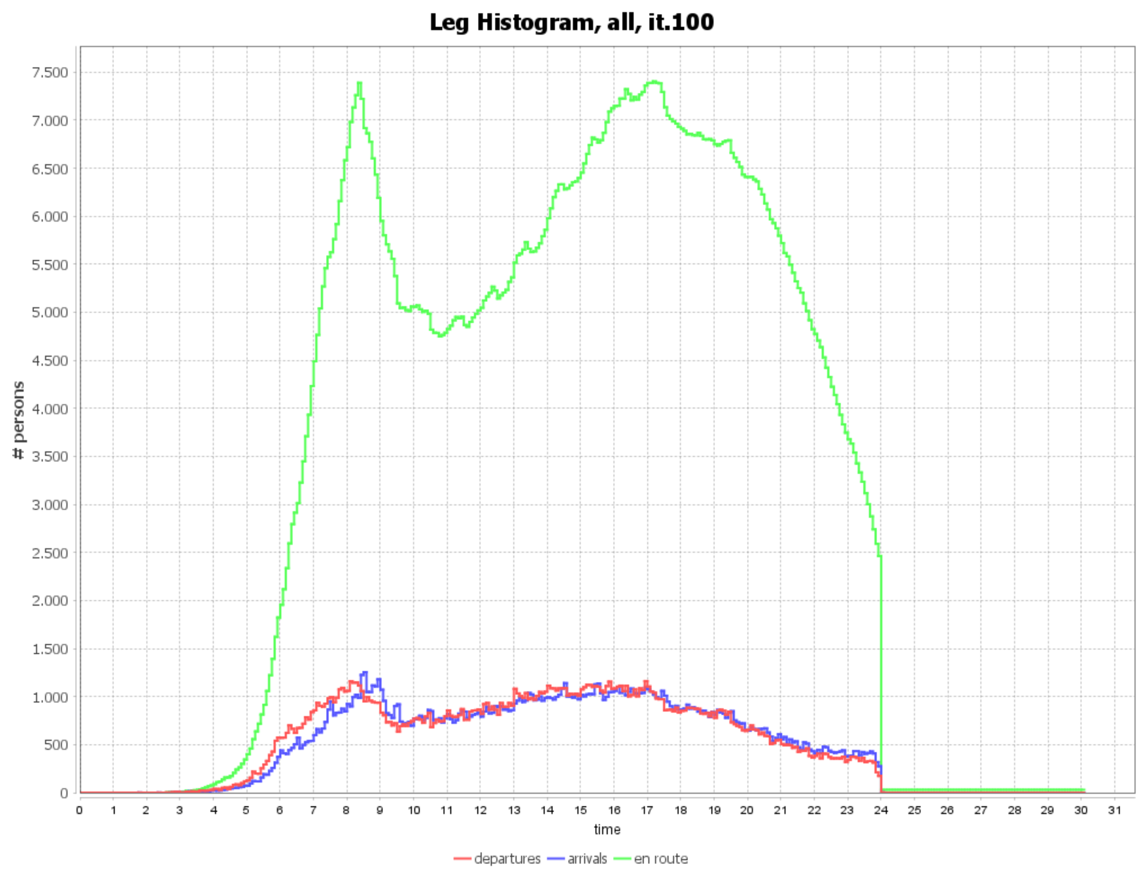

Figure C.1.3: Histogram for the ridesharing scenario with a disturbance (500 vehicle fleet size) showing the number of leg departures in red, leg arrivals in blue, and legs of agents currently en-route to their destination in green.

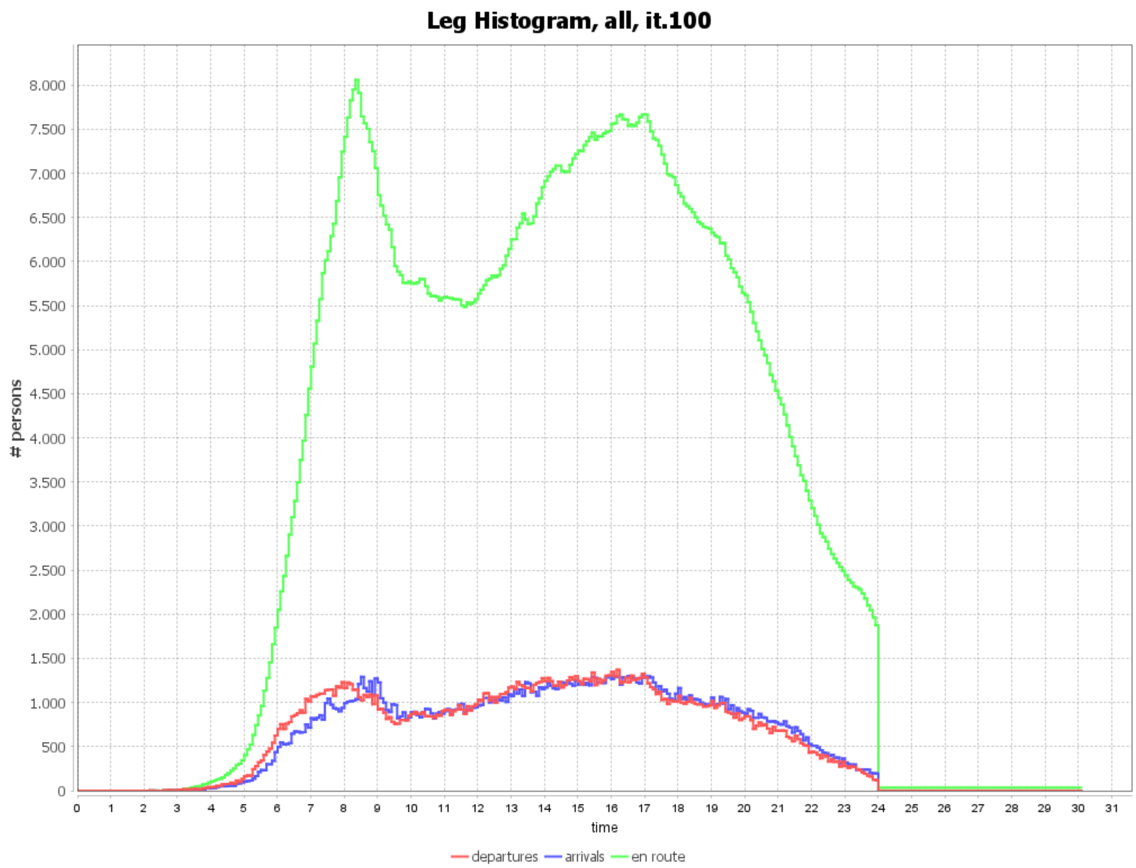

Figure C.1.4: Histogram of the ridesharing scenario with large fleet size and no disturbance showing the number of en-route trips in green, departing trips in red, and arriving trips in blue. These are counted in 5 minute bin periods.

C.2 Scorestats

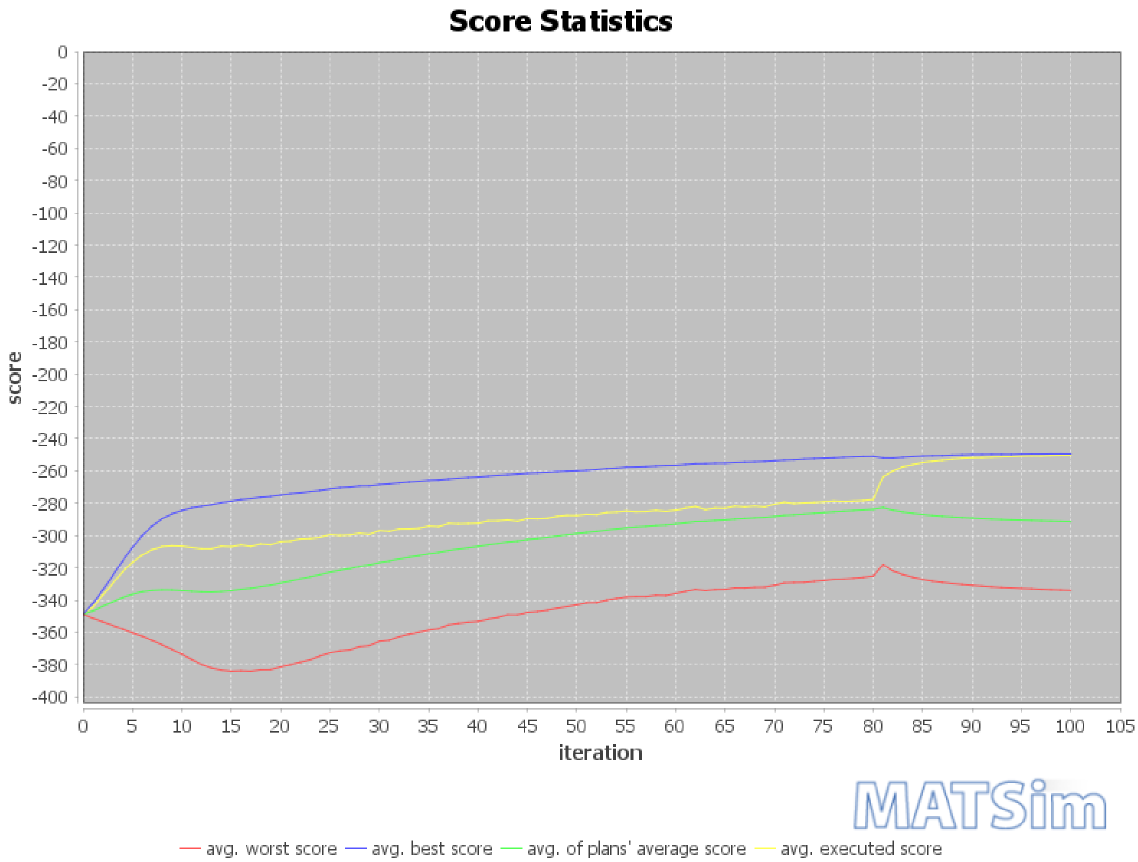

Figure C.2.1: Score statistics for the large fleet ridesharing scenario without disturbance.

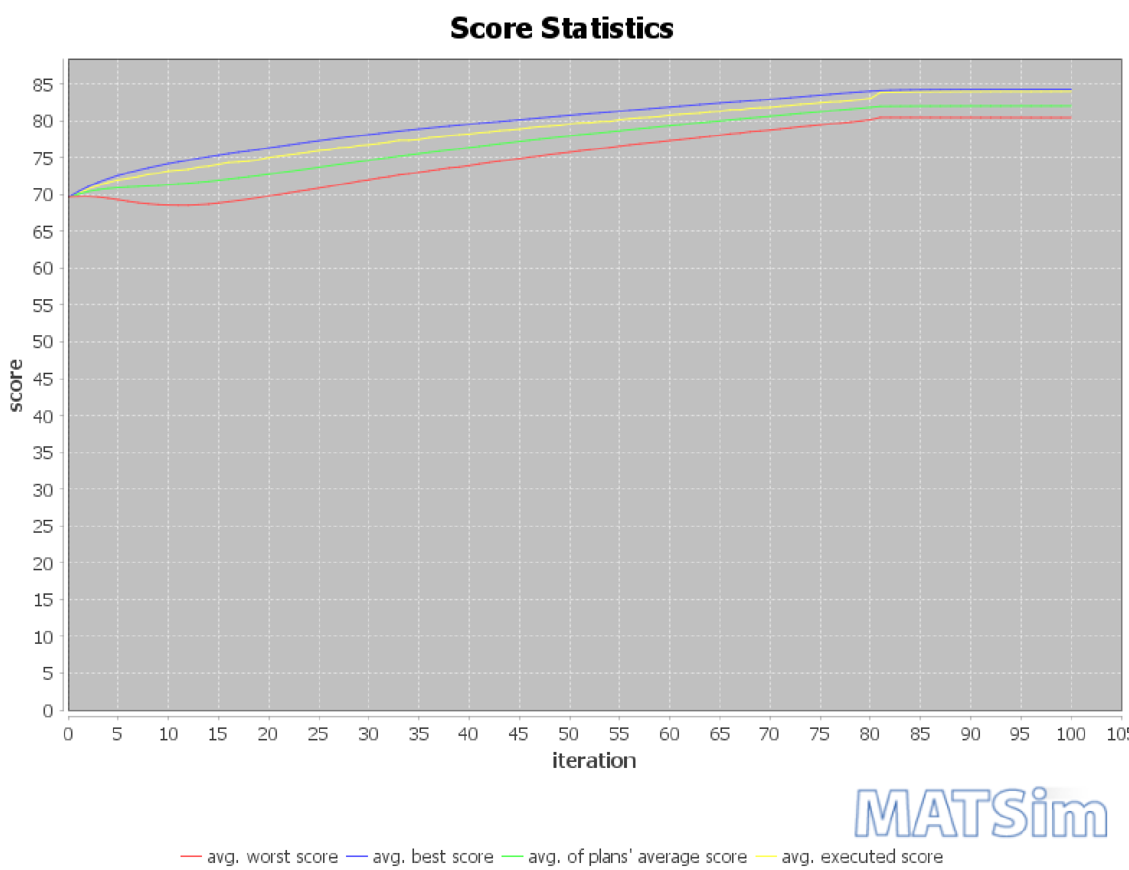

Figure C.2.2: Score statistics for the car only scenario without disturbance.

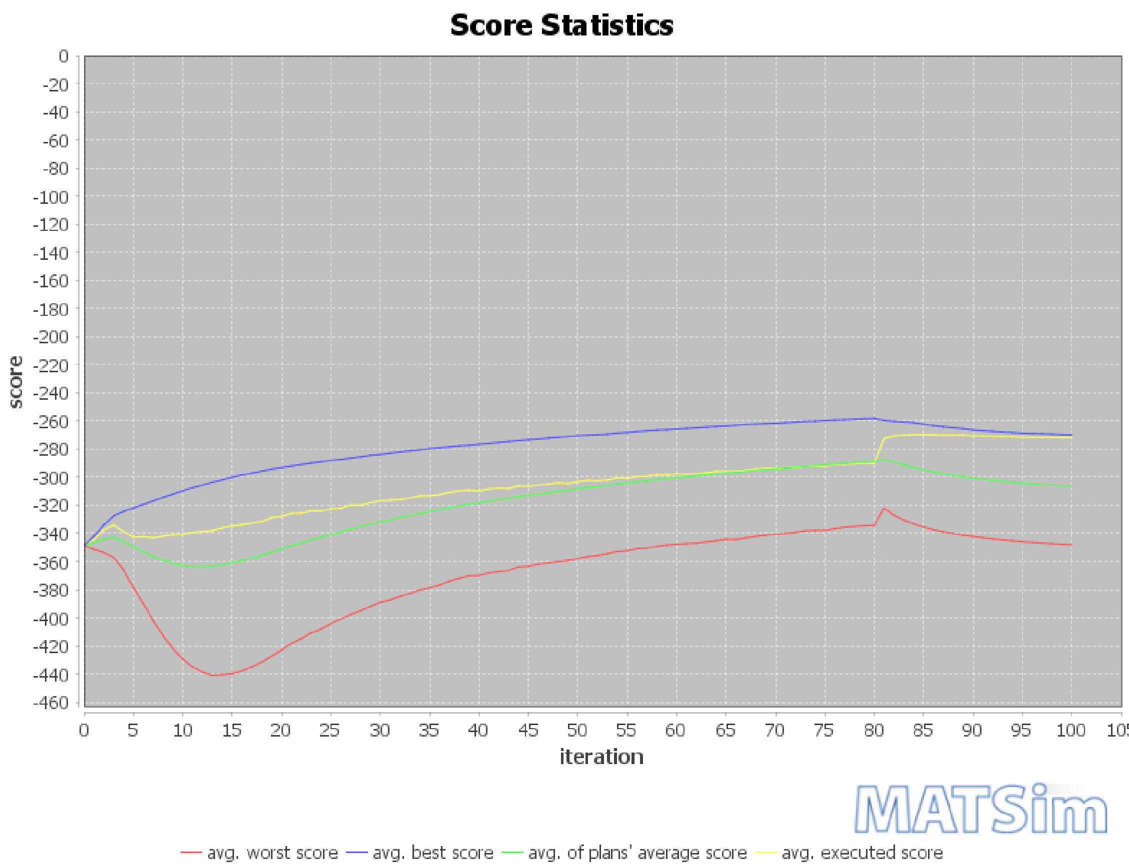

Figure C.2.3: Score statistics for the small fleet ridesharing scenario with disturbance.

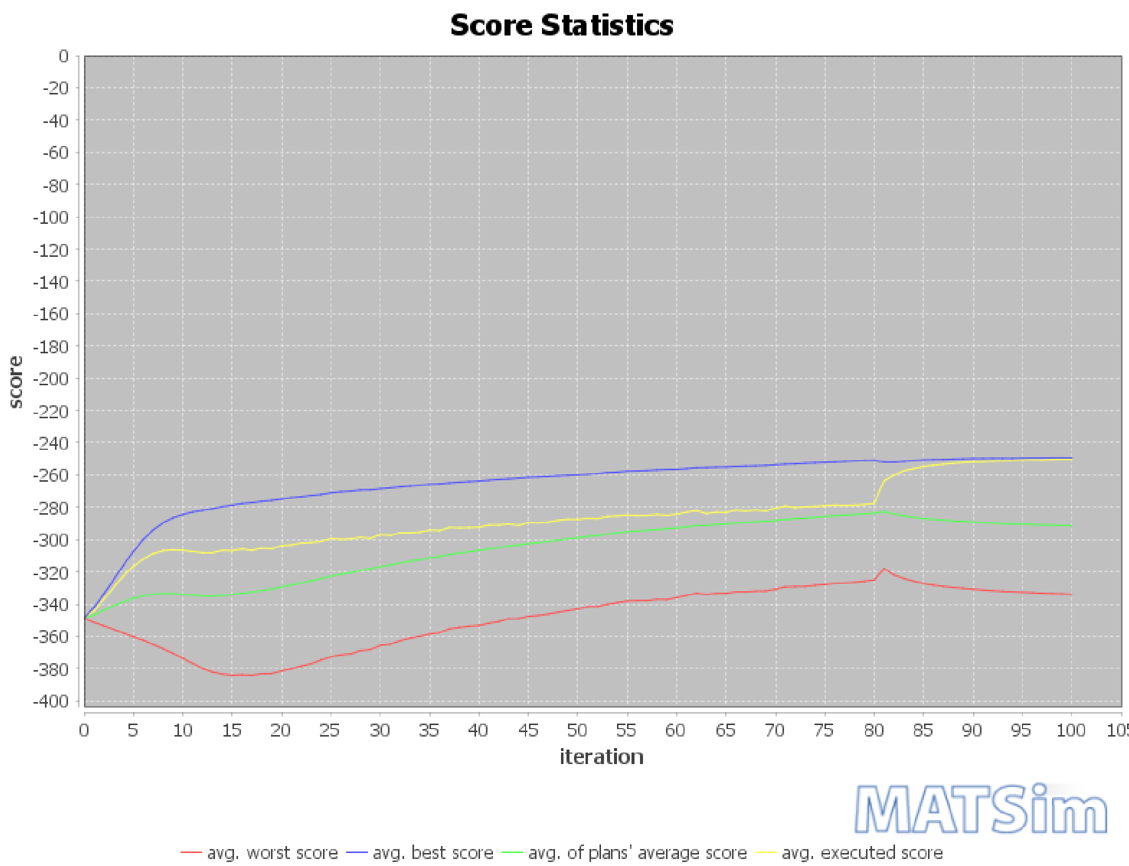

Figure C.2.4: Score statistics for the large fleet ridesharing scenario with disturbance.

C.3 Ridesharing usage profiles

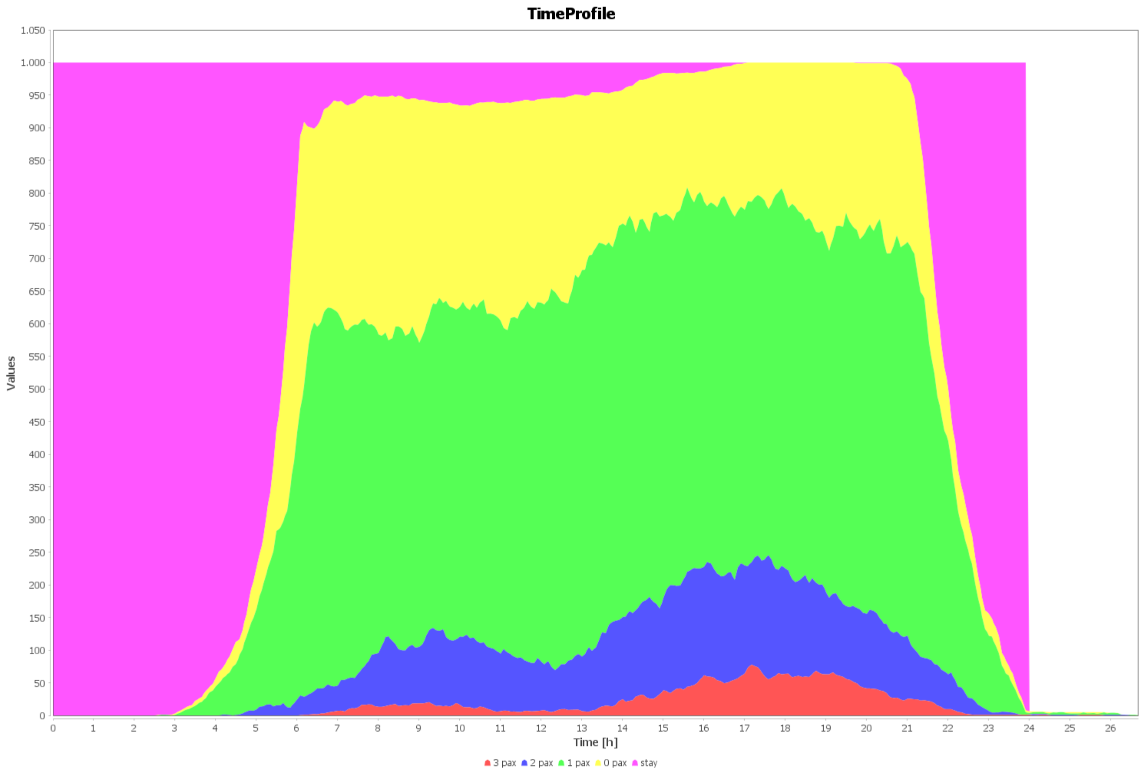

Figure C.3.1: Usage profiles for the large fleet ridesharing scenario without disturbance. Note that "pax" means passenger.

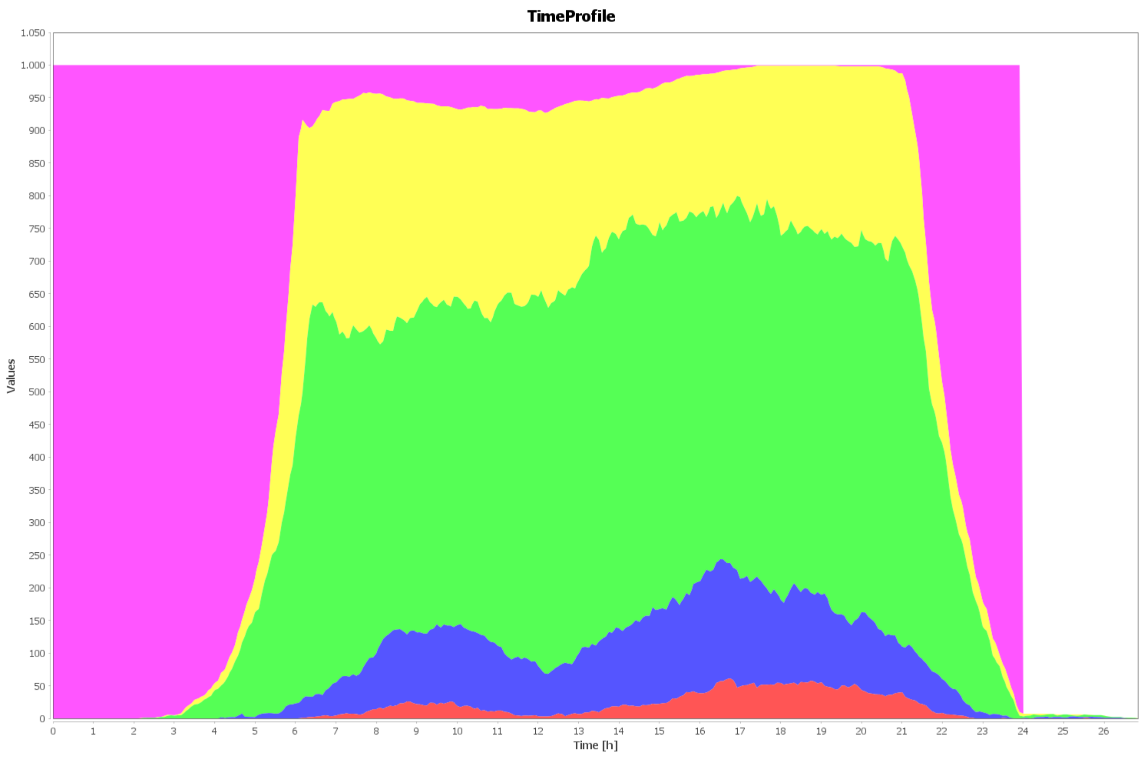

Figure C.3.2: Usage profiles for the large fleet ridesharing scenario with disturbance. Note that "pax" means passenger.

C.4 Ridesharing wait times

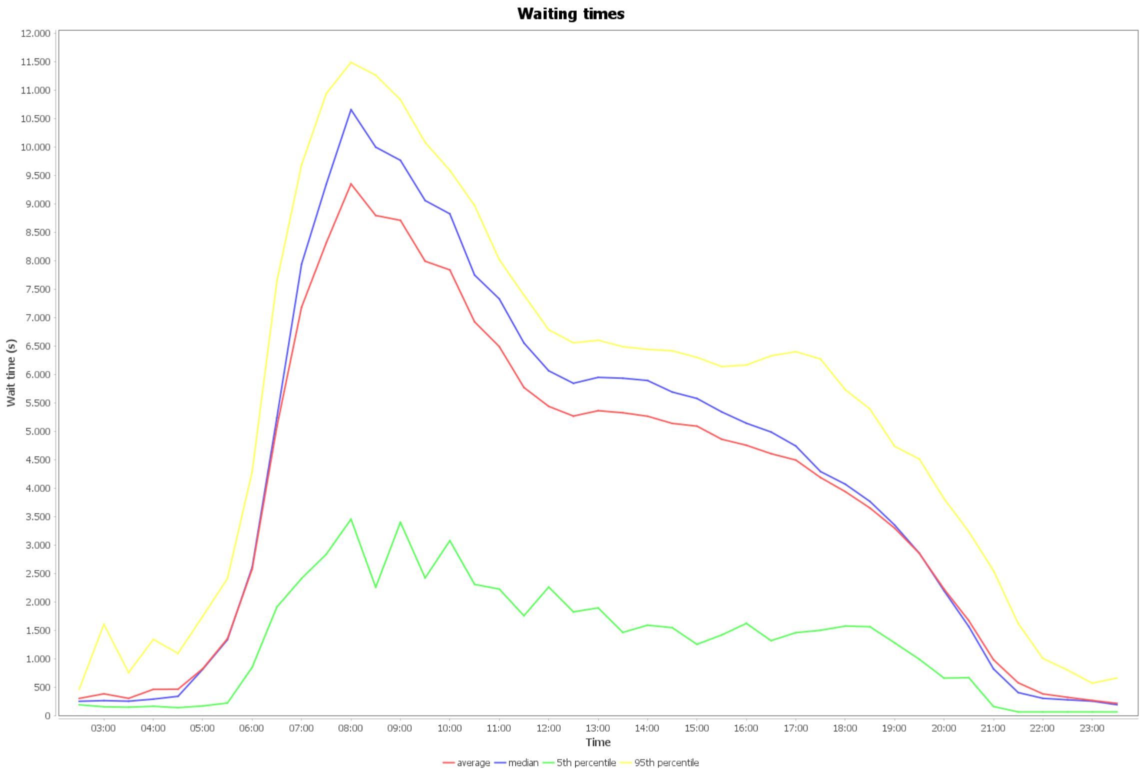

Figure C.4.1: Waiting times for the large fleet ridesharing scenario without disturbance.

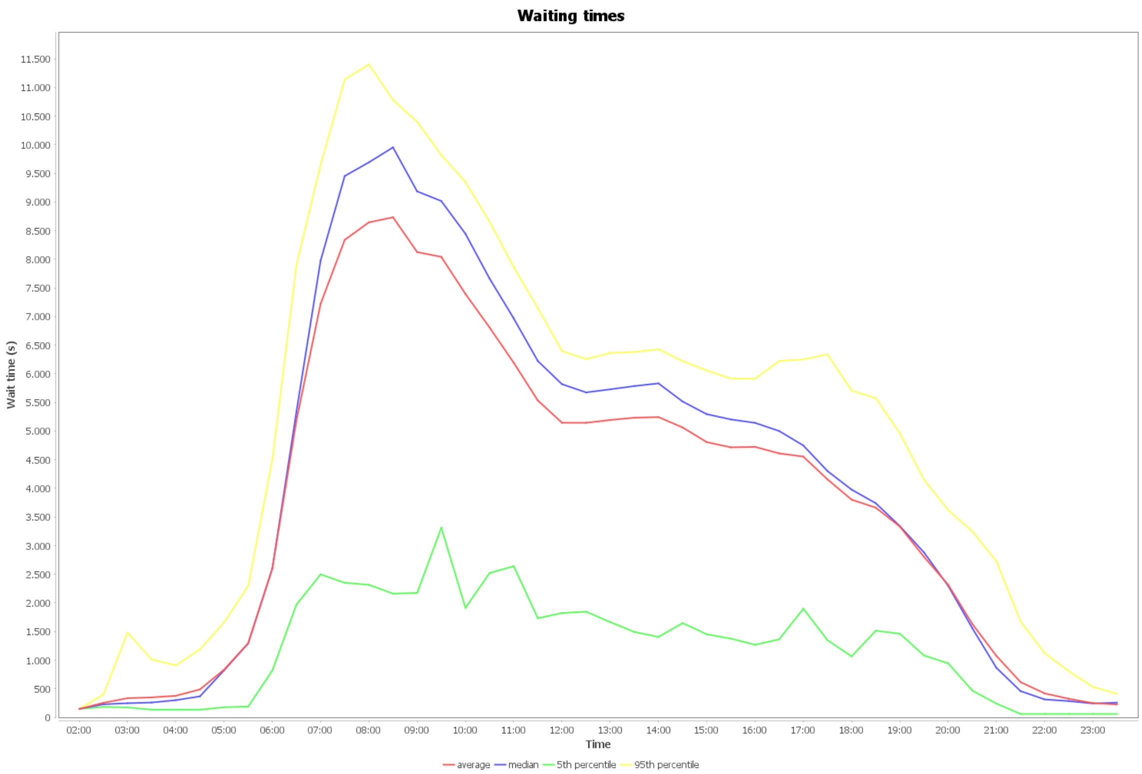

Figure C.4.2: Waiting times for the large fleet ridesharing scenario without disturbance.

C.5 Ridesharing requests

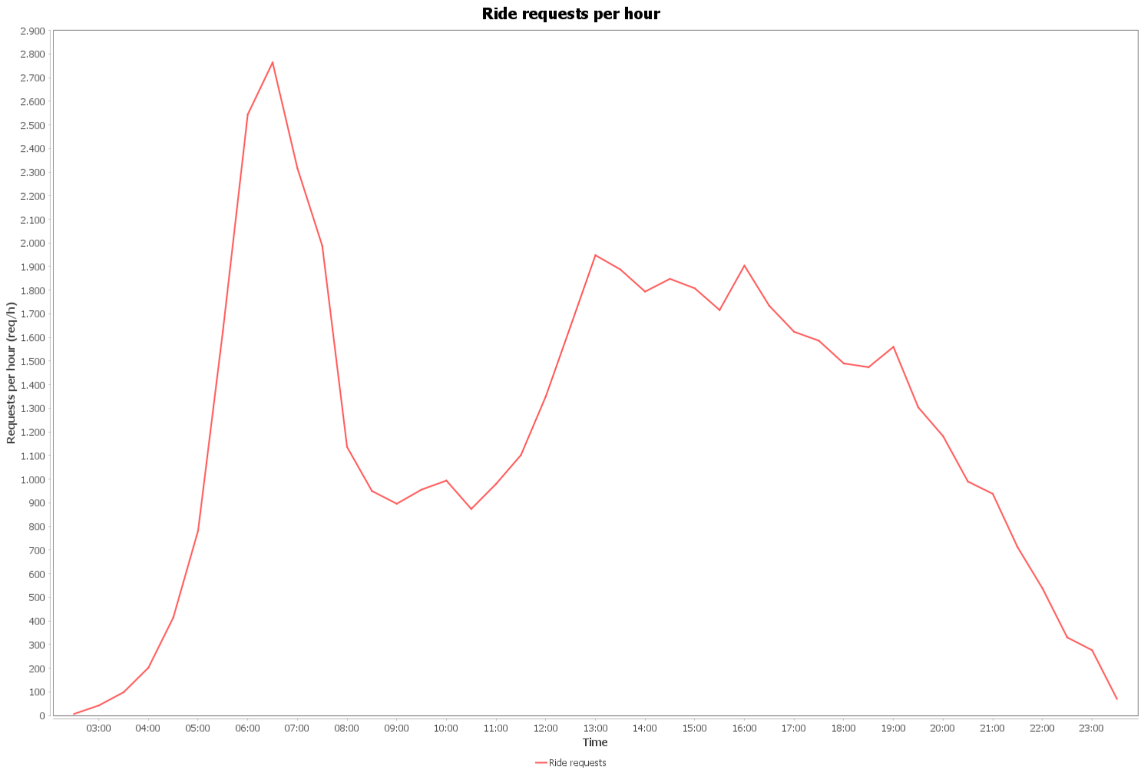

Figure C.5.1: Ridesharing requests for the large fleet ridesharing scenario without disturbance.

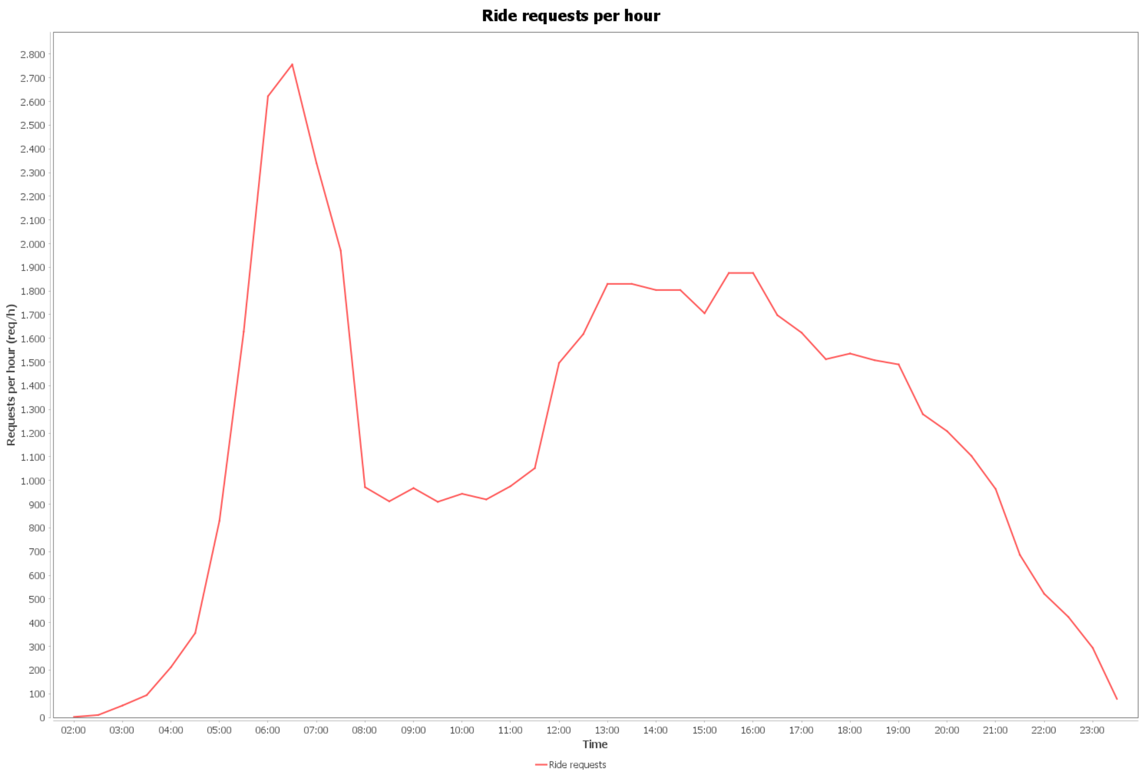

Figure C.5.2: Requests made for the large fleet ridesharing scenario with disturbance.

C.6 A13 results

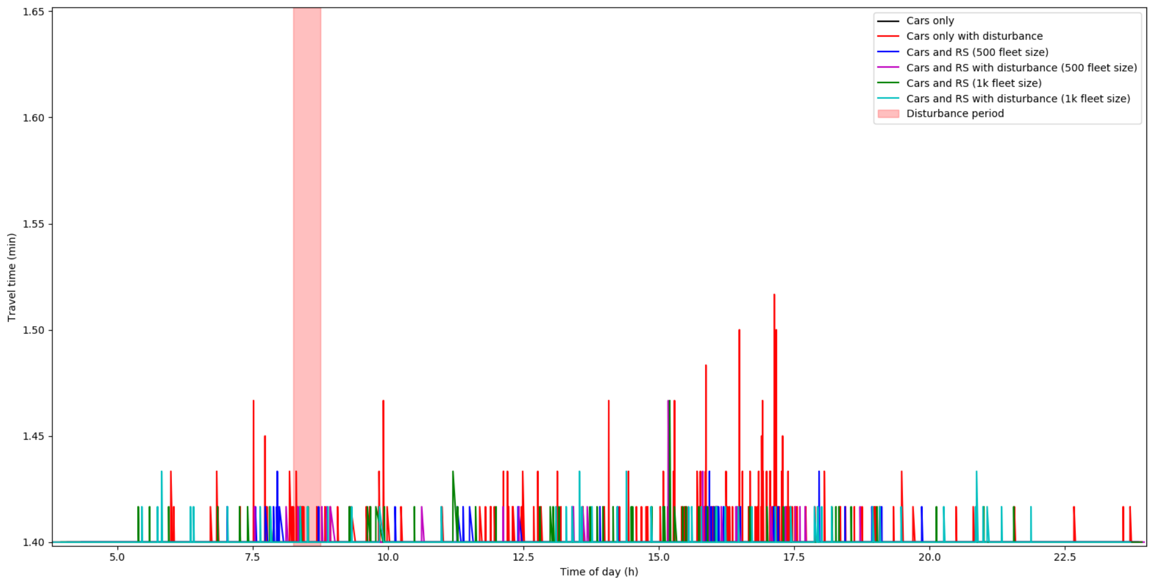

Figure C.6.1: Link travel time stats on the A13 roadway towards Rotterdam.