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# Analytical Modelling of On-Demand Ride Pooling Impacts

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*Dedicated to my mum and dad…*

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## Abstract

On-demand ride pooling (ODRP) services have the potential to improve the traffic conditions in our cities while offering a convenient mobility option for the customers. The aim of this thesis is to analyze the system-wide impacts of an ODRP service from the perspective of cities, operators, and customers. The analytical modelling approach is used to capture these impacts. Firstly, an analytical model investigating the influence of service quality parameters (SQP) and network modelling details on the percentage of shareable trips in an area is developed. Secondly, an analytical model examining the traffic impacts of an ODRP service is built. Lastly, a general analytical model combining the requirements of customers, operators and cities is presented, allowing an exploration of the framework conditions and system parameters in which a win-win-win situation for customers, operators and cities can be achieved. The developed analytical models are tested by means of an agent-based simulation and a microscopic traffic simulation for a case study in the city of Munich. These analytical models allow for a system-wide analysis of the ODRP impacts requiring less input data and computational time compared to the currently used agent-based simulations and hence, they are easily transferable to other cities. Consequently, the results of this thesis would assist policy makers and operators in effective planning and implementation of ODRP services.

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# 1. Introduction

## 1.1 Motivation

The increased urban population has caused higher levels of traffic demand in our cities. Private vehicles, albeit offering a convenient and flexible mode of transportation, are used less than 10% of the day and have an average vehicle occupancy of only 1.3 passenger per vehicle [MITCHELL ET AL., 2010], causing large quantity of occupied parking and street space. On the other hand, traditional public transportation – even though a sustainable transportation mode – might lack convenience and flexibility, due to rigid schedules and restricted coverage area, and is often unattractive for the customers. The common use of smart phones nowadays, and the resulting data availability and connectivity, enable the emergence of new customer-centric services. Among these services, the so called on-demand mobility services, are filling the gap between private vehicles and traditional public transportation. These services offer door-to-door transportation and have seen a rapid growth in recent years, increasing at the same time the concerns about their impacts in our cities.

Studies have shown that on-demand ride hailing services (e.g., *Uber*, *Lyft*, *Didi*, *Free Now* etc.) can reduce the parking space [HENAO & MARSHALL, 2019] and increase the vehicle utilization due to optimized assignments between customers and vehicles [ERDMANN ET AL., 2020]. However, the on-demand ride hailing services (ODRH), serving only one passenger per vehicle, might also negatively impact urban traffic and increase the vehicle kilometers travelled (VKT) in the system due to the increase of empty vehicle trips generated while picking up customers [DANDL ET AL., 2017; MACIEJEWSKI & BISCHOFF, 2018; SCHALLER, 2018]. To overcome the drawbacks of ODRH services in terms of increased VKT, on-demand ride pooling services (e.g., *Uber Pool*, *Lyft Shared*, *Didi Express*), where trips with similar trajectories are matched together and customers can share both their ride and the travel price with somebody else, might be a potential solution. Research studies have revealed that the on-demand ride pooling (ODRP) services can reduce the VKT [ALONSO-MORA ET AL., 2017; FIEDLER ET AL., 2018; ENGELHARDT ET AL., 2019a] and can potentially improve also traffic congestion and environmental impacts in our cities [International Transport Forum, 2016, 2017].

The introduction of an ODRP service in urban areas depends on the customers' willingness to use the service, the operator's readiness to offer the service and the disposition of the city to accept such a service. Albeit the expected positive impacts of the ODRP services from simulation studies, the results highly depend on the modelling of the system and the selection of the system parameters. Therefore, it is important to explore in which ODRP system parameters an ODRP service can be attractive for the customers, beneficial for the operators and additionally contribute to improved traffic conditions.

The customers' willingness to use the ODRP service and hence share a trip with somebody else, depends on the service quality parameters and service price [ALONSO-GONZÁLEZ ET AL., 2020a; GURUMURTHY & KOCKELMAN, 2020; KRUEGER ET AL., 2016]. The main service quality parameters which influence the customer decision to use the ODRP service are waiting time, the time during which the customer waits to get picked up by a vehicle, and the deviation from the direct travel distance due to detour to pick up other passengers. The customer would therefore opt for a ODRP service which guarantees low waiting time and detour time [KRUEGER ET AL., 2016]. In order to compensate for the additional detour time, the customer would also expect a lower service price compared to an ODRH service.

The customer demand for an ODRP service and the service quality parameters, together with city parameters, are the main factors influencing the possibility to find shareable trips in an area, known as shareability [TACHET ET AL., 2017]. Intuitively, the higher the ODRP demand is, the higher are the chances to match similar trips. High values of a delay time parameter (sum of waiting time and detour time) contribute to high shareability values, because allowing more time for operators to search for shareable trips increases the number of options to really find a match. However, the attractiveness of an ODRP service from customers' perspective decreases with increased delay time. Consequently, this trade-off makes it necessary to analyze in detail the factors which influence the shareability.

Shareability is an important parameter as it might also affect the profitability of the service, depending on the pricing model used by the operator. In the case when the customers are offered a cheaper price, regardless if a match with somebody else is found or not, a low number of shared trips might result in negative monetary impacts for the operator. This happens when an ODRP customer requests a ride, but it is not possible to find a feasible match. It is reported that only 30% of the trips with *uberPOOL* are actually shared with somebody else [SHAHEEN & COHEN, 2018]. In this case, the customer would travel alone, but nevertheless pay a lower price compared to ODRH, resulting in lost revenues for the operator, which in extreme cases could even force the ODRP operator to terminate the whole service [HAWKINS, 2019].

Low sharing potential negatively impacts also the traffic conditions in urban areas. This effect occurs as for small chances to find shareable trips, the possibility to save VKT by trip sharing is limited and the desired positive impact of ride pooling on the reduction of traffic congestion might be low, if at all existent. As depicted by ENGELHARDT ET AL. [2019a], a reduction in VKT is expected to be seen only after a certain market penetration of the ODRP passenger demand for which higher shareability can be achieved.

Hence, it is necessary to firstly recognize and analyze the factors influencing the possibility to find shareable trips in an area. This is quite important as shareability might directly influence the traffic efficiency and the profitability of an ODRP service. In order to enjoy the potential benefits of a successful ODRP service, it is important to understand in which framework conditions, i.e., ODRP demand, service quality parameters and system characteristics, a win-win-win situation for customers, operators and cities can be achieved. This is the key motivation of this thesis.

## 1.2 Research Gaps

**The first identified research gap (RG 1) is the unavailability of studies which investigate analytically the impact of specific service quality parameters (RG 1.a) and network modelling details (RG 1.b) on the possibility to find shareable trips in an area.**

**RG 1.a:** As previously mentioned, a key determinant of a successful ODRP service is the possibility to find shareable trips in an area. Previous studies have shown that the matching rate is influenced by service quality parameters, such as waiting time, detour time, reservation time [STIGLIC ET AL., 2016; TACHET ET AL., 2017; FAGNANT & KOCKELMAN, 2018; SANTI ET AL., 2014a]. Most of these studies are performed by using agent-based simulations, which suffer from high computational time and high input data. Additionally, they might also hide important impacts that are not possible to be easily verified due to the high complexity of the agent-based simulations. The exception is the study from TACHET ET AL. [2017] in which the impact of a delay time parameter, which is the sum of waiting time and detour time, is captured by an analytical model. This provides an estimation of shareability for different ODRP passenger demand levels by using only little input data and not requiring high computational time. However, this study is restricted to modelling of only the delay time parameter impact, without considering the separate influence of maximum waiting time and detour time. Even though these parameters might both effect the customer negatively (with small divergences depending on the customers' preference about their perceived waiting time or added in-vehicle time), their impact in traffic efficiency and the operator's profitability might vary. Therefore, it is important to analyze analytically their distinct effect on shareability values. **The analytical modelling of the separate impact of these**

**parameters and additional parameters, such as reservation time and boarding time,** – an approach that would overcome the disadvantages of using agent-based simulations – is currently not available in literature.

**RG 1.b:** Albeit its advantages, analytically deriving the impact of service quality parameters on shareability requires some simplifications which would allow a closed analytical expression of shareability [TACHET ET AL., 2017]. Firstly, a Euclidian topology is assumed to accommodate vehicle movements. The origins of passenger trips are supposed to be uniformly distributed in time and space, and the passenger trip destinations are assumed to be located in a disk with a certain radius, corresponding to the average trip distance. Additionally, the vehicles are assumed to be immediately available at the position where the customers request a ride, hence the fleet size is considered to be infinite. As noted, the way the system is modelled directly influences shareability. Therefore, it is important to explore the influence that these simplifications have on the results, to determine in which conditions the analytical model is valuable. Consequently, a step-by-step analysis is necessary to examine the separate impact of these assumptions, and thereby defining **the impact that ODRP modelling complexity, such as network topology, the patterns of passenger trip distribution, optimization objectives, changing velocity and fleet size**, have on the theoretical shareability and the experienced shared rides.

**The second distinguished research gap (RG 2) is the lack of studies about the exploration of the system-wide traffic impacts of an ODRP service.**

**RG 2.a:** The introduction of ODRP services is expected to reduce the number of vehicles in the streets due to shared trips and therefore the average velocity of the city can be improved. However, as the current studies consider only the reduction of VKT for the pooling vehicle fleet, neglecting the interaction with other vehicles which will still be present in the system [ALONSO-MORA ET AL., 2017; FAGNANT & KOCKELMAN, 2018; ENGELHARDT ET AL., 2019a], it is still unclear **to what extend the reduction in VKT influences the overall traffic efficiency in urban areas.**

**RG 2.b:** Moreover, these studies are based on agent-based simulations, which as aforementioned albeit providing detailed modelling of the system, require a high amount of input data and computational time, in addition to the concern that not every behavior of the agents is fully understood. Therefore, usually the analysis is limited to scenario-based analysis. Traffic impact of an ODRP system are recently examined theoretical by KE ET AL. [2020]. However, they assumed a ride pooling system that uses a very simple matching algorithm based only on the maximum waiting time (referred in their study as 'matching time window'), which is not realistic in real-life ODRP service operations. Hence, for a system-wide analysis of ODRP traffic impacts and easier transfer of the analysis to other cities, **an analytical model is necessary to investigate the traffic impacts of ride pooling depending on the ODRP set of service quality parameters and modelling details.**

**RG 2.c:** Furthermore, the average velocity in the city is assumed to be constant in most of the ride pooling simulation studies and likewise in the analytical shareability study. As a result, they are not able to capture the changes in average velocity of the road network due to the effect of shared trips generated by the ODRP service. Increasing the average velocity means that the vehicles can travel further and hence the chances to find shareable trips will be higher. Even though this issue is recently recognized in literature [LEHE & PANDEY, 2020], the **additional impact that the change of velocity has on the shareability value is still not captured by the current shareability model** [TACHET ET AL., 2017].

**The third recognized research gap (RG 3) is the absence of an overall model that can capture the benefits of ODRP services from customers', operators', and cities' perspective.**

**RG 3.a:** Even though ODRP profitability is investigated for scenario-based studies [AGATZ ET AL., 2011; FAGNANT & KOCKELMAN, 2018; KUCHARSKI & CATS, 2020], a model that can **determine analytically the profitability** of the ODRP service and investigate the circumstances when the system can be profitable is not available.

**RG 3.b:** Consequently, also the existence of **a general analytical model**, which can **explore in which framework conditions the ODRP services can be beneficial** from the perspective of customers, operators and cities, is currently lacking.

## 1.3 Research Aim and Research Questions

The aim of this thesis is to develop a general analytical model that can capture the requirements of different ODRP stakeholders and analyze the impact of ODRP influencing parameters. By using the advantages of analytical modelling, the developed model would require fewer input data and computational time and would be easily transferable to other cities. This would allow for a system wide analysis of the ODRP impacts and would help to explore in which conditions a win-win-win situation in terms of customers, operators and cities can be achieved. Consequently, this model would assist in effective planning and implementation of ODRP services.

In order to achieve the main aim of the thesis and fill the research gaps (RG) previously identified in *Section 1.2*, the following main research questions are formulated:

1. How do service quality parameters (SQP), such as detour time, maximum waiting time, short-term reservation time and boarding/disembarking time, network modelling details and vehicle routing optimization objectives, impact the percentage of possible shared trips in an area? (Addressing RG 1.a and RG 1.b → Model: *Section 3.1*; Results: *Section 5.1*)

2. What are the traffic impacts of ODRP services and how does the change in average velocity due to ride pooling effect the possibility to find shareable trips? (Addressing RG 2.a, RG 2.b and RG 2.c → Model*: Section 3.2*; Results: *Section 5.2*)

3. Under which framework conditions a win-win-win situation can be achieved, corresponding to an ODRP service that is beneficial in terms of improvement of traffic efficiency, operators' profitability, and customers' attractiveness? (Addressing RG 3.a and RG 3.b → Model: *Section 3.3*; Results: *Section 5.3*)

## 1.4 Research Contributions

The main contribution of this thesis is the ability to represent the complex impacts of the ODRP service by analytical modelling, which allows for a quick investigation of the impact of different ODRP influencing parameters, without needing much input data, computationally expensive simulations or real-life pilots.

The contributions for each of the research questions are highlighted below:

- **Analytical modelling of shareability impact factors, including service quality attributes and network modelling details (**RG 1.a and RG 1.b; *Section 3.1* and *Section 5.1*)
  Analytical shareability models are developed to examine the impacts of service quality parameter, such as detour time, maximum waiting time, boarding or disembarking time and reservation time, on the percentage of shared trips in an area. These models are tested by means of agent-based simulations. These shareability models provide

novel insights about the influence that the service quality parameters, modelling details and vehicle-passenger matching objective have on shareability.

- **Analytical modelling of the ODRP traffic impacts and the additional effect that changes in average velocity due to shared trips have on shareability** (RG 2.a, RG 2.b and RG 2.c; *Section 3.2* and *Section 5.2*)
  The shareability model from the first main contribution and the macroscopic fundamental diagram (MFD) of a city are used to analytically derive the ODRP traffic impact model, which is then validated by means of microscopic traffic simulations. This model contributes to the literature by exploring the traffic impacts of ODRP service for a wide range of system parameters, considering not only the ODRP vehicle fleet but also the other vehicles in the network, and additionally investigating the effect that changes in average velocity due to shared trips have on shareability.

- **Analytical modelling of the ODRP traffic efficiency, operator's profitability and customer attractiveness** (RG 3.a and RG 3.b; *Section 3.3* and *Section 5.3*)
  The previously developed models are extended to investigate the ODRP services in terms of traffic efficiency, operator's profitability and attractiveness for customers. This general model provides novel insights in identifying the framework conditions when the ODRP win-win-win situation between all stakeholders can be achieved.

The analytical models developed in this thesis could be used by operators or cities for a better system-wide planning and implementation of an ODRP service. These models have a great potential because they can be used to quickly estimate:

(1) the shareability rate that can be reached in an area when offering different quality of service to the customers → giving the operators the ability to explore which areas are more suitable to offer the ODRP service,
(2) the traffic impacts of varying market penetration rates of the ODRP service → providing the cities with the opportunity to investigate the impact of such a service,
(3) the profitability of ODRP service → giving the operators the possibility to examine if and when the ODRP service can be profitable,
(4) the ODRP win-win-win situation for cities, operators and customers → defining the framework conditions when the ODRP service can be beneficial for the three stakeholders.

## 1.5 Thesis Outline

The thesis outline is shown in Figure 1.1. The following *Chapter 2* will provide the literature review on the ODRP topic, starting with current operational examples and continuing with available research studies in the field. The analytical models used to examine the ODRP impacts will be presented in *Chapter 3*. Firstly, the shareability model capturing the impact of various SQP and network modelling detail on the percentage of shared trips in an area will be described. Secondly, the traffic impact model will be explained. Lastly, a general model capturing the benefits for cities (in terms of traffic efficiency), operators (in terms of monetary profitability) and customers (in terms of attractiveness to use the ODRP service) will be presented. In *Chapter 4* the simulation configuration used to validate the models for the case study of Munich will be described. The evaluation and results for each of the developed models will be depicted in *Chapter 5*. Finally, *Chapter 6* will conclude the thesis by presenting the conclusion and outlook.

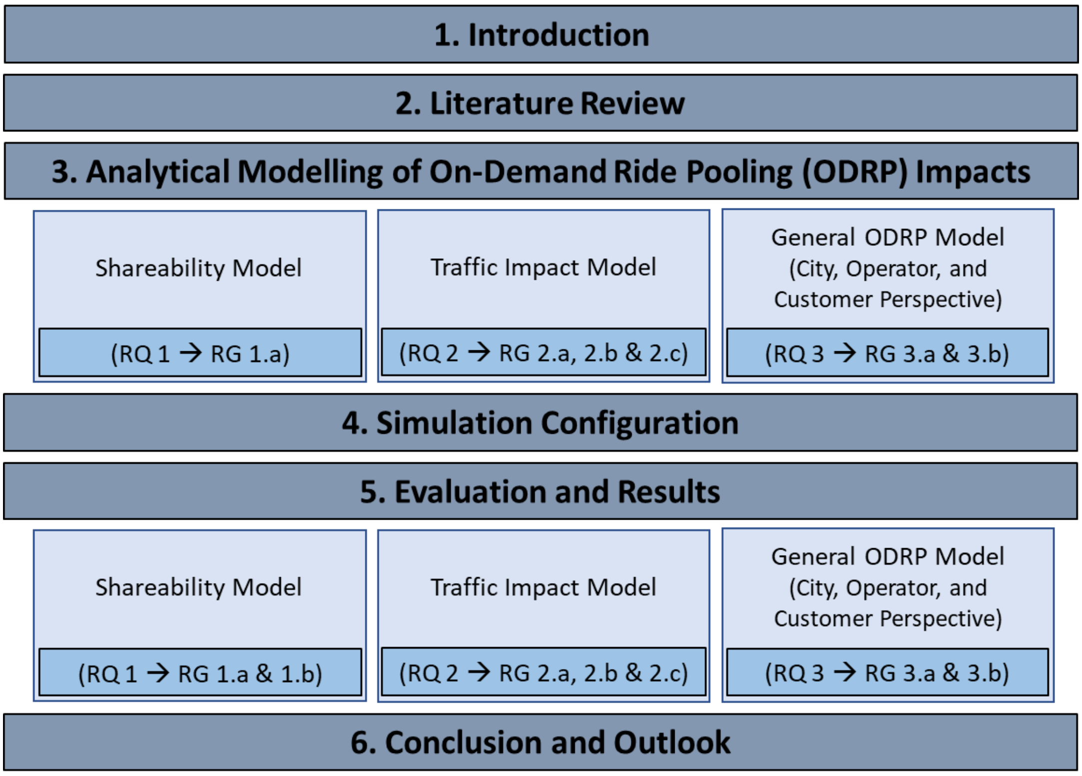



**Figure 1.1** Thesis outline.

# 2. Literature Review

In this chapter, an introduction, definition, and classification of different ride pooling services from the literature will be provided. It will be followed by a discussion on different factors contributing to a successful implementation of pooling services from the perspective of customers, operators and cities. Then different modelling approaches used to analyze the ODRP impact factors will be explained.

## 2.1 Ride Pooling Services: Definition, Classification and Operational Examples

Ride pooling is a service where customers traveling in the same direction and during the same time interval, share their trips fully or partly and hence split the cost of the trip. The concept of ride pooling is quite old, having its origin since World War I, when the US economy was in decline and some entrepreneurial vehicle owners decided to pick up passengers on the street for a 'jitney' (five cent fare) [2009]. However, with the advancement in technology, the increased use of smartphones, data availability and access to real-time information, pooling services have evolved from self-organized services to more sophisticated app-based services. There are different types of pooling services available, categorized by SHAHEEN & COHEN [2018] into three main categories: core pooled services (including jitneys, traditional public transit and shuttles, which operate without the use of an app), ride sharing and on-demand ride pooling services. A summary of the classification is provided in Figure 2.1.

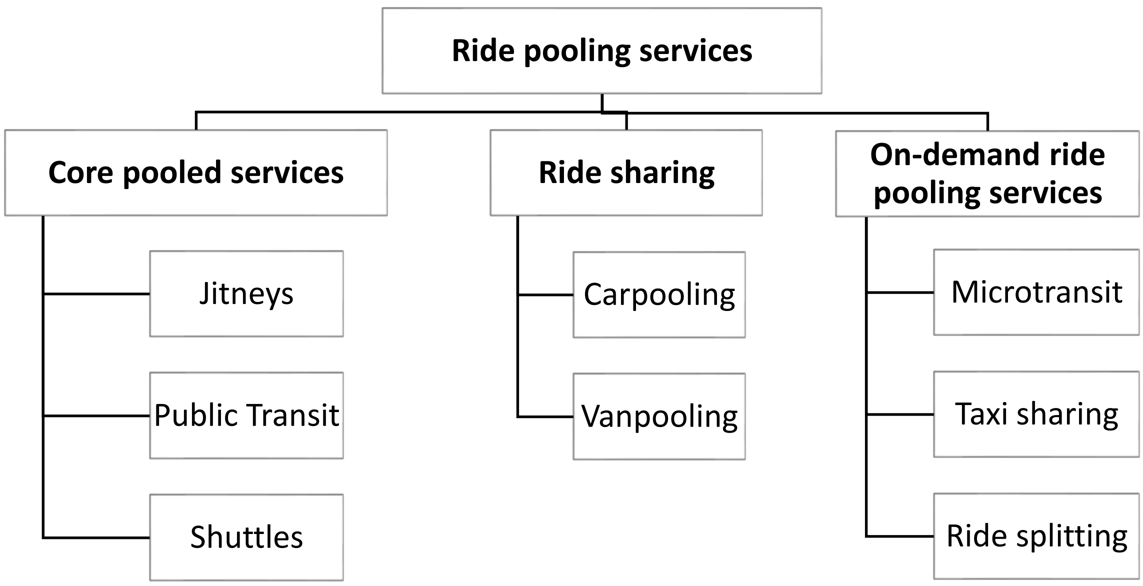



**Figure 2.1** Ride pooling services classification based on [SHAHEEN & COHEN, 2018].

In the following, ride sharing services will be briefly explained and the focus will be more on on-demand ride pooling services as in this thesis the impacts of an on-demand ride pooling service, which can have similar characteristics to taxi sharing, ride splitting or microtransit with flexible routes are investigated.

### 2.1.1 Ride sharing

In ride sharing services, drivers and riders share the operating expenses and could share in some cases also the driving responsibility. They consist of carpooling and vanpooling, which differ from each other by the number of passengers who share the same vehicle. Carpooling is limited to six passengers per vehicle, whereas in vanpooling seven up to 15 passengers can be allocated in the same vehicle [Shaheen & Cohen, 2018]. Carpooling can be divided in two subcategories: sharing of the car trips between people who already know each other (for instance, family members or coworkers) or casual carpooling (for people who do not know each other). Casual carpooling can be organized without technological aid and is known also as ‘slugging’ [Chan & Shaheen, 2012; Shaheen et al., 2016] or it can be facilitated by an app or website. One of the most well-known carpooling online platforms is *BlaBlaCar*, which operates in 22 countries [BlaBlaCar], most of them located in Europe [Vleugels, 2019]. *BlaBlaCar* is an online marketplace for intercity travel which connects drivers and travelers who have similar origin-destination pairs and want to share the costs of their trips.

### 2.1.2 On-demand ride pooling services

With the new advancement in technology and the increased use of smartphones, on-demand ride services have gained popularity due to increased user convenience and accessibility. Passengers can request a ride immediately or specify the required pick-up time by using smartphone apps and a service provider makes sure they are picked up within the required pick-up time. According to Shaheen & Cohen [2018] three groups of on-demand ride pooling services can be distinguished: microtransit, ride splitting and taxi sharing.

**Microtransit**

The term ‘microtransit’ is used for fixed or flexible routes and scheduled or on-demand shuttle services, which use buses or vans. It is a mode of transportation that can be positioned between private vehicles and public transportation. Microtransit is widely used in Asia and Latin America, however with the advancement in technology, cities in Europe and North America are also exploring this mode and offering pilot services.

Some examples of microtransit in US and European cities are *Chariot*, *Via*, *IsarTiger*, *Moia* and *CleverShuttle*. *Chariot* was acquired by Ford Motor Company in September 2016 and ceased operation in February 2019, reportedly due to low numbers of requested trips [HAWKINS, 2019]. The *Via* platform offers various mobility services, starting from services with fixed schedules and routes to completely dynamic services [Via, 2019]. In Europe, *Via* was previously known under the name *ViaVan*. *ViaVan* was founded in 2017 as a joint venture between *Mercedes-Benz* and *Via*, operating in Berlin, London, Amsterdam and Milton Keynes. Now *ViaVan* is completely owned by *Via* [Via, 2021]. Via works closely with cities and has also experimented with a different deployment of microtransit by offering first- and last-mile service to/from public transportation stations like the one in Seattle, Washington [Via NYC, 2019]. Usually, it does not offer door-to-door service, but directs customers to the closest street corner, where they are picked up. The passengers pay a fixed price for the trip, based on the kilometers travelled and not the number of passengers. Only if a passenger books a ride for multiple people at the same time, the price per passenger is half of the normal ticket price [Via, 2019]. *IsarTiger* is a pilot project operated by *MVG*, which is a company owned by the municipality of Munich and responsible for operating the public transport in the city. The service offered by *IsarTiger* is complimentary to public transportation. The vehicles have flexible routes and schedules, which are generated automatically on demand [MVG]. *Moia* is part of *Volkswagen Group* and operates a ride pooling service in Hamburg and Hannover. When using *Moia* the customers have the option to choose between three trip offers with varying waiting times, arrival times or prices and then they would have to walk until the closest virtual stop where a vehicle would pick them up [Moia, 2021]. *CleverShuttle* is another microtransit service currently available in two German cities. Its customers share their trips and the costs, even when no match can be found [CleverShuttle, 2021].

**Ride splitting**

Ride sourcing companies, also known as ride hailing or transportation network companies, offer user-centric services, such as on-demand mobility services, by connecting drivers (who use their own vehicle) with passengers. These services, which use smartphone apps to make the match between drivers and passengers, have rapidly gained popularity. Some examples of them are *Uber*, *Lyft* and *Didi Chuxing (DiDi)*. In contrast to taxis, which mainly have fixed prices, ride sourcing companies use surge pricing during peak times to balance the supply and demand by attracting more drivers to serve trip requests. In addition to the ride hailing services, where only one passenger at a time is served by a vehicle, these companies offer also ride splitting services. Ride splitting is a term used for a service in which the customers share the trip with somebody else and split their costs.

Some examples of ride splitting services are *Lyft Shared* (previously *Lyft Line*), *Uber Pool* and *DiDi Express*. *Uber Pool* and *Lyft Shared* were launched in 2014 and only after three years, *Uber Pool* was operating in 36 cities internationally [HAWKINS, 2018] and *Lyft Shared* was available in 16 US cities [SHAHEEN & COHEN, 2018]. However, only 20% of the *Uber Pool* trips were shared trips and *Lyft Shared* trips accounted for 40% of *Lyft* rides [SHAHEEN & COHEN, 2018]. *Uber Pool* offered in 2018 *Uber Express Pool* which was presented in 12 US cities and costs up to 50% less than *Uber Pool* [NICHELSBURGS, 2018; HAWKINS, 2018]. *Uber Express Pool* requests customers to walk until a common pick-up/drop-off spot in order to increase the pooling rate and to decrease the detour time needed to pick up additional passengers [Express Pool, 2021]. Using the same concept as *Uber Express Pool*, *Lyft* also rolled out *Shared Saver* in 2019 [LEKACH, 2019].

**Taxi sharing**

The surge in popularity of ride sourcing has made it challenging for taxis to remain in the market, albeit most of the taxi service are largely regulated by laws. In order to keep up with the technological development, taxis have upgraded their services to ‘e-hailing’ services, where similar to ride sourcing services, passengers can use an app to request a taxi ride. This app is operated and maintained by a taxi company or by an external company. In contrast to ride sourcing companies, the prices of taxis are regulated locally, and they do not use surge pricing during peak times when the demand is higher. Some of the e-hailing services in North America include *Flywheel*, *Curb* and *iTaxi* [SHAHEEN & COHEN, 2018]. Since February 2019, e-hailing services of *mytaxi*, *BEAT*, *Clever Taxi* and *Kapten* are merged and operated by *FreeNow* (a mobility joint venture of two automotive companies: *Daimler* and *BMW*) [DILLET, 2019]. Currently, *FreeNow* e-hailing services operate in more than 100 European cities [FREE NOW, 2021a]. The services offered by the above-mentioned services are also referred to as ride hailing services, where only one passenger per vehicle is served at the same time.

Taxi sharing refers to taxi trips which are shared among two or more passengers, in which the riders share also the cost of the trip. In the US, the possibility to use the taxi as a shared one depends on the type of license possessed by the taxi [SHAHEEN & COHEN, 2018]. Examples of taxi sharing services in US are *Bandwagon*, which offered shared rides mainly starting from airports or bus terminals, *Via* and *Curb*, which partnered together to offer shared rides in New York City [HU, 2017]. In Europe, *FreeNow* also currently offers the *Match* option to share taxi trips for customers who have similar origins and destinations. The customers also share the costs of the rides by saving up to 50% in comparison to the costs of one passenger per vehicle trip. The *Match* option guarantees that the customer always pays less, even when a match is not found [FREE NOW, 2021b].

## 2.2 On-Demand Ride Pooling Services: Requirements, Modelling, and Impacts

This thesis focuses on analyzing the impact of on-demand ride pooling services in general. Hence, the on-demand ride pooling service that is considered is similar to a microtransit with flexible routes, taxi sharing or ride splitting, where a customer requests a ride via a smartphone app. A fleet operator then uses matching algorithms to check if it is possible to share this trip with another one and assigns a vehicle (with or without a customer already on-board) to this customer. The routes that the vehicle takes are therefore flexible and depend on the trip requests, the possibility to share trips, vehicle assignment objectives and traffic conditions in the network. From now on, this type of service is referred to as 'on-demand ride pooling (ODRP) service'. Whereas an on-demand service serving only individual passengers similar to ride sourcing or e-hailing, will from now on referred to as 'on-demand ride hailing (ODRH) service'.

A successful implementation of an ODRP service depends on the satisfaction of the requirements of three main stakeholders: customer, operator, and city. In general terms, the customer should be willing to use the service, thus share the trip with somebody else; the operator should offer an ODRP service and thus it is important to be able to find trips which could be shared and be profitable at the same time; and the city should accept the deployment of such a service if it has the potential to improve the traffic efficiency and the environmental conditions. Figure 2.2 illustrates some of on-demand ride pooling requirements, modelling and impacts from the perspective of customers, operators, and cities. These aspects will be described in detail in this section. In addition, a summary of some of the ODRP studies currently available in the literature is available in Tab. 2.1.

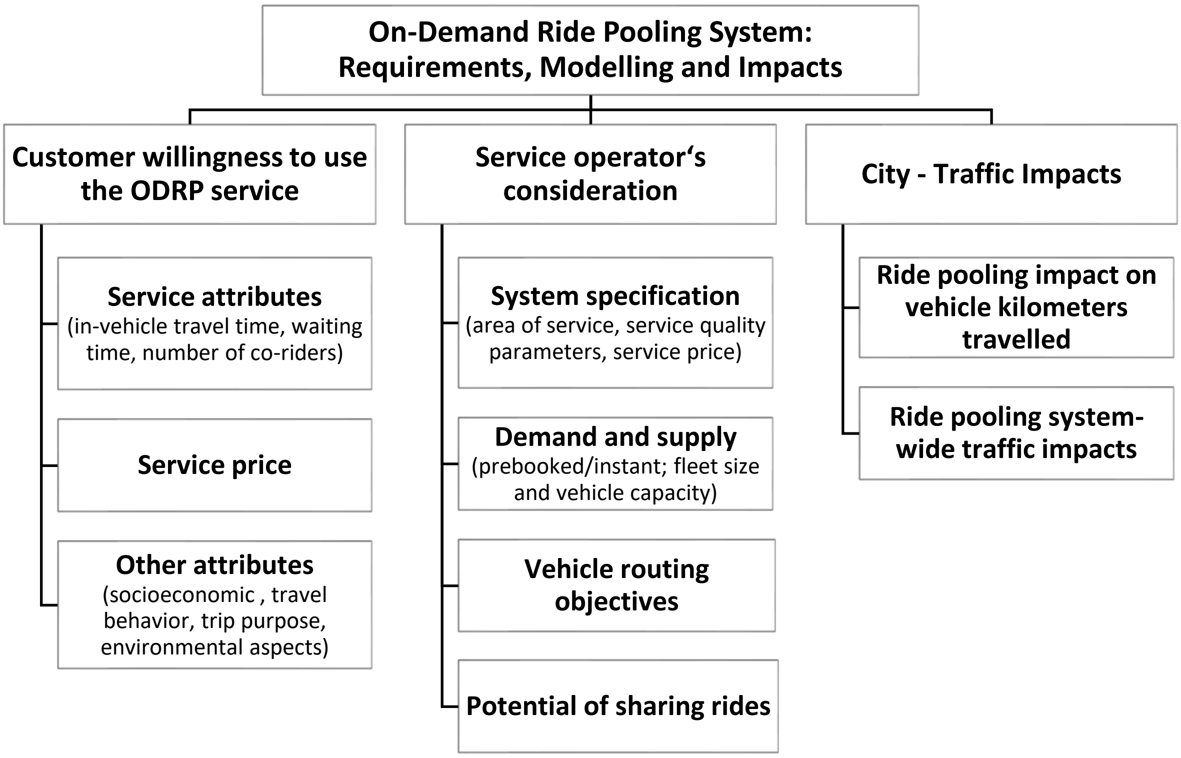



**Figure 2.2** On-demand ride pooling system: Requirements, Modelling and Impacts.

### 2.2.1 Customer willingness to use the ODRP service

Albeit on-demand mobility services are popular, with Uber alone serving around 14 million trips per day [Uber, 2021], only around 20% of the on-demand trips requested are pooled rides [CHEN ET AL., 2018]. Hence, a successful operation of ride pooling services depends initially on the customer willingness to use the ODRP service and share the trip with somebody else. The main determinants of the customer willingness to use the ODRP service are service attributes and travel costs [KRUEGER ET AL., 2016; CHEN ET AL., 2017; GURUMURTHY & KOCKELMAN, 2020; ALONSO-GONZÁLEZ ET AL., 2020a]. Other factors such as socioeconomic attributes, travel behavior and trip purpose also influence the use of ODRP [KRUEGER ET AL., 2016; GURUMURTHY & KOCKELMAN, 2020; CHEN ET AL., 2017; LAVIERI & BHAT, 2019; AL-AYYASH ET AL., 2016]. Moreover, environmental and social benefits play a role as well in the general acceptance of shared services [MATTIA ET AL., 2019; GOMPF ET AL., 2020].

As with every service offered, also in the ODRP case the quality of the service and the travel costs are essential to attract customers to use such a service. The total travel time of an ODRP trip is comprised of the waiting time to be picked up and the in-car travel time. Part of the in-vehicle travel time is the detour time or the deviation from the direct travel route to pick up additional passengers. KRUEGER ET AL. [2016] found that in-vehicle travel time, waiting time and travel costs are key factors in determining the acceptance of ride sharing services. CHEN ET AL. [2017] identified a more profound impact of in-vehicle travel time and travel costs on the willingness of people to share the trip with somebody else, whereas other factors such as waiting time or weather were considered to have a lower impact on the decision. Recently, GURUMURTHY & KOCKELMAN [2020] also found that the attractiveness of ODRP services increases for small added travel time (or detour time) resulting from shared rides. In line with the previous studies, ALONSO-GONZÁLEZ ET AL. [2020a] underpinned that travel time and cost greatly affect the percentage of ODRP requests.

Additionally, the number of co-riders influences the individual's choice to adopt to ODRP services. AL-AYYASH ET AL. [2016] found that if the ride was shared between a maximum of two passengers, the percentage of people willing to accept ODRP was 7-8% higher compared to the case when the ride is shared by a maximum of five or more passengers. Similarly, ALONSO-GONZÁLEZ ET AL. [2020a] found that the preference of a pooled ride with a maximum of two additional passengers is 5-13% higher than the preference for a ride with four additional passengers, concluding that an advanced information that the ride is shared to a maximum of two additional passenger can increase the number of ODRP requests.

Regarding socioeconomic attributes, a strong relation between the age and the acceptance of the ride pooling services is found [KRUEGER ET AL., 2016; LAVIERI & BHAT, 2019; GURUMURTHY & KOCKELMAN, 2020]. KRUEGER ET AL. [2016] found that customers of a young age are more likely to use ODRP services. The same results were confirmed recently by GURUMURTHY & KOCKELMAN [2020], which claim that an aging population has lower interest in sharing/pooling services, making these services dependent mainly on the young generation. Regarding other socioeconomic attributes, LAVIERI & BHAT [2019] revealed that individuals with high income and the ones who work full-time or are self-employed show a lower tendency to adopt to ODRP.

Travel behavior of individuals also influences the willingness to adopt to ODRP services. KRUEGER ET AL. [2016] found that persons who are multimodal have a higher possibility of adoption to either individual or pooled services, while LAVIERI & BHAT [2019] discovered that individuals who do not use a car to commute have higher chances to easily use these services. In order to increase the attractiveness of ODRP services to private car users, a high level of service should be offered to them. This is supported by the findings of AL-AYYASH ET AL. [2016], in which the level of service was found to be the most important determinant for the ODRP acceptance from private car users. Whereas for public transportation users the travel costs were considered the most significant attribute.

The purpose of the trip also influences the likelihood of using an ODRP service. KRUEGER ET AL. [2016] show that ride pooling is favored compared to individual trips for shopping trips, while according to LAVIERI & BHAT [2019] female and young passengers, together with the ones who own an individual car are less probable to use the ODRP service for commuting trips.

### 2.2.2 Service operator's consideration

From the operator's perspective, an ODRP service in general terms is seen as solving the problem of serving a set of customer requests by using a set of vehicles, while making sure that two or more requested rides are shared, if possible. Decomposing the general ODRP problem into sub-problems, it contains issues regarding:

- ride pooling system specification,
- demand and supply characteristics,
- how to efficiently match the supply and demand (assigning vehicles to passengers) by using effective vehicle routing objectives,
- potential to share rides (possibility to find two or more trips which can be shared).

**Ride pooling system specification**

Some of the initial choices that the operator should make for a successful ODRP offer are: 1) the selection of the area of service, 2) service quality parameters, and 3) the price offered to the customers. Cities with a high density of population are found to be favorable for an effective ODRP offer due to higher chances of finding shareable trips [SANTI ET AL., 2014a]. The set of SQP which comprise an ODRP offer, can include: 1) the time a customer waits to get picked up, 2) the detour time or the deviation from the direct travel route, 3) the reservation time, which specifies if it is possible to book a ride in advance (reservation time higher than 0) or not (reservation time equal to 0). While the SQP define the kind of quality of service offered to the customers, when it comes to solving the ODRP problem, they are considered as time constraints by the operator (more on this topic below in *Vehicle routing objectives*). Pricing is another important parameter to be considered. This stems from the fact that customers would potentially only accept to share the ride with somebody and hence experience travel discomfort due to increased travel time as a result of trip sharing, only if in exchange they pay a lower price for the ride compared to the other available alternatives. A research study from KUCHARSKI & CATS [2020] predicts that the potential ODRP services in terms of vehicle-hour reduction is possible for discount levels ranging between 10% and 30% lower than the ODRH price, while the savings of the currently offered ODRP services range from 25% to 60% compared to ODRH services [SHAHEEN & COHEN, 2018].

**Ride pooling demand and supply**

The type of the ODRP booking system defines what type of information will be available for the demand generation. The ODRP booking systems can be reservation-based (also known as prebooked systems) or instant (also known as online systems). Based on the type of booking system of an ODRP service, two types of generated trip requests are distinguished: static and dynamic. Trip requests are considered static, for the reservation-based ride pooling when the trip demand is known in advance [SANTI ET AL., 2014a; TACHET ET AL., 2017], i.e., the customers can reserve a ride for a later point in time. Whereas for instant ODRP booking systems, in which trip demand is not known beforehand, but instead is generated instantaneously, the trip requests are considered dynamic [ALONSO-MORA ET AL., 2017; ENGELHARDT ET AL., 2019a], i.e., the customers can request a trip instantly on demand without the need for a reservation in advanced.

The demand used as an input for ride pooling case studies was generated from: taxi data [TACHET ET AL., 2017; BISCHOFF ET AL., 2017; SANTI ET AL., 2014a; ALONSO-MORA ET AL., 2017], observed ride pooling trips, private vehicle trips [ENGELHARDT ET AL., 2019a; FIEDLER ET AL., 2018; ZWICK ET AL., 2021] or synthetic travel demand data [HOSNI ET AL., 2014; DAGANZO & OUYANG, 2019; KE ET AL., 2020]. In almost all the cases considered, with the exception of KUCHARSKI & CATS [2020], demand is assumed to be exogenous, i.e., fixed or scenario-based, and not sensitive to service quality of the ODRP service or price.

From the supply side, the fleet size and the vehicle capacity considerations are crucial to determine the quality of service. These parameters directly influence the degree of demand fulfillment, i.e., the percentage of served trip requests, and the customer waiting times to get picked up. From one side, the operator could opt for a minimum fleet size to reduce the cost, but from the other side, a large enough fleet size would be necessary to offer a better quality of service to the customers by increasing the percentage of served customers while offering them short waiting times to be picked up. Hence, the service provider has to consider the trade-off between the service cost and the quality of service offered to the customers. In the current research studies, the vehicles are either assumed to be promptly available at the trip request origin [SANTI ET AL., 2014a; TACHET ET AL., 2017] or the fleet size is considered to be a predefined parameter [ALONSO-MORA ET AL., 2017; ENGELHARDT ET AL., 2019a]. In order to determine the necessary fleet size to serve a given on-demand service demand without any significant delay incurred by the passengers, VAZIFEH ET AL. [2018] have identified a scalable solution to tackle this problem.

Considering the customer perspective, vehicle capacity defines the maximum number of passenger with whom they can share the trip, which as mentioned before is an important aspect to determine the customer willingness to use the service [ALONSO-GONZÁLEZ ET AL., 2020a]. Considering the perspective of the operator, the vehicle capacity influences the decision to select the type of vehicles necessary to be used in the fleet. Furthermore, this parameter is important to determine the computational complexity of the ride pooling problem. SANTI ET AL. [2014a] limited the capacity of vehicles to 2 and argued that a capacity of 3 would be heuristically feasible and more than 3 would be computationally not feasible. While ALONSO-MORA ET AL. [2017] extended the concept of SANTI ET AL. [2014a] and were able to test capacity larger than 2, including capacity 4, 8 and 10.

In order to cope with imbalances of demand and supply, strategies of vehicle repositioning in areas of high demand could be a useful approach to balance the demand and supply while increasing the quality of service offered to the customers [WEIKL & BOGENBERGER, 2013]. Therefore, such repositioning strategies could increase the percentage of served request and decrease waiting times or travel times [POULS ET AL., 2020], however they could have the disadvantage of producing more VKT in the system [BISCHOFF & MACIEJEWSKI, 2020].

**Vehicle routing objectives**

In the ODRP realm, the problem of matching the demand and supply is known as the problem of assigning vehicles to passengers and selecting the routes which the vehicles will take. The selection of the routes is performed by defining an objective for the vehicle routing algorithm. Different vehicle routing objectives can be distinguished depending on the domain where the operator wants to have a positive impact on. Thus, the vehicle objectives can be classified in three main categories which represent the perspective of customers, operators and cities and are given below:

- Customers favor minimizing of the waiting times [FAGNANT & KOCKELMAN, 2018], travel times [SANTI ET AL., 2014a], delays [ALONSO-MORA ET AL., 2017] and travel prices.
- Operators could opt for minimization of the operational costs or vehicle-hours, maximization of profit, maximization of served trips or maximization of shared trips [HOSNI ET AL., 2014; TACHET ET AL., 2017].
- Cities are concerned about system performance and could prefer minimizing vehicle kilometers travelled (VKT) and improving traffic efficiency.

Hence, vehicle routing optimization could include a single objective, when only one of the above criteria is considered or multiple objectives, when a combination of different objectives is used. Some objectives such as the minimization of VKT [AGATZ ET AL., 2011; FIEDLER ET AL., 2018; ENGELHARDT ET AL., 2019a] might be considered to satisfy both operator's and city's requirements. However, using objectives from different perspective could also lead to clashing optimal solutions, as for instance minimizing the waiting times from customer side in most of the cases would not lead to an optimal solution regarding minimum vehicle fleet size from operator side. However, it is necessary to include different perspectives for the optimization objective to account for these conflicting solutions and have a better overall mobility system behavior.

As mentioned earlier, the considered SQP from customer perspective, such as waiting times or detour times, are identified as time constraints for solving the vehicle routing optimization problem for operators. As such, these constraints should not be exceeded in order to satisfy the customers' requirement toward the ODRP service. The time constraints can either be fixed, by specifying a maximum value of the parameters [SANTI ET AL., 2014a; TACHET ET AL., 2017] or a maximum value compared to the percentage of the total trip time [ENGELHARDT ET AL., 2019a; FAGNANT & KOCKELMAN, 2018], or flexible, based on a compensatory function which relates the detour time, the ODRP travelling discomfort and the compensation in terms of fare reduction that the customers get by sharing their ride [KUCHARSKI & CATS, 2020].

The solution approaches of the ODRP services could be classified in online and offline ones. The online solution approaches are used for online ODRP systems and hence the focus is on the speed and the efficiency of the solution [SIMONETTO ET AL., 2019], while offline solution approaches focus on the system-wide impacts [TACHET ET AL., 2017; DAGANZO & OUYANG, 2019; KUCHARSKI & CATS, 2020; KE ET AL., 2020].

**Potential of sharing rides**

One crucial factor determining the successful operation of ODRP services is the possibility to find trips which can be shared between passengers in an operating area. Even though more ODRP services are becoming available to the customers, the possibility to actually share a trip with another passenger is reportedly quite low, for instance in a current ODRP service in Chengdu the percentage of shared trips is only 6-7% [LI ET AL., 2019]. Hence, some companies, like *Uber, Lyft* and *Via,* are experimenting with different models (*Uber Express POOL*, *Lyft Shared Saver*), where they do not offer door-to-door service, but passengers have to walk to the closest intersection in order to increase the percentage of shared trips and decrease the detour time. However, this option would diminish one of the crucial advantages of the ODRP service of offering door-to-door transportation.

Therefore, the question that arises is: What are the factors which influence the potential to share rides in a door-to-door ODRP service? Intuitively, the higher the number of trips generated in an area is, the higher are the chances to find shareable trips. However, strict time constraints imposed to the system by SQP (e.g., low detour times or low waiting times), decrease the flexibility of the ODRP system and hence, the available number of options for trip sharing between passengers is lower. However, low detour times and low waiting times might increase the attractiveness of the customers to use the ODRP service. Hence, the operators should have a more profound understanding of this trade-off and additionally, an investigation of the influence that other system parameters have on the potential to find shareable trips is necessary.

SANTI ET AL. [2014a] assumed that two trips are shareable with each another if their paths overlap at least partially and if their arrival times do not exceed the direct travel times of both trips by more than a predefined delay time parameter. In order to handle large problem instances for a set of known trips, in a more efficient way compared to the insertion heuristics approach, they introduced the concept of shareability networks to define the percentage to shareable trips in the system. In this type of network, each trip is represented by a node and the nodes are connected by a link if a possible match between the trips is theoretically found. Depending on the objective of the optimization, trips are matched together, e.g., for the objective of maximizing the percentage of shared trips, trips are matched together so that they can achieve the maximum possible number of matches. The shareability value is then defined as the relative value of the trips that can be shared to the total number of trips. SANTI ET AL. [2014a] show that with increasing the delay time parameter, shareability quickly approaches 100% for the New York taxi trip data. However, the results differ depending on the type of information available, i.e., static (trip information is known well in advance) or dynamic (trip information is available in periods of one minute). For a delay time of only one minute, shareability is found to be around 95% and 30% for static and dynamic systems, respectively. The results show that even for a small delay time shareability can be quite high for dense areas like New York City. However, the authors argue that less dense cities can also show a good potential by performing a subsampling of the data set to represent low passenger trip generation areas.

In order to test the shareability concept in other cities and to generalize the influencing factors, TACHET ET AL. [2017] introduced an analytical model which is based on the concept of shareability shadows. A shareability shadow is a geometrical area where the origins and destinations of a trip should be in order for it to be shareable with an existing trip, whose trajectory is represented by a straight line. They showed that shareability, for the case when the optimization objective is to maximize the percentage of shared trips in the area, can be described quite well by an analytical function. According to this analytical formulation, shareability is negatively related with the surface of the area and positively related with the number of passenger trips per hour generated in an area, average velocity and a delay time parameter. They tested their model with taxi data from New York City, San Francisco, Singapore and Vienna and found that albeit the passenger trip generation rate in the considered cities and their topologies are quite different, the function matches quite well the simulated data.

### 2.2.3 Traffic impacts

The traffic impact of ODRP services can be divided in ODRP impact on VKT and ODRP impact on system-wide traffic efficiency. While there are multiple studies regarding the ODRP vehicle kilometers travelled impact, the studies regarding ODRP system-wide traffic impacts are limited.

**Ride pooling impact on vehicle kilometers travelled (VKT)**

On-demand mobility service serving passengers individually or ODRH services, are considered to increase the VKT in the system due to empty trips generated while going to pick up passengers or even due to induced trips [MACIEJEWSKI & BISCHOFF, 2018; DANDL ET AL., 2017; FIEDLER ET AL., 2017]. Hence, they often contribute to increased level of congestion in a city. ODRP services on the other side have the potential to reduce the total VKT in the system by compensating the generated empty trips to pick up passengers by the saved VKT from sharing with each other trips which have similar trajectory are occur during the same time span. This can contribute to improved traffic conditions and reduced pollution in cities [International Transport Forum, 2016, 2017].

Traffic impacts of an ODRP service for individual cities have been analyzed in different studies, where the authors used agent-based simulations to derive the reduction in VKT in the system. AGATZ ET AL. [2011] suggested that ride pooling in the city of Atlanta can reduce the VKT even for low demand levels and analyze the benefit of using a sophisticated optimization method compared to a greedy matching. For New York City, Alonso Mora et al. [2017] showed that the travel distance in New York City can be reduced by substituting 98% of taxi trips served by 13000 taxies by ODRP trips served with a fleet of 3000 vehicles. For their case study, the travel distance decreases with higher ODRP passenger demand, vehicle capacity and delay time. FAGNANT & KOCKELMAN [2018] studied the impact of ride pooling in Austin, Texas and identified that a replacement rate lower than 11% of the total internal trips would result in increased

VKT in the system and a break-even point, where no additional VKT are generate, would only occur for a replacement of around 11%. The authors predict that meaningful reduction might happen provided that the market share of ODRP reaches 20-50%. In a case study in Berlin substituting taxi trips with ODRP trips, BISCHOFF ET AL. [2017] found that VKT saving of the ODRP service vary between 15-20% compared to the base scenario. MARTINEZ & VIEGAS [2017] analyzed the impact of an ODRP service in Lisbon in the extreme case where all private vehicles, taxi and bus trips are replaced by ODRP trips either similar to a taxi-like system or bus-like system with a 30 minutes booking in advance and found significant reduction in VKT (30% reduction for the best scenario) and emission (40% reduction). Replacing private vehicle trips with ODRP trips in the city of Prague, FIEDLER ET AL. [2018] showed that the ODRP service can reduce the VKT in the system by producing 60% of the vehicle kilometers generated by private vehicles and to 35% of the vehicle kilometers generated by a ride hailing system. The results also showed that the average vehicle occupancy of the ODRP fleet increases for lower ODRP service quality offered to the customers (e.g., for high delay time). A similar study is performed for the Munich city where up to 15% of private vehicle trips are substituted with ODRP service [ENGELHARDT ET AL., 2019a]. The results show that ODRP service impact in reduction of VKT can be noticeable after a certain penetration rate of the ODRP service, which in the Munich case study corresponds to 5% substitution of private vehicle trips with ODRP trips. Recently, ZWICK ET AL. [2021] studied the ODRP impact in Munich as well and similarly they show a reduction of VKT, but with the burden of increasing the average noise exposure as a result of more traffic generated in residential areas.

**Ride pooling system-wide traffic impacts**

The studies mentioned above and almost all ODRP studies in the literature are performed by using agent-based simulations, which are not suitable to derive the impacts of an ODRP service on the system-wide traffic conditions, which could be the case if the agent-based model is coupled with a microscopic traffic simulation model. Therefore, they consider only the impact of the ODRP vehicle fleet in VKT reduction, without consideration of the interaction with other vehicles present in the network. Including this aspect would provide an analysis of the impact of the ODRP service on the network state, which is currently scarce in the literature.

The traffic state of a system-wide network is typically represented by the macroscopic fundamental diagram (MFD). The MFD (sometimes also referred as network fundamental diagram) expresses the relation of the average velocity $v$ in the network, the traffic flow $q$ (number of vehicles that pass a reference point per unit of time), and the traffic density $k$ (number of vehicles per unit distance of the network) and was initially derived for highway sections [GREENSHIELDS, 1935]. Later, it was discovered that an alike relation is valid also for urban areas. Daganzo [2007] introduced a functional form of the MFD for urban networks that relates travel production (expressed in vehicle-meters) and accumulation (expressed in vehicles), which was then validated by Geroliminis and Daganzo [2008]. There are different methods to derive the MFD for urban areas which include: the use of detectors or floating car data [GEROLIMINIS & DAGANZO, 2008, 2007], microscopic traffic simulations [DANDL ET AL., 2021; BRACHER & BOGENBERGER, 2017] or analytical derivations [DAGANZO & GEROLIMINIS, 2008; LAVAL & CASTRILLÓN, 2015; TILG ET AL., 2021].

The benefits of the functional form of the MFD have been exploited in ODRH service studies as a background for dynamic urban traffic modeling in order to establish a revenue maximization platform [LUO & SAIGAL, 2017] and for dynamic modeling and control of a network taxi dispatch system [RAMEZANI & NOURINEJAD, 2018]. The MFD has been used recently also in ODRP studies. For instance, DANDL ET AL. [2021] used the MFD to quickly estimate the travel time in the network due to changes in service demand for a multi-modal system including ODRP. Additionally, KE ET AL. [2020] used the potential of the MFD to establish a model to describe traffic congestion for ride sourcing markets and compare the travel times for ODRH passengers, ODRP passengers and private vehicle users.

## 2.3 Modelling Approaches for On-Demand Ride Pooling

Different modelling approaches are used in order to represent different phenomena in the realm of ODRP in a simple and understandable way and then analyze the ODRP impacts. The most commonly used ODRP models are agent-based models and only a few studies use analytical models to access ODRP impacts [TACHET ET AL., 2017; DAGANZO & OUYANG, 2019; KE ET AL., 2020].

### 2.3.1 Agent-based models for on-demand ride pooling

Agent-based models are used to model the actions of individual agents, which are autonomous entities making decisions based on a set of rules, and the simultaneous interaction of multiple agents with each other. The goal of using agent-based models is to model complex phenomena or systems and to assess the impact that the individual behavior of agents and the interaction between multiple agents have on the whole system. Agent-based modeling approaches use the power of computers in order to explore the competitive interactions between agents which are not possible to be captured by a pure mathematical model [BONABEAU, 2002; WILENSKY & RAND, 2015].

Most of the studies about assessing the impact of ODRP have been performed by using agent-based simulation models. These can be simulations developed independently by researchers in software programs, such as C++ [AGATZ ET AL., 2011; FAGNANT & KOCKELMAN, 2018] and Python [ENGELHARDT ET AL., 2019a] being the most used programming language for this purpose, or well-known open-source large-scale agent-based transport simulations such as MATSim [BISCHOFF ET AL., 2017; ZWICK ET AL., 2021].

The main agents in this context are customers, vehicles, and the fleet operator [ALONSO-MORA ET AL., 2017; ENGELHARDT ET AL., 2019b]. The interactions between these agents are based on their individual properties and behavior, and the decisions specified by the fleet operator. For instance, the customer who wants to travel from a certain position to another one, is treated as an agent which sends a request to the ODRP system, where she specifies the position where she wants her trip to start and end and the time when she wants to get picked up, either instantly or at a specific time, depending on the ability of the ODRP system to allow reservation of requests in advance. Depending on the kind of the ODRP system, the amount of time the customer is willing to wait to get picked up and the acceptable temporal deviation from the direct travel route could be specified by the customer, however in most of the cases, these parameters are predefined by the fleet operator. Vehicle agents, having a certain capacity to accommodate customers on board, drive in the network and transport customers from a specific origin to a specific destination. The decision to serve which customer and at which time in an efficient way is made by the fleet operator. Mathematically, this decision is derived by solving an optimization problem, where the operator specifies the vehicle routing objectives and a set of rules to achieve these objectives, while guaranteeing that the customers will be served within their preferred time constraints [ENGELHARDT ET AL., 2019b].

One key advantage of using agent-based simulation models is that they can provide detailed modelling of operational aspects of a vehicle fleet. Moreover, with agent-based models heterogenous fleets can be modelled and depending on the type of agent-based models also the online operations of an ODRP service can be analyzed [SIMONETTO ET AL., 2019]. Nevertheless, agent-based models need a lot of input data, the main ones being specific demand data and city network details, which are not always easy to acquire. Hence, they are specific for a city and in order to study the impacts of the ODRP services in other cities, the same amount of input data and effort is needed. Agent-based models are also computationally very expensive. In the case of ODRP studies, where there are quite a lot of parameters to be considered, the investigation of the impact that these parameters have on the result would require a large number of simulations and hence a large amount of computational time. As each agent in the network is modelled individually, with increasing

ODRP passenger demand, the number of customer agents also rises, increasing thereby also the computational time. Moreover, the ODRP optimization problem solved in the agent-based simulations is usually NP-hard problem and hence the computational time rises with increasing problem size, which in the ODRP service problem is represented by the increased ODRP passenger demand. Furthermore, due to their complexity, the agent-based models sometimes hide important interactions and thereby the effect of certain parameters is not easily understood.

### 2.3.2 Analytical models for on-demand ride pooling

In general, analytical models describe a system using mathematical concepts and therefore, a phenomenon can be more comprehensively described. Additionally, the impact of a single parameter of the model on the overall system can be easily interpreted and understood, as this impact can be analytically represented. Furthermore, the input data needed for an analytical model is low and its computational time negligible. Hence, when deciding of which modelling technique to use for the analyses of a problem, the general approach taken is the use of analytical modelling, if the system can be realistically represented by a set of solvable equations, which can be a challenging task to achieve in a lot of cases.

ODRP systems are complex systems and the behavior of their agents and the interactions between them can be difficult to be described by a set of solvable analytical equations. Therefore, contrary to the large number of existing ODRP agent-based simulation studies, the number of ODRP studies which use the analytical modelling approach to analyze the impacts of ODRP services is scarce.

Spieser et al. [2014] used an analytical model to solve the problem of finding the vehicle fleet size necessary to accommodate the transport demand of a given city for an autonomous ODRH service. They considered two problems: the problem of finding the minimum fleet size and the problem of finding a performance-driven fleet size, which ensures a certain quality of service offered to the customers. Using a similar goal, but another analytical approach, Daganzo & Ouyang [2019] developed a simple analytical model that relates the user travel time with the fleet size for a certain demand level considering also ODRP service in addition to ODRH service. However, the model from Daganzo & Ouyang [2019] is not valid for heavy demand systems and uses a very simplistic assignment algorithm which is not likely to be used by operators. In the case of the ODRP service, this algorithm prioritizes customers' pick-ups over drop-offs, allowing for an infinite detour time parameter, which will most certainly not be accepted by the customers. These assumptions need further investigation which would allow for a more realistic representation of an ODRP system and would therefore contribute to a better planning of an ODRP service.

TACHET ET AL. [2017] analyzed the impact of the ODRP service by using analytical modelling and presented an equation that describes the impact of ODRP passenger demand, city area, velocity, and a delay time parameter (which is the sum of the maximum waiting time and the detour time) on the percentage of shared trips in an area. They also show that their model holds for different cities, allowing for its generalization. However, their model is firstly restricted to only investigate the achievable percentage of shareable trips in an area where an ODRP service is offered. Secondly, the delay time parameter in their study is the sum of the detour time and the maximum waiting time, therefore in the analytical shareability model by TACHET ET AL. [2017] the individual effects of the detour time and the waiting time alone are not examined. Moreover, the impact of other SQP, such as reservation time, the boarding/disembarking time, or network modelling details are also not investigated. Furthermore, the analytical model of shareability by TACHET ET AL. [2017] is valid only for the optimization objective of maximizing the percentage of shared trips and is validated by taxi data. The validity of the model for other cities or other types of passenger demand data is not considered up to now.

KE ET AL. [2020] recently used theoretical modeling to analyze the congestion effects of a system, explicitly represented by a MFD while considering ODRH service, ODRP service and private vehicles. They examined and compared the overall travel time of ODRP and ODRH customers and private car users and identified some scenarios where the implementation of the ODRP service could contribute to achieve the win-win situation between ODRP, ODRH customers and private car users regarding lower experienced travel times. The authors found that what they refer to as ‘matching time window’, which corresponds to the pick-up waiting time is a key decision variable affecting the stationary equilibrium state. Similarly as in previous studies [SANTI ET AL., 2014a; TACHET ET AL., 2017], also in this study it is shown that higher values of the matching time window increase the pool-matching probability, the customers would have to wait longer to get picked up though. However, to simplify the theoretical analyses of an otherwise very complex interaction of the parameters of an ODRP system, their method assumes a simple matching strategy considering only the proximity of origins and destinations. Therefore, they only investigate the impact of waiting time on the travel time of different users of the system, without considering in-route deviations (or detour distance).

| Paper | Study area | Demand data | Booking system | Service parameters | Vehicle routing objective | Modelling approach | Profitability |
|---|---|---|---|---|---|---|---|
| [AGATZ ET AL., 2011] | Atlanta | travel demand data | prebooked | delay | minimize VKT | agent-based | yes |
| [ALONSO-MORA ET AL., 2017] | New York | taxi data | instant | $\Delta$, $t^{max}$, $t^{b}$ | minimize delay | agent-based | no |
| [BISCHOFF ET AL., 2017] | Berlin | taxi data | instant | $t^{max}$, $\Delta$, $t^{b}$ | minimize travel time | agent-based | no |
| [DAGANZO & OUYANG, 2019] | Synthetic | synthetic | prebooked | delay | not considered | analytical | no |
| [DANDL ET AL., 2021] | Munich | OD demand model | instant | $t^{max}$, $\Delta$, $t^{b}$ | minimize VKT and delay | agent-based | yes |
| [ENGELHARDT ET AL., 2019a] | Munich | OD (PV) demand model | (short-term) prebooked | $\Delta$, $t^{max}$, $t^{b}$ | minimize VKT | agent-based | no |
| [FAGNANT & KOCKELMAN, 2018] | Austin | OD demand model | instant | $\Delta$, $t^{max}$, $t^{b}$ | minimize waiting time | agent-based | yes |
| [FIEDLER ET AL., 2018] | Prague | OD (PV) demand model | instant | delay, $t^{b}$ | minimize VKT | agent-based | no |
| [KE ET AL., 2020] | Synthetic | synthetic | prebooked | $t^{max}$ | not considered | analytical | no |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [KUCHARSKI & CATS, 2020] | Amsterdam | multimodal data from activity-based model | prebooked | $t^{max}$, $\Delta$, $t^{b}$ | minimize travel time, maximize utility | agent-based | yes |
| [MARTINEZ & VIEGAS, 2017] | Lisbon | multimodal survey data | instant and prebooked | $t^{max}$, delay | minimize travel time | agent-based | no |
| [SANTI ET AL., 2014a] | New York | taxi data | instant and prebooked | delay | maximize shared rides, minimize travel time | agent-based | no |
| [TACHET ET AL., 2017] | New York, San Francisco, Singapore, Vienna | taxi data | prebooked | delay | maximize shared rides | analytical | no |
| [ZWICK ET AL., 2021] | Munich | travel demand model based on survey data | instant | $t^{max}$, $\Delta$, $t^{b}$ | unclear | agent-based | no |
| **THIS THESIS** | **Munich** | **OD (PV) demand data** | **instant and (short-term) prebooked** | $\boldsymbol{t^{max}}$, $\boldsymbol{\Delta}$, $\boldsymbol{t^{b}}$ | **maximize shared rides and minimize VKT** | **analytical** | **yes** |

**PV:** private vehicles, **OD**: origin-destination
$\boldsymbol{t^{max}}$: waiting time, **Δ**: detour, **delay**: sum of detour and waiting time, $\boldsymbol{t^{b}}$**:** boarding/disembarking time
**VKT**: vehicle kilometers travelled

**Tab. 2.1** Summary and classification of on-demand ride pooling (ODRP) studies.

**Key Takeaways – Research Gaps**

- Most of the ODRP studies are performed by using agent-based simulations, which even though providing detailed modelling of the system, require large input data and computation time, while studies using analytical modelling approach are scarce.
- **RG 1** – The potential of shared trips investigated analytically by the shareability model of TACHET ET AL. [2017] does not take into account the separate impact of detour time and maximum waiting time and the additional influence of boarding time and reservation time on the percentage of shared trips in an area. Additionally, the impact of network modelling details, such as network topology, demand patterns, optimization objective and inhomogeneous velocity on shareability are not examined currently.
- **RG 2** – The system-wide traffic impacts of ODRP service are currently examined by considering only the reduction of VKT by the ODRP fleet. KE ET AL. [2020] consider also the background traffic, however they use a simple matching approach, without considering the impact of the vehicle routing optimization objectives in the results.
- **RG 3** – A general analytical model which can capture the ODRP benefits in terms of cities' traffic efficiency, operators' monetary profitability and customer attractiveness to use the service, which could provide the system parameters and the framework conditions in which the ODRP service win-win-win situation could be achieved, is currently not available in the literature.

# 3. Analytical Modelling of On-Demand Ride Pooling Impacts

This chapter will provide a description of the analytical models developed to capture the impacts of ODRP services, which will help to achieve the aim of this thesis. In *Section 3.1*, the analytical shareability models which examine the influence of SQP on the percentage of shared trips in an area will be presented. The analytical model of the traffic impacts of ODRP service will be elaborated in *Section 3.2*. Lastly, *Section 3.3* will provide a general model which can capture the benefits of an ODRP service from the perspective of the customers, the operator and the city.

## 3.1 Analytical Modelling of On-Demand Ride Pooling Shareability

This section describes the analytical models that are developed to explore the impact of SQP on shareability. Two different models are established depending on the type of booking system: 1) instant, when the ODRP passenger ride is requested instantly; and 2) reserved, when the ODRP passenger ride is prebooked.

### 3.1.1 General model set-up

As mentioned before the benefits of ride pooling are tightly tied with the possibility to find shareable trips in an area. TACHET ET AL. [2017] already investigate in this realm and found that shareability depends on ride pooling passenger demand generation $\lambda_{\mathrm{p}}$, average city velocity $v$, the surface of an operating area $\Omega$ and a maximum delay time parameter, which is the sum of maximum waiting time to get picked up $t^{max}$ and the deviation from the direct travel distance or detour time $\Delta$. However, in their study, TACHET ET AL. [2017] assume that all the requests are known well in advance and the only service quality parameter they consider is the delay time.

In order to profoundly investigate the influence of different parameters on the percentage of shared trips in an urban area (or shareability), the models established in this chapter are inspired by [TACHET ET AL., 2017] and are extended in two directions:

- Incorporation of the impacts of the type of booking system on the shareability model considering an instant booking system and a short-term prebooking system.
- Modelling of individual influences of SQP, such as maximum waiting time, detour time and boarding/disembarking time in the shareability model.

Inclusion of these two directions in the shareability model contributes to addressing the research gap RG 1.a, regarding the analytical exploration of the impact of maximum waiting time, detour time, boarding/disembarking time, and the type of booking system (or reservation time) on shareability, which are currently not analytically investigated in the literature. The evaluation of the shareability model in *Section 5.1* will address the research gap RG 1.b, regarding the impact of network modelling details on shareability.

Shareability is defined as the probability to find trips with similar spatial and temporal trajectories in a defined operating area. For two trips to be shareable with each other, they should satisfy the following general conditions:

- A partial overlapping of trip trajectories in space and time should exist.
- The detour from the direct travel distance should not be longer than a detour time parameter $\Delta$, usually specified by the service operator.
- The passenger should get picked up within a specified maximum waiting time parameter $t^{max}$.

The trajectory of a given trip $T_a(t_a, O_a, D_a)$, which starts at time $t_a$, originates at $O_a$ and has the final destination at $D_a$, is specified by the red line in Figure 3.1 and Figure 3.2. Assuming that the trips follow the shortest path between two points in a Euclidean space, their trajectory is considered to be a straight line. Following this assumption, a vehicle that accommodates trip $T_a$, at the point of time $t$ will be located at position $r_a(t)$. In order to find another trip $T_x$ which could be shareable with this existing trip $T_a$, the question that requires an answer is: Where exactly should the origin and destination of the new trip $T_x$ be in order for this trip to be shareable with the existing trip $T_a$?

The shareability shadow explained in the following subsection answers this question. The concept of the shareability shadow introduced by TACHET ET AL. [2017] is a key concept in the development of the shareability models. Shareability shadow is a geometrical area defining the position in space where the origin and destination of a trip could be for this trip to be shareable with a previously existing trip, while making sure that the time constraints defined by the SQP are not violated. For different booking systems, different shareability shadows are constructed depending on the relation of time constraints imposed by SQP. The SQP considered in this part depend on the type of the ODRP booking system.

### 3.1.2 On-demand ride pooling instant booking system

In this part, the shareability for an instant (or online) booking system, where the passengers want to get picked up immediately, is investigated. For the instant ODRP booking system, the impacts of the following SQP on shareability are modelled: maximum waiting time that a customer waits to get picked up by a vehicle $t^{max}$ (referred from now on as maximum waiting time), the temporal deviation from the direct travel distance $\Delta$ (referred from now on as detour time) and the time a customer needs to board or disembark the vehicle $t^{b}$. Differently from the shareability model from TACHET ET AL. [2017] which considers only the impact of a delay time parameter on shareability, in order to model the individual impacts of SQP on shareability, in this thesis this delay time parameter is divided in its two main components: the maximum waiting time $t^{max}$ and the detour time $\Delta$.

**Shareability shadow for an instant booking system**

In order to define the shareability for the instant booking system, firstly the shareability shadows should be built. As described, the shareability shadow is a region in the vicinity of a trip trajectory, which specifies the spatial position of where the origin and destination of a trip should be in order to be shareable with an existing trip. The SQP are considered as time constraints for the operator and as such they restrict the options to find shareable trips. Hence, in the creation of the shareability shadow, each of the service quality parameters is represented by a geometric shape, which defines the spatial constraints where a trip could start or end in order to be shareable with an existing trip without violating the time constraint specified by each of these service quality parameters. The shareability shadow is then formed by the intersection of all geometric shapes, representing the simultaneous fulfillment of various constraints defined by all the considered service quality parameters.

The customers using the ODRP service would not accept a large in-vehicle deviation from the direct travel route, therefore from the basic requirements needed to be fulfilled in order for a trip to be shareable, the detour time constraint should not exceed $\Delta$. Hence, the diversion from the original vehicle trajectory of trip $T_a$ (given by the red line in Figure 3.1) should not be longer than $v\Delta$, which determines the distance in space the vehicle can reach to find shareable trips for the allowed detour time $\Delta$, in an area where the average velocity is $v$. The geometric shape representing the detour time constraint is shown in Figure 3.1 by the gray rectangle area with height $2v\Delta$.

Assuming that the vehicle which accommodates trip $T_a$ at the point in time $t$ is at position $r_a(t)$, for instant ODRP booking system where the passengers want to be picked up as soon as possible, the vehicle has the possibility also to pick up a request $T_x$ whose origin is located backward of the vehicle's direction of travel (on the left side of point $r_a(t)$). However, this could happen only if the time needed to travel back to pick up the other passenger and continue forward in the direction of travel is no longer than the specified detour time constraint Δ. This condition is satisfied by a parabolic function shown in the left side of $r_a(t)$.

If the origin of the request $T_x$ is in the forward direction of travel, on the right side of $r_a(t)$, the spatial location of the origin of the request is defined by a circle with origin $r_a(t)$ and a radius $vt^{max}$, as the passenger to which request $T_x$ belongs can wait a maximum amount of time equal to $t^{max}$ until a vehicle picks her up. Nevertheless, considering that the customer on board of the vehicle would not allow a deviation longer than the detour time, this area is restricted by the allowed detour time represented by the gray rectangle.

The resulting area where the origin of a new request $T_x$ must be in order to be shareable with request $T_a$ is constructed by the merger of both areas on the left and right side of $r_a(t)$ defined by the maximum waiting time and detour time constraints.

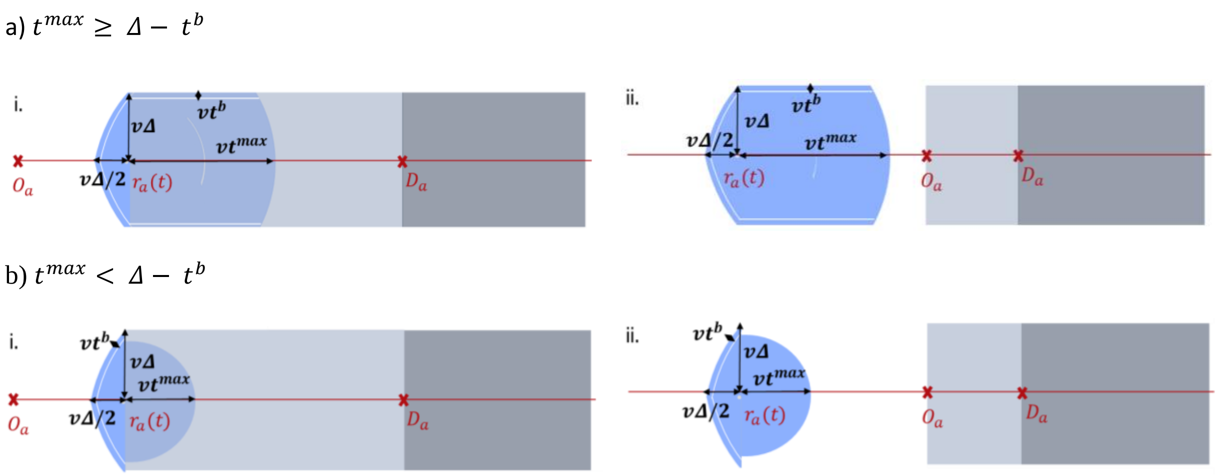



**Figure 3.1** Shareability shadow for the instant booking system for two main cases: a) Shareability shadow for $t^{max} \geq \Delta - t^b$ and b) Shareability shadow for $t^{max} < \Delta - t^b$. In the forward sharing probability (i.) trip $T_a$ starts before trip $T_x$ and in the backward sharing probability (ii.) trip $T_x$ starts before trip $T_a$.

Lastly, the parameter of the boarding/disembarking time $t^b$ constraint is considered as time lost for the customer inside the vehicle, who would not tolerate a larger deviation from her direct travel time than the specified detour time. Hence, the impact of boarding time $t^b$ constraint is modelled by subtracting the boarding time from the detour time Δ, as each passenger experiences on average one boarding/disembarking process during which another passenger boards or disembarks the vehicle.

There are two possibilities for the starting time of trip $T_x$ in order for it to be shareable with trip $T_a$. The start time of the trip $T_x$ could be either before or after the starting time of trip $T_a$. If the trip $T_x$ starts after the starting time of trip $T_a$, $r_a(t)$ denotes the position in which the vehicle that serves trip $T_a$ is at the point in time $t$ (Figure 3.1.a.i, Figure 3.1.b.i). For the other case, when trip $T_x$ starts earlier than the originating time of trip $T_a$, $r_a(t)$ is assumed to be a hypothetical location at which the vehicle which will serve trip $T_a$ could be at the point in time $t$ (Figure 3.1.a.ii, Figure 3.1.b.ii) [TACHET ET AL., 2017].

The final resulting shape of the origin area of trip $T_x$ depends on the interrelation between different SQP. Hence, two different shareability shadows are distinguished:

a) If the maximum waiting time is larger than the detour time minus the boarding time ($t^{max} \geq \Delta - t^b$), the shareability shadow is shown in Figure 3.1.a.

b) If the maximum waiting time is smaller than the detour time minus the boarding time ($t^{max} < \Delta - t^b$), the shareability shadow is shown in Figure 3.1.b.

For each of these shareability shadows, there are two additional cases, which depend on when the starting time of trip $T_x$ is:

i. If the trip $T_x$ starts after the starting time of the existing trip $T_a$, the shareability shadow is given in Figure 3.1.a.i and Figure 3.1.b.i. This is also known as the forward ($f$) sharing probability.

ii. If the trip $T_x$ starting time is before the starting time of the existing trip $T_a$, the shareability shadow is shown in Figure 3.1.a.ii and Figure 3.1.b.ii. This is also known as the backward ($b$) sharing probability.

As a result, for a trip $T_x$ to be shareable with an existing trip $T_a$, the origin of trip $T_x$ should be within the specified blue area around $r_a(t)$ (denoted as ε) in order for the detour time, maximum waiting time and boarding/disembarking time constraints to be satisfied. While the trip $T_x$ destination should be located either before the destination of the existing trip $T_a$, given by the light grey rectangle (denoted as $\in_1$), or after the destination of trip $T_a$, given by the dark grey rectangle (denoted as $\in_2$), in order for the trajectories of the trips to be at least partially shareable.

### Shareability model for instant booking system

Considering the above-mentioned cases, the probability that trip $T_x$ is shareable with trip $T_a$ ($P^{f,b}$) is the sum of the probabilities $\Gamma^{f,b}_{(\varepsilon \curvearrowright \in_1 \cup \in_2)}$ that the trip $T_x$ originates in the area ε and has its destination either in area $\in_1$ ($\Gamma^{f,b}_{(\varepsilon \sim \in_1)}$) or in area $\in_2$ ($\Gamma^{f,b}_{(\varepsilon \sim \in_2)}$), as shown in Equation (1). As mentioned before, there are two cases depending on the starting time of trip $T_x$ in relation with trip $T_a$. Therefore, two cases for forward ($T_x$ starts later than $T_a$) and backward ($T_x$ starts earlier than $T_a$) sharing probability are distinguished, denoted in the following formula as $f$ and $b$, respectively.

$$P^{f,b}(t|t_a,\, O_a,\, D_a) = \Gamma^{f,b}_{(\varepsilon \sim \in_1)} + \Gamma^{f,b}_{(\varepsilon \sim \in_2)} \;\; = \Gamma^{f,b}_{(\varepsilon \sim \in_1 \cup \in_2)} \tag{1}$$

To determine the probability that a passenger trip generated at time $t$ is possible to be shared with an upcoming or former trips through its time extent, the forward $(P_f)$ and the backward $(P_b)$ probabilities are taken into account by using the subsequent formula [TACHET ET AL., 2017]:

$$P(t) = P_f(t) + \left(1 - P_f(t)\right) P_b(t) \tag{2}$$

In order to come up with solvable equations, some assumptions are necessary for this model. It is assumed that the origins of the trips are uniformly distributed in the area and trip generation is performed based on a Poisson distribution, whereas their destinations are selected to be uniformly distributed within a disk with radius R, which denotes the maximum trip distance.

The shareability is derived as a result of the combination of the probability to find shareable trips together with the probability that trips are generated in time and in the corresponding area of interest and therefore, integrating over the respective time and space.

The final shareability formula is given in Equation (3), where a new dimensionless quantity $L^{on}_{sq}$ is introduced representing the changes in the shareability shadows as a result of online generation of request for the instant ODRP booking system and the further consideration of the influence of additional SQP. Therefore 'on' refers to the consideration of online generation of requests and 'sq' refers to the influence of the additional SQP on shareability. As previously mentioned, two forms of shareability shadows are distinguished based on the relation of SQP with each other, hence there are two different formulas of $L^{on}_{sq}$.

$$S = 1 - \frac{1}{2{L_{sq}^{on}}^3}\left(1 - e^{-L_{sq}^{on}}\right)\left(1 - \left(1 + 2L_{sq}^{on}\right)e^{-2L_{sq}^{on}}\right) \tag{3}$$

$L_{sq}^{on}$ depends on:

City parameters

Service quality parameters

For $t^{max} \geq \Delta - t^b$:

$$L_{SQ}^{on} = \frac{v^2\lambda_p}{\Omega}(\Delta - t_b)^3\left(\frac{2}{3*\pi} + \frac{1}{\pi}\sqrt{\left(\frac{t_{max}}{\Delta - t_b}\right)^2 - 1} + \frac{1}{\pi}\left(\frac{t_{max}}{\Delta - t_b}\right)^2 sin^{-1}\frac{\Delta - t_b}{t_{max}}\right), \tag{4}$$

And for $t^{max} < \Delta - t^b$:

$$L_{sq}^{on} = \frac{v^2\lambda_p}{\Omega}(\Delta - t_b)^3\left(\frac{2}{3*\pi} + \frac{1}{2}\left(\frac{t^{max}}{\Delta - t^b}\right)^3\right). \tag{5}$$

| average velocity | operating area | pooling demand | detour time | maximum waiting time | boarding time |
|---|---|---|---|---|---|

### 3.1.3 On-demand ride pooling short-term prebooking system

In this part, the shareability for a short-term ODRP prebooking system, where the passengers have the option to reserve a trip short-term in advance is examined. As a prebooking system is considered in this part, the influence that reserving the trip short-term in advance has on shareability are investigated, hence the impact of a short-term reservation time or prebooking time $t^{res}$ is modelled. In addition, similarly to the previously described instant ODRP booking model, the separate impacts of other SQP are also modelled, and hence the separate effect of the maximum waiting time $t^{max}$ and the detour time $\Delta$ on the possibility to find sharable trips in an area is considered.

**Shareability shadow for short-term prebooking system**

In order to define the shareability for a short-term prebooking system, the example and the problem are the same as stated in *Subsection 3.1.2*. Therefore, solving the problem of finding the shareability for the total operation area, starts with solving the problem of defining where the origin and destination of trip $T_x$ could be in order for this trip to be shareable with trip $T_a$. As mentioned, the shareability shadow is a key aspect to find these areas, which consequently contribute to derive the shareability in an operating area.

The main difference between the short-term ODRP prebooking system and the instant ODRP booking system is that in the prebooking system the influence of the reservation time $t^{res}$ is also considered. As the shareability shadow is constructed by taking into account the impact of SQP, due to the additional SQP of the reservation time $t^{res}$ included in the prebooking system, the shareability shadow of this ODRP system therefore should consider also the impact of the reservation time. Hence this difference is the main contributor to the alteration between the instant and prebooking shareability models in this thesis.

The shareability shadow for the short-term prebooking system is given in Figure 3.2. Trip $T_a$ is specified by its origin $O_a$, destination $D_a$ and the starting time $t_a$, where the red line is the trip trajectory. The shareability shadow is specified by the time constraints imposed by the SQP, which specify the area where the origin and destination of a trip $T_x$ should be in order to be shareable with trip $T_a$. Firstly, the restriction coming from the detour time $\Delta$ and maximum waiting time $t^{max}$ will be described and then the restriction imposed by the reservation time $t^{res}$ will be explained.

The first restriction comes from the detour time parameter and similar as in the ODRP instant booking system, the grey rectangle with height $2v\Delta$ specifies the restriction imposed by the detour time constraint given by the gray rectangle in Figure 3.2. At the point in time t, the vehicle which serves $T_a$ is located at position $r_a(t)$. As passengers cannot wait longer than a specified maximum waiting time $t^{max}$ for a vehicle to pick them up, the origin of trip $T_x$ is also in this case located in a disk with source $r_a(t)$ and radius $vt^{max}$. The area of this disk is further constrained by the allowed detour time $\Delta$, as the passenger on-board of the vehicle would not allow a deviation larger than its specified initial detour time.

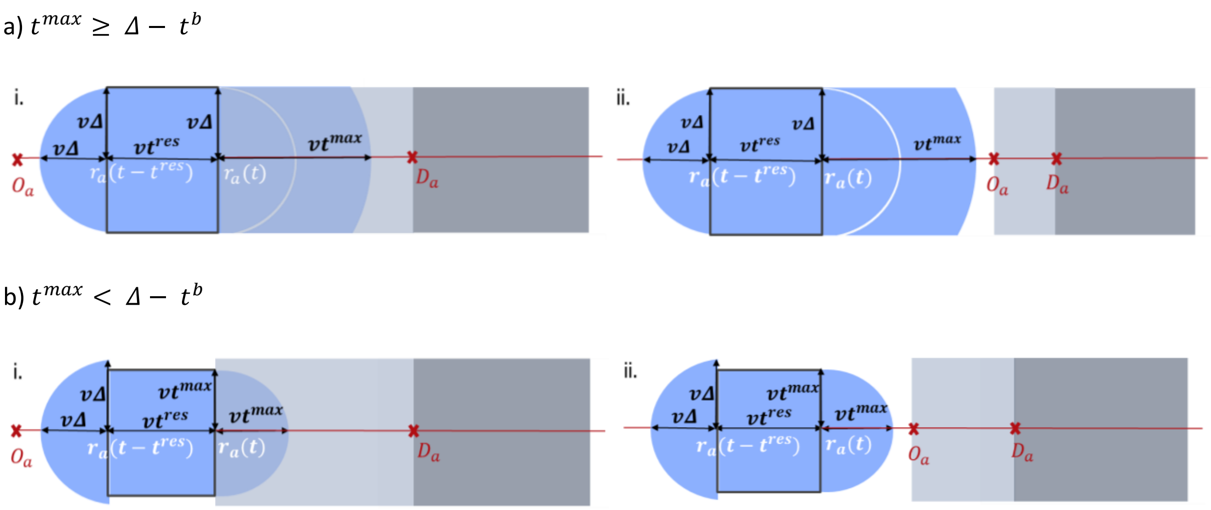



**Figure 3.2** Shareability shadow for the short-term reserved booking system for two main cases: a) Shareability shadow for $t^{max} \geq \Delta - t^b$ and b) Shareability shadow for $t^{max} < \Delta - t^b$. In the forward sharing probability (i.) trip $T_a$ starts before trip $T_x$ and in the backward sharing probability (ii.) trip $T_x$ starts before trip $T_a$.

The main difference of the shareability shadow between the short-term prebooking system and the instant booking system lies in the modelling of the impact of the short-term reservation time parameter $t^{res}$. As reserving a trip short-term in advance is possible in the ODRP prebooking system, the assumption made is that the service operator has knowledge about the generation of new passenger requests a certain time in advance corresponding to $t^{res}$. Based on this assumption, it could be possible for the vehicle positioned at location $r_a(t - t^{res})$ to travel backward of its direction of travel to pick up customers, whose trip origin is located inside a disc with radius $v\Delta$ and center at the point $r_a(t - t^{res})$, while still not deviating from the direct travel time more than the allowed detour time constraint. As the operator has prior knowledge regarding request generation, the vehicle positioned at $r_a(t - t^{res})$ at the point in time $t - t^{res}$ is supposed to serve all the trips with origin inside the bold black rectangle between $r_a(t - t^{res})$ and $r_a(t)$ (Figure 3.2). The short-term reservation time $t^{res}$ defines the length of the rectangle ($vt^{res}$), whereas the height of the rectangle is specified by the smallest of the detour time and maximum waiting time to make sure the fulfillment of both these constraints. Hence, the height of the rectangle is either $2v\Delta$ for $t^{max} \geq \Delta$ or $2vt^{max}$ for $t^{max} < \Delta$. The intersection of the geometric shapes of the above-mentioned areas specified by the detour time, maximum waiting time and reservation time, defines the region where the origin of a trip $T_x$ should be in order to realize a possible match with trip $T_a$.

The relation of different SQP with each other, specifies two different shareability shadows:

a) If maximum waiting time is larger than the detour time ($t^{max} \geq \Delta$), the shareability shadow is given in Figure 3.2.a.

b) If the maximum waiting time is smaller than the detour time ($t^{max} < \Delta$), the shareability shadow is given in Figure 3.2.b.

Like the ODRP instant booking system, for each of the above-mentioned shareability shadows, there are two extra cases, depending on when the starting time of trip $T_x$ is:

i. If the trip $T_x$ starts after the starting time of the existing trip $T_a$, the shareability shadow is given in Figure 3.2.a.i and Figure 3.2.b.i. This is also known as the forward sharing probability.

ii. If the trip $T_x$ starting time is before the starting time of the existing trip $T_a$, the shareability shadow is shown in Figure 3.2.a.ii and Figure 3.2.b.ii. This is also known as the backward sharing probability.

Hence, in order to find a trip $T_x$ which is shareable with an existing trip $T_a$, the origin of $T_x$ should be within the specified blue area so that the detour time, maximum waiting time and reservation time constraints to be fulfilled. In order for the trajectories of the trips to be at least partly shareable, the destination of the trip $T_x$ should be positioned either before the destination of the existing trip $T_a$ (given by the light grey rectangle) or after the destination of the trip $T_a$ (given by the dark grey rectangle).

Additionally, a limit for which a further increase of the reservation time does not result in increased the chances to find shareable trips in an area is designed. Therefore, it is estimated that when the reservation time is higher or equal to two times the maximum waiting time, there is no significant difference in shareability due to the inability of the vehicle to reach all the locations within the bold black rectangle between $r_a(t - t^{res})$ and $r_a(t)$ within the predefined maximum waiting time.

**Shareability model for a short-term prebooking system**

Following the same assumptions and logic described in the Shareability model for instant booking system, the final shareability formula for the short-term prebooking system is analogous to the one given there and is given by Equation (6). Nevertheless, the new dimensionless quantity $L_{sq}^{res}$ reflects the changes in shareability shadow for the short-term ODRP prebooked system, where 'res' refers to the short-term reservation time for the trip booking option and 'sq' refers to the additional service quality parameter impact on shareability. Similar to the instant booking system, two forms of shareability shadows are also noted in this system based on the dependencies between SQP, thus two different formulas of $L_{sq}^{res}$ are depicted (Equation (7) and (8)).

$$S = 1 - \frac{1}{2L_{sq}^{res}}\left(1 - e^{-L_{sq}^{res}}\right)\left(1 - \left(1 + 2L_{sq}^{res}\right)e^{-2L_{sq}^{res}}\right) \tag{6}$$

$L_{sq}^{res}$ depends on:

City parameters | Service quality parameters

For $t^{max} \geq \Delta$:

$$L_{sq}^{res} = \frac{v^2\lambda_p}{\Omega}\Delta^3\left(\frac{1}{2} + \frac{2t^{res}}{\pi\Delta} + \frac{1}{\pi}\sqrt{\left(\frac{t^{max}}{\Delta}\right)^2 - 1} + \frac{1}{\pi}\left(\frac{t^{max}}{\Delta}\right)^2 \sin^{-1}\frac{\Delta}{t^{max}}\right), \tag{7}$$

And for $t^{max} < \Delta$:

$$L_{sq}^{res} = \frac{v^2\lambda_p}{\Omega}\Delta^3\left(\frac{1}{2} + \frac{2t^{max}t^{res}}{\pi\Delta^2} + \frac{1}{2}\left(\frac{t^{max}}{\Delta}\right)^3\right). \tag{8}$$

| average velocity | operating area | pooling demand | detour time | maximum waiting time | reservation time |
|---|---|---|---|---|---|

**Key Takeaways – Shareability Model**

- In this section two different analytical shareability models are developed for an instant and a prebooked ODRP booking system.
- The models capture the impact of the following parameters on shareability:
  - ODRP passenger demand generated per hour $\lambda_p$,
  - city parameters (surface area $\Omega$ and average velocity in the city $v$),
  - SQP (detour time, maximum waiting time, boarding/disembarking time and reservation time).
- These analytical models contribute to fill the first introduced research gap regarding further exploration of SQP impact on shareability by means of analytical modelling.

## 3.2 Analytical Modelling of On-Demand Ride Pooling Traffic Impact

In this section, the traffic impact of ODRP services will be explored by using analytical modelling. The section will start with an introduction to the general model that will be presented in this part. Then, the vehicle trip reduction model as a result of potential pooled trips will be described. Subsequently, modelling of the impact that the vehicle trip reduction has on average velocity in a city will be explained and finally, the modified shareability model, which includes the second order effect that increased average velocity as a result of shared trips has in shareability will be presented.

### 3.2.1 General model set-up

As described in *Subsection 2.2.3*, until now the traffic impacts of ODRP services are indirectly investigated by using the reduction of VKT in the system and considering only the impact of the ODRP fleet, without taking into account the influence of other road users (RG 2.a). Moreover, all the considered studies, with the exception of KE ET AL. [2020] whose approach is theoretical, are performed by using agent-based simulations. The agent-based simulations albeit providing detailed modelling approach, suffer from large amounts of input data and computational time, apart from the concern that the behavior of some agents might not be completely understood. And even in the theoretical study by KE ET AL. [2020], they assumed an ODRP system that used a very simple matching based only on the maximum waiting time and assuming an infinite detour time, which does not realistically represent the operation of an ODRP service (RG 2.b). Moreover, the average velocity in the city is assumed to be constant in most of the ODRP simulation and analytical studies currently available (with the exception of [LEHE & PANDEY, 2020; BILALI ET AL., 2020b]). Consequently, these studies are incapable of capturing the alteration in average velocity in the network due to the impact of pooled trips when an ODRP service is introduced. If the average velocity in the network is higher, the reach of the vehicles within the allowed detour time is higher and hence the chances to find shareable trips will increase. However, the impact that the change of velocity has on the shareability is currently not captured analytically in the literature by the available shareability model from TACHET ET AL. [2017] (RG 2.c).

Thus, to fill the before-mentioned research gaps, this section includes:

- an investigation of the impact of ODRP services in traffic efficiency considering the interaction of the ODRP fleet and other vehicles presented in the network by means of analytical modelling, providing a method in which the effects of influencing parameters are better understood, while saving computational time and requiring few input data (addressing research gap RG 2.a),

- consideration of not only the influence of the maximum waiting time in analytical modeling of traffic impacts of the ODRP service, but also the impact of other SQP, such as detour time, boarding time, reservation time, by using the analytical shareability model (described in the previous *Section 3.1*) as a basis for the ODRP traffic impact model (addressing research gap RG 2.b),
- analytical exploration of the second order effect of velocity on shareability, analyzing the impacts that the reduced vehicle trips due to the ODRP service have on average velocity in the city, and how these impacts influence the shareability results (addressing research gap RG 2.c).

The shareability models described in the previous *Section 3.1* give as an output the percentage of shared passenger trips in a city depending on SQP and city parameters (average velocity $v$ and surface area $\Omega$). The SQP on which these shareability models depend on are detour time $\Delta$, maximum waiting time $t^{max}$, boarding time $t^{b}$ and reservation time $t^{res}$, which are predefined by the service operator and the ODRP passenger demand reflected by the requested ODRP passenger trips per hour $\lambda_p$. Regarding the city parameters, the shareability models in *Section 3.1* assume that the average velocity $v$ does not change as a result of the introduction of an ODRP service in the given city. Hence the average velocity in a city $v$ is always equal to the average velocity of a base scenario $v_0$, i.e., $v = v_0$.

However, as a result of shared passenger trips due to the introduction of the ODRP service, the total number of vehicles in the system is expected to be reduced. The reduction of the vehicle trips in the system depends on the percentage of shared trips in the area for a certain base average velocity $S(v_0)$ and the ODRP passenger demand $g\left(S,\, \lambda_p\right)$. The reduction of vehicles in the system has the potential to increase the average velocity to a higher value $v_1$. As the average velocity is an input for the shareability model, an increase in average velocity consequently means an increase in shareability $S(v_1)$.

The interrelated dependencies between shareability $S$, vehicle trip generation in the system $g$ and average velocity $v$ are illustrated in the loop diagram in Figure 3.3. The analytical model of ODRP traffic efficiency established in this study shows how the ODRP services have the potential to improve the average velocity and to additionally increase the chances to find shareable trips. In the rest of the section, firstly the model of vehicle trip reduction in the system as a result of trip sharing by the ODRP service will be described (the blue box in Figure 3.3). Then the model relating average velocity and vehicle trips generation by using the fundamental diagram of traffic flow will be presented (the orange box in Figure 3.3). The section will conclude with the description of the modified shareability model, which captures the impact that changes on the average velocity (or a dynamic average velocity) have on shareability.

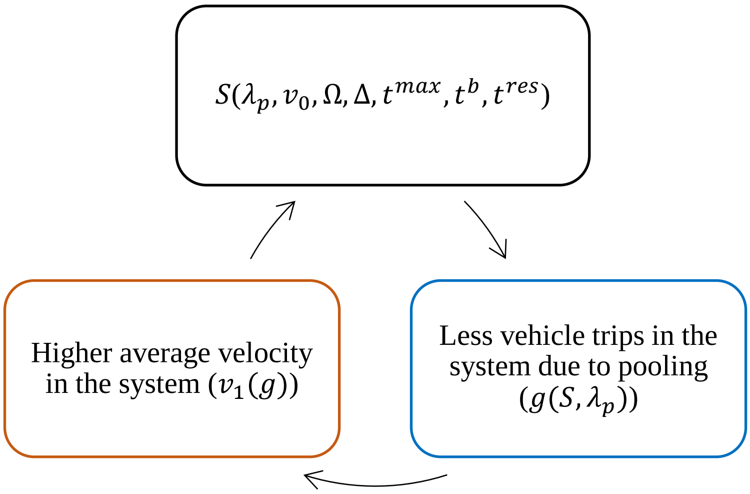



**Figure 3.3** Interrelations of shareability $S$, vehicle trips generated in the system $g$ and average velocity $v$. The number of vehicles in the system is expected to be reduced due to trip sharing $S(v_o)$. This reduction in vehicle trips $g(S, \lambda_p)$ would potentially increase the average velocity in the city to $v_1$. Consequently, the shareability values will further increase $S(v_1)$.

### 3.2.2 Modeling of vehicle trip reduction

In order to model the vehicle trip reduction in the system while considering the interaction of different vehicle types, a system where passengers either use their private vehicles and travel alone or they use an ODRP service and share the vehicle trip with somebody else is assumed. A gradual penetration of the ODRP services is considered, and hence private vehicles and ODRP vehicle fleet will share the same street network.

Firstly, the difference between the passenger trip generation rate $\lambda$ and vehicle trip generation rate $g$ is explained. The former is the total trips generated per hour by passengers and the later represents the total number of vehicle trips generated per hour in the road network. The total generated passenger trips per hour $\lambda$ are composed of passenger trips made alone $\lambda_a$ and requested ODRP (or pooled) passenger trips $\lambda_p$. It should be mentioned here that a requested pooled passenger trip refers only to the generated ODRP passenger trip demand and does not mean that this trip is actually shared with another passenger. Similarly, the total number of vehicle trips generated per hour $g$ is composed of vehicle trips made alone

$g_a$ and pooled vehicle trips $g_p$. Alone vehicle trips per hour $g_a$ represent traveling alone in a private vehicle and is equal to the passenger trip generation rate $\lambda_a$ ($g_a = \lambda_a$). Meanwhile, as passengers can share vehicle trips with each other by using the ODRP service, the number of ODRP vehicle trips $g_p$ depends on the ODRP passenger trip demand $\lambda_p$, the possibility to find shareable trips in an area $S$ and the vehicle capacity $\phi$ as illustrated by Equation (9).

$$g_p = \lambda_p(1 - S) + \frac{S\lambda_p}{\phi} \tag{9}$$

The first part of the equation shows that for the trips that are not possible to be shared, the vehicle trips are equal to the passenger trips and in the second part of the equation, it is shown that for passenger trips which can be shareable, the vehicle trips will be reduced according to the shareability $S$ and the vehicle capacity $\phi$. As shown in the equation, when the shareability is higher than zero, the number of ODRP vehicle trips $g_p$ is going to be lower than the number of requested ODRP passenger trips, due to the simultaneous vehicle trip sharing by the passengers. However, this equation only provides the lowest achievable number of ODRP vehicle trips, as the shareable passenger trips are assumed to have identical origins and destinations and in addition, the empty pick-up trips and reallocation trips are not considered.

Considering both the alone vehicle trips and pooled vehicle trips, allows the calculation of the total number of the vehicle trips generation per hour in the street network which is defined by the following equation for a shareability value derived in Equations (3)-(8) of *Section 3.1* depending if the ODRP booking system is instant or prebooked.

$$g = g_a + g_p = \lambda_a + \left(\lambda_p(1 - S) + \frac{S\lambda_p}{\phi}\right) \tag{10}$$

Having less vehicle trips in the street network has a great potential to improve the average velocity, hence improving the traffic conditions in the city.

### 3.2.3 Modeling of average velocity and vehicle trip generation relation

As vehicle trip reduction in the system offers the opportunity to improve the average velocity, the interrelation of these two parameters will be explored in this subsection by using the benefits of the MFD of traffic flow. Hence, the system-wide impact that the vehicle trip reduction due to the ODRP service has on the average velocity in the city will be modelled analytically.

**Macroscopic fundamental diagram**

As mentioned in the *Subsection 2.2.3*, the MFD, providing a functional form of the relation of average velocity in a city and the traffic density or traffic flow, has been used by researchers also for ODRH [LUO & SAIGAL, 2017; RAMEZANI & NOURINEJAD, 2018] and ODRP [DANDL ET AL., 2021; KE ET AL., 2020] studies. Recently, KE ET AL. [2020] used the benefits of the MFD to build a theoretical model that compares the travel times of ODRH passengers, ODRP passengers and private vehicle users in an attempt to analyze the system-wide traffic impact of an ODRP service. However, they only considered the maximum waiting time for passenger trip matching and assumed an infinite detour time.

The functional form of the MFD connecting the average velocity and flow is found to be similar with that of a parabola. Therefore, in order to derive an analytical relation of the two traffic flow parameters, it is assumed that it resembles the parabolic function given by Equation (11) and illustrated in Figure 3.4, in which the vertex of the parabola is given by V$(q_c, v_c)$, where $v_c$ and $q_c$ are the average velocity and the traffic flow at network's capacity and the parameter $a$ is derived by simulation data fitting.

$$(v - v_c)^2 = 4a(q - q_c) \tag{11}$$

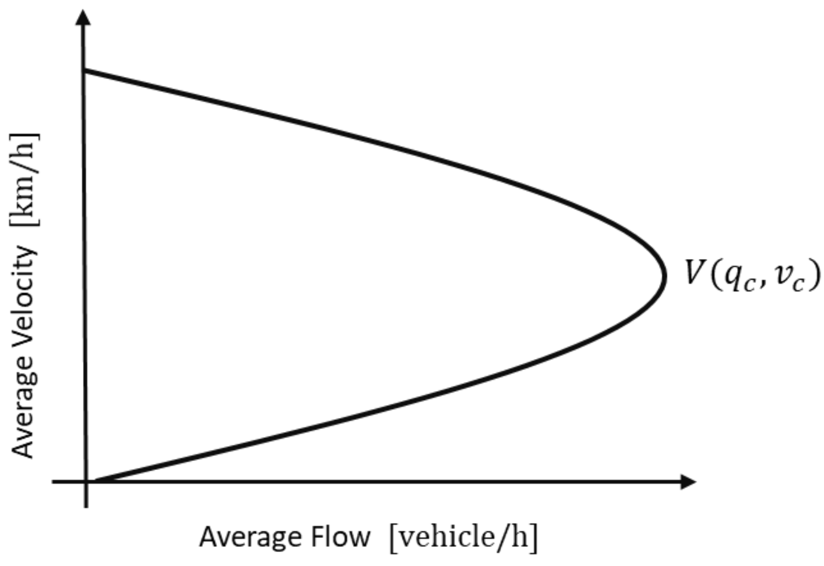



**Figure 3.4** Functional form of an MFD showing the relation of average velocity and average flow.

In this thesis, the benefits of the defined functional form of the MFD are exploited in order to derive an analytical relation of average velocity and vehicle trips generated per hour in the system. There are different ways how an MFD for a city can be derived. An MFD for an urban area is designed here by using microscopic traffic simulations. In order to design the MFD for this thesis by means of simulations, the approach proposed by GEROLIMINIS & DAGANZO [2008] is used. Hence, the average velocity $v_e^i$ and flow $q_e^i$ for each network edge $e$ of length $l_e$ is extracted every time interval $i$, and the weighted average velocity and flow for the whole network are derived by the equations below:

$$v^i = \frac{\sum_{e \in E} v_e^i l_e}{\sum_{e \in E} l_e} \tag{12}$$

$$q^i = \frac{\sum_{e \in E} q_e^i l_e}{\sum_{e \in E} l_e} \tag{13}$$

**Modelling average velocity and vehicle trip generation relation based on MFD**

In this part, a simple method to analytically derive the traffic density of an area is presented. For a general case, an ODRP service offered in the operation area specified by the boundary rectangle in Figure 3.5 is considered.

Four different vehicle trip types exist in this area depending on where their origins and destinations are located:

- vehicle trips type (1), which have both the origin and destination inside the operation area,
- vehicle trips type (2), whose origin is located inside the operation area, but the destination is outside,
- vehicle trips type (3), whose destination is positioned inside the operation area, but their origin is located outside, and
- vehicle trips type (4), whose origins and destination are both located outside the operation area, but their route choice passes through the area.

As an ODRP service offered in a defined operating area is assumed in this thesis, vehicle trips type (1) are the ones of interest as the potential future ODRP vehicle trips. Additionally, as there will be different market penetration rates of ODRP services and the alone vehicle trips are also part of the vehicle trips type (1), the ODRP vehicle trips will coexist with alone vehicle trips. As the ODRP service considered does not serve trips with origins or destinations outside the defined operation area, the background traffic in the network is defined by vehicle trips type (2), (3) and (4). These vehicle trips will remain unchanged during the study, as the effects coming from a scenario where vehicles can park at the border of the operation area and continue the trip inside the city by using the ODRP service are ignored in this study. To derive the traffic density of a pre-defined operating area, the impact of vehicle trips type (1), (2) and (3) are taken into account and the impact of vehicle trips type (4) are neglected assuming that in a large number of urban areas a highway ring belt exists to reduce the pass-through traffic in the city.

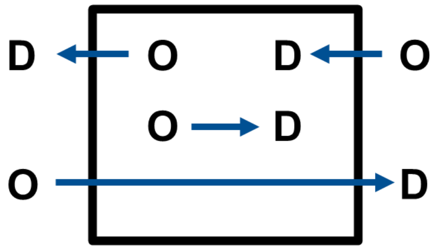



**Figure 3.5** Illustration of different types of vehicle trips in an operating area, depending on where their origin (O) or destination (D) is situated, inside or outside the boundary of the area.

The traffic density of an area of consideration is specified as the average number of vehicles per unit of distance in the area. The average number of vehicles in the area, according to Little's Law is derived by multiplying the vehicle trip generation rate with the average time that the vehicles are present in the system [LITTLE & GRAVES, 2008].

Considering this definition, the traffic density for vehicle trips type (1) $k_{od}$, which have both origin and destination inside the defined operation area, is derived by Equation (14), where the hourly generated number of vehicle trips type (1) is $g_{od}$ (referred to also as $g$ *in Subsection 3.2.2*), the average time the vehicles spend in the system is equal to their average travel duration, where $l_{od}$ is the average trip length for this trip type and $v$ is the average velocity in the area, and the total length of the network is $L$.

$$k_{od} = \frac{g_{od}\frac{l_{od}}{v}}{L} \tag{14}$$

As the defined operation area also contains vehicle trips type (2) and (3), having only the origin or the destination inside the operation area and acting as the background traffic, their contribution in the overall traffic density in this area is considered as well. Therefore, the background traffic density $k_b$ is derived by Equation (15) considering both vehicle trips type (2) and (3). In this equation, the average generated number of vehicle trips per hour which have only the origin (destination) located within the operation area is noted by $g_o$ ($g_d$) and their average vehicle trip length is given by $l_o$ ($l_d$). In contrast to vehicle trips type (1), which are located entirely within the operation area, the vehicle trips type (2) and (3) are partly located within the defined area, hence to capture this effect the parameters $p_o$ and $p_d$ provide the fraction of the vehicle trip length that is located within the operation area for vehicle trips type (2) and (3), respectively.

$$k_b = \frac{g_o \frac{p_o l_o}{v} + g_d \frac{p_d l_d}{v}}{L} \tag{15}$$

The total traffic density of the defined area is then calculated by summing up the contributions of vehicle trips type (1), (2) and (3) to the traffic density and the result is given by Equation (16).

$$k = k_{od} + k_b = \frac{g_{od} \frac{l_{od}}{v} + g_o \frac{p_o l_o}{v} + g_d \frac{p_d l_d}{v}}{L} \tag{16}$$

After substituting $q = vk$ in Equation (16) according to the fundamentals of the MFD, the relation of traffic flow $q$ and vehicle trips generated within the area $g_{od}$ is analytically defined by using the following formula:

$$q = \frac{g_{od} l_{od} + g_o p_o l_o + g_d p_d l_d}{L} \tag{17}$$

The vehicle trips of interest in this study are vehicle trips type (1) $g_{od}$, having origin and destination within the operation area. Therefore, for a given network traffic flow, solving Equation (17) for $g_{od}$, the number of vehicle trips type (1) generated per hour in the system is calculated by using Equation (18).

$$g_{od} = \frac{qL - (g_o p_o l_o + g_d p_d l_d)}{l_{od}} \tag{18}$$

In order to get the analytical expression of the average velocity and the vehicle trips generation rate relation the analytical formulation of the MFD given by a parabola function in Equation (11) is used. Then the traffic flow $q$ is replaced in Equation (11), by the traffic flow and vehicle trip generation relation defined by Equation (17). Hence, the analytical relation of the average velocity $v$ and vehicle trips generated within the operation area of interest $g_{od}$, which is captured by Equation (19), is derived. Mind that shareability on its own, among others depends of average velocity and pooled passenger trips generation rate $S(v, \lambda_p)$. As noticed, the average velocity takes two different values, based on the state of the network of consideration. When the network is in its free flow state, the analytical average velocity is captured by Equation (20) and when the network is in the congested state the average velocity is derived by Equation (21) .

$$(v - v_c)^2 = 4 * (a) * \left(\frac{g_{od}l_{od} + g_o p_o l_o + g_d p_d l_d}{L} - q_c\right) = 4 * (a) * \left(\frac{\left((\lambda_a + \lambda_p(1-S) + \frac{S\lambda_p}{\phi}\right) l_{od} + g_o p_o l_o + g_d p_d l_d}{L} - q_c\right) \quad (19)$$

For $v > v_c$:

$$v = v_c + \sqrt{4 * (a) * \left(\frac{g_{od}l_{od} + g_o p_o l_o + g_d p_d l_d}{L} - q_c\right)} \quad (20)$$

And for $v < v_c$:

$$v = v_c - \sqrt{4 * (a) * \left(\frac{g_{od}l_{od} + g_o p_o l_o + g_d p_d l_d}{L} - q_c\right)} \quad (21)$$

### 3.2.4 Modified shareability model

As mentioned in *Subsection 3.2.1*, the aim of this study is not only to capture the traffic impacts of ODRP service but also to explore the additional impacts that an improved average velocity has on the probability to find shareable trips. Thus, these impacts are elaborated in this part by introducing the modified shareability model, in which contrary to the shareability model by TACHET ET AL. [2017], the velocity parameter is a dynamic one.

*Subsection 3.2.3* describes the methodology used to analytically derive the relation of the average velocity and the vehicle trip generation in the system by using the MFD of a city of consideration and the shareability model, which provides the reduction of the generated vehicle trips per hour in the system given in Equation (10). Hence, the impact that changes in vehicle trip generation rate as a result of the implementation of an ODRP service have on the average velocity of a city or area of interest can be estimated by using this method.

By deriving the relation of the average velocity and the vehicle trip generation rate and by considering that the vehicle trip generation rate depends on the shareability value, Equation

(19) consequently gives also the relation of the average velocity and the shareability. Hence in this model, the velocity parameter is not a constant parameter that does not change when the ODRP passenger trip demand changes, rather the average velocity is considered to fluctuate according to the ODRP passenger trip demand and the design details of the ODRP service, which are reflected in the shareability value calculation.

As a result, the modified shareability model is derived by replacing the dynamic velocity formula given by Equation (19) into the shareability Equations (3)-(8). The modified dimensionless quantity ${L_{sq}^{on}}_{mod}$ considering a dynamic average velocity for the instant ODRP booking system is taken as an example here and its formulas are given in the next equations:

For $t^{max} > \Delta - t^b$

$$ {L_{sq}^{on}}_{mod} = \left(\frac{\left(v(S)\right)^2 \lambda_p}{\Omega}\right)(\Delta - t^b)^3 \left(\frac{2}{3\pi} + \frac{1}{\pi}\sqrt{\left(\frac{t^{max}}{\Delta - t^b}\right)^2 - 1} + \frac{1}{\pi}\left(\frac{t^{max}}{\Delta - t^b}\right)^2 \sin^{-1}\frac{\Delta - t^b}{t^{max}}\right) \tag{22} $$

and for $t^{max} < \Delta - t^b$

$$ {L_{sq}^{on}}_{mod} = \left(\frac{\left(v(S)\right)^2 \lambda_p}{\Omega}\right)(\Delta - t^b)^3 \left(\frac{2}{3\pi} + \frac{1}{2}\left(\frac{t^{max}}{\Delta - t^b}\right)^3\right). \tag{23} $$

If the dimensionless quantity ${L_{sq}^{on}}_{mod}$ or ${L_{sq}^{res}}_{mod}$ are replaced in the general shareability equations (Equation (3) and Equation (6), respectively), a non-linear equation for the shareability value calculation is encountered, which is solved by using the Newton-Raphsod iterative method [VENKATESHAN & SWAMINATHAN, 2014].

$$ F(S) = S - 1 + \frac{1}{2\left({L_{sq}^{\frac{on}{res}}}_{mod}\right)^3}\left(1 - e^{-{L_{sq}^{\frac{on}{res}}}_{mod}}\right)\left(1 - \left(1 + 2{L_{sq}^{\frac{on}{res}}}_{mod}\right)e^{-2{L_{sq}^{\frac{on}{res}}}_{mod}}\right) = 0 \tag{24} $$

**Key Takeaways – Traffic Impact Model**

- The models introduced in this section can explore analytically the traffic impact of an ODRP service by deriving the impact that sharing a vehicle trip with somebody else has on average network velocity.
- Additionally, they can also capture the benefits that the average velocity improvement has on further increasing the percentage of shared trips in the urban environment, as the vehicles can reach further distances during the same amount of detour time as a result of higher network velocity.
- These analytical models contribute to fill the second distinguished research gap (RG2).

## 3.3 Analytical Modeling of On-Demand Ride Pooling Benefits

In this section a general analytical model capturing the system-wide benefits of an ODRP service from the perspective of the customers, operators and cities will be introduced. The section will start with stating the general model set-up. Then, the individual modeling of the impacts of the three ODRP stakeholders: cities, operators and customers (in terms of traffic efficiency, service's profitability for the operator and the customers attractiveness to use the ODRP service) will be described.

### 3.3.1 General model set-up

Albeit ODRP services have been extensively studied, to the best of the author's knowledge a general analytical model which captures the overall impact of ODRP services is currently not available in the literature. One reason for this lack is that the ODRP services are characterized by complex relations between influencing parameters, which are very difficult to be modelled analytically. The approach used in this study is based on the previously developed analytical models of shareability (*Section 3.1*) and traffic efficiency (*Section 3.2*) and allows for a quick estimation of the ODRP service benefits using the advantages of the analytical modelling approach (*Subsection 2.3.2*).

The overall analytical model introduced in this section addresses the final research gap (RG 3) introduced in this thesis and is quite important for a system-wide evaluation of ODRP benefits as this model considers the ODRP service impacts in terms of:

- city benefits regarding improvement in traffic efficiency (represented here by the average velocity in the network) and in which parameter space this would be possible,
- ODRP service monetary profitability for the operator and in which framework conditions that can be achieved (addressing research gap RG 3.a),
- customer attractiveness to use an ODRP service, by answering the question of when would the benefits that a customer receives by paying a lower price for the ride surpass the disadvantage caused by increased customer travel time as a result of the detour time from the trip pooling of the ODRP service.

Moreover, this procedure can derive in which parameter space ODRP services can be beneficial and more specifically it sheds light on the influence of the following aspects:

- For which demand level of the ODRP passenger trips an ODRP system can be beneficial?

- What is the influence that SQP (detour time, maximum waiting time, boarding time, reservation time) can have on the results?
- How do city parameters, such as the level of congestion in a city given by the average velocity and the concentration of ODRP passenger trip demand depending on the surface of the operating area, effect the chances for an ODRP service to be beneficial?

The previously described models of shareability (*Section 3.1*) and ODRP traffic efficiency (*Section 3.2*) are used as a basis for creating the general analytical model capturing the ODRP service impacts in terms of traffic efficiency, operator's profitability and customer attractiveness to the use the ODRP service. The procedure used to model this general system is shown in Figure 3.6.

The shareability model described in *Section 3.1* is the foundation of the general ODRP impact model. This model derives the percentage of shareable trips in an area based on ODRP passenger trip demand $\lambda_p$, city parameters, service quality parameters and network modelling details. The percentage of shareable trips is a key factor to determine the reduction of the number of vehicle trips in the system due to the ODRP service and consequently, the traffic impacts of the ODRP service, which are modelled in *Section 3.2*. In order to derive the profitability of an ODRP service offer, information about the required fleet size, VKT and the trip duration, together with the selected pricing strategy defined by the service operator, would be needed. The output of the vehicle reduction model can be used for the estimation of the required ODRP fleet size and the VKT in the system. While the output of the ODRP traffic impact model, which is the change in average velocity, can be used to derive the new average vehicle trip duration as a result of the ODRP service. Lastly, the customer attractiveness to use an ODRP service is derived by a maximum detour time that the customers would tolerate while getting a cheaper price for the use of the ODRP service as a compensation.

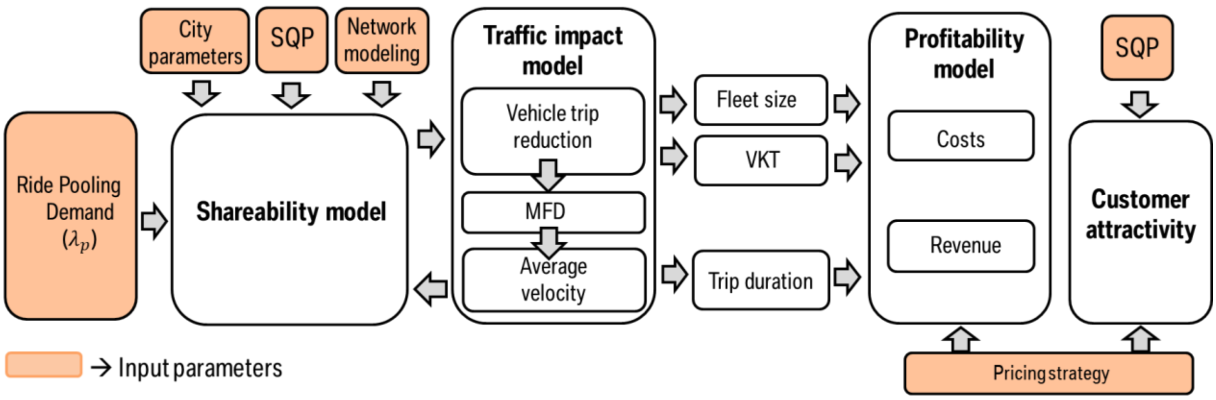



**Figure 3.6** Analytical procedure for estimating the benefits of an ODRP system.

### 3.3.2 Traffic efficiency benefits

In order to derive in which parameter space, the ODRP service can be beneficial from the city perspective in terms of improved average velocity, the model of the average velocity estimation depending of vehicle trips generated in an area explained in *Subsection 3.2.3* is considered. The basis for this model is the shareability model (*Section 3.1*), which provides the percentage of passenger trips which can be shared in an area depending on a set of SQP, ODRP passenger demand $\lambda_p$ and network modelling details. Having this knowledge of shareability for an operation area and the vehicle capacity, the reduction of vehicle trips as a consequence of vehicle trip sharing between customers is derived. Consequently, the traffic impacts of the ODRP service, and hence the change in average velocity, are modelled by using the vehicle trip reduction model and the well-known MFD for a given city (*Section 3.2*). The resulting average velocity formula depending on the number of vehicle trips generated in the system is given by Equations (19)-(20)(21).

The vehicle reduction model described in *Subsection 3.2.2*, assumes that the ODRP passenger trips have similar origins and destinations and therefore the effect of the detour distance is not taken into account. In this part, the general vehicle trip reduction model of *Subsection 3.2.2* is extended to include also the additional vehicle trips caused by the detour distance. Therefore, for the passenger trips which are possible to be shared, the increase in their trip length as a result of sharing and the experienced detour distance is considered. This is modelled by adding to the number of vehicle trips also the added trip length portion as a consequence of the extra detour distance, considering the average trips length to be $l_{od}$. This addition is given by $\frac{v\varepsilon\Delta}{l_{od}}$. As the detour time that is reported from simulation studies is lower than the maximum detour time, for this study the parameter $\varepsilon$ is introduced to account for the experienced detour time in the simulation and hence the added detour distance is $v\varepsilon\Delta$. The total modified vehicle trip number $g_{od_{mod}}$ considering also the detour distance is given by Equation (25).

$$g_{od_{mod}} = \lambda_a + \left(\lambda_p(1-S) + \frac{S\lambda_p}{\phi}\left(1 + \frac{v\varepsilon\Delta}{l_{od}}\right)\right) \tag{25}$$

The impact that the change in vehicle trip reduction will have on the average velocity in a city is then captured by using the model of average velocity and vehicle trip generation in Equations (19) – (21).

### 3.3.3 Operator's profitability

In this part the monetary profitability of an ODRP service for the operator is modelled. The profitability of the ODRP service is calculated by the general revenue minus costs formulation. The costs are calculated based on the estimated VKT and the fleet size of the ODRP fleet, while the revenues are calculated based on the pricing strategy used. As mentioned before, the information about VKT, fleet size, trip duration and pricing strategy used are needed as an input in order to derive the costs and revenues of an ODRP offer.

$$\text{ODRP Profit} = \text{Revenue} - \text{Cost} \tag{26}$$

**ODRP Costs**

Firstly, the VKT of an ODRP service (denoted here at $\text{VKT}_{\text{ODRP}}$) will be derived by using the vehicle reduction model (*Subsection 3.2.2*) as a base and extending it to account also for the detour distance caused while picking up additional passengers. Hence, the $\text{VKT}_{\text{ODRP}}$ are derived via the following formula:

$$\text{VKT}_{\text{ODRP}} = \lambda_p(1-S)l_{od} + \frac{\lambda_p S}{\phi}(l_{od} + v\varepsilon\Delta) \tag{27}$$

For the vehicle trips which are not shareable, the VKT are derived by multiplying the number of non-shareable ODRP vehicle trips $\lambda_p(1-S)$ with the average trip length $l_{od}$ (first part of the formula), whereas for the shareable vehicle trips, the VKT are derived by multiplying the number of these vehicle trips $\frac{\lambda_p S}{\phi}$ with the sum of average trip length $l_{od}$ and the additional detour length driven by the vehicles in a city where the average velocity is $v$. As mentioned before, for most of the ODRP research simulation studies, the actual detour time realized in reality is lower than the maximum detour time. Therefore, the parameter $\varepsilon$ is introduced to capture this aspect and the detour time is therefore $\varepsilon\Delta$ and not the maximum one $\Delta$. The additional travel length to be realized during the actual detour time $\varepsilon\Delta$ is thus $v\varepsilon\Delta$.

The minimum vehicle fleet size required for a certain on-demand service offer, in the context of ODRH, is a topic that has attracted a lot of attention as it is directly related to the initial costs of the ODRP service [Bösch et al., 2018; Negro et al., 2021] and the service quality that can be achieved by this certain fleet size [Vazifeh et al., 2018]. As the detailed investigation of the optimum fleet size is not within the scope of this thesis, in this study is assumed that the cost per kilometer $\kappa_{km}^{p}$ includes the costs of the fleet size and thus, the total costs are a multiplication of the cost per kilometer $\kappa_{km}^{p}$ and the total $\mathrm{VKT_{ODRP}}$, which on its own among others depends on ODRP passenger trip demand $\lambda_p$, the shareability value $S$, vehicle capacity $\phi$ and average trips length $l_{od}$. The shareability value moreover depends on SQP, city parameters and network modelling details. The total cost formula is shown in the equation below:

$$\mathrm{Cost} = \mathrm{VKT_{ODRP}} * \kappa_{km}^{p} = \left(\lambda_p(1-S)l_{od} + \frac{\lambda_p S}{\phi}(l_{od} + v\varepsilon\Delta)\right)\kappa_{km}^{p} \tag{28}$$

**On-demand ride pooling revenues**

The revenue of the ODRP service depends on the ODRP passenger trip demand $\lambda_p$ and the pricing strategy used by the service operator. The pricing strategy used can be based on travelled distance, travel time, considering both travel distance and travel time or other. Conditional to the used pricing strategy, the revenue also depends on average trip length, average velocity, and the defined price per kilometer $\gamma_{km}^{p}$ and price per minute $\gamma_{min}^{p}$ value that the customers have to pay in order to use the ODRP service.

For the case when the pricing strategy used is based on distance, the direct travel distance is considered assuming that the customers would not be willing to pay for the deviation needed to pick up additional passengers, thus the revenue calculation where price is based only on distance for a price per kilometer $\gamma_{km}^{p}$ is shown in the formula below:

$$\mathrm{Revenue_{DISTANCE}} = \text{Direct travel distance} * \gamma_{km}^{p} = \lambda_p l_{od} \gamma_{km}^{p} \tag{29}$$

A similar approach is used for the case when price is based on the travel time, where only the direct travel time for a trip with average length $l_{od}$ in a city with average velocity $v$ is used. The resulting formula for a price per minute value of $\gamma_{min}^{p}$ is given by Equation (30). If the impact of ODRP service on average velocity is taken into account, the new average velocity could be derived by using Equations (19)-(20)(21).

$$\mathrm{Revenue_{TIME}} = \text{Direct travel time} * \gamma_{min}^{p} = \lambda_p \frac{l_{od}}{v} \gamma_{min}^{p} \tag{30}$$

Consequently, if the pricing strategy is based both on distance and time, the revenue calculation formula is defined by the equation below:

$$\text{Revenue}_{\text{DISTANCE\&TIME}} = \lambda_p l_{od} \gamma_{km}^p + \lambda_p \frac{l_{od}}{v} \gamma_{min}^p \tag{31}$$

### 3.3.4 Customer attractiveness for shared rides

As described in *Subsection 2.2.1*, customer willingness to use the ODRP service depends mainly on the willingness to share a trip with somebody else, SQP and the price. Consequently, the customers would accept the discomfort of sharing a trip with somebody else and deviate from the direct travel distance only if they are offered a cheaper price compared to the available options. Studies have shown that users who are more willing to use the ODRP service are the ones who are already using other on-demand mobility options [LAVIERI & BHAT, 2019]. Therefore, the customer attractiveness to use the ODRP service is compared in this case with the ODRH service. In order to derive an upper bound for the detour time that the customer would be willing to accept for a reduced price compared to ODRH service, a utility-based approach is used, similar to the one introduced by KUCHARSKI & CATS [2020].

The utility of using an on-demand service (hailing or pooling) is defined based on price and time and is given in Equation (32) and (33) accordingly. The logic here will continue by assuming that the price that the customers must pay for a trip depends only on the trip distance. Therefore, in order to monetarize the trip performed with on-demand mobility services, the trip length $l_{od}$ is multiplied by the price per kilometer for the hailing $\gamma_{km}^h$ and pooling $\gamma_{km}^p$ service, respectively. The parameter $\beta_c$ in the equations represents the cost sensitivity.

The travel time of a customer includes the time a customer spends waiting for the vehicle to pick her up $t^{max}$ and the in-vehicle travel time. In the case of the ODRH service the travel time is equal to the direct travel time given by $t_{od}$, whereas for the ODRP service case the travel time equals to the direct travel time plus the given maximum detour time $\Delta$. The maximum detour time is used in this case, as the perceived detour time for the customers is considered to be the one that is specified initially by the operator and not the realized one. To monetarize the travel time, its value is multiplied by the value of time given by the parameter $\beta_t$. As passengers usually perceive waiting time as longer than the travel time, the parameter $\beta_w$ is added to encounter for this aspect. The customers using an ODRP service also experience a discomfort during their ride as a result of sharing the trip with somebody else, that is why the parameter $\beta_p$ is added to capture the discomfort of a pooled trip [ALONSO-GONZÁLEZ ET AL., 2020a].

Hence, the utility of an ODRH service is given by the equation below:

$$U_i^h = \gamma_{km}^h \beta_c l_{od} + \beta_t (t_{od} + \beta_w t^{max}) \tag{32}$$

Whereas the utility of an ODRP service is given by the equation below, assuming that the waiting time that the passenger waits to get picked up is the same for ODRH and ODRP services:

$$U_{i,r}^p = \gamma_{km}^p \beta_c l_{od} + \beta_t \left(\beta_p (t_{od} + \Delta) + \beta_w t^{max}\right) \tag{33}$$

When the difference in utilities given by Equation (34) is higher than zero, it provides the service quality boundary showing when the customers are willing to use the ODRP service instead of the ODRH service.

$$U_{i,r} = U_{i,r}^p - U_i^h = (\gamma_{km}^p - \gamma_{km}^h)\beta_c l_{od} + \beta_t \beta_p (t_{od} + \Delta) - \beta_t t_{od} \tag{34}$$

Thus, the customers would be willing to accept a detour time of $\Delta_{\text{accepted}}$, given by the formula below, for a certain reduction of ODRP price compared to ODRH price:

$$\Delta_{\text{accepted}} < \frac{\beta_c}{\beta_t \beta_p} \left(\gamma_{km}^h - \gamma_{km}^p\right) l_{od} - t_{od} \left(1 - \frac{1}{\beta_p}\right) \tag{35}$$

In this way, a boundary of the detour time service quality parameter is defined showing that the customers would accept the discomfort of ODRP service by sharing the trip with somebody else and a maximum increase in travel time given by the detour time $\Delta_{\text{accepted}}$, only if a certain reduction in price compared to the ODRH service is guaranteed.

**Key Takeaways – General ODRP Model**

- The models presented in this section explore analytically the benefits of an ODRP service from the perspective of cities, operators and customers.
- The system-wide evaluation of ODRP benefits presented here, considers:
  - city benefits – impact of ODRP service in average velocity improvement in the network and in which parameter space (e.g., ODRP passenger demand and SQP set) this would be possible,
  - operator's monetary profitability – in which framework conditions (e.g., ODRP passenger demand and SQP set) that can be achieved,
  - customer attractiveness toward the use of the ODRP service – how it is influenced by the ODRP price, the value of time and the discomfort of sharing.
- The analytical models presented in this section address the final research gap (RG 3).

# 4. Simulation Configuration

In this chapter the simulation configuration will be provided. The chapter will start with a description of the operating of the ODRP service used to validate the ODRP analytical models developed in *Chapter 3*. Then the simulation frameworks used for the validation will be explained, starting with the explanation of an ODRP agent-based simulation and continuing with the description of a microscopic traffic simulation model of the city of Munich.

## 4.1 On-Demand Ride Pooling Operation Area

In order to test the established analytical models an ODRP service is assumed to operate in the Munich area shown in Figure 4.1, which is positioned around the city center of Munich. The ODRP operation area has a surface of 221 km$^2$ and a total network length of 2450 km. The selected operation area in this study is determined by a demand driven analysis which showed a higher concentration of private vehicle trip origin-destination (OD) relations in the vicinity of the city center of Munich and hence, the resulting compact operating area is shown in Figure 4.1 [ENGELHARDT ET AL., 2019a].

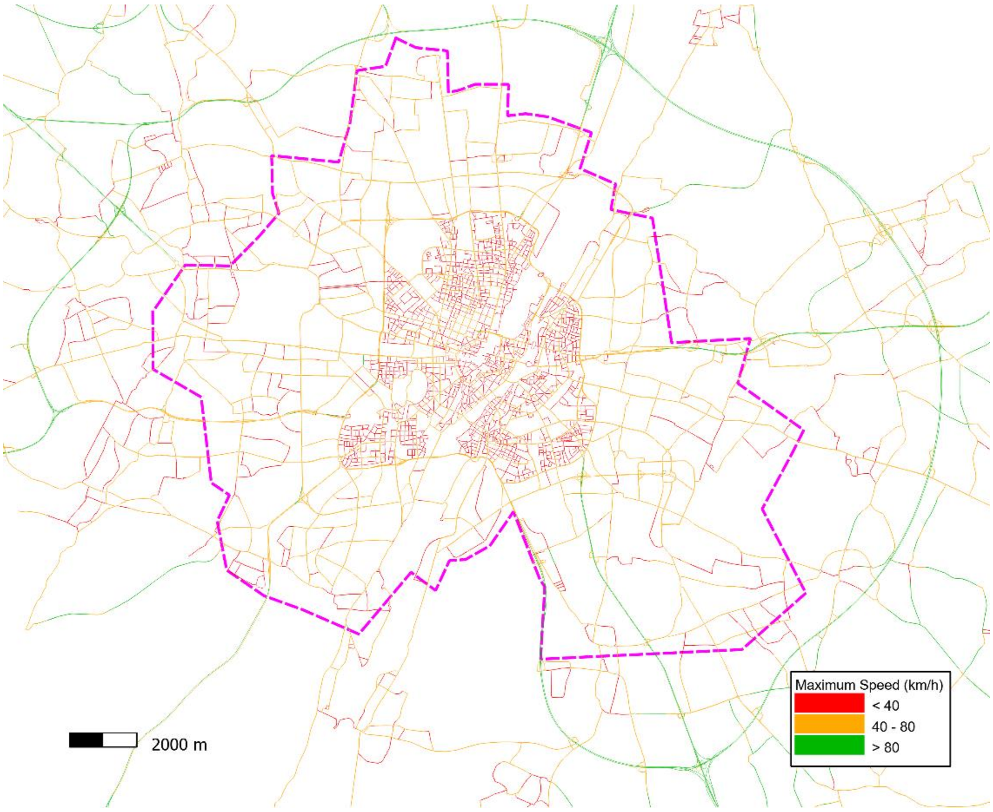



**Figure 4.1** Munich operation area of the ODRP service.

The given operation area contains 154 districts, and each district is represented by a centroid. The demand of private vehicle trips within this area is defined based on OD matrices, which specify vehicle movement between the centroids. In order to access the network, vehicles start and end their trip in what are called as access points, which are positioned near to the main streets of the network. Each centroid is linked to a group of access points. The Munich network of consideration contains 1423 access points. The vehicle trips start randomly from these access points based on the entries of the OD matrices. The OD data of private vehicle trips represent the private vehicle demand for an average working day in Munich measured every 15 minutes. The accumulation of OD matrices reflects 1.2 million daily private vehicle trips performed within Munich operating area.

Assuming gradual market penetration rate of ODRP service, private vehicle trips are replaced with pooled vehicle trips based on different penetration rate of the service. Detailed scenario design will be described in the following chapter in *Chapter 5*.

## 4.2 Simulation Frameworks

In order to test the developed ODRP analytical models for an ODRP service operating in the city of Munich, an agent-based simulation and a microscopic traffic simulation are used. For testing the first analytical shareability model presented in *Section 3.1* and capturing the impact of SQP on the percentage of shareable trips in an area, an agent-based simulation is used. Whereas to validate the ODRP traffic impact model illustrated in *Section 3.2* and exploring the system-wide traffic impact of an ODRP service, a microscopic traffic simulation is used.

### 4.2.1 Agent-based simulation

An agent-based simulation is chosen to compare the analytical model of ODRP service quality parameters impact (*Section 3.1*), as it provides detailed modelling of the ODRP system and thus, it can be observed if the complex interaction of the system can be represented by the developed analytical model and what is the impact of the assumptions made for generating close expressions. The agent-based simulation used in this study is based on [ENGELHARDT ET AL., 2019b; BILALI ET AL., 2020a] and is extended to model the ODRP system in different level of network modelling details. An explanation on the general ODRP agent-based framework will be provided in this part. ENGELHARDT ET AL. [2019b] provide more details about the algorithm and the comparison of this framework with an insertion heuristic one.

### General agent-based simulation setup

The main agents of the simulation framework are the customers of the ODRP service, the vehicles, which serve these customers, and the fleet operator, who offers the ODRP service and decides the order in which passenger requests are served by vehicles.

The state of the ODRP vehicle fleet is updated every time steps of 1s, during which vehicles may move toward their destination, new request may enter the system and current customers might encounter a vehicle boarding or alighting process, which similar to the analytical model is supposed to be $t^b$. In the case the vehicle does not have a request assigned to it, the vehicle remains in the current location. The optimization algorithm used by the fleet operator to calculate new vehicle assignments is performed every decision time step of 30 seconds and not every simulation step of 1 second, due to its high computational time. The framework of the agent-based simulation assignment procedure is illustrated in Figure 4.2.

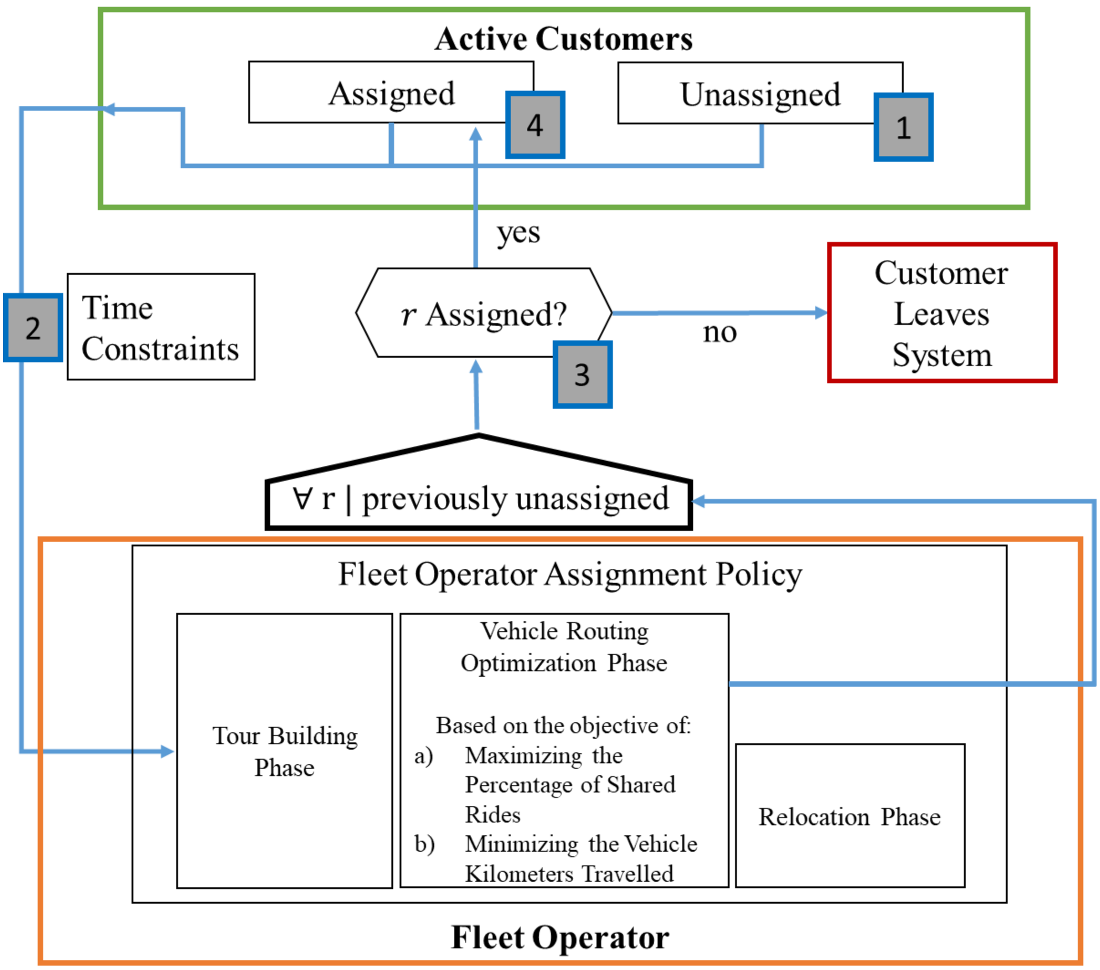



**Figure 4.2** Agent-based simulation framework assignment procedure based on [BILALI ET AL., 2020a].

**Network topology modelling**

In order to investigate the influence that different depth of network modeling of the ODRP system have on the shareability results, the operating area is modelled by using two different network topologies. The network topologies considered in this study are Euclidian topology and street network graph. The street network graph is divided in two different topologies depending on if the average velocity in the network is constant or variable. A detailed description of these types of topologies is provided below:

- The first topology used to model the ODRP operating area corresponds to what is referred here as **Euclidian topology** (T: E). In this network topology vehicle move from one position to the other within this operation area by following bee lines, the location of the vehicles and the positions of customer trips origin and destination are given as 2D-coordinates and travel distances between two locations are calculated based on Euclidian distance. Assuming a certain average network velocity $v_0$ during the whole simulation, the travel times are thus derived.
- The second topology is a **street network graph**. For this type of network topology, a given street network is represented by the graph $G = (N, E)$, where $N$ are nodes of the graph corresponding to network intersections and $E$ are edges, representing different streets in the network. Customers are supposed to start or end their trip in what are named as access points, which correspond to a set of nodes in the network $N_a \in N$. Vehicles travel through the network after the fleet operator calculates the vehicle routes. Consequently, the routes of the vehicles are represented by a sequence of nodes and edges in $G$ which show how two points with given origins $O \in G$ and destinations $D \in G$ are connected. The route calculation is based on the information of the edge travel time. The routes with the shortest time, and hence travel times and travel distances for these routes, are calculated by using a Dijkstra algorithm with preprocessing methods [DELLING ET AL., 2009] or by using preprocessed travel times among access points. In order to define the time a vehicle needs to traverse an edge $e \in E$, a time-dependent travel time $t_e(t)$ is given to each edge. To capture the impact of inhomogeneous travel times, for the same street network graph, two different cases are distinguished:
    - Street network topology, where the average travel velocity in each edge is the same. (T: G Avg)
    - Street network topology, where for each hour there are different average velocities for each edge extracted from a microscopic traffic simulation. (T: G)

**Customers**

A customer who wants to use the ODRP system and travel from a certain position to another one, at the point in time $t_r$ can send a request to the system (by using a smartphone app for instance), specifying the position where she wants her trip to start $O_r$ and end $D_r$. When the customer request enters the system for the first time, it belongs to the unassigned “Active Customers” group (Figure 4.2: green rectangle, point 1). In accordance with the analytical model, the customer is willing to wait a maximum amount of time given by $t^{max}$ to get picked up and she accepts a maximum temporal deviation from the direct travel route or detour time of $\Delta$. For a prebooking ODRP system, which allows reservation of requests, the customer can prebook her ride $t^{res}$ time in advance. In the succeeding decision time step, the service operator decides whether to accept or reject the customer request. In the case when the request is accepted, the operator must serve the customer within the defined SQP or time constraints (Figure 4.2: point 2), which are checked during the fleet operator assignment policy phase (Figure 4.2: orange rectangle). If this is not possible and the request is unassigned (Figure 4.2: point 3, “no”), the customer leaves the system unserved (Figure 4.2: red rectangle). If the time constraints are fulfilled and the request is assigned (Figure 4.2: point 3, “yes”), then the customer request enters the group of assigned “Active Customers” (Figure 4.2: green rectangle, point 4).

**Fleet operator**

The operator’s vehicle fleet is comprised of a size of $N_v$ alike vehicles, having a certain capacity $\phi$ to accommodate customers on board. The vehicles of the ODRP vehicle fleet drives in the operation area and carry customers from a specific origin to a specific destination. The decision to serve which customer and at which time in an efficient way is made by the fleet operator. Mathematically, this decision is derived by the vehicle routing objectives defined by the fleet operator and a policy, given by a set of rules to achieve these objectives which need to be optimized, while guaranteeing that the customers will be served within the given time constraints [ENGELHARDT ET AL., 2019b].

The fleet operator algorithm used in this study contains three main phases performed during the following decision time steps: the tour-building phase, the vehicle routing optimization phase, and the relocation phase (Figure 4.2: orange rectangle). An explanation of these phases will be described below.

*Tour-building phase*

The purpose of the tour-building phase is to derive for each vehicle of the ODRP fleet all possible feasible tours necessary to accommodate the active passenger requests in the system. In the next phase, these tours will serve as a solution space to achieve the objective of the vehicle routing optimization. In general, a tour is an ordered set of boarding and disembarking stops for a set of requests and a specific vehicle. Whereas a feasible tour for a vehicle is defined as a tour satisfying all the time constraints imposed by the SQP and customer boarding or disembarking at the access points in the network, while making sure the number of customers inside the vehicle does not exceed $\phi$. The idea of the construction of the tour algorithm is based on [ALONSO-MORA ET AL., 2017] and is adopted by [ENGELHARDT ET AL., 2019b]. Every feasible tour that a vehicle $v_x$ can follow to serve a certain set of requests $\{r_{i1}, r_{i1}, r_{i1}, \dots, r_{in}\}$ is bundled to what is called a Vehicle-To-Request-Bundle (V2RB).

*Vehicle routing optimization phase*

In order to solve the vehicle route assignment problem for the ODRP service, the selected objectives need to be firstly defined. The primary objective is to serve as many customers as possible. While there are two different secondary objectives considered in this study. These objectives are responsible for rating every feasible tour based on what is expected to be achieved from them.

The first vehicle routing optimization objective used in this study is to maximize the percentage of trips that is possible to be shared in the operation area. Hence, for this optimization function the number of shareable requests, is the used rating parameter. The second vehicle routing optimization objective considers the perspective of cities, which require decrease in VKT in the whole city and operators, which require low operational costs (also a consequence of lower VKT). Thus, the selected optimization objective is to minimize the VKT achieved by computing the “saved distance” of each tour. In the absence of the ODRP system, the total driven distance of all the requests $r$ that a tour contains would be equal to the sum of their direct travel distance $d_r^{direct}$. In the presence of the ODRP system the driven distance of a tour, which contains also shared passenger trips within a vehicle, is given by $d_\xi$. Hence, for a given tour $\xi$, its saved distance is calculated by subtracting the total driven distance of all the requests of the tour in the absence of the ODRP system and the driven distance of the tour $d_\xi$ in the presence of an ODRP system, given by the equation below:

$$U[\xi] = \left(\sum_{r\in\xi} d_r^{direct}\right) - d_\xi \tag{36}$$

The global vehicle routing objective is to maximize either the percentage of shareable trips or the saved driven distance (depending on the selected objective), while maximizing the number of served requests. The vehicle routing optimization problem can be expressed as an Integer Linear Problem, where each V2RB is rated by the highest objective value of its corresponding tours, given by the set of equations below:

$$\max_{z,x}: \quad \sum_{k,j} u_{kj} z_{kj} - \sum_i V_p\, x_i \tag{37}$$

$$\text{s. t.:} \quad x_i + \sum_{k\,\in K(i)} \sum_j z_{kj} = 1 \;\forall\, i \mid r_i \in R_u, \tag{38}$$

$$\sum_{k\,\in K(l)} \sum_j z_{kj} = 1 \;\forall\, l \mid r_l \in R_a, \tag{39}$$

$$\sum_k z_{kj} \le 1 \,\forall\, j\,. \tag{40}$$

The global objective is given by Equation (37), where $u_{kj}$ represents the objective value of the V2RB of vehicle $j$ which accommodates the request-bundle $k$ and $V_p$ is a penalty value. When the penalty value is high, it shows that the objective of maximizing the assigned requests is the prioritized one. In the case the equivalent V2RB is assigned, the decision variable $z_{kj} \in \{0,1\}$ take the value of 1 and if not, it takes the value 0. Equation (38) makes sure that each customer request $i$, which is part of the unassigned set of requests $R_u$, is maximally allocated in only one V2RB $k$ that holds the request $i$ part of the request-bundle $K(i)$. For an unassigned request, the decision variable $x_i \in \{0,1\}$ gets the value 1, and 0 otherwise. In this model re-assignments are possible and therefore, Equation (39) is used to guarantee each customer request that belongs to the group of already assigned requests $R_a$ is re-assigned again. Equation (40) assures that each vehicle $j$ is assigned to only one V2RB.

*Relocation phase*

In order to cope with the problem of vehicles being positioned in unfavorable areas with low demand and unable to serve customers in other high demand areas within the allowed time constraints, a basic reallocation strategy is used. The operation area is separated into regions and the alteration of the anticipated demand and supply within each region is computed for a duration of 30 minutes in order to derive the excess in demand within the region. Every 5 minutes an optimization problem is solved and reallocated vehicles which are idle in the anticipated high demand regions to accommodate the unfulfilled demand. As a detailed description of relocation procedures is not within the scope of this thesis, more information on the reallocation procedure used here are provided in [ZHANG & PAVONE, 2016].

### 4.2.2 Microscopic traffic simulation

A microscopic traffic simulation is selected for the evaluation of the ODRP traffic impact model presented in *Section 3.2*, as this type of simulation gives the possibility to capture in detail the dynamics of traffic for the whole city. Thus, not only the ODRP fleet is modelled, but also other vehicles present in the network. This gives as the opportunity to investigate the system-wide change in average velocity due to the introduction of an ODRP service in the whole city, which is not possible to be investigated by the currently used ODRP agent-based simulations.

The microscopic simulation environment used in this part is AIMSUN [BARCELÓ & CASAS, 2005]. The microscopic traffic simulation model for Munich built in AIMSUN is similar to the one used by DANDL ET AL. [2017]. This model includes Munich region restricted by the federal highway A99, where the arterial network within this region contains detail information about the road infrastructure, the number of lanes, the capacities, and the corresponding speed limit. Every street within the city center of Munich enclosed by the inner ring is constructed in the microscopic simulation as shown also in Figure 4.1. A detailed modelling of the intersection geometry and the traffic signal configuration is provided, where the actual traffic signal plan of 70 intersections was acquired from the city of Munich and the rest were adopted to fit the demand [DANDL ET AL., 2017]. The calibration of the network was performed by using loop detector data. More details regarding the AIMSUN microscopic traffic simulation model of Munich used in this study can be found in [DANDL ET AL., 2017].

In this model the traffic demand for ODRP service and the private/alone vehicles is generated in the form of OD matrices depending on the penetration rate of the ODRP service and the possibility to find shareable trips in the area defined by the shareability model. More details about the scenarios tested will be provided in the following section.

# 5. Evaluation and Results

This chapter will provide a detailed analysis of the validity of the developed analytical models. Firstly, in *Section 5.1* the validation of the analytical model describing the impact of the SQP on the percentage of shared trips in an area by means of an agent-based simulation model is explained. Secondly, the validation of the analytical model capturing the impact that an ODRP system have on traffic efficiency is validated by using a microscopic traffic simulation is described in *Section 5.2*. Thirdly, the impact of the ODRP model in traffic efficiency, operator's profitability and customer attractiveness toward the service will be described in *Section 5.3*. Then, *Section 5.4* will provide an illustration of the parameter space in which the ODRP win-win-win-win situation can be achieved. And lastly, the main results of the chapter will be discussed in *Section 5.5*.

## 5.1 On-Demand Ride Pooling Shareability Evaluation

In this part the analytical model capturing the impact of SQP on the percentage to find shareable trips in an area given in *Section 3.1* will be validated by means of the agent-based simulation framework described in *Subsection 4.2.1*. The results of the validation of the instant booking ODRP model are explained here, where firstly the developed scenarios will be explained and then the results of the validity of the analytical model for different demand level, network modelling details and SQP will be presented. The validation of the short-term prebooked ODRP model can be found in [Bilali et al., 2019].

### 5.1.1 Scenario design

This part offers information about ODRP passenger demand, vehicle fleet size choice and different types of network topologies modelled to assess the validity of the analytical model depending on the used modelling details. Lastly, the scenario design and the evaluation procedure used to assess the results is described.

**ODRP passenger demand**

As previously mentioned, the validity of the analytical model in *Section 3.1* which derives the percentage of trips which can be shared in an area or shareability, is tested for an ODRP system in the city of Munich where private vehicle trips are substituted with ODRP vehicle trips in different levels of market penetration. Therefore, the available private vehicle data of Munich is subsampled to account for small market penetration rate, varying from 0.1% to 5% of private vehicle trips in Munich. In order to get the new subsampled data of OD matrices for the ODRP passenger trip generation, the total OD matrices of private vehicle trips in Munich are multiplied with the selected demand penetration rate. The demand of ODRP passenger requests is formed by using Poisson processes and three different seeds are created for the whole day. Given the specific OD-relation, an access point within the region of origin or destination is selected randomly as a starting or ending point for a passenger request, respectively.

**ODRP Vehicle supply**

In the analytical model fleet size is not explicitly considered, but it is assumed that a vehicle from the ODRP vehicle fleet will be available instantly at the origin of the generated request. However, in reality the selection of the fleet size has a high influence on the performance of the ODRP system and hence on the shareability results. If the selected fleet size is too small and not capable to accommodate a given ODRP passenger trip demand, then a lot of passenger trips will be rejected. In this undersaturated state, the fleet control objective of serving as much customers as possible is dominating the assignment of vehicle tours and the flexibility on choosing specific (i.e., shared) routes is limited. Therefore, the shareability results will be thereby influenced. As a result, in this study a large enough fleet size is used to be able to satisfy the ODRP passenger trip demand without encountering this problem. Therefore, a fleet size ranging from 100 to 1500 vehicles, depending on the given ODRP passenger trip demand, fulfilled this requirement. Simulations have shown that for fleet sizes larger than the selected one in the study the results remain stable. The vehicles are initially randomly spread between access points in the network according to probabilities proportional with the anticipated ODRP passenger trip demand of the entire day at these access points.

**Network topologies**

In order to evaluate the validity of the analytical model in *Section 3.1* and to investigate the impact of modelling details, the network is modelled in different modeling depths. Thus, three types of network topologies are designed, where vehicles move in the network according to vehicles routes specified by the algorithms used to find shareable trips:

- Euclidian topology (T: E), where vehicle move from one position to the other within the operation area by following straight lines.
- Street network graph, where the average travel velocity in each edge is the same. (T: G Avg)
- Street network graph, where for each hour there are different travel times corresponding to each edge. (T: G)

The network average velocity is extracted from the microscopic traffic simulation described in *Subsection 4.2.2* and is equal to $v_o = 28.8\frac{km}{h}$. This value is derived by dividing the total sum of all the length of the edges with the total travel time of all edges using Equation (12). This average velocity is used for the Euclidian topology (T: E) and for the street network graph with homogeneous average travel velocity (T: G Avg). Whereas for the street network graph with inhomogeneous edge travel time (T: G), the edge travel time is extracted from the microscopic traffic simulation every hour.

**Scenarios and evaluation procedure**

The analytical model presented in *Section 3.1* derives the shareability value in a given operation area and for a set of SQP, such as maximum waiting time, detour time and boarding/alighting time, depending on the ODRP passenger trip request demand level $\lambda_p$. Thus, the analytical model shows how the percentage of possible shared trips in an area changes depending on different demand levels. The validity of this analytical model is tested by using the simulation framework explained in *Subsection 4.2.1* and the previously described simulation setup for various scenarios.

Each scenario contains the same network topology, SQP and vehicle routing objective function. A set of simulations define one scenario. These simulations have the same network topology, SQP and objective function, but different selected ODRP fleet size and demand share, given as a portion of the private vehicle trips in Munich. Each of the simulations represents a 24-hour ODRP service operation time. The results of each simulation are split in 30-minutes bins, which compared to the average trip length is 2.5 times higher and thus the spill over of trips among time bins is reduced. For each time bin $t$ the following values are calculated:

1. The modified pooled/ODRP passenger request generation rate $\rho(t)$ given by the equation below:

$$\rho(t) = \frac{\lambda_p(t)}{\Omega}\frac{v(t)^2}{v_o^2} \tag{41}$$

   In Equation (41), $\lambda_p(t)$ is the ODRP passenger demand generated in a given time, which is considered to be an exogenous parameter for this study. The surface of the operation area is given by $\Omega$ and the average velocity in this area for a given point in time is given by $v(t)$. To capture the impact of inhomogeneous travel velocity within the 30-minutes time bins, the average velocity parameter $v(t)$ is scaled out by dividing it with a base average velocity value $v_o$.

2. The theoretical shareability or the experienced shared rides:
   a. **The theoretical shareability value** is found by dividing the number of passenger requests for which a shared ride could **theoretically** be found $\lambda_{S,th}(t)$ with the total number of passengers requesting an ODRP ride $\lambda_p(t)$ within the given time bin $t$ and is shown in the following equation:

$$S_{th}(t) = \frac{\lambda_{S,th}(t)}{\lambda_p(t)} \tag{42}$$

   In a given time bin, the number of passenger requests which belong in at least one of the tours defined in the tour building algorithm phase in which a shared ride could be possible is given by $\lambda_{S,th}(t)$. However, this value is considered theoretical, as it is not guaranteed that this tour would be assigned to a vehicle in the optimization phase.
   b. **The experienced shared rides value** is found by dividing the number of passenger requests, which truly **experience** a shared ride $\lambda_{S,e}(t)$ with the total number of passengers requesting an ODRP ride $\lambda_p(t)$ for a given time bin $t$ (Equation (43)). To 'truly experience a shared ride' means that these passengers partially share the trip with somebody else in the simulation environment.

$$S_e(t) = \frac{\lambda_{S,e}(t)}{\lambda_p(t)} \tag{43}$$

Combining the set of simulations results which built one scenario, gives the final shareability results for one scenario. To avoid discrepancy in results due to unserved ODRP passenger requests, the data points for which the relative number of served requests within a time bin is lower than 95% are omitted from the evaluation. The $\rho$-axis is further binned in 50 bins which have the same size in order to have a good visualization of the results. For each of these bins, the resulting data point is derived by calculating the average values of the modified pooled passenger request generation rate and the shareability/shared rides.

All the parameters of the analytical model and the simulation, together with their notations and values are summarized in Tab. 5.1.

| Constant Parameter | Math Notation | Description | Value | Unit |
|---|---|---|---|---|
| Surface area | $\Omega$ | Surface of the operation area | 221 | $km^2$ |
| Average velocity | $v_o$ | Network's average velocity | 28.8 | km/h |
| Vehicle capacity | $\phi$ | The maximum number of passengers who can share a trip at the same time | 2 | passenger |
| Penalty value for unassigned request | $V_p$ | Penalty value for unassigned request | 40000 | - |
| Fitting parameter | $n$ | Fitting parameter for the shareability prediction model given by Eq. (44) | 0.80 | - |
| Fitting parameter | $k$ | Fitting parameter for the shareability prediction model given by Eq. (44) | 0.065 | - |
| **Variable Parameter** | **Math Notation** | **Description** | **Value / Relation** | **Unit** |
| Average velocity | $v(t)$ | Network's average velocity at a given time | | km/h |
| Boarding/disembarking time | $t^b$ | The time that the customer needs to board/disembark the vehicle | 0, (30), (60) | second |
| Maximum waiting time | $t^{max}$ | Maximum time the passenger waits to be picked up | (4), 5, (6) | minute |
| Detour time | $\Delta$ | Temporal deviation from the direct travel time | (4), 5, (6) | minute |
| Shareability / Shared rides | $S$ | Percentage of trips which can be shared within an operation area derived analytically | Eq. (3), (4), (5), (44) | % |
| Pooled/ODRP passenger trip generation rate | $\lambda_p$ | Pooled/ODRP passenger trips requests generated per hour and completed by the ODRP service | | passenger trip/h |
| Penetration rate / ODRP passenger demand penetration rate | $p$ | Portion of pooled/ODRP passenger trips divided by the total passenger trips | 0.1 – 5.0 | % |
| Fleet size | $m$ | Number of ODRP vehicle fleet used to accommodate the ODRP demand | 100 – 1500 | vehicle |
| Modified pooled/ODRP passenger trip generation rate | $\rho(t)$ | Modified pooled/ODRP passenger trip generation rate | Eq. (41) | $\frac{1}{\mathrm{km^2 h}}$ |

| Simulation Characteristics | Characteristic | Acronym |
|---|---|---|
| Network Topology | Euclidian Topology | T: E |
| | Street Graph Network with homogeneous velocities | T: G Avg |
| | Street Graph Network with time dependent velocities | T: G |
| Vehicle Routing Optimization Objective | Saved Distance | O: SaD |
| | Shared Rides | O: ShR |
| **Evaluation** | **Characteristic** | **Acronym** |
| Percentage of Shareable Passenger Trip Requests of the ODRP Service | Experienced Shared Rides in the simulation | $S_e$ |
| | Theoretically possible Shared Trips during the simulation | $S_{th}$ |

**Tab. 5.1** Parameters of the analytical and agent-based simulation model, their notations and values. The variable parameters which do not contain a bracket specify the SQP for the base scenario.

### 5.1.2 Results

In this part the results of the validation of the analytical model for an instant booking ODRP system (*Subsection 3.1.2*) will be shown. Firstly, the impact of the network modelling details will be explored and then the validity of the model for different SQP will be investigated.

#### Network modelling impact

The analytical model of the SQP impact derives the possible percentage of shared trips in an area. In this part it will be examined if the analytical model represents the shareability or shared rides results for any of the considered cases. Moreover, the difference between the possible shared trips and the experienced shared trips derived by the agent-based simulation results will be investigated. Furthermore, the impact of increased network modelling details on the theoretical and/or actual experienced shared rides will be explored.

Thus, five cases, which differ from each other by the network topology used, velocity, optimization objective and the evaluation of shareability or shared rides, are distinguished. The separate impact of these modelling details is captured by changing the parameters one at a time. Tab. 5.2 gives a summary of all the considered cases.

| Acronym | Topology | Velocity | Vehicle Routing Objective | Evaluation |
|---|---|---|---|---|
| **T: E, O: ShR, $S_{th}$** | Euclidian | Homogeneous | Shared Rides | Theoretical shareability |
| **T: E, O: ShR, $S_e$** | Euclidian | Homogeneous | Shared Rides | **Experienced shared rides** |
| **T: E, O: SaD, $S_e$** | Euclidian | Homogeneous | **Saved Distance** | Experienced shared rides |
| **T: G Avg, O: SaD, $S_e$** | **Street Network Graph** | Homogeneous | Saved Distance | Experienced shared rides |
| **T: G, O: SaD, $S_e$** | Street Network Graph | **Inhomogeneous** | Saved Distance | Experienced shared rides |

**Tab. 5.2** Different network modelling details and evaluation cases. The color corresponds to the color of the shareability/shared rides results in **Figure 5.1**.

Figure 5.1 illustrates the analytical model and the agent-based simulation results of the shareability and the shared rides depending of the modified pooled passenger request generation rate for all of the above-mentioned cases and for an ODRP service when the detour time $\Delta$ and the maximum waiting time $t^{max}$ are considered to be equal to 5 minutes, and the boarding time $t^b$ is assumed to be zero ($\Delta = 5$ minutes, $t^{max} = 5$ minutes, $t^b = 0$ s).

It is shown that for the case when the ODRP system is modelled in the agent-based simulation using an Euclidian topology (T: E), the average velocity in the network is assumed constant and the vehicle routing objective of the optimization is to maximize the percentage of shared rides (O: ShR), the results of the theoretical shareability value ($S_{th}$) derived from the agent-based simulation model fit quite well to the shareability curve given by the analytical model. This happens as this case represents the best the assumptions made in the analytical shareability model for an instant booking system regarding vehicle moving in a Euclidian network topology and constant average velocity in the network. Moreover, Equations (3(3)-(4)(5) for this ODRP system also derive the theoretically possible shareability in an area, corresponding with the evaluation method of this case.

The analytical and simulated results for the first case (T: E, O: ShR, $S_{th}$) follow the same trend for the whole range of the considered modified pooled passenger request generation. Shareability increases very quickly for low penetration rate, reaches around 95% when the modified request generation is around 5 $\frac{1}{km^2 h}$ and saturates at around 15 $\frac{1}{km^2 h}$. However, a trend of deviation of the results compared to the analytical model for low and high modified request generation is observed. One main reason for this trend of deviation is that the analytical model and the simulation model use different assumption regarding passenger request distribution. From one side, in the analytical model it is assumed that the origins of the passenger requests are uniformly distributed in time and space and from the other side, in the simulation model the demand of the passenger request is inhomogeneous in time and space. These different assumptions result in different behavior between analytical and simulated shareability for low modified request generation. Albeit homogeneous distribution of passenger trip requests might seem an ideal system condition, it might not always have positive effects in term of higher chances to find shareable trips. This is especially true for low penetration rate, for which in terms of shareability it is more beneficial for the ODRP system to have spatial and temporal correlation of passenger trips. Similar patterns are observed for instance when considering commuter trips. This effect is reflected in the difference between the analytical and simulated shareability results in the low penetration rate area. There it is shown that the simulated shareability values are higher than the values predicted by the analytical model as a result of superior advantages of spatial and temporal passenger trip correlation compared to uniformly distributed trips. For high modified pooled passenger demand the reverse effect is observed. When having uniformly distributed demand, the chances to find sharable trips are the same everywhere in the area. However, when the ODRP passenger trip request demand is inhomogeneous, there will be areas in the network with scare request generation and thereby low chances to find shareable trips. Hence, the total simulated shareability for high demand levels is lower than the one estimated by the analytical model.

For the second case (T: E, O: ShR, $S_e$), a different evaluation scheme is chosen and 'shared rides' are considered to be only the passenger trips which actually experience a shared ride in the simulation. Using this evaluation scheme, the value of shareability anticipated by the analytical model differs from the actual value of experienced 'shared rides' $S_e$ as the way the vehicles are assigned to passenger trips is not considered by the analytical model. As an example, if there are three requests, from which one of the requests is shareable with both the other requests, but these two requests cannot be shared with each other, in theory there are two options in which the trips can be shared, however in reality only one of them happens as one passenger cannot be served by two vehicles. Therefore, the shareability in this case is 100% and the shared rides value is only 66%. It is observed that for low modified request generation the results of shared rides are similar to the shareability results. As the modified pooled passenger request generation increases, the shared ride values drop by around 10% compared to shareability for medium modified pooled passenger requests and almost approach 100% for high modified request generation. As explained before, this alteration is noticed as the passenger trips that actually experience a shared ride differ from the ones which could theoretically be shareable, as in reality the chances to share a trip are restricted by combinatorial constraints. These combinatorial constraints limit the number of trips which can be served by vehicles. Hence, for low modified pooled passenger request, the shared rides and the theoretical shareability do not differ that much as the chances to find shareable trips are anyways low and the combinatorial constraints hardly influence the tour choice. Whereas, for high passenger trip demand, the difference in the results becomes smaller due to the high number of passenger trips which ensures that a shared ride can be offered for each passenger request.

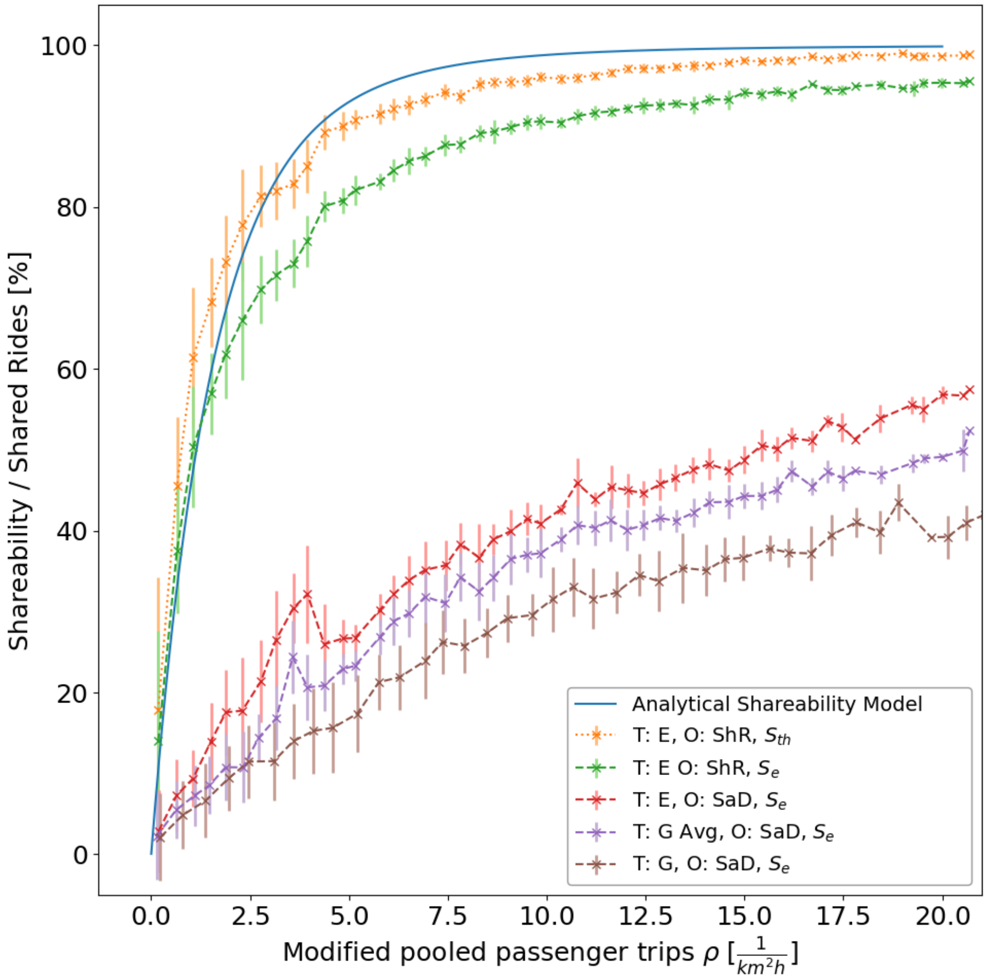



**Figure 5.1** Analytical and simulated shareability and shared rides for various network modelling details and evaluation cases specified in Tab. 5.2.

The next case (T: E, O: SaD, $S_e$) shows the impact that the optimization objective used for vehicle routing has on the shared ride results. Therefore, keeping all the other parameters the same, the optimization objective is changed from maximizing the percentage of shared trips in the area into maximizing the saved distance travelled (O: SaD). This optimization objective is closer to improving the traffic efficiency in a city as it is equivalent with minimizing the VKT in the system. The effect of the change of the optimization objective is noticed to be quite high, causing a reduction in shared rides by up to 50%. For low ODRP passenger demand the chances to find shared rides are quite low for this case. They increase for higher demands, but do not pass 60% for the considered case when the maximum ODRP passenger demand corresponds to 5% of the private vehicle trip demand in Munich. Albeit the optimization objective of maximizing the percentage of shared trips could be considered in line with maximizing the saved distance, as the VKT are reduced because of shared trips, this outcome shows that this is not necessarily true. Thus, sometimes it might be more efficient in terms of VKT reduction to serve the customers one after the other than to make large detour just for the sake of increasing the number of shared trips, even though the time constraints which allow trips to be shareable are not violated. This result stresses the huge impact of the selected vehicle routing optimization objectives for the ODRP system and clarifies that a large number of shareable trips is not necessarily an indicator of an efficient ODRP system, at least not in terms of traffic efficiency.

In this step (T: G Avg, O: SaD, $S_a$), the influence of the network topology in the percentage of shared rides is explored. In the cases considered until now, it was assumed that the vehicles move in the network following straight lines which correspond to a Euclidian topology. Now, the ODRP system is modelled as a street network graph with the same constant average velocity throughout the network as in the Euclidian topology (T: G Avg, O: SaD, $S_e$) and assume that the vehicles move in the network corresponding to the real street network of Munich. As in the previous cases, all the other parameters are kept the same to better capture the network topology impact on the shared ride results. The results show that the shared rides decrease additionally for this case. This occurs as the vehicles albeit travelling with the same average velocity as in the Euclidian network have to traverse longer distances in the street network graph, as the distance can never be shorter than the straight line between two points. Consequently, the vehicles need more time to pick up passengers and also more time to drop them off at their destinations. This leaves less available time to be able to serve additional trips and therefore, due to the restrictions imposed from the time constraints, the number of shared rides decreases additionally.

The last considered (T: G, O: SaD, $S_e$) case captures the impact of inhomogeneous network velocity in the shared rides results. The time dependent travel times are extracted from the microscopic traffic simulation explained in *Subsection 4.2.2*. This step increases the model realism as normally the fleet's vehicles experience time dependent travel times. In order to exclude the impact of average velocity alteration, the modified request generation given by

Equation (41) is used. A further decrease in the shared rides is noticed in this case, caused only by the inhomogeneous average velocity in the edges of the street graph network. It should be mentioned here that the average velocity is extracted from the microscopic traffic simulation for which the traffic generation in the network is based on private vehicle data. As in this study a substitution of private vehicle trips with ODRP trips is assumed, the areas which have a high demand of ODRP service are therefore the areas with the lowest velocity of the network edges, usually happening in the city center of Munich. Consequently, the travel time in the network increases, lowering in this way the chances to find shared rides.

**Service quality parameters impact**

In the previous part, the impacts of the network modelling details on shareability or shared rides results are investigated, and light is shed on the importance of the modelling details of the agent-based simulation. In this part, the impact that the SQP of detour time $\Delta$, maximum waiting time $t^{max}$ and boarding/disembarking time $t^{b}$ have on the results will be explored. These parameters are the time constraints which need to be fulfilled in order to find feasible tours.

To explore these impacts, firstly two cases are selected from the network modelling details cases for further investigation:

1. The first case in Tab. 5.2 (T: E, O: ShR, $S_{th}$), representing the best the predictions of shareability derived from the analytical model. For this case the ODRP system is modelled by assuming Euclidian topology with homogenous average velocity, optimization objective is to maximize the percentage of share trips and the evaluation considers the theoretical possible shareability achieved in the operation area.
2. The last case in Tab. 5.2 (T: G, O: SaD, $S_e$), where the modelling details resemble the most the real-world conditions of a potential ODRP service. In this case, network topology is considered to be a street network graph with time dependent average velocity on its edges, the optimization objective is to maximize the saved VKT and the evaluation considers only the actually experienced shared rides.

Consequently, two main questions, corresponding to the two before-mentioned cases, arise:

1. Can the analytical model predict the shareability values for varying SQP when the ODRP system modelling follows similar assumptions as the analytical model (T: E, O: ShR, $S_{th}$)?
2. Having observed huge differences between the results of the analytical model and the most detailed simulation model of the ODRP system (case T: G, O: SaD, $S_e$), shown in

Figure 5.1 by the brown simulated data, can the analytical model still be used to estimate shared rides for different SQP?

In order to investigate these impacts, different scenarios with varying detour times, maximum waiting times and the boarding/disembarking times are designed and tested. Initially, the validity of the analytical model for the first case (T: E, O: ShR, $S_{th}$) is elaborated and later the relevance of the analytical model for the second considered case (T: G, O: SaD, $S_e$) is discussed.

Figure 5.2.a illustrates the shareability and shared ride values for scenarios where the detour time changes taking the following values $\Delta \in \{4 \text{ minutes}, 5 \text{ minutes}, 6 \text{ minutes}\}$. It is observed that for all the considered detour time values, simulated shareability fit quite well the shareability curve derived from the analytical model. It is important to mention that a curve fitting is not used in this case (T: E, O: ShR, $S_{th}$) and it is remarkable that the analytical model can capture so well the complex interactions of the ODRP system and predict quite well the results. Increasing the detour time means that the constraints to find shareable trips are more relaxed and therefore the chances to find shareable trips will increase. The opposite is true when the detour time decreases. The shareability in this case reduces as by decreasing the allowed detour time, the chances to find shareable trips also decrease. It is also noticed that the impact of inhomogeneous spatial distribution of requests varies for different detour time. For low passenger demand and lower detour times, this effect causes larger underestimation of the shareability by the analytical model (which considers uniform demand distribution) compared to the scenario when the detour time is higher. Whereas for high passenger demand the analytical model overestimates the shareability values for both low and high detour time.

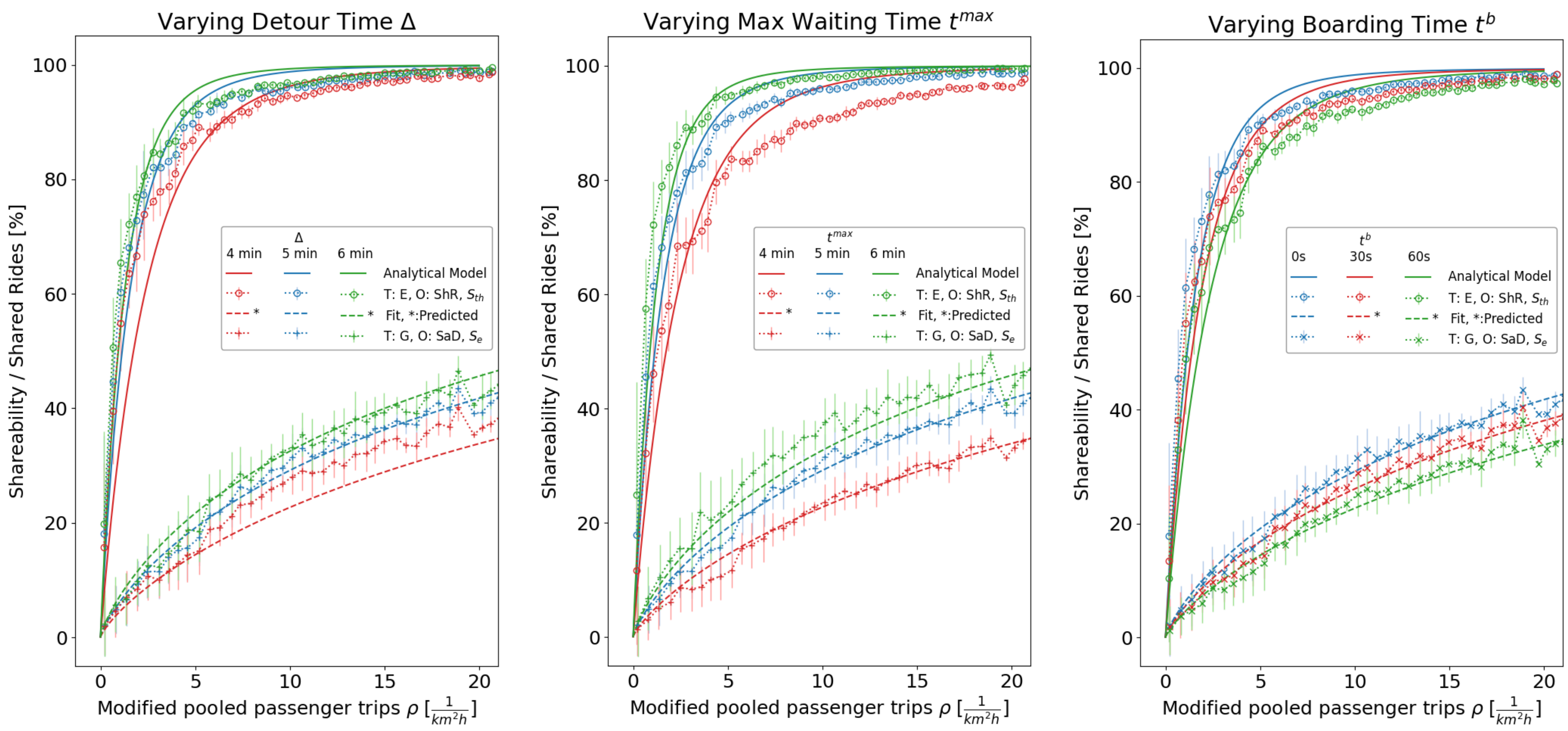
Figure 5.2.b depicts the impact of maximum waiting time on shareability/shared rides by considering various values of the maximum waiting times $t^{max} \in \{4min, 5min, 6min\}$. Similar effect as for the differences in shareability observed for different detour time is noticed here as well. Decreasing the maximum waiting time means that the chances to find shareable trips decrease due to tighter time constraints imposed in the system. This effect is reflected by the analytical model and the simulated shareability data for the first case (T: E, O: ShR, $S_{th}$). Contrary to the impact of the inhomogeneity of the request distribution results for different detour time showing a different magnitude of deviation of shareability in the area of low passenger demand, when varying the maximum waiting time these differences in the magnitude of the deviation from the analytical model are more noticeable for the high passenger demand region and low values of maximum waiting time.

Figure 5.2.c shows the impact of boarding time $t^b \in \{0s, 30s, 60s\}$ in the shareability and shared rides results. It is shown that the impact of the boarding time has on the simulated shareability results is similar to the impact that the detour time has on shareability, i.e., increasing the boarding time with 1 minute has a similar effect on the reduction of shareability as decreasing the detour time by 1 minute. Considering a certain increase in the boarding time, the actual possible detour time is consequently decreased as the boarding/disembarking time is perceived as lost time for the in-vehicle customers. Hence this time constraint also influences the possibility to find feasible tours. Moreover, higher boarding/disembarking times means that the assigned customers spend more time in the vehicle and therefore in the system, restricting the flexibility of the system for future ODRP passenger demand. This result is in line with the assumption used in the analytical model where boarding or disembarking time is considered as time loss for the customers on board on the vehicles and therefore, it is subtracted from the detour time.

Before elaborating on the results for the lower curves in Figure 5.2, the evaluation procedure of the this considered case is firstly explained.

The results explained until now show that the analytical model is able to represent quite well the shareability value for the case (T: E, O: ShR, $S_{th}$) where the ODRP system is modelled by using Euclidian topology with homogeneous velocity and the optimization objective is to maximize the percentage of shareable trips, without any additional fitting procedure needed. However, as noticed in Figure 5.1, with increasing the model complexity and realism the deviation of the results from the predicted analytical curve increases. Hence, in this part the answer to the second question posed earlier is provided and it is explored if the analytical model can be used for predictions of the impact of SQP on the shared rides for the last considered case (T: G, O: SaD, $S_e$) in Tab. 5.2, which corresponds to the one with the most realistic modelling details, showing huge deviations compared to the analytical model (Figure 5.1).

As previously explained in *Subsection 2.3.1*, agent-based simulations used to capture the impact of ODRP services require a lot of input data and are computationally expensive, thus having an analytical model capturing these complex effects and being able to evaluate the ODRP system performance, without the need to run multiple simulations, can be quite a good advantage. Therefore, for the cases where the ODRP system is modelled with high levels of detail, a method is presented here to estimate the shared rides for different SQP by using as a basis the analytical models described in *Section 3.1* and the data from the agent-based simulation for only the base scenario having the following SQP $\Delta = 5\,\text{minutes}$, $t^{max} = 5\,\text{minutes}, t^b = 0\,s$.




a) $t^{max} = 5$ minutes, $t^b = 0\ s$  b) $\Delta = 5$ minutes, $t^b = 0$ s  c) $\Delta = 5$ minutes, $t^{max} = 5$ minutes

**Figure 5.2** Shareability and shared rides for various: a) detour time Δ, b) maximum waiting time $\boldsymbol{t^{max}}$ and c) boarding time $\boldsymbol{t^b}$. The same colors refer to the same set of SQP used. Upper Curves show the validation of the analytical model with simulated data showing the theoretical shareability ($\boldsymbol{S_{th}}$) for the case (T: E, O: ShR, $S_{th}$). Lower Curves illustrate the comparison of the simulated data showing the experienced shareability ($\boldsymbol{S_e}$) with the shareability prediction model for the most realistic case (T: G, O: SaD, $S_e$).

This prediction method is built on two main aspects:

- Firstly, a function that fits the data of the detailed ODRP model case for the base scenario and is able to represent the afore-mentioned combinatorial constraints of the ODRP system is needed. SANTI ET AL. [2014a] found that a function of this type $f_{n,k}(x) = 100\ \frac{k\ x^n}{(1+k\ x^n)}$ fits the ODRP system shareability data quite good. This function naturally contains combinatorial constraints and is also used in biochemistry to represent statistically the methods of particle bonding. More information are provided in [SANTI ET AL., 2014b]. Compared to the original shareability function curve, this new function will provide another shape of the shared rides curve which could be able to represent analytically the shared ride for different modelling detail cases of the ODRP system.
- Secondly, it is assumed that the impacts of the network topology, the selected vehicle routing objective function, the inhomogeneity of demand and the velocity of edges are captured by the fitting parameters $k$ and $n$ and that all the assumptions made in the analytical model to derive the shareability shadows are valid in this case as well.

Hence, the prediction model for a detailed modelling of an ODRP system is described by the following function:

$$f_{n,k}(L_{sq}^{on}(\Delta, t^b, t^{max})) = 100\ \frac{k\ {L_{sq}^{on}}^n}{\left(1 + k\ {L_{sq}^{on}}^n\right)}, \tag{44}$$

Where $L_{sq}^{on}$ is given by Equation (4) and (5). The same would hold for the short-term prebooked ODRP system with $L_{sq}^{res}$, but as mentioned, the consideration is limited only for the instant ODRP booking system in this part.

The explained fitting prediction method is applied to the most detailed ODRP system modelling case (T: G, O: SaD, $S_e$) for the base scenario where $\Delta = 5min,\ t^{max} = 5min, t^b = 0s$, shown in Figure 5.1 by the brown color. Fitting the simulated data for this scenario with the fitting curve given by Equation (44), the fitting parameters $n$ and $k$ are found to be: $n = 0.80, k = 0.065$. Keeping these fitting parameters fixed, in the next step Equation (44) is used again to estimate the shared rides for the scenarios with different SQP. The effect of different SQP is captured analytically by the dimensionless parameter $L_{sq}^{on}$.

The predicted curves derived by using the explained prediction method are noted in the legend of Figure 5.2 with an asterisk symbol, whereas the scenario without the star symbol corresponds to the fitted curve of the base scenario. From the results shown in the lower part of Figure 5.2, it is noticed that the prediction model used in this study anticipates quite well the simulated data for the case (T: G, O: SaD, $S_e$) for different maximum waiting time $t^{max}$

and boarding time $t^b$. However, forecasts for different detour time $\Delta$ show some alteration from the predicted analytical model. The reason for this alteration is because for instance when increasing the detour time constraint, the number of possible shareable trips captured analytically by the impact that the detour time has on the shareability shadow increases in a higher manner compared to the increase of the actually experienced shared trips in the agent-based simulation. This happens as the number of feasible tours which also fulfill the optimization objective of minimizing VKT is lower than the total feasible tours for which rides are possible to be shared.

This effect is not seen for the other parameters of the maximum waiting time $t^{max}$ and boarding time $t^b$, as the time constraint imposed by these parameters does not affect the driven VKT in the system, thus they do not affect the tour distance. The first parameter $t^{max}$ is the time the customer waits to be picked up; thus the vehicle is not generating extra kilometers with increasing this time constraint and similarly for the boarding time $t^b$, the vehicles do not produce any additional VKT while the customers are boarding or alighting the vehicle. Therefore, the shareability shadow for different values of maximum waiting time $t^{max}$ and boarding time $t^b$ is able to capture quite well the impact that these time constraints have on shared rides by using the analytical prediction model given by Equation (44).

## 5.2 On-Demand Ride Pooling Traffic Impact Evaluation

This section will explore the validity of the analytical model of traffic impacts of an ODRP system, presented in *Section 3.2* by means of the microscopic traffic simulations AIMSUN described in *Subsection 4.2.2*. Firstly, the scenarios built to test the model are described. Then the results of the model validity are illustrated and finally, the traffic impacts of different penetration rate of ODRP while considering also the impact of other vehicles in the system in addition to the ODRP vehicle fleet, are explored.

### 5.2.1 Scenario design

In this part firstly a description of the scenarios used to construct the MFD will be given, and it will be followed by defining the scenarios necessary to test the traffic impact of ODRP service, considering ODRP passenger demand and vehicle supply in the network.

**Macroscopic fundamental diagram scenario design**

As the MFD is used in order to derive the impact of an ODRP system on traffic efficiency, firstly the scenarios used for the MFD construction are defined. In this study, the MFD is built based on simulation data extracted by the microscopic simulation of AIMSUN described in *Subsection 4.2.2*. In order to build the MFD for the city of Munich, different macroscopic simulations for the time range 06:00 to 24:00 are run. As described, the demand given by OD matrices connecting different centroid of the network, corresponds to private vehicle trips in Munich. While constructing the MFD it is necessary that the network is at capacity, therefore the demand of private vehicle trips in Munich is artificially increased in order to bring the network to the capacity state. Hence, two additional simulations are run where the OD demand is increased by 10% and 20% of the total private vehicle trips demand in Munich by multiplying the existing OD with the corresponding factors, 1.1 and 1.2. From these simulation runs, every 10 minutes one data point representing the value of the networks average velocity and traffic flow is derived by using Equations (12) and (13), respectively. Thus, by plotting the collection of these data points in one similar graph, the MFD for the city of Munich is constructed by using simulation data from the microscopic traffic simulation AIMSUN.

**ODRP Passenger trip demand**

The demand for the ODRP system in this study is considered to be exogeneous and thus, private vehicle passenger trip demand is substituted with ODRP passenger trips for different market penetration rate of the ODRP service. As the ODRP service is offered only within the borders of the operation area defined in Figure 4.1, only passenger trips which have both their origins and destinations within the area of operation, corresponding to vehicle trips type (1) (*Subsection 3.2.3*) will be replaced by ODRP passenger trips. In order to explore the traffic impacts of ODRP service for different demand shares, alone/private passenger trips are substituted with pooled passenger trips for different levels of demand penetration rate given by $p = \frac{\lambda_p}{\lambda}$, where $\lambda_p$ is the pooled/ODRP passenger trip demand generated per hour and $\lambda$ is the total hourly passenger trip demand in the area (including both pooled passenger trips and alone passenger trips). To design different penetration rate, different scenarios where $p$ takes values of 0%, 5%, 25%, 50%, 75% and 100% are developed. For the base scenario $p = 0\%$, as for this scenario all the traffic demand in Munich is considered to be fulfilled by private vehicle trips and the number of requested ODRP/pooled passenger trips is equal to 0. The scenario when $p = 100\%$, corresponds to the hypothetical extreme case when all the alone/private passenger trips in Munich are substituted by the ODRP passenger trips.

**Vehicle supply**

The aim of the study is not only to investigate the traffic impact of ODRP vehicle fleet, but also the impact of other vehicles presented in the system. Therefore, in the microscopic simulation AIMSUN, selected to examine these impacts, it is differentiated between vehicle trip demand generated from the ODRP service and from other vehicle types present in the network. Hence, the total vehicle trip demand generated in the network is comprised of:

1. The alone vehicle trips (part of vehicle trips type (1))
2. The pooled vehicle trips (part of vehicle trips type (1))
3. The background vehicle traffic from vehicle trips type (2), (3) and (4)

These vehicle trips are designed in AIMSUN by three different OD matrices:

1. *Matrix (A),* representing the private or alone vehicle trips type (1) ($g_a$)
2. *Matrix (P)*, representing ODRP vehicle trips type (1) ($g_p$)
3. *Matrix (B),* representing the background vehicle traffic derived from vehicle trips type (2), (3) and (4))

The first two matrices represent the vehicle trips with both their origins and destinations inside the operation area. Both these matrixes, *matrix (A)* of private/alone vehicle trips and *matrix (P)* of ODRP vehicle trips, will vary based on the passenger trip demand for the ODRP service (or penetration rate $p$). *Matrix (B)* represents the background traffic in the network and gives the OD of vehicle trips which only start (vehicle type (2)) or only end (vehicle type

(3)) inside the operation area or cross the area (vehicle type (4)). Thus, behaving as a background traffic, these vehicle trips remain the same throughout the study.

For the base scenario, where the demand for the ODRP service is zero, the vehicle trips demand is represented by the base demand *matrix* $A_0$. For the ODRP service considered here, it is assumed that the ODRP vehicle trips and private/alone vehicle trips have similar origins and destinations. Thus, the demand of ODRP vehicle trips is generated by scaling the base demand matrix $A_0$ depending on the penetration rate of ODRP service and the reduced number of vehicle trips modelled in *Subsection 3.2.2*. Hence, for a certain ODRP penetration rate $p$, the number of alone vehicle trip generated per hour $g_a$ given by the OD-s of the *matrix (A)* is modified based on Equation (45) by scaling the base demand matrix $A_0$.

$$g_a = \lambda_a = (1 - p) * A_0 \tag{45}$$

When introducing the ODRP service for a given penetration rate of the service, changes in the ODRP passenger trip demand are illustrated by Equation (46).

$$\lambda_p = p * A_0 \tag{46}$$

To convert the change in ODRP passenger demand $\lambda_p$ into changes of generated ODRP vehicle trip $g_p$, and modify accordingly *matrix (P)* of ODRP vehicle trips, Equation (9) developed in *Subsection 3.2.2* is used to derive the vehicle trip reduction in the system when the ODRP service is introduced. As noted in this equation, the reduction of the ODRP vehicle trips depends on the shareability or shared rides value $S$ for the selected ODRP system, the ODRP passenger trip demand $\lambda_p$ and the vehicle capacity $\phi$. Shareability on its own depends additionally on the optimization objective and the set of SQP. The optimization objective used in this part for vehicle assignment is chosen to be in accordance to the societal benefits of improving traffic conditions by reducing the VKT in the network and its goal is to minimize the VKT in the system. Thus, to derive the shareability depending on the generated ODRP passenger trip demand per hour for our considered ODRP system, the prediction model introduced in *Section 5.1.2* is used and applied for the case when the network topology of Munich is represented by a street graph network with surface Ω and the average velocity in the area is homogeneous and equal to $v_o$. For this case, the network of topology considers constant average velocity, contrary to the network topology with inhomogeneous travel times (forth case in Tab. 5.2) used for the prediction model in the previous *Subsection 5.1.2*. Hence, the new fitted parameters $k$ and $n$ are found by fitting the simulation data of this network topology defined by the third case (T: G Avg, O: SaD, $S_e$) in Tab. 5.2 – for the base scenario when the SQP for the ODRP service of consideration are: $\Delta = t^{max} = 5$ minutes and $t^b = 0$

seconds – to the prediction model given by Equation (44). The new parameters are found to be: $k = 0.126$ and $n = 0.829$. Assuming that the vehicle capacity $\phi$ is 2, i.e., maximum two ODRP passenger can simultaneously share a vehicle trip, the ODRP vehicle trip reduction and thereby the modified values of *matrix (P)* is derived by using Equations (9).

**Scenarios and evaluation procedure**

As the benefits of ODRP system are believed to be more prominent for a network with high level of congestion, the scenario where the traffic demand in the network of Munich is 10% higher than the current private vehicle trip demand, is selected as the base scenario in this part. The ODRP service is considered to be provided in the Munich operation area given in Figure 4.1. As the congestion level is higher during the peak time, this ODRP service is assumed to be offered during the morning peak time from 07:00 to 10:00.

For the base scenario, the average velocity for every edge in the network is extracted every time slice of 10 minutes and derive the average velocity of the whole network by using Equation (12). The calculated average network velocity $v_o$ during the morning peak time for the base scenario is 39.2 km/h. This average velocity is different form the one used in *Section 5.1*, as the AIMSUN network has undergone more extensive calibration procedures, which thereby affected the average network velocity. Nevertheless, the benefit of the analytical model of shareability are emphasized also in this case, as the shareability curve can be easily modified to take into account the current average velocity $v_o$ by modifying the dimensionless unit $L_{sq}^{on}$ using Equation (4) from the ODRP instant booking system shareability modelling, without needing extra computationally expensive agent-based simulations.

To examine the impact that different penetration rate of ODRP service have on the average velocity of the network, the network's average velocity for each of these scenarios is derived by the same procedure used for the base scenario, where for each time interval during the morning peak time the average velocity of each edge is used to calculate the total network's average velocity using Equation (12).

A detailed description of the parameters of the model, their math notations and their corresponding values is provided in Tab. 5.3.

| Constant Parameter | Math Notation | Description | Value | Unit |
|---|---|---|---|---|
| Surface area | $\Omega$ | Surface of the operation area | 221 | km$^2$ |
| Network length | $L$ | Total length of the network | 2450 | km |
| Velocity at capacity | $v_c$ | Average velocity when the system is at capacity | 39.2 | km/h |
| Flow at capacity | $q_c$ | Average flow when the system is at capacity | 457 | vehicle/h |
| Average velocity during the morning peak | $v_o$ | Original average velocity during the morning peak for the base scenario | 39.2 | km/h |
| The parameter of the parabola | $a$ | Parabolic function parameter derived by data fitting | 0.062 | - |
| Average vehicle trip length of vehicle trips type (1) | $l_{od}$ | Average trip length for vehicle trips which have the origin and the destination in the operation area | 5.16 | km |
| Average vehicle trip length of vehicle trips type (2) | $l_o$ | Average trip length for vehicle trips which have only the origin in the operation area | 17.5 | km |
| Average vehicle trip length of vehicle trips type (3) | $l_d$ | Average trip length for vehicle trips which have only the destination in the operation area | 17.5 | km |
| % of $l_o$ inside the operation area | $p_o$ | % of $l_o$ inside the operation area | 51 | % |
| % of $l_p$ inside the operation area | $p_d$ | % of $l_p$ inside the operation area | 46 | % |
| Detour time | $\Delta$ | Temporal deviation from the direct travel time | 5 | minute |
| Maximum waiting time | $t^{max}$ | Maximum time the passenger waits to be picked up | 5 | minute |
| Boarding/disembarking time | $t^b$ | The assumed time that the customer needs to board/disembark the vehicle | 0 | minute |
| Vehicle capacity | $\phi$ | The maximum number of passengers who can share a trip at the same time | 2 | passenger |
| Fitting parameter | $k$ | Fitting parameter for the shareability prediction model given by Eq. (44) | 0.126 | - |
| Fitting parameter | $n$ | Fitting parameter for the shareability prediction model given by Eq. (44) | 0.829 | - |

| Variable Parameter | Math Notation | Description | Value / Relation | Unit |
|---|---|---|---|---|
| Average velocity | $v$ | Network's average velocity at a given time | | km/h |
| Average traffic flow | $q$ | Network's average traffic flow at a given time | | vehicle/h |
| Average traffic density | k | Network's average traffic density at a given time | | vehicle/km |
| Shareability | $S$ | Percentage of trips which can be shared within an operation area | Eq. (4), (5), (44) | % |
| Penetration rate / replacement rate / ODRP passenger demand penetration rate | $p$ | Portion of pooled/ODRP passenger trips divided by the total passenger trips ($p = \frac{\lambda_p}{\lambda}$) | 0, 5, 25, 50, 75, 100 | % |
| The initial private vehicle matrix | $A_0$ | The initial private vehicle OD matrix | | passenger trip/h |
| Alone/private passenger trip generation rate | $\lambda_a$ | Alone/private passenger trips generated per hour in an area and completed by private vehicles | $(1-p) * A_0$ | passenger trip/h |
| Pooled/ODRP passenger trip generation rate | $\lambda_p$ | Pooled/ODRP passenger trips requests generated per hour and completed by the ODRP service | $p * A_0$ | passenger trip/h |
| Alone/private vehicle trip generation rate | $g_a$ | Alone/private vehicle trips generated per hour by private vehicles | $g_a = \lambda_a$ | vehicle trip/h |
| Pooled/ODRP vehicle trip generation rate | $g_p$ | Pooled/ODRP vehicle trips generated per hour by the ODRP service | $g_p$ → Eq (9) | vehicle trip/h |
| Total vehicle trip generation rate in the operation area | $g_{od}$ or $g$ | Total vehicle trips generated per hour in the operation area of the ODRP service of vehicle trips type (1) | $g = g_a + g_p$ →Eq (10) | vehicle trip/h |
| Vehicle trips generation rate of vehicle trips type (2) | $g_o$ | Hourly generation rate of the vehicle trips which have only the origin in the operation area | | vehicle trip/h |
| Vehicle trips generation rate of vehicle trips type (3) | $g_d$ | Hourly generation rate of the vehicle trips which have only the destination in the operation area | | vehicle trip/h |

**Tab. 5.3** Description of the parameters of the ODRP traffic impact analytical model, their math notations, and their corresponding values or relations.

### 5.2.2 Results

In this subsection, firstly the MFD for Munich will be built by using data from the microscopic simulation AIMSUN. Then the analytical model relating the average velocity with vehicle trip generation in the network will be validated with the simulation data. By using this model, the traffic impacts of ride pooling for different penetration rate of the ODRP service will be examined. And the subsection will be finalized by validation of the modified shareability model, which explores the impact that ODRP will have in further increasing the percentage of shared trips in an area.

**Macroscopic Fundamental Diagram for Munich operation area**

The analytical model capturing the traffic impacts of an ODRP system is based on the macroscopic fundamental diagram for a city. Therefore, the MFD for the operation area in the city of Munich is firstly built and the result is shown in Figure 5.3.

The data points representing the relation of average velocity and traffic flow of the network for a time period of every 10 minutes are generated by using Equations (12) and (13), respectively. The complete data points set is derived from running three different scenarios with different vehicle trip demand as described in MFD scenario design in *Subsection 5.2.1*, where for two of these scenarios the vehicle trip demand in the network is artificially increased.

As mentioned, Figure 5.3 illustrates the MFD for Munich, where the x-axis gives the network's average traffic flow values, and the y-axis gives the network's average velocity. It can be observed that most of the traffic flow-velocity data points are located in the area of the free flow regime, therefore the Munich operation area of consideration experiences most of the time free flow velocity in its street network in average. In general, the simulated average velocity for the Munich network of consideration is high considering that it is an urban area. However, the reason of having these high values of average velocity is that the selected area also includes city highways and motorways with high-speed limits which increase the total network's average velocity.

During the morning and afternoon peak times, when the vehicle trip demand increases, the network reaches its capacity and thereby approaches the unstable state of the network. When the demand decreases after passing the peak time, the system does not recover immediately after having reached high congestion levels. This effect is shown by a clockwise hysteresis loop which is noticed for each of the selected scenarios [DAGANZO, 2007], represented by the data points which during the uploading phase (i.e., decreasing demand after peak time) have lower average velocity compared to the loading phase (i.e., increasing demand) for the same traffic flow value.

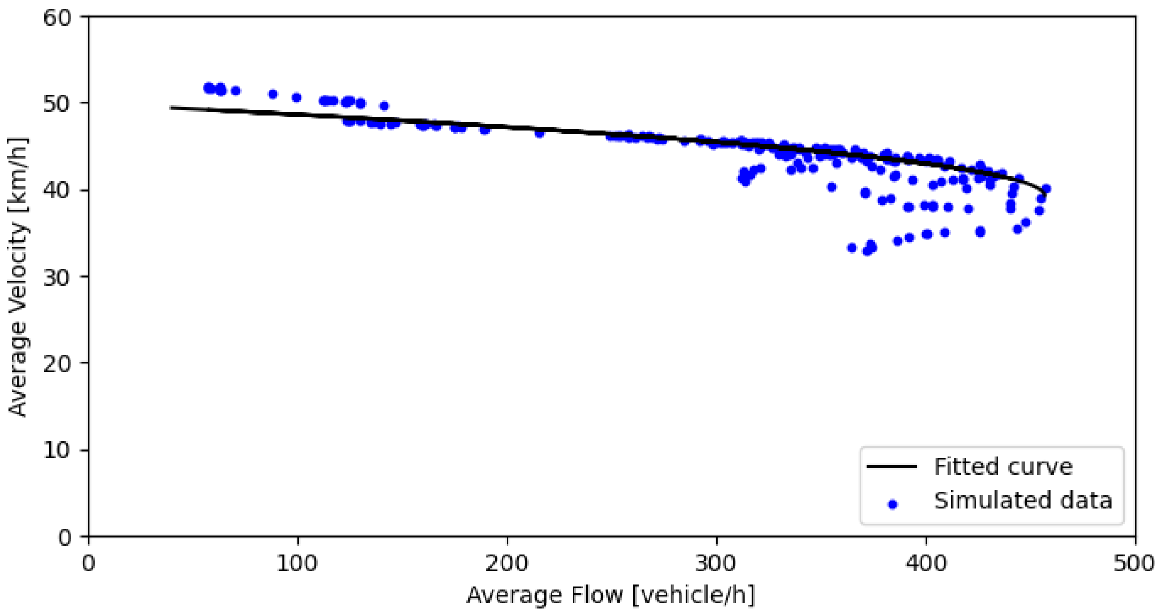



**Figure 5.3** Macroscopic fundamental diagram showing the relation of average velocity and average traffic flow for Munich.

It is determined that the network is at its capacity or optimum state when the traffic flow is at its maximum level. Hence, from the MFD in Figure 5.3 the maximum traffic flow of the network is defined to be $q_c$. The average network velocity corresponding to this point is the average velocity when the network is at capacity $v_c$. From the simulated scenarios the values of the average traffic flow and average velocity when the Munich network is at capacity are 457 vehicles/h and 39.2 km/h, respectively.

Until now the MFD is derived by the simulated data points, however in order to use the MFD to examine the traffic impact of an ODRP system, an analytical form of the MFD function is needed. Thus, assuming the functional form of the MFD resembles the equation of a parabola [KE ET AL., 2020], Equation (11) is used to define the MFD graph. As the network for our selected base scenario is mainly in the free flow regime, the simulated data points defining the shape of the MFD are also situated in this regime. Hence, the simulated data are fitted to the Equation (20) showing the relating of average velocity and traffic flow when the velocity is higher than the velocity at capacity ($v > v_c$). By considering that the point where the network is at capacity $V(q_c, v_c)$ corresponds to the vertex of the parabola, the parabolic function parameter $a$ is found to be equal to 0.62. The fitted curve is given by the black solid line in Figure 5.3 and it denotes the analytical form of the MFD for Munich.

By substituting the values of velocity and traffic flow at capacity and the parabolic parameter, the MFD of Munich is analytically expressed by using the following equation for the free flow regime state:

$$v = v_c + \sqrt{4a(q - q_c)} = 39.2 + \sqrt{4 * 0.62 * (q - 457)} \quad (47)$$

**Relation of average velocity and vehicle trip generation**

This part initially shows how the necessary network information to derive the analytical model of average velocity and vehicle trip generation is extracted. Then the validation of the model with data from the microscopic traffic simulation is explained.

*Network information*

In order to validate the analytical model capturing the relation of the average velocity and vehicle trip generation in the network, firstly some information about the network parameters which affect the results should be extracted. The required network parameters are given in Equation (16), which gives the total traffic density of the network by considering vehicle trips which start and end within the operating area (vehicle trips type (1)) and the background traffic, which contains vehicle trips having only the origin (destination) inside the operation area and the destination (origin) outside or vehicle trip type (2) (vehicle trip type (3)). This necessary network information includes the trip lengths for the three vehicle types considered. In addition, for vehicle type (2) and (3) it is required to know also the percentage of the trip located inside the operating area, as that is the trip part which contributes to the background traffic density in the network.

To extract the trip length of the vehicle trips type (1), (2) and (3), the centroid statistic approach in AIMSUN is used. Firstly, all the centroids within the operation area of the ODRP service are extracted. Then, for each of these centroids, the total number of vehicle trips and the total driven kilometers for each vehicle type are calculated. For each vehicle type, dividing the respective total VKT by the total number of vehicles generated gives the corresponding average trip length, which is 5.16 km, 17.5 km and 17.5 km, for vehicle trips type (1), (2) and (3), respectively.

For vehicle trips which have only their origin or destination within the operation area (vehicle trips type (2) and (3)), the information of the portion of the trip distance which is located inside the area is also needed. Hence, for the vehicle trips which originate or end within the operation area, all the routes which join their origins and destinations are derived. For the route which is frequented the most by the vehicles, the identification numbers and the lengths of the sequence of links which define this route is extracted. Then the links which are located inside or outside of the operation area are identified. Consequently, the vehicle trip length located within the operation area, is calculated by the summing the length of the links which are positions within this area. The fraction of the vehicle trip length performed inside the operation area is thereby derived by dividing the afore-mentioned vehicle trip length completed inside the area with the overall vehicle trip length. Performing the same procedure for each simulation hour, the average values of fraction of vehicle trip length within the area is found to be 51% and 46% for vehicle trips type (2) and (3), correspondingly.

*Average velocity and vehicle trip generation relation*

The network information of Munich (explained in the previous part) is substituted in Equation (17) and hence, the traffic flow in the network of the city of Munich is analytically derived depending on the number of vehicle trips type (1) originating and ending inside the operation area $g_{od}$. If the traffic flow and vehicle trip generation relation (Equation (17)) modified for the city of Munich case is substituted in the general MFD Equation (20) for the free flow regime, the general relation of average velocity and vehicle trip generation per hour for the Munich area is defined.

This analytical relation is validated by using the microscopic traffic simulation AIMSUN and the results of both the analytical model and the simulated data points are illustrated in Figure 5.4. The dark blue data points are generated by the combining the vehicle trip generation per hour in the system and the simulated average velocity. The light blue data points provide the analytical relation between the parameters, where the vehicle trips per hour is calculated analytically by Equation (18), when the average traffic flow in the network is known, and the average velocity is extracted from the simulation. Thus, the validity of Equation (18), showing the analytical relation of vehicle trip generation and the traffic flow, and Equation (20), showing the analytical relation of velocity and vehicle trip generation, will be described in the following.

Firstly, to test the validity of Equation (18), the simulated and analytical data points are compared and a pretty good correlation among them is observed. This shows that the analytical model used to analytically derive the number of vehicle trips generated in the network $g_{od}$ (given by Equation (18)), when knowing the traffic flow $q$ in the system and the network and vehicle trip information, represents quite well the real generated vehicle trips in the simulation network when the system is in the free flow regime. Albeit a good correlation is found in general between the simulated and the analytical data, there are a few data points from the set of the dark blue simulated data points which are scattered. These scattered data points correspond to the unstable network regime and the area depicted by the clockwise hysteresis loop seen in Macroscopic fundamental diagram showing the relation of average velocity and average traffic flow for Munich. Figure 5.3 of the Munich MFD. Nevertheless, the model in this study is tested only for the free flow regime of the network and in order to examine the feasibility of the model also for the congested regime further analysis is necessary.

Secondly, the validity of Equation (20) and thereby the validity of the analytical model developed to capture the relation of the average network velocity and vehicle trip generation ($g_{od}$) are also examined. The light blue line in Figure 5.4 is the functional form of this relation given analytically by Equation (20). For the Munich case study, it is observed that the analytical curve represents quite well the simulated and the analytical data as seen in Figure 5.4, with the exception of the scattered simulated data points below the curve which as previously mentioned correspond to the hysteresis loop of the MFD.

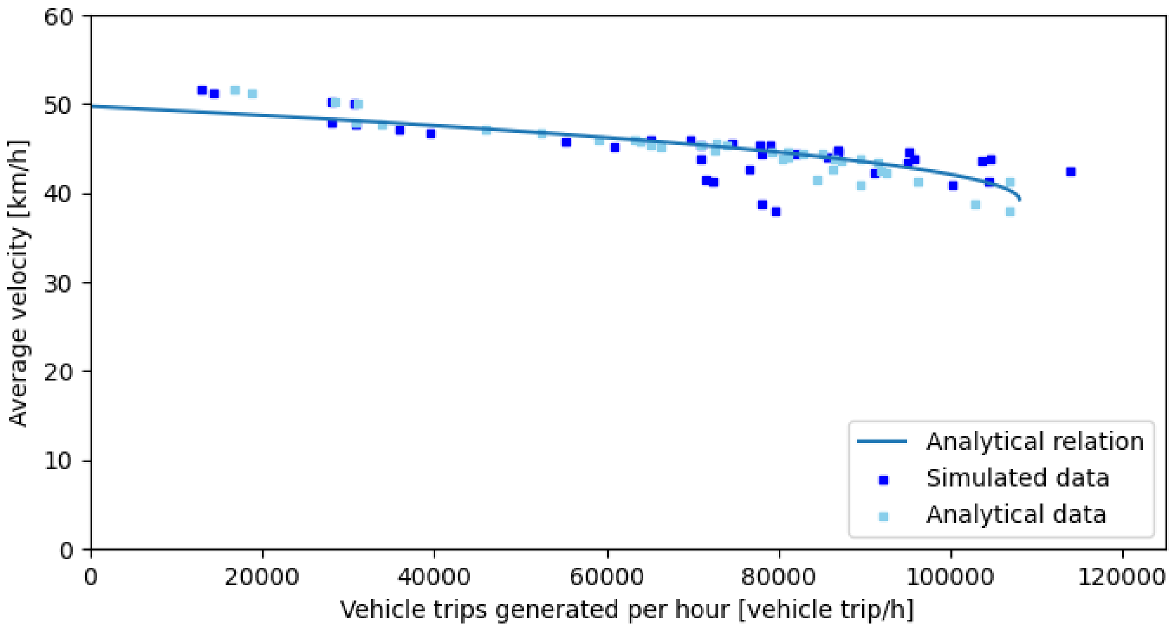



**Figure 5.4** The analytical and simulated relation of the average velocity and vehicle trips generated per hour $g_{od}$ in the network.

Being able to derive the relation of the average velocity and vehicle trip generation in the network analytically, by only using the MFD of a certain area together with network and trip information for the corresponding area, is quite an important step to derive analytically the traffic impact of an ODRP service and to avoid using high amount of input data and computationally expensive agent-based simulations. This relation provides information on the impact that the change of the total vehicle trips in the network $g_{od}$ due to the use of an ODRP service have on the network's average velocity. For a given penetration rate of the ODRP system represented by the ODRP passenger trip demand $\lambda_p$, the shareability or the shared rides that can be achieved in the ODRP operation area for a certain set of SQP and a given optimization objective can be derived. After calculating the shareability value, the reduction of the total vehicle tris in the network $g_{od}$ as a result of shared vehicle trips $g_p$ due to the use of the ODRP service will be derived using Equation (10). The reduction of the total vehicle trips in the system is used an input value for Equation (20), which analytically derives the impact that this reduction has on the average velocity in the network.

This analytical model will be used to capture the traffic impacts of ODRP for different penetration rate of the service and additionally, it will also be used to analytically capture the impact that the offered ODRP service has on further improving the percentage of shared trips in an area as a result of improved average velocity in the network.

**Traffic impacts of the ODRP service**

Contrary to the previous studies which consider indirectly the traffic impacts of ODRP service by the reduction of VKT of only the ODRP vehicle fleet, in this study the traffic impacts of the ODRP service are explored by including the impact of other road users in addition to the impact of the ODRP vehicle fleet. Hence, the traffic impacts of an ODRP service, when the ODRP passenger demand represents different portions of the total private vehicle passenger demand in Munich, are examined. Thereby different scenarios where the penetration rate of the ODRP system varies from 5% to 100% are designed, while also considering the private/alone vehicle trips that are present in the network. The results are compared to a base scenario for which the ODRP demand is zero and the private/alone vehicle trip demand is 10% higher than the current private vehicle trip demand in Munich.

For each of these scenarios with different penetration rate of the ODRP demand, the private/alone vehicle trips given by *matrix (A)* and pooled vehicle trips given by *matrix (P)* are modified using the approach explained in *Subsection 5.2.1*. The ODRP system that is considered in this case refers to an instant booking ODRP system, offered in Munich city for the morning peak time from 07:00 – 10:00 and where the maximum waiting time and detour time are each equal to 5 minutes, and the boarding time is assumed to be zero. Aiming for increasing the societal benefits by introducing the ODRP system in the urban areas, the selected optimization objective for vehicle routing assignments is to minimize the VKT in the system. To measure the traffic efficiency, the commonly used key performance indicator of the average velocity of the operation area is chosen.

The results of the changes in average velocity during the morning peak time for the base scenario and for the scenarios with different penetration rate of the ODRP demand are illustrated in Figure 5.5. The data points depicted in this figure denote network's average velocity calculated every 10 minutes using Equations (12) which uses the average velocity of all the edges in the network extracted from the AIMSUN microscopic simulation. Figure 5.5 shows that at the beginning of the morning peak time even for the base scenario, the network is not congested shown by a rather high the average velocity. However, the average velocity for this scenario starts decreasing, having its lowest values from 08:00 – 09:00 and starts slowly increasing again after 09:00. It is observed that for all the ODRP scenarios tested, there is not a notable improvement in average velocity at the beginning of the morning peak time due to the fact that the network is in the free flow condition during this time span even for the base scenario. Therefore, in this case a further improvement in network's average velocity is not possible. However, when the level of congestion in the network increases and its average velocity decreases, the benefit of the ODRP system in improving the average velocity in the network start to be visible. This highlights that the benefits of ODRP service in improving the traffic efficiency in urban areas are more prominent for congested cities and consequently, as higher level of congestion occur during the peak times, the ODRP service impacts are more noticeable during this time span.

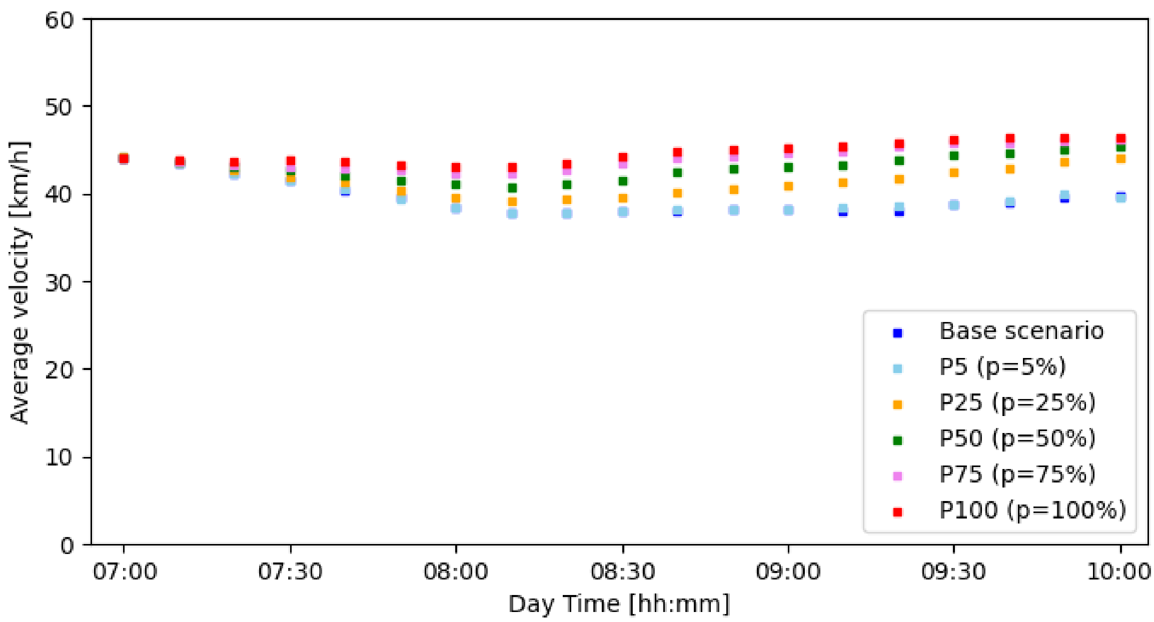



**Figure 5.5** Average velocity for the Munich network during the morning peak time for different penetration rate of the ODRP passenger demand.

As anticipated, the improvement in average velocity is higher with increasing the penetration rate of the ODRP service. This happens as there are more passengers who are willing to share the trip with somebody else and as shareability directly depends on the ODRP passenger demand $\lambda_p$, consequently a high passenger demand means that the chances that the fleet operator has to find shareable trips are higher. Therefore, the number of vehicles in the system will be lower, leading to reduced VKT and higher network velocity.

Figure 5.6 illustrates the improvement of the average velocity for the network of the city of Munich relative to the base scenario, where the demand for ODRP passenger trips is zero. It is observed that in the extreme case where all the private vehicle trips in Munich are substituted with the ODRP vehicle trips for the penetration rate of 100% (Scenario P100), the velocity in Munich area could rise by up to 20% compared to the base scenario. For the lowest considered ODRP penetration rate of 5% (Scenario P5), it is noted that the effect of the ODRP service in the network velocity is negligible. This implies that the positive impacts of ODRP on traffic efficiency are not projected to be noticed for low penetration rate of the ODRP service. Nevertheless, when the ODRP service demand and hence its penetration rate will grow higher, the improvement in average velocity is expected to be more significant, as seen also in Figure 5.6. Taking as an example scenario P25, for an ODRP passenger demand penetration rate of 25%, the increase in average velocity compared to the base scenario is up to 10%. This infers that with increasing the ODRP penetration rate, the improvement of average velocity will be higher, and thereby stressing that ODRP services have to account for a significant share of the total vehicle trip demand in order for its impacts on traffic to be noticeable.

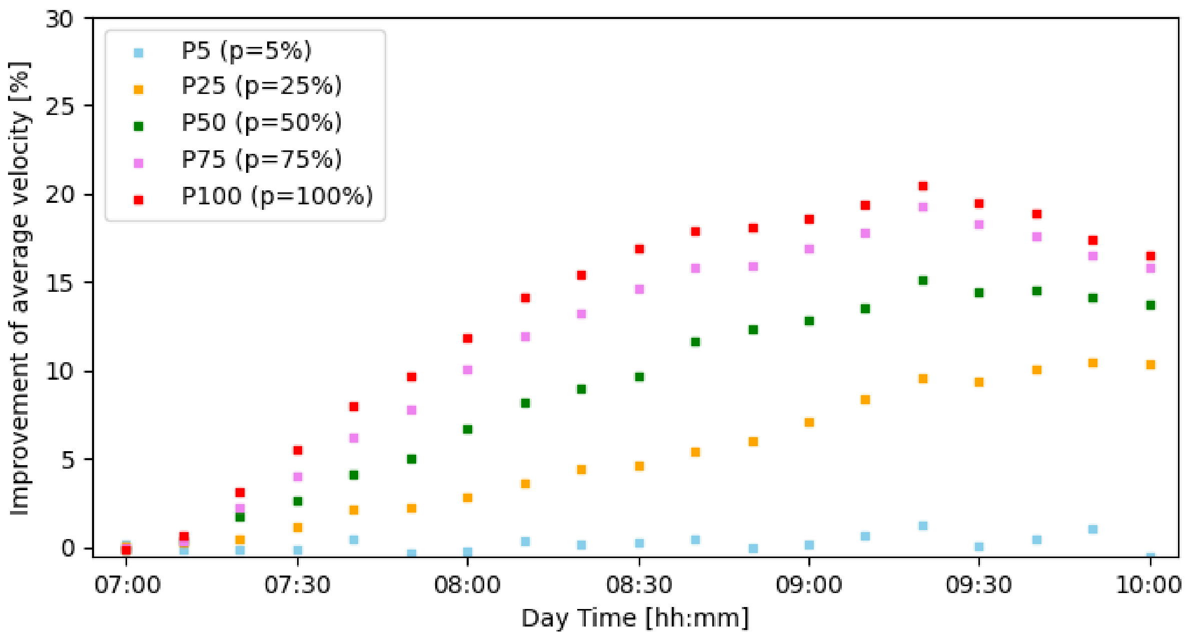



**Figure 5.6** Improvement of the average velocity of the Munich network during the morning peak time for different penetration rate of the ODRP passenger demand compared to the *Base scenario*, where the penetration rate of the ODRP passenger demand is equal to 0.

**Modified shareability model**

Analyzing the traffic impacts of an ODRP service in the previous part has shown that the average velocity in the network is expected to increase when the ODRP service is introduced, and the marginal effect of this improvement will depend on the market penetration of the ODRP passenger demand. As the average velocity of a city is an input for the shareability model, when this value gets higher, shareability is also expected to increase. This occurs as vehicles can reach further distances during the allowed detour time, thereby increasing the chances to find shareable trips. In the shareability model by TACHET ET AL. [2017], average velocity is assumed to be a constant parameter, which would not change regardless of the improvement in average velocity that ODRP would yield. In this thesis, a dynamic velocity is incorporated in the analytically modified shareability model as shown in Equations (22)-(24) and this model is tested with results from AIMSUN simulation.

Figure 5.7 depicts the simulated shareability values from simulation and the analytical curves for both the original and the modified shareability. The dotted gray line represents the original shareability curve for a constant velocity $v_o$ which is the average velocity of the base scenario. The solid gray line represents the modified shareability curve which considers the second order effect of improved average velocity and shows that the shareability value can further increase by incorporating a dynamic velocity. Due to a quite high average velocity ($v_o = 39.2\ km/h$) for the base scenario, which offers limited opportunities for improvement, the difference between the two shareability curves is not very significant. Nevertheless, even though the impact is small, the enhancement of the shareability values due to the improved average velocity imply that by improving traffic condition as a result of the ODRP service, the chances to find shareable trips in an area can additionally increase. The black dots in Figure 5.7 represent the simulated shareability values calculated by using the improved network's average velocity derived from AIMSUN simulation for the simulated scenarios with different penetration rate of the ODRP passenger demand: 5%, 25%, 50%, 75% and 100%. It is observed that the simulated shareability values fit quite well with the modified shareability curve. Albeit a small, noticed improvement of the modified shareability values in the case study of Munich due to small increase of average velocity, in general the findings are quite important as they suggest that for cities with higher level of congestion, the ODRP service might contribute to higher improvements of the average velocity and consequently, further increasing the chances to find shareable trips.

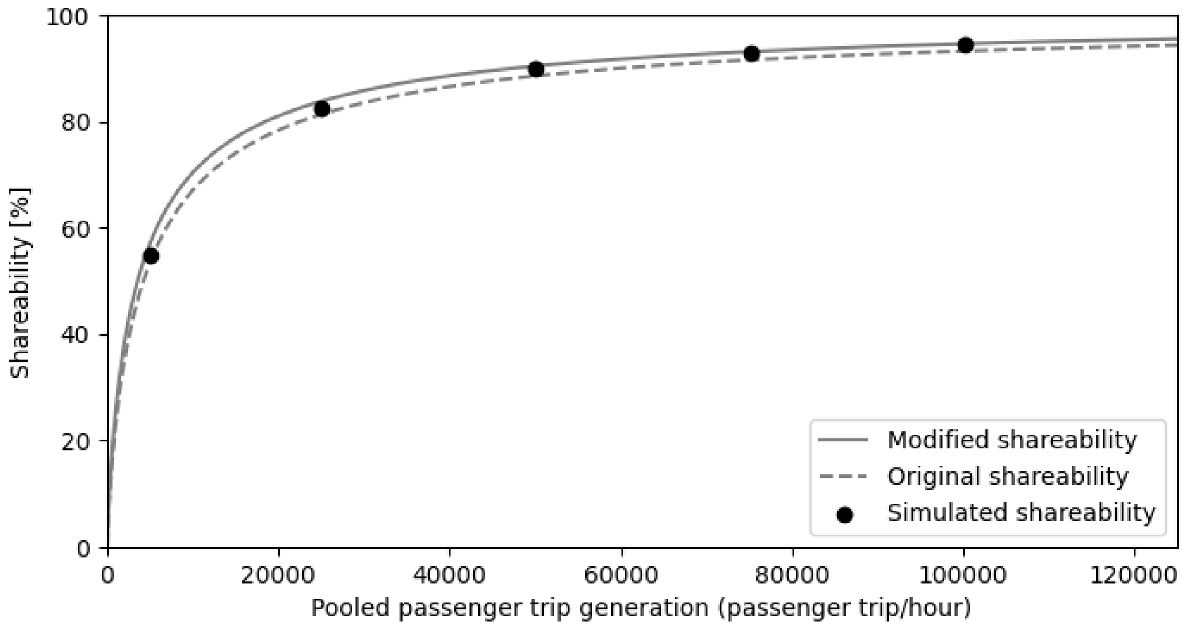



**Figure 5.7** Analytical and simulated shareability for different pooled/ODRP passenger trip generation rate per hour $\lambda_p$.

## 5.3 On-Demand Ride Pooling Benefits Evaluation

This section will explore the result of the general ODRP model presented in *Section 3.3*, investigating in which conditions an ODRP service can be beneficial from the perspective of cities, operators and customers, considering improvement in traffic efficiency, monetary profitability of the ODRP service operator and the conditions when a pooled ride is attractive for the customers. Firstly, the scenario design will be provided and then the results of the model will be shown.

### 5.3.1 Scenario design

This part will start with a description of the ODRP service parameters used for further investigation of the ODRP benefits. Then the scenarios considered for analyzing the societal benefits, operator's profitability and customer's attractiveness of the ODRP service will be provided. A description of all the parameters used in the general ODRP model is provided in Tab. 5.4.

**ODRP service parameters**

Similarly to the previous part (*Section 5.2*), an instant booking ODRP service operation in the Munich operation area of Figure 4.1 is considered, where the surface area is 221 km$^2$ and the average velocity in the network is $v_o = 39.2\ km/h$. The ODRP demand representing the number of ODRP passenger requests per hour equal to $\lambda_p$ is assumed to be exogeneous. This demand is also one of the input parameters of the general analytical model of ODRP impacts.

As the most prominent benefits of an ODRP service are associated with the improvement of traffic conditions in our cities, similarly to *Section 5.2*, the vehicle routing optimization objective used by the fleet operator is to minimize the VKT in the system and the network topology of Munich is represented by a street graph network. Using this optimization objective, the shareability for the considered operation area, different set of SQP ($\Delta$, $t^{max}$, $t^b$) and ODRP passenger demand $\lambda_p$ is calculated by using the prediction model approach (given by Equation (44)) described in *Subsection 5.1.2* and previously applied in *Section 5.2.*

Different from the validation of the other models, where a scenario-based set of SQP of the ODRP service is assumed, here a rather continuous change of the SQP and their impact on the results is considered. Therefore, the detour time value $\Delta$ varies from 1 to 15 minutes, the maximum waiting time $t^{max}$ takes values of 2, 5, 10 and 15 minutes and boarding/disembarking time $t^b$ is assumed to be 0 minutes for simplicity. The ODRP system is considered restrictive, normal or flexible for a maximum waiting time of 2, 5 and 10 (15) minutes, respectively.

**Societal benefits scenarios**

In order to investigate the impact of the ODRP in the society, the changes in the average velocity in the city by using Equation (20) are tested, showing the relation of average velocity and vehicle trips generated in the network. Instead of the general $g_{od}$ taking into account private/alone vehicle trips and ODRP/pooled vehicle trips with similar origins and destinations, in this part the modified total vehicle trip generation in the system is used considering also the additionally VKT from the ODRP detour distance given by Equation (25). In accordance with simulation studies [ENGELHARDT ET AL., 2019a], the experienced detour time is assumed to be half of the maximum detour time, therefore the parameter $\varepsilon$ is considered to be 0.5. The ODRP vehicles are assumed to serve maximum 2 passengers simultaneously and therefore, the vehicle capacity $\phi$ is equal to 2. Hence, the changes in average velocity will be captured for different ODRP passenger demand and various detour time values $\Delta$, while considering four different cases when the maximum waiting time $t^{max}$ is 2, 5, 10 and 15 minutes.

**ODRP operators' profitability scenarios**

To calculate the monetary benefits of the ODRP system from the operators' perspective, the costs and revenues of the service should be calculated and therefore, cost per kilometer and the pricing strategy used should be firstly defined.

The cost per kilometer for the ODRP service are assumed to be similar to the cost per kilometer of an ODRH service, which considers the costs of the on-demand mobility service fleet operator and the platform provider. Assuming the use of vehicles with a normal internal combustion engine, the ODRP total operation cost per kilometer $\kappa_{km}^{p}$, including also the vehicle fleet costs are supposed to be equal to $\kappa_{km}^{p} = 1.55\ €/km$ [NEGRO ET AL., 2021].

As for the revenue calculation in this numerical example, the ODRP fare that the customers should pay in order to use the service is only based on distance. The ODRP price per kilometer $\gamma_{km}^{p}$ is calculated based on the ODRH service price per kilometer $\gamma_{km}^{h}$ assuming a certain percentage reduction in price $\gamma$ when using the ODRP service compared to using the ODRH service. Therefore, a reduction of $\gamma$ = 30%, 25%, 20%, 10%, would mean that the ODRP price per kilometer $\gamma_{km}^{p}$ is calculated by using the following formula, where the ODRH price is considered to be $\gamma_{km}^{h} = 1.5\ €/km$, similar with the ODRH price in [KUCHARSKI & CATS, 2020]:

$$\gamma_{km}^{p} = (1-\gamma) * \gamma_{km}^{h} \tag{48}$$

As a result, four different scenarios with different price reduction are defined, for three different maximum waiting time values $t^{max}$ equal to 2, 5 and 10 minutes and various detour time $\Delta$.

**Customers' attractiveness to use the ODRP service scenarios**

The main factors determining the customers willing to use the ODRP service are the SQP and price. A customer would use an ODRP service only if the benefit she might get from the reduced price would surpass the disadvantage cause by the detour time. Hence, the customer could allow a deviation from her direct travel distance when using the ODRP service and at the same time she would expect to pay less for an ODRP ride compared to an ODRH ride.

In order to derive when can an ODRP service be attractive for the customers, the accepted detour time $\Delta_{\text{accepted}}$ is calculated by using Equation (35), which is the maximum detour time that the customer would accept for a certain price reduction compared to ODRH price. The accepted detour time as shown in Equation (35) depends on several parameters which include the value of time $\beta_t$, the waiting time discomfort $\beta_w$, the pooling discomfort $\beta_p$ and a cost sensitivity factor $\beta_c$.

In the base scenario of this study, the cost sensitivity factor $\beta_c$ (representing the disutility of the price and time components) takes the value of -1. The value of time $\beta_t$ is assumed to be -13.56 €/h in accordance to the value of time in the German context [SHOMAN, 2019]. The discomfort of pooling parameter $\beta_p$ is however not a well-known parameter, albeit recent research in stated preference choice experiments provide first estimations for the value of this parameter [ALONSO-GONZÁLEZ ET AL., 2020b]. In this study the discomfort of pooling $\beta_p$ is selected to be 1.3, similar with [KUCHARSKI & CATS, 2020]. Then a sensitivity analysis is performed to examine how different values of the value of time $\beta_t$ and the discomfort of pooling $\beta_p$ parameters effect the value of accepted customer detour time.

| Constant Parameter | Math Notation | Description | Value | Unit |
|---|---|---|---|---|
| Surface area | $\Omega$ | Surface of the operation area | 221 | $km^2$ |
| Network length | $L$ | Total length of the network | 2450 | km |
| Velocity at capacity | $v_c$ | Average velocity when the system is at capacity | 39.2 | km/h |
| Flow at capacity | $q_c$ | Average flow when the system is at capacity | 457 | vehicle/h |
| Average velocity during the morning peak | $v_o$ | Original average velocity during the morning peak for the base scenario | 39.2 | km/h |
| The parameter of the parabola | $a$ | Parabolic function parameter derived by data fitting | 0.062 | - |
| Average vehicle trip length of vehicle trips type (1) | $l_{od}$ | Average trip length for vehicle trips which have the origin and the destination in the operation area | 5.16 | km |
| Average vehicle trip length of vehicle trips type (2) | $l_o$ | Average trip length for vehicle trips which have only the origin in the operation area | 17.5 | km |
| Average vehicle trip length of vehicle trips type (3) | $l_d$ | Average trip length for vehicle trips which have only the destination in the operation area | 17.5 | km |
| % of $l_o$ inside the operation area | $p_o$ | % of $l_o$ inside the operation area | 51 | % |
| % of $l_p$ inside the operation area | $p_d$ | % of $l_p$ inside the operation area | 46 | % |
| Boarding/disembarking time | $t^b$ | The assumed time that the customer needs to board/disembark the vehicle | 0 | minute |
| Vehicle capacity | $\phi$ | The maximum number of passengers who can share a trip at the same time | 2 | passenger |
| Shareability fitting parameter | $k$ | Fitting parameter for the shareability prediction model in Eq. (44) | 0.126 | - |
| Shareability fitting parameter | $n$ | Fitting parameter for the shareability prediction model in Eq. (44) | 0.829 | - |

| | | | | |
|---|---|---|---|---|
| Parameter for detour time reduction | $\varepsilon$ | Parameter capturing the experienced detour time | 0.5 | - |
| ODRP service operator's cost per kilometer | $\kappa_{km}^{p}$ | ODRP service operator's cost per kilometer including ODRP vehicle fleet costs | 1.55 | €/km |
| ODRH service customer's price per kilometer | $\gamma_{km}^{h}$ | ODRH service price per kilometer that the customer pays | 1.5 | €/km |
| Value of time | $\beta_t$ | The value of time for the passengers | -13.56 | €/h |
| Waiting discomfort | $\beta_w$ | A parameter showing the perceived customer waiting time | - | - |
| Pooling discomfort | $\beta_p$ | A parameter capturing the discomfort of a shared ride | 1.3 | - |
| Cost sensitivity factor | $\beta_c$ | A parameter representing the disutility of the option | -1 | - |
| **Variable Parameter** | **Math Notation** | **Description** | **Value / Relation** | **Unit** |
| Detour time | Δ | Temporal deviation from the direct travel time | 0 – 15 | minute |
| Maximum waiting time | $t^{max}$ | Maximum time the passenger waits to be picked up | 5, 10, 15, 20 | minute |
| Shareability | $S$ | Percentage of trips which can be shared within an operation area | Eq. (4), (5), (44) | % |
| Average velocity | $v$ | Network's average velocity at a given time when the ODRP service is introduced | $v\ (g_{od_{mod}}) \rightarrow$ Eq. (20) and (21) | km/h |
| Average traffic flow | $q$ | Network's average traffic flow at a given time | | vehicle/h |
| Average traffic density | k | Network's average traffic density at a given time | | vehicle/km |
| Alone/private passenger trip generation rate | $\lambda_a$ | Alone/private passenger trips generated per hour in an area and completed by private vehicles | | passenger trip/h |
| Pooled/ODRP passenger trip generation rate | $\lambda_p$ | Pooled/ODRP passenger trips requests generated per hour and completed by the ODRP service | | passenger trip/h |

| | | | | |
|---|---|---|---|---|
| Alone/private vehicle trip generation rate | $g_a$ | Alone/private vehicle trips generated per hour by private vehicles | $g_a = \lambda_a$ | vehicle trip/h |
| Pooled/ODRP vehicle trip generation rate | $g_{p_{mod}}$ | Pooled/ODRP vehicle trips generated per hour by the ODRP service | Eq. (25) | vehicle trip/h |
| Total vehicle trip generation rate in the operation area | $g_{od_{mod}}$ | Total vehicle trips generated per hour in the operation area of the ODRP service of vehicle trips type (1) | $g_a + g_{p_{mod}}$ | vehicle trip/h |
| Vehicle trips generation rate of vehicle trips type (2) | $g_o$ | Hourly generation rate of the vehicle trips which have only the origin in the operation area | | vehicle trip/h |
| Vehicle trips generation rate of vehicle trips type (1) | $g_d$ | Hourly generation rate of the vehicle trips which have only the destination in the operation area | | vehicle trip/h |
| ODRP vehicle kilometers travelled | $VKT_{ODRP}$ | The VKT travelled by the ODRP service | $g_{p_{mod}} * l_{od} \rightarrow$ Eq. (27) | km/h |
| Discount | $\gamma$ | ODRP service customer price reduction compared to ODRH service price | $30, 25, 20, 10$ | % |
| ODRP service customer's price per kilometer | $\gamma_{km}^{p}$ | ODRP service price per kilometer that the customer pays | $(1-\gamma) * \gamma_{km}^{h}$ | €/km |
| ODRP service customer's price per minute | $\gamma_{min}^{p}$ | ODRP service price per minute that the customer pays | | €/minute |
| ODRP service operator's total cost | Cost | The total cost of the ODRP service for the operator | $VKT * \kappa_{km}^{p} \rightarrow$ Eq. (28) | €/h |
| ODRP service operator's total revenue | Revenue | The total revenue of the ODRP service for the operator when the pricing strategy is only based on distance | $\lambda_p l_{od} \gamma_{km}^{p} \rightarrow$ Eq. (29) | €/h |
| ODRP service operator's total profit | Profit | The total revenue of the ODRP service for the operator | Revenue – Cost | €/h |
| Accepted customer detour | $\Delta_{\text{accepted}}$ | Customers would allow a deviation of $\Delta_{\text{accepted}}$ to compensate for the reduced ODRP price | Eq. (35) | minute |

**Tab. 5.4** Description of the parameters of the general ODRP analytical model capturing the benefits of the ODRP service from the perspective of cities, operators and customers. Their math notations and their corresponding values or relations are also depicted.

### 5.3.2 Results

In this part the results of the general analytical model of the ODRP impacts will be explored. Firstly, the parameter space where the ODRP service can be beneficial for the society, in terms of improved traffic conditions will be described. Then, the monetary profitability of the operator will be investigated. And lastly, the customer attractiveness toward sharing a ride will be captured.

**Benefits for the society**

The introduction of ODRP services is anticipated to improve the traffic conditions in urban areas. The general analytical model presented in *Subsection 3.3.2* is used in this part to explore in which parameter space the ODRP service can be beneficial for the society, i.e., for which ODRP passenger demand, detour time, maximum waiting time etc., the ODRP service has the potential to improve the traffic efficiency.

Figure 5.8 illustrates the average velocity in Munich operation area for different ODRP passenger demand level $\lambda_p$, various maximum detour time $\Delta$ and different maximum waiting time $t^{max}$. The color of the graph shows the changes in average velocity. An improvement in average velocity, and therefore better traffic conditions in the city, are shown by the blue color. The darker the blue color is, the higher is the average velocity in the city. Whereas the red color would mean that the average velocity in the city is lower than the base scenario (when the ODRP service is not introduced and ODRP passenger demand level $\lambda_p$ is zero). The white color shows that the average velocity remains the same as in the base scenario and there is no significant improvement in average velocity in the area due to the shared trips. The value of the average velocity for these graphs is derived by using Equation (20), where $g_{od} = g_{od_{mod}}$ given by Equation (25). This represents the relation of average velocity and vehicle trips generated in the system for the free flow regime, where the modified total vehicle trip generation in the system includes also the additionally VKT from the ODRP detour distance.

It is noted in Figure 5.8 that for small penetration rate of the ODRP passenger trip demand $\lambda_p$ the introduction of the ODRP service in the city of Munich does not improve the average velocity for the considered parameter space (shown by the white color in the graphs). The smallest ODRP passenger demand penetration rate for which an improvement in average velocity is possible is noted to be at around 7000 trips/h for detour values ranging from 4-6 minutes and maximum waiting time of 15 minutes (Figure 5.8.d). With decreasing the maximum waiting time, this critical value of the ODRP passenger trip demand for which average velocity in the city starts increasing gets larger (Figure 5.8.a, Figure 5.8.b and Figure

5.8.c), meaning that the positive impacts of ride pooling in traffic efficiency will be noticed for higher penetration rate of ODRP demand. The reason for these results is that by decreasing the maximum waiting time, the chance to find shareable trips – and consequently shareability – also decreases, as the constraint of the maximum waiting time reduces the options to find shareable trips. Therefore, the lower number of shareable trips decreases the possibility to reduce the number of vehicle trips generated in the system, decreasing therefore the chances to have higher average velocity in the system.

It is observed that the detour time has a different impact on the result compared to the impact of the maximum waiting time, since detour time contributes also to the addition of vehicle trips in the system as a result of the detour distance imposed by the ODRP service. Whereas the maximum waiting time does not influence the vehicle trips in the system, as it is the time the customer waits to be picked up. It is shown that for low detour time, even when the ODRP passenger demand is high the improvement in average velocity is restricted, as the chances to find shareable trips are very low for small values of detour time. With increasing detour time, the system starts to see positive traffic impacts for lower ODRP passenger demand penetration, as the shareability increases when the value of the detour time constraint gets higher. However, after a certain detour time, which is referred here as the optimum detour time, the ODRP passenger demand when the system's average velocity starts to improve shifts to the right (representing higher ODRP demand penetration rate). This happens as higher values of the detour time, do not only contribute to higher shareability values, but also to higher generated detour distance. For detour time higher than the optimum one, the generated detour distance in the system is higher than the benefits that the detour time has on increasing the shareability, therefore the positive impact of the ODRP service in average velocity is observed for higher ODRP passenger penetration rate.

Figure 5.8 illustrates the optimum detour time for each of the considered maximum waiting time of 2 (Figure 5.8.a), 5 (Figure 5.8.b), 10 (Figure 5.8.c) and 15 (Figure 5.8.d) minutes. It is noted that the optimum detour time is lower for higher maximum waiting time. The reason for this is that when the maximum waiting time takes high values its impact on the shareability is more prominent compared to the influence of low detour times, therefore the optimum detour time, where the disadvantages of the detour distance surpass the benefits of increased shareability is lower. With rising values of the maximum waiting time, it is shown that the changes in average velocity between the graphs start to diminish. As an example, for a detour of one minute, when changing the maximum waiting time from 2 minutes to 5 minutes the difference in the ODRP demand where the system start to show positive impacts is around 10000 trips/h, whereas when changing from maximum waiting time of 5 minutes to 10 minutes the difference is around 5000 trips/h. Mind also that the difference in ODRP demand change is bigger, albeit larger changes in the maximum waiting time, as in the first case there is only a three minutes difference in maximum waiting time and in the second case the difference is 5 minutes. This difference decreases even further when $t^{max}$ changes from 10 minutes to 15 minutes.

The average velocity in the city is higher than the base scenario in all the graphs of Figure 5.8 showing that in the considered parameter space the total number of vehicle trips generated, even when adding the extra trip length from the detour time, is lower or similar to the vehicle trips of the base scenario, since in Equation (25) $v(0.5\Delta)$ is always smaller than $l_{od}$ for $\Delta < 15\,\text{minutes}$ as the average trip time in Munich is around 8 minutes. Therefore, in the considered scenario analysis, the average velocity in the city can either remain the same or increase, but it does not decrease.

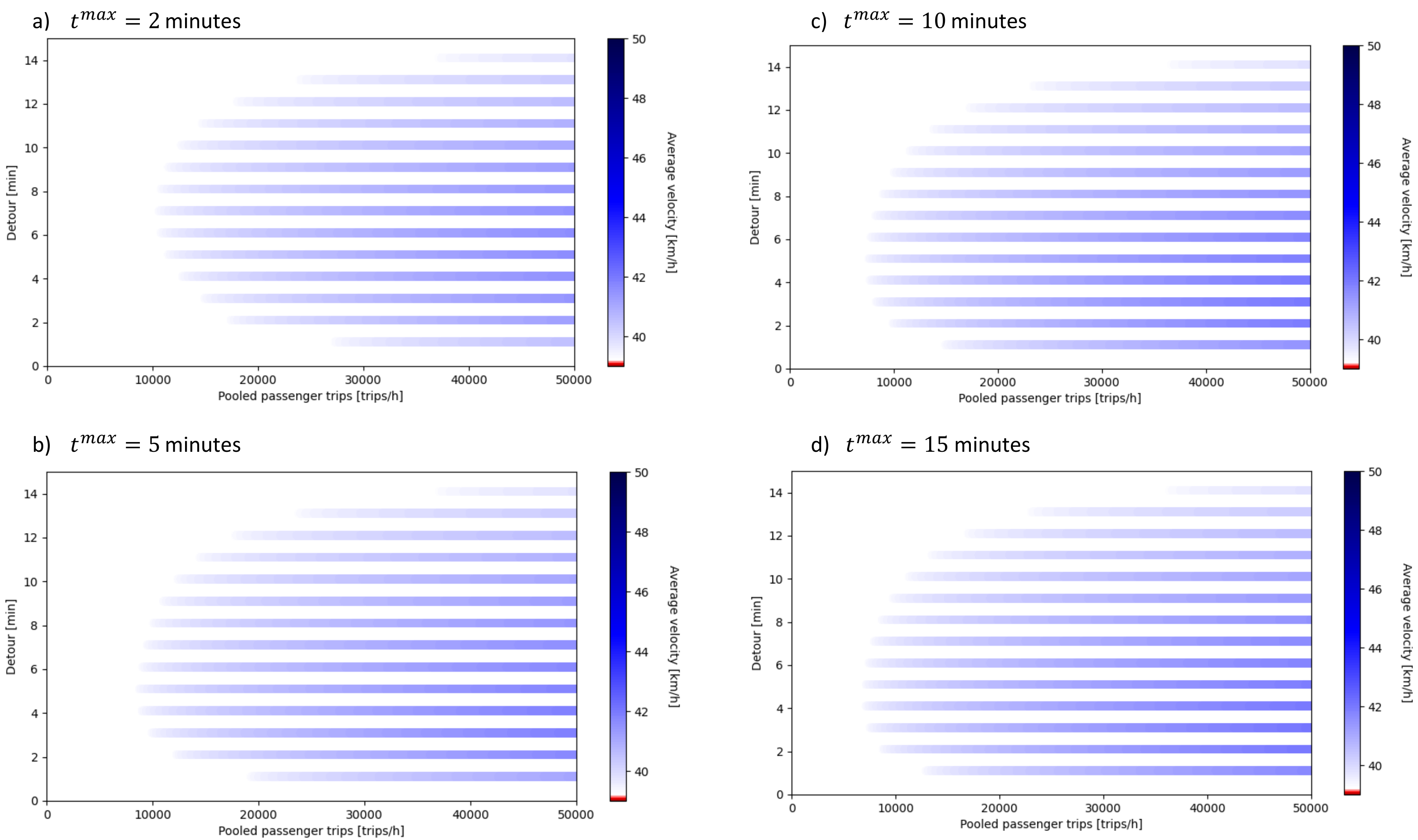



**Figure 5.8** Average velocity in Munich area for different ODRP passenger demand level $\lambda_p$, various detour time Δ and different maximum waiting time $t^{max}$. Different graphs show the average velocity when a) $t^{max}$ = 2 minutes, b) $t^{max}$ = 5 minutes, c) $t^{max}$ = 10 minutes and d) $t^{max}$ = 15 minutes.

**Benefits for the operators**

In this part the results of the monetary profitability model presented in *Subsection 3.3.3* and capturing the profitability of the ODRP service from the operator perspective will be illustrated and the parameter space when the service can be profitable will be defined by investigating the scenarios defined in *Subsection 5.3.1*.

The monetary profitability of the ODRP service in this part is calculated by using Equations (26) – (29). For different ODRP passenger demand $\lambda_p$ and various detour time Δ, Figure 5.9, Figure 5.10 and Figure 5.11, illustrate the profitability for maximum waiting time $t^{max}$ equal to 2, 5 and 10 minutes, respectively. According to the selected maximum waiting time the ODRP system is considered as restrictive (Figure 5.9), normal (Figure 5.10) or flexible (Figure 5.11). For each of these figures, subplots a), b), c) and d) refer to different discount levels $\gamma$, meaning that the ODRP price per kilometer $\gamma_{km}^{p}$ is 30%, 25%, 20% and 10% of the ODRH price per kilometer $\gamma_{km}^{h}$ as given in Equation (48). The base ODRH price considered here is equal to 1.5 €/km, similar to the price values used in KUCHARSKI & CATS [2020]. The red color of the plots show that the system is not profitable and the darker the red color is, the larger are the monetary loss of the ODRP service. Whereas the blue color shows that the system is profitable and the darker the blue color is, the more profitable is the ODRP service. The white color shows the brake-even point, where the cost and the revenue of the ODRP service are equal. The green line defines the accepted customer detour time $\Delta_{\text{accepted}}$ for the given ODRP discount $\gamma$, however more explanation will be provided for this in the next part.

In Figure 5.9 the ODRP profitability for a restrictive ODRP system, when the maximum waiting time equals to 2 minutes, is calculated for different discount levels. It is shown that for discount $\gamma$ of 30% (Figure 5.9.a) and 25% (Figure 5.9.b) the ODRP service is not profitable in the considered parameter space for ODRP passenger demand level of up to 50000 trips/h and detour time of up to 15 minutes. For a discount $\gamma$ of 20% (Figure 5.9.c) and within the considered ODRP passenger demand, the profitability of the system is limited only for a certain range of ODRP demand and for the service quality parameter of the detour time within the range of 3 to 8 minutes. The lowest ODRP passenger demand level for which the system starts to be profitable for this discount level is around 25000 trips/h when the detour time is 6 minutes. In the case when the discount $\gamma$ is only 10% of the ODRH price (Figure 5.9.d), the ODRP system is profitable in the majority of the parameter space and even for low ODRP passenger demand. This happens as the operator’s total cost reduction due to trip sharing outperforms the decrease in revenue due to the lower price offered to the customers and therefore the ODRP system is profitable.

Figure 5.10 illustrates the profitability results for a normal ODRP system where the maximum waiting time is 5 minutes. It is observed that even though also in this case the ODRP system is not profitable for discount $\gamma$ of 30% (Figure 5.10.a), it starts to be profitable for a discount of 25% (Figure 5.10.b). As expected, the profitable parameter space area increases for discount 20% (Figure 5.10.c) and 10% (Figure 5.10.d). The area is also larger than the same discount scenarios for the case when the maximum waiting time is equal to 2 minutes, as with increasing values of maximum waiting time the chance to find shareable trips and hence shareability also increases, reducing in this way the $\mathrm{VKT_{ODRP}}$ and hence the total cost of the ODRP system, as shown in Equation (28).

Figure 5.11 shows the profitability results for a flexible ODRP system when the maximum waiting time is 10 minutes. The ODRP system for this case starts to be profitable for a lower discount level that equals to 30%, however profitability is reached only for high ODRP passenger demand level of more than 30000 trips/h. The parameter space where the system is profitable increases with the reduction of the discount and similarly with the previous case, the profitable area is larger than the one shown in Figure 5.10 for the same discount level, as for a flexible ODRP system with higher values of the maximum waiting time constraint, the shareability is consequently higher. In this case, for a low discount of 10% (Figure 5.11.d), the profitability of the ODRP service is observed even for low ODRP passenger demand of about 2500 trips/h and low detour time of only 1 minute.

An interesting observation is distinguished for the cases when the ODRP system is profitable (in Figure 5.9 (c and d), Figure 5.10 (b, c and d) and Figure 5.11), where the existence of an optimum detour time is determined. This is defined as the point with the lowest ODRP passenger demand for which the ODRP system starts to be profitable. Considering the example of Figure 5.10.c for a normal ODRP system with maximum waiting time of 5 minutes and discount of 20%, it is noted that for low detour time of 1 minute the ODRP system is not profitable for the considered range of ODRP demand. However, when the detour time increases, the ODRP demand where the system starts to be profitable decreases (i.e., the ODRP system can be profitable for lower penetration rate) due to increased shareability values as a result of higher detour time which contribute to cost reduction. However, after a certain detour time (5 minutes in this example), which is referred as the optimum detour time, the ODRP passenger demand where the system starts to be profitable shows an increasing trend. This happens as after this point of optimum detour time, the disadvantages coming from increased detour distance, which consequently influence the increase of the operator costs, surpass the advantages that the detour time has on increasing the shareability, thereby decreasing the operation costs. Hence, increasing the detour time more than this optimum is not beneficial in terms of operator's profitability. A similar behavior is noticed also in the previous part, which analyzes the ODRP impact on average velocity in the city, where similarly an optimum detour time from city's perspective is defined.

Another quite important aspect in the analysis the system's profitability is that intuitively it could be expected that with increasing the ODRP passenger demand it would come a point where the system would be profitable, however, this is not always the case. In the described cases, it is observed that for low detour time, with increasing ODRP demand the monetary loss of the system become higher (shown by the darker red color). The reason for this behavior is that the operator has very low chances to find shareable trips, but still keeps offering the customers a cheaper price. This adds up in reduced revenues and increased total monetary loss when the ODRP passenger demand gets higher. Similar observation is noticed for high values of detour time in all the scenarios of Figure 5.9, Figure 5.10 and Figure 5.11, where if increasing the ODRP passenger demand, the system not even does not become profitable, but in the contrary, its monetary losses becomes higher (shown by the darker red color). In this case the reason for the increased monetary losses is associated with increased total cost of the ODRP system, as with higher allowed detour time, the total VKT in the network increase, due to increased detour distance to pick up additional passengers.

These results can be important for the operators to derive in which conditions the ODRP system that they want to offer will be profitable. By using these finding they could decide what kind of SQP they want to offer to the customers by defining the detour time and the maximum waiting time of the ODRP system. This model also gives an estimation for them to anticipate the ODRP penetration rate necessary for them to be profitable for the offered type of the ODRP service defined by the selected SQP.

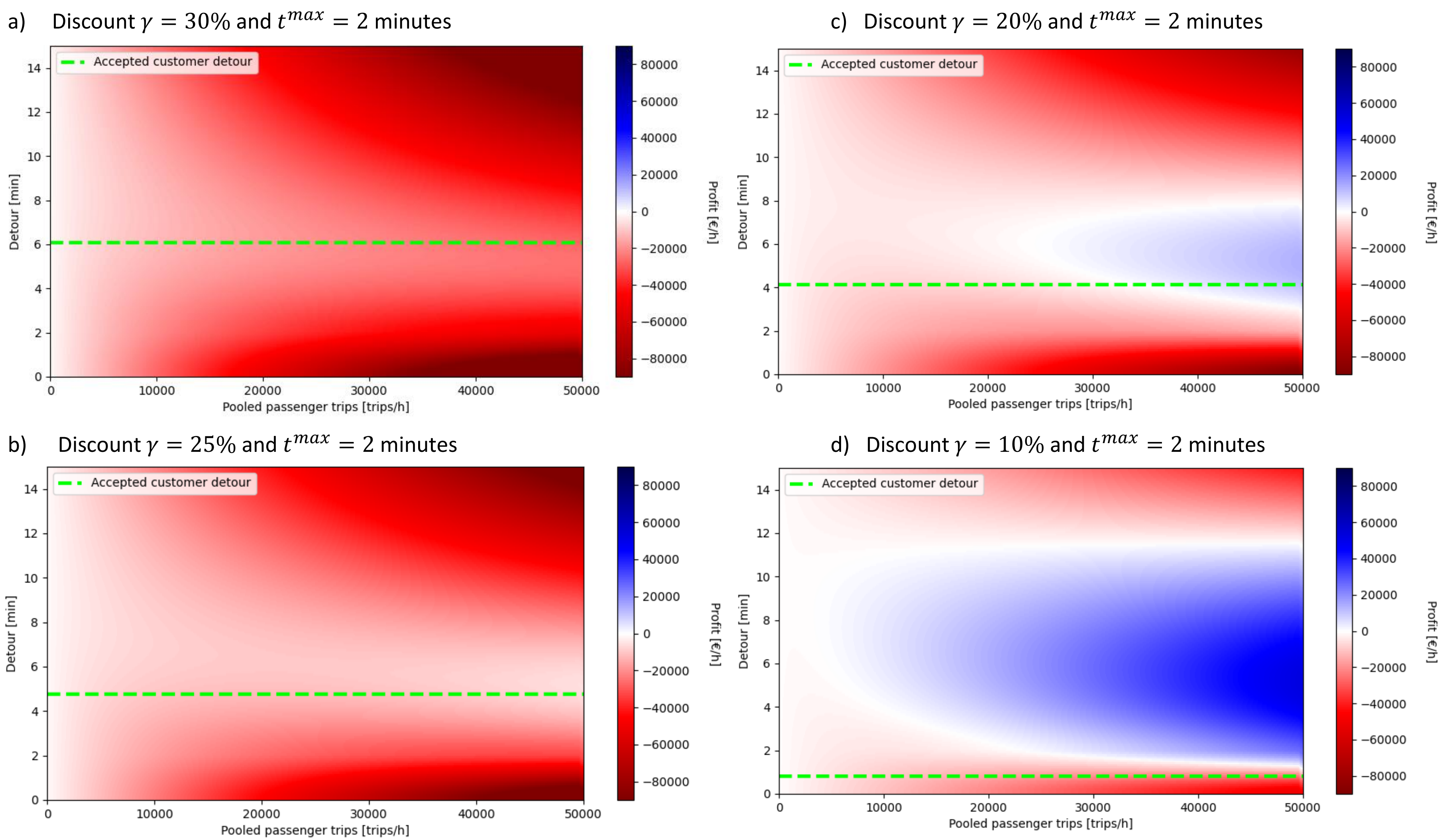



**Figure 5.9** Operator's monetary profitability in Munich for maximum waiting time $t^{max} = 2$ **minutes**, different ODRP passenger demand $\lambda_p$, various detour time $\Delta$. Different subplots correspont to different discount $\gamma$ (ODRP price = $(1-\gamma)$ * ODRH price): a) $\gamma = 30\%$, b) $\gamma = 25\%$, c) $\gamma = 20\%$, d) $\gamma = 10\%$. The green dotted line represents the accepted customer detour time until which the customer considers the ODRP service as attractive.

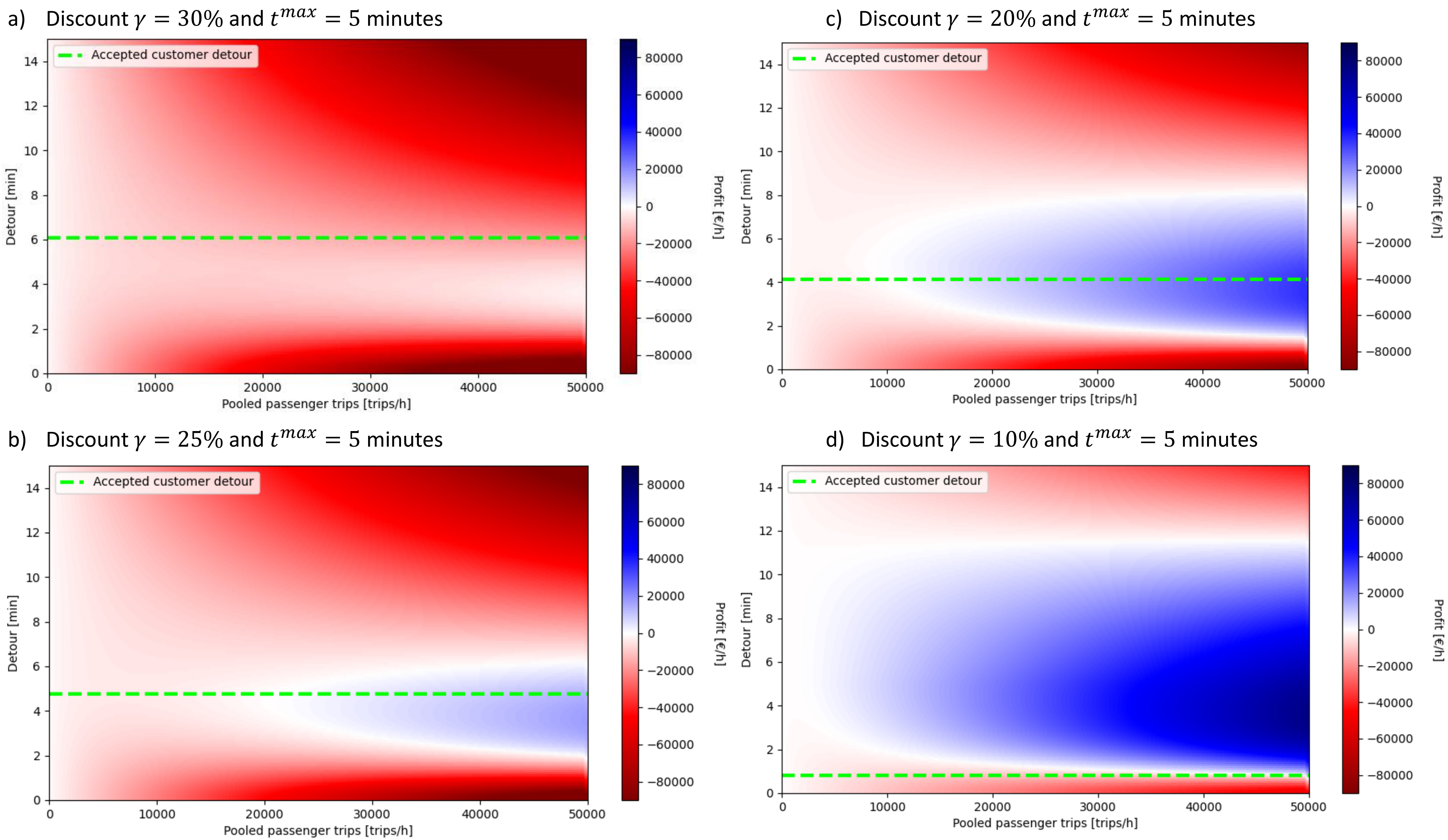



**Figure 5.10** Operator's monetary profitability in Munich for maximum waiting time $\boldsymbol{t^{max} = 5}$ **minutes**, different ODRP passenger demand $\lambda_p$, various detour time $\Delta$. Different subplots correspont to different discount $\gamma$ (ODRP price = $(1-\gamma)$ * ODRH price): a) $\gamma = 30\%$, b) $\gamma = 25\%$, c) $\gamma = 20\%$, d) $\gamma = 10\%$. The green dotted line represents the accepted customer detour time until which the customer considers the ODRP service as attractive.

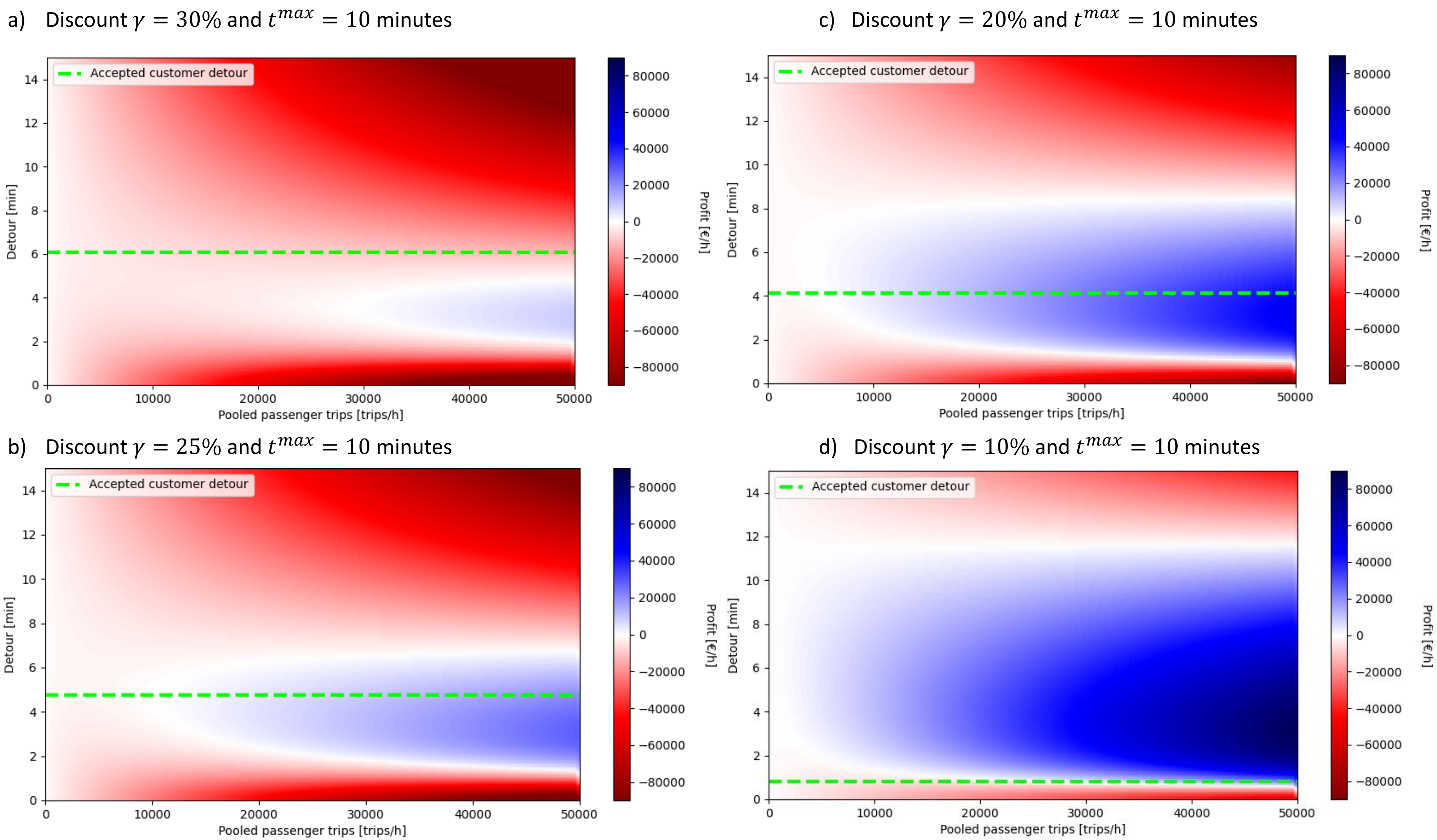



**Figure 5.11** Operator's monetary profitability in Munich for maximum waiting time $\boldsymbol{t^{max} = 10}$ **minutes**, different ODRP passenger demand $\lambda_p$, various detour time $\Delta$. Different subplots correspont to different discount $\gamma$ (ODRP price = $(1 - \gamma)$ * ODRH price): a) $\gamma = 30\%$, b) $\gamma = 25\%$, c) $\gamma = 20\%$, d) $\gamma = 10\%$. The green dotted line represents the accepted customer detour time until which the customer considers the ODRP service as attractive.

**Benefits for the customers**

When analyzing the ODRP service benefits, the customers certainly play a key role in determining the overall success of the service. In this part the conditions when an ODRP service would be attractive for the customers are analyzed.

The ODRP attractiveness for customers is investigated by using the approach described in *Subsection 3.3.4*, where the willingness of customers to use the ODRP service is compared with the willingness of the customers to use an ODRH service. Hence, the accepted customer detour time is derived from Equation (35), which is the maximum detour time that the customer would be willing to accepted for a certain price reduction. More specifically, it answers the question of what is the detour that the customer is willing to tolerate for a certain compensation coming from paying a lower price compared to the ODRH price. As shown in Equation (35), the accepted customer detour time value in addition to the changes in price per kilometer between ODRH service $\gamma_{km}^{h}$ and ODRP service $\gamma_{km}^{p}$, depends also on the parameters defining the value of time $\beta_t$ and the pooling discomfort $\beta_p$. In this study the value of time $\beta_t$ is considered to be equal to 13.56 €/h, in accordance to the value of time in Germany specified in [SHOMAN, 2019] for a vehicle passenger with an average income, and the pooling discomfort $\beta_p$ is assumed to be equal to 1.3, similar to [KUCHARSKI & CATS, 2020].

By keeping the value of time and the discomfort of pooling parameters fixed and equal to the above-mentioned values, the accepted customer detour time in Figure 5.9, Figure 5.10 and Figure 5.11 (shown by the dotted green line) is calculated by using Equation (35). As expected for lower discount values, the maximum accepted customer detour time decreases. For instance, when the discount is 10% of the ODRH price, the accepted detour time is only 1 minute, i.e., that the customers would not accept a higher detour time for this low-price reduction. However, when the discount is higher, for instance in the case when $\gamma = 30\%$, the customer would tolerate a higher detour of 6 minutes for the cheaper price that she is going to pay for the ODRP service compared to the ODRH service.

As mentioned, the accepted customer detour time will change with changing values of the value of time $\beta_t$ and the pooling discomfort $\beta_p$ parameters. Therefore, in order to explore the impact of these parameters on the results, Figure 5.12 illustrates the accepted customer detour time values for various values of the value of time parameter $\beta_t$ and the pooling discomfort parameter $\beta_p$ for the scenarios where the discount $\gamma$ is equal to $30\%$ (Figure 5.12.a), 25% (Figure 5.12.b), 20% (Figure 5.12.c) and 10% (Figure 5.12.d). It is shown that for higher values of time and pooling discomfort parameters, the detour time accepted by the customers decreases (noted by the darker colors). This occurs because the extra travel time spend is more 'costly' for the customers for higher values of time $\beta_t$. Similar for the pooling discomfort, for higher values of the pooling discomfort $\beta_p$ parameter, the customers perceive the time they share the trip with somebody else as more discomfortable, therefore the acceptable detour time decreases in this case as well. Intuitively, when the values of the pooling discomfort $\beta_p$ and value of time $\beta_t$ parameters are low, the accepted customer detour time increases (noted by the light colors), allowing for higher system flexibility for the operators. Different subplots in Figure 5.12 show how the accepted customer detour time alters for different discount levels $\gamma$. For low discount values $\gamma = 10\%$ and the accepted customer detour time is lower than 4 minutes for the majority of the considered values of the parameters, taking its highest value in the range 4 – 6 minutes for only a small range of $\beta_p$ and $\beta_t$ values (Figure 5.12.d). With increasing discount value, i.e., lower ODRP price, the range of the accepted detour time increases. For instance, for the lowest discount of 30% (Figure 5.12.a), the highest accepted detour time values are within 16 – 18 minutes range and the lowest are between 2 – 4 minutes.

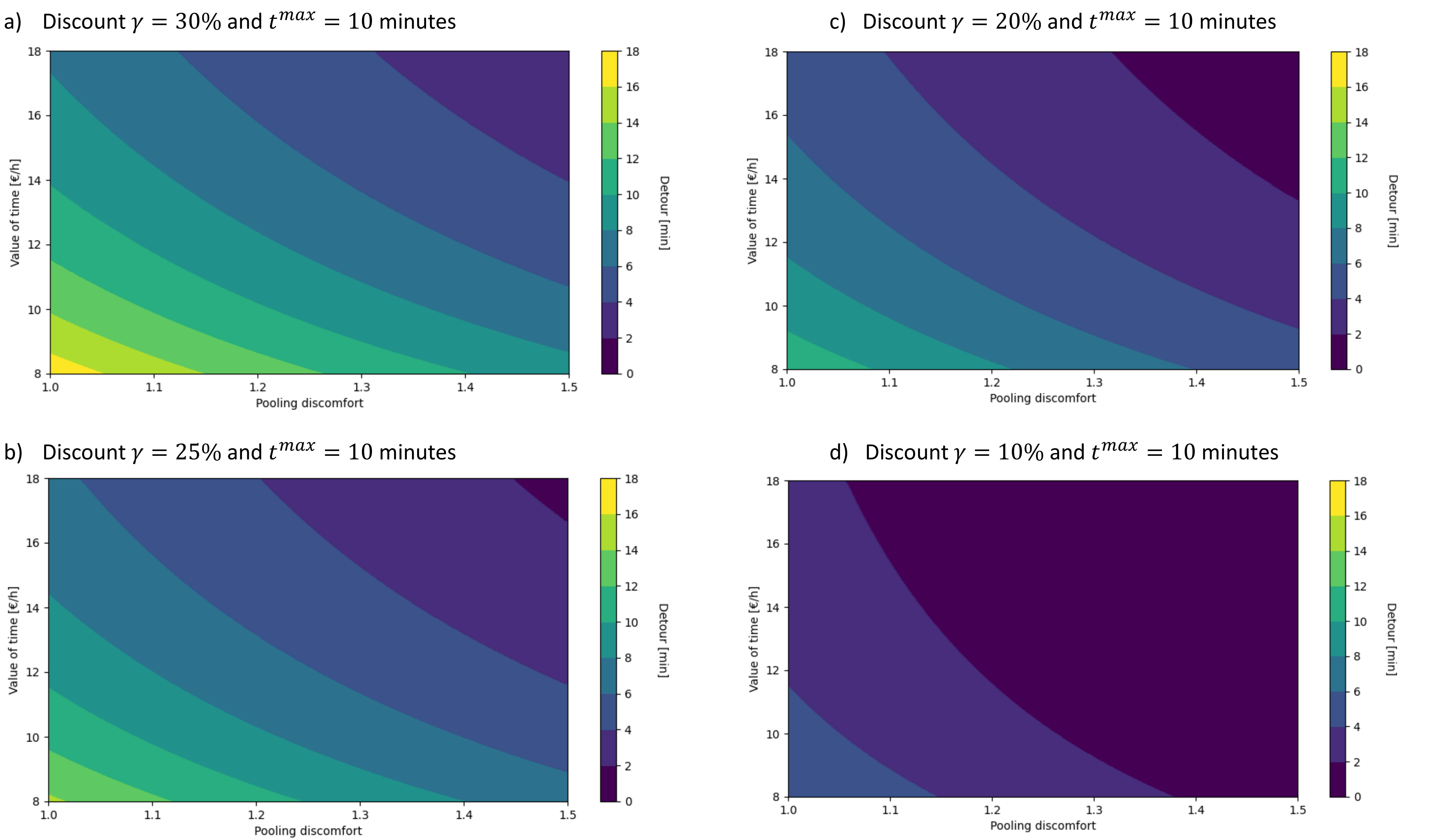



**Figure 5.12** Accepted customer detour time $\Delta_{\text{accepted}}$ for different value of time $\beta_t$ and pooling discomfort $\beta_p$. Different subplots provide the accepted customer detour time for various discount levels: a) $\gamma = 30\%$, b) $\gamma = 25\%$, c) $\gamma = 20\%$ and d) $\gamma = 10\%$.

## 5.4 On-Demand Ride Pooling WIN-WIN-WIN Situation

As already mentioned, the overall aim of this thesis is to explore under which conditions the win-win-win situation for cities, operators and customers can be achieved. After presenting the models developed in this thesis and testing them by means of an agent-based simulation and a microscopic traffic simulation, the separate benefits of an ODRP service offered in an operation area in Munich, considering the perspective of the city, the operator and the customers as specified in *Subsection 5.3.1,* are determined.

In this part, the benefits for city, operator and customers are combined and the win-win-win situation between them is determined. The win for the city would occur in the case when the average velocity in the city is higher than in the base scenario. The win for the operator would imply that the profitability is higher than zero. And lastly, the win for the customer would be when the detour time is lower that the accepted customer detour time, which is specified based on the customer's willingness to accept the deterioration of the service quality given by the addition of the detour time in compensation to the reduced price compared to the ODRH service. The results illustrated in Figure 5.13, Figure 5.14 and Figure 5.15 show in which parameter space the ODRP service can be beneficial for all the three stakeholders. More specifically, for different maximum waiting times of $t^{max}$ of 2 (Figure 5.13) , 5 (Figure 5.14) and 10 (Figure 5.15) minutes, they provide the range of ODRP passenger demand $\lambda_p$ and detour time Δ for which the win-win-win situation can be achieved. Different subplots (a, b, c and d) illustrate the results for different discount rates offered to the customers, where $\gamma$ is equal to 30%, 25%, 20% and 10%, respectively.

The break-even line for the city (given in black) shows that in those points the average velocity in the city remains the same as in the base scenario where the ODRP service was not introduced. At the same time, this line provides the threshold for the traffic benefits of the ODRP to be positive. On the right side of this line, the ODRP system is beneficial for the city. The break-even line for the operator in blue indicates the points where the ODRP system profitability is zero. Similar to the city break-even line, the ODRP system is profitable on the right side of this blue line. The threshold of the customer win is provided by the green line which is the maximum allowed customer detour time. A win for the customer is obtained below this green line. Consequently, the intersection of these lines (shown by the yellow area) determines the parameter space of the detour time and the ODRP passenger demand for which the ODRP win-win-win is possible. If the yellow area or the break-even lines of the customer or the operator are not visible in the plot, it means that the break-even and the win-

win-win situation cannot be achieved within the considered detour time and ODRP passenger demand parameter space.

Figure 5.13 provides the results for a restrictive ODRP system where the maximum waiting time is only 2 minutes. It can be observed that the win-win-win is noticed only in Figure 5.13.c where the discount $\gamma$ is 20%. And even in this case, the ODRP passenger demand for which the win-win-win is achieved is quite high and equal to around 45000 trips/h. For the first two subplots in Figure 5.13.a and Figure 5.13.b, the win from the operator perspective cannot be achieved for the considered ODRP passenger demand range. Therefore, the total win-win-win is not possible in this case. Whereas in Figure 5.13.d, even though the win-win for operator and city can be achieved, for the considered discount level of only 10% the win for the customers is restricted to a detour time of lower than around 1 minute. As within this detour time range the win for the operator is not possible, consequently the total win-win-win is not achieved.

Figure 5.14 illustrated the results for a normal ODRP system where the maximum waiting time is 5 minutes. For this normal ODRP system, the win-win-win is realized in Figure 5.14.b and in Figure 5.14.c for discounts of 25% and 20%, respectively. The ODRP passenger demand necessary to achieve this state is still high, nevertheless it is lower than for the previous case when the maximum waiting time was 2 minutes. The win-win-win state can be achieved for ODRP demand higher than 22000 trips/h and 14000 trips per hour for discounts of 25% and 20%, accordingly. However, the detour time parameter range for the win-win-win to happen is much higher than in the previous case (Figure 5.13.c), ranging from 2 – 5 minutes and 2 – 3.5 minutes for Figure 5.14.b and in Figure 5.14.c respectively. As in Figure 5.13.a for a discount of 30% and a maximum waiting time of 2 minutes, the win-win-win is also not possible in Figure 5.14.a for the same discount but a higher maximum waiting time of 5 minutes, because the operator’s win is not attainable within the ODRP passenger demand range. The win-win-win is not possible also in Figure 5.14.d as the customers’ win is limited to detour time values of shorter than 1 minute, for which a win for the operator and the city cannot be achieved.

Figure 5.15 shows the results for a flexible ODRP system where the maximum waiting time is 10 minutes. It is observed that a win-win-win situation is achieved for 3 out of 4 cases considered. For this maximum waiting time, the win-win-win is achieved also for a discount of 30% (Figure 5.15.a), which was not noted in Figure 5.13.a and Figure 5.14.a for lower maximum waiting times of 2 and 5 minutes, respectively. The parameter space for this state corresponds to the yellow area in Figure 5.15.a for an ODRP passenger demand of more than 30000 trips/h and detour time values in the range of 2 – 5 minutes. A better compromise for the achievement of the win-win-win is observed in Figure 5.15.b and Figure 5.15.c for discount values of 25% and 20%, respectively. For both cases, the parameter space where the system can be profitable from city, operator and customers perspective is larger. Nevertheless, for a discount of 20% as shown in Figure 5.15.c, the win-win-win starts to be visible for lower ODRP passenger demands (less than 10000 trips/h) compared to Figure 5.15.b for the case when the discount is 25% (more than 10000 trips/h). Compared to the previous cases (Figure 5.13 and Figure 5.14), the operators profitability here (Figure 5.15) is achievable for a larger parameter space (starting with a lower ODRP demand) as longer maximum waiting time contributes to increases revenues due to higher chances to find shareable trips, without increasing the VKT driven and hence keeping the costs the same and increasing the profitability. The total win-win-win parameter space area of Figure 5.15.c is almost similar to the win-win-win area of Figure 5.15.b. This occurs as even though the ODRP passenger demand for a win-win-win state in the case presented in Figure 5.15.b is higher than in Figure 5.15.c, the maximum allowed detour time for the customers' win in Figure 5.15.b is longer than in Figure 5.15.c (3.5 and 5 minutes, correspondingly). Similar to the previous cases with maximum waiting times of 2 (Figure 5.13.d) and 5 (Figure 5.14.d) minutes, the win-win-win is also not attained for a discount of 10% in Figure 5.15.d due to very low values of maximum customer detour times, which do not allow benefits for the city and the operator.

The results of this part show that even though a restrictive ODRP system (Figure 5.13) can be desirable for the customers, the total win-win-win can hardly be achieved. A normal ODRP system (Figure 5.14) has higher chances to attain a win-win-win for a large parameter space compared to a restrictive ODRP system. However, the more flexible the ODRP system is, like the one in Figure 5.15, the larger is the parameter space for which the win-win-win is possible. Therefore, this kind of system might be more desirable to achieve the goals of the three ODRP stakeholders. Additionally, the discount plays an important role in the results, showing that a discount of 25% or 20% could be beneficial. A discount of 30% albeit desirable for customers, might not provide monetary benefits for the operator. Whereas a discount of 10% even though providing high profitability for the operator, might not attract customers to opt for the ODRP service due to low monetary compensation for the deterioration of the service quality due to additional experienced detour time. To conclude, a win-win-win situation is anticipated to be achieved for a larger parameter space for a flexible ODRP system and a discount range of 25% and 20%.

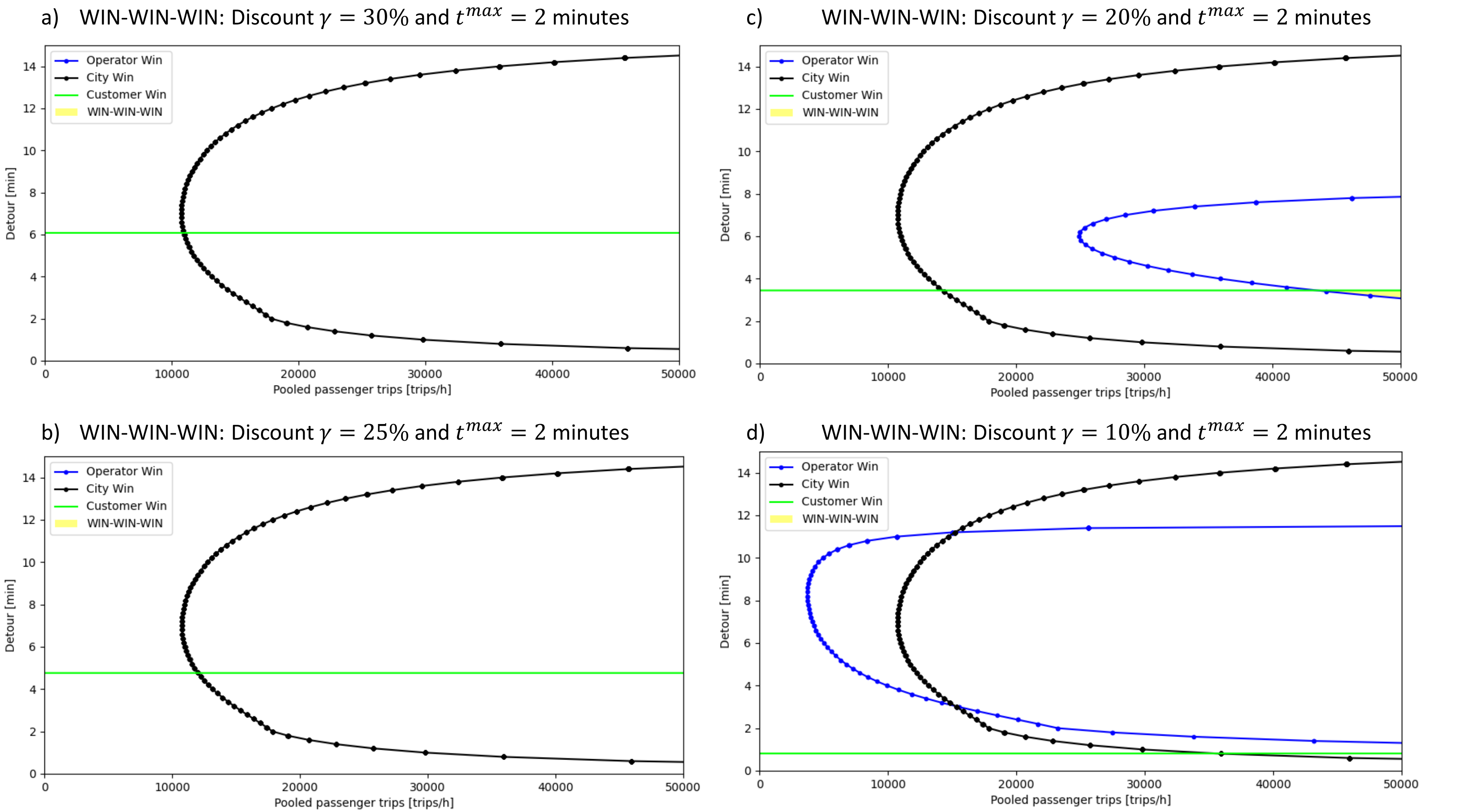



**Figure 5.13** WIN-WIN-WIN for the customers, the operator and the city for an ODRP service in Munich for a maximum waiting time $t^{max} = \mathbf{2\ minutes}$, varying ODRP passenger demand $\lambda_p$ and detour time $\Delta$. Subplots correspont to different discount $\gamma$ (ODRP price = $(1-\gamma)$ * ODRH price): a) $\gamma = 30\%$, b) $\gamma = 25\%$, c) $\gamma = 20\%$, d) $\gamma = 10\%$. The parameter space where the ODRP system is beneficial for the city, operator and customers is situated on the right of the black line, on the right of the blue line, and below the green line, respectively. The win-win-win situation is shown by the yellow area.

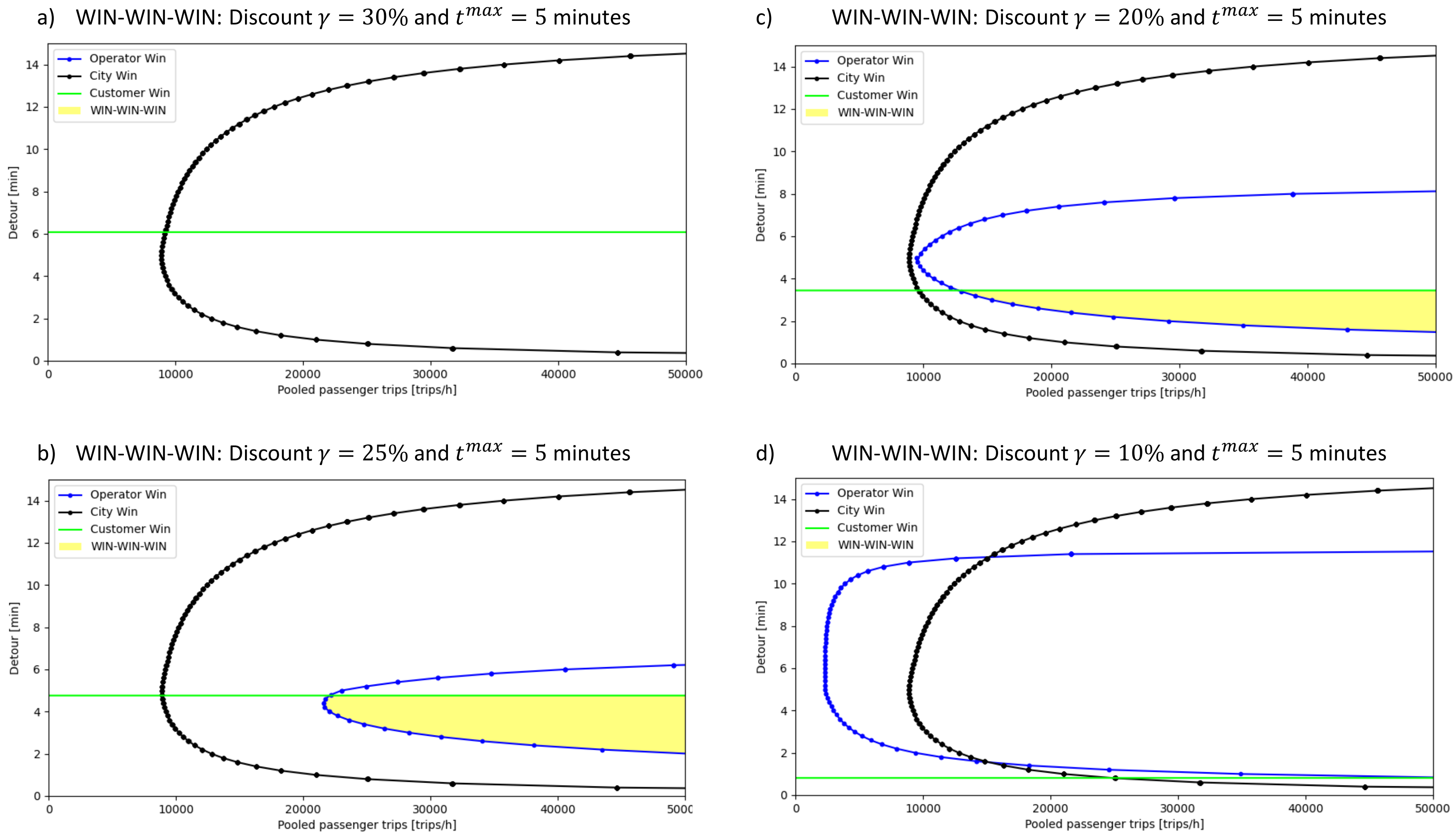



**Figure 5.14** WIN-WIN-WIN for the customers, the operator and the city for an ODRP service in Munich for a maximum waiting time $\boldsymbol{t^{max} = 5}$ **minutes**, varying ODRP passenger demand $\lambda_p$ and detour time $\Delta$. Subplots correspont to different discount $\gamma$ (ODRP price = $(1-\gamma)$ * ODRH price): a) $\gamma = 30\%$, b) $\gamma = 25\%$, c) $\gamma = 20\%$, d) $\gamma = 10\%$. The parameter space where the ODRP system is beneficial for the city, operator and customers is situated on the right of the black line, on the right of the blue line, and below the green line, respectively. The win-win-win situation is shown by the yellow area.

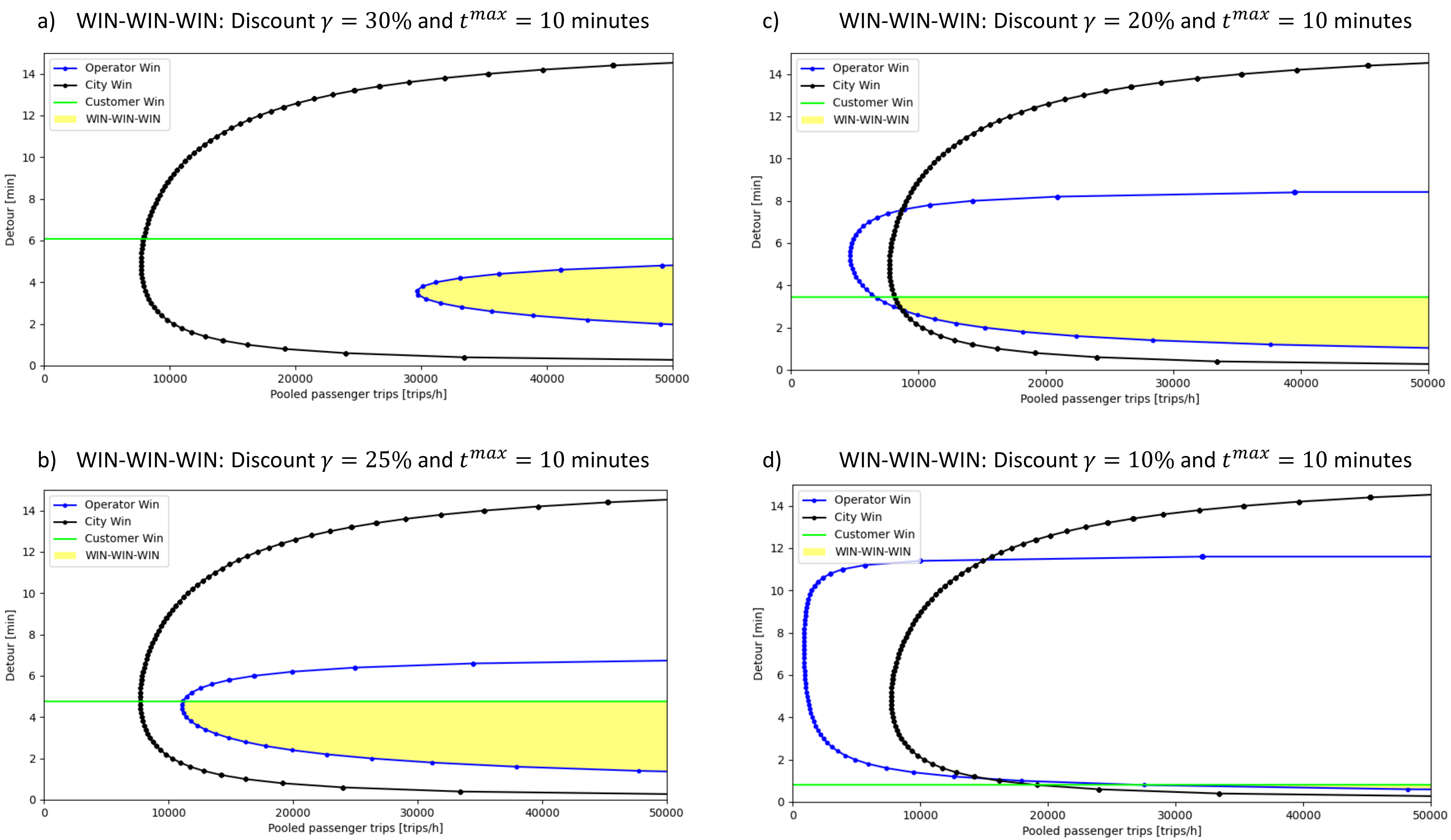



**Figure 5.15** WIN-WIN-WIN for the customers, the operator and the city for an ODRP service in Munich for a maximum waiting time $t^{max}$ = **10 minutes**, varying ODRP passenger demand $\lambda_p$ and detour time $\Delta$. Subplots correspont to different discount $\gamma$ (ODRP price = $(1-\gamma)$ * ODRH price): a) $\gamma = 30\%$, b) $\gamma = 25\%$, c) $\gamma = 20\%$, d) $\gamma = 10\%$. The parameter space where the ODRP system is beneficial for the city, operator and customers is situated on the right of the black line, on the right of the blue line, and below the green line, respectively. The win-win-win situation is shown by the yellow area.

## 5.5 Discussion of the Main Results

In order to achieve the main aim of the thesis and to determine where in the parameter space the win-win-win situation from city, operator and customers can be achieved, different analytical models were developed to capture the ODRP shareability, traffic efficiency, service profitability and attractiveness of the customers. The use of the analytical modelling approach contributes to the analysis of the ODRP impact as this approach does not require a large amount of input data and computational time or expensive real-world pilots.

### 5.5.1 On-demand ride pooling shareability main results

The validation of the analytical ODRP shareability model capturing the impact of SQP on shareability is performed by means of an agent-based simulation. It is shown that the analytical model is able to predict the theoretical shareability for the case when the operation area was represented by a Euclidian topology with a homogeneous average velocity and the optimization objective was to maximize the percentage of shared trips. This occurs as the selected network modelling parameters correspond to the assumptions used in the analytical model to derive closed form formulas. This finding is important as it shows that the complex effects of the ODRP service can be captured by a simple analytical model that does not require any fitting and needs only a small amount of input data and short computational times.

As expected, the simulation results show that when increasing the detour time and maximum waiting time, the shareability/shared rides also increase. This happens as longer maximum waiting times and detour times lead to higher chances to find shareable trips, reflected also in a larger area of the shareability shadow (Figure 3.1). Lower values of these SQP have consequently the opposite effect on shareability/shared rides. The boarding time parameter is depicted to have the same influence on the results as the detour time, as it is considered to be lost time for the in-vehicle customers and also for the operator, as during this time the vehicle is standing still and not approaching the customers' destination.

Nevertheless, by increasing the model complexity and thereby, the realism of the ODRP system, it was shown that the percentage of experienced shared trips is lower than the one predicted by the analytical model. However, the impacts that the network topology and inhomogeneous velocity distribution have on the results is relatively small – a result which is also depicted by TACHET ET AL. [2017]) – compared to the impact of the optimization objective. The selection of the optimization objective is noticed to have the highest influence on the percentage of shared trips in this study. For an optimization objective of maximizing the saved VKT, the percentage of shared rides drops significantly, in some cases up to 50%. These results indicate that the operator must carefully select the optimization objective in order to maximize the potential of ODRP service to pool trips with each other.

A prediction model was developed to analytically estimate the shared rides for the most realistic ODRP network modelling (the fourth case in Tab. 5.2), for an optimization objective of minimizing the VKT, a real street network with inhomogeneous velocity distribution. This model is based on data fitting for one simulation scenario and then the shared rides for the other scenarios with a different SQP are analytically estimated. This prediction model shows a good anticipation of the results for the Munich operation area for varying maximum waiting times, detour times and boarding times. Even though the full potential of the benefits of analytical modelling cannot be exploited due to the dependency of the data of one simulated scenario, this prediction model still contributes to significant saving in computational time for a system-wide exploration of ODRP service quality parameters' impact on shareability/shared rides.

### 5.5.2 On-demand ride pooling traffic impact main results

The ODRP traffic impact model provides the analytical relation of the average velocity and the vehicle trip generation in the network by using the shareability model and the MFD. The validation of the analytical model by means of microscopic traffic simulations in the Munich operation area shows that the traffic impacts of an ODRP service could be estimated well for the free flow regime. Being able to analyze the traffic impacts of an ODRP service analytically is a very important contribution for two reasons: 1) it provides a quick estimation of the ODRP traffic impacts for a wide range of ODRP service quality parameters, and 2) the investigation considers also the impact of background traffic on the results, which is currently not considered in the literature. In addition, the method used to validate the analytical ODRP traffic impact model could be used as a simplified approach to analyze the system-wide traffic impact of an ODRP service.

The impact that the ODRP service, for which the optimization objective is to minimize the VKT, has on the average velocity in Munich is derived by substituting different percentages of private vehicle trips with ODRP vehicle trips. Firstly, it is important to note that the benefits of the ODRP are depicted for the peak times only. During the off-peak hours the average velocity is already high, and an additional improvement is limited. Additionally, it is observed that the higher the penetration rate of the ODRP passenger demand is, the higher is the improvement of the average velocity. For a 100% substitution, the improvement in average velocity is shown to be up to 20%. Nevertheless, for an ODRP penetration rate of 5%, the average velocity in Munich does not change much. This occurs as the number of ODRP vehicle trips is quite small compared to private/alone vehicle trips to have a significant impact on the average velocity in the city. This implies that the benefits of the ODRP in traffic efficiency will be noticeable for a higher penetration rate than 5%. Therefore, cities would have to be patient and promote the use of ODRP services in order to profit in long-term from the positive impact of the ODRP service in traffic efficiency.

Another important contribution is the modelling of the second order impact of velocity on shareability. It is shown that by introducing the ODRP service the average velocity in the network will be higher. These results suggest that the potential positive impact of ODRP services in improving the average velocity in a city, are going to be of significant importance also for operators as by the average velocity increase, the chances to find shareable trips also get higher. This is caused by the fact that the vehicles can reach further distances for the same amount of detour time as a result of higher network velocity and increasing the spatial area of reach means that the potential to find shareable trips will consequently increase. The results for the city of Munich show that by the introduction of the ODRP service the shareability will further increase, however the change is not very high as the average velocity was already high in the base scenario. Nevertheless, for cities with higher levels of congestion it is expected that the second order effect of velocity on shareability will be more significant.

### 5.5.3 On-demand ride pooling benefits main results

The ODRP traffic impacts, the ODRP service profitability and the customer attractiveness to use the ODRP service are modelled analytically. The results determine the ODRP win-win-win situation between the city, the operator, and the customers.

The traffic impact model is extended to take into account also the extra VKT due to detour time. The results show that for low penetration rates the improvement in average velocity cannot be achieved in all the scenarios considered. However, with increasing ODRP demand, higher average velocities in the network are observed as a results of trip sharing. The ODRP passenger demand range for which an improvement in the average velocity in the system is observed depends on the detour time value. A rather important result is the determination of the optimum detour time, which determines the lowest ODRP passenger demand for which the system’s average velocity starts increasing. For low detour time values the percentage of shared trips is low and it requires a large ODRP passenger demand in order for trip pooling to contribute to improved average velocity in the city. With increasing the detour times, the shareability increases and therefore the system becomes profitable for lower ODRP passenger demand. Nevertheless, this happens until a certain detour time (optimum detour time). For detour times larger than the optimum, the increase in VKT in the system due to the increase of detour time is higher than the saving of VKT by trip sharing. That is the reason why the ODRP passenger demand for which the system starts to show improved average velocity becomes higher. For a restrictive, normal or flexible ODRP system, specified by the maximum waiting time, the optimum detour time ranges from 4 – 7 minutes. These findings could be used for better planning of the SQP of an ODRP system which aims to be efficient.

While the ODRP traffic efficiency depends on SQP, of which the detour time was shown to have a considerable effect due to the direct influence on the VKT, the ODRP profitability results show that in addition to the SQP, the system's profitability largely depends on the ODRP price. As in this study the ODRP price compared to the ODRH is considered, the discount parameter becomes one of the most important parameters. It is shown that for a restrictive ODRP service, the system is hardly profitable and even for low discount values the profitability is limited. For normal and flexible ODRP systems, the parameter space in which the system is profitable starts to increase as the system flexibility contributes to a higher percentage of shared trips in the area. An optimum detour time for the system's profitability can also be achieved in this case. For low detour times, the shareability is low and consequently the revenues are low as well. This occurs as the passengers would pay less than what they would pay when using a ODRH service, but nonetheless they would travel alone as a match would not be possible. For detour times higher than the optimum detour time, the additional costs caused by the additional VKT as a result of the detour time, are higher than the benefits of increased revenue due to high shareability. Therefore, for high detour times the system profitability shrinks. Another notable observation is that the set of SQP needs to be carefully selected. The reason is that contrary to intuitively expected, higher ODRP passenger demand rates do not necessary contribute to a profitable ODRP service after a certain penetration rate. Rather for a given ODRP service quality parameter set, it might happen that when increasing the ODRP passenger demand, the monetary losses of the system become larger, due to higher costs or smaller revenues.

Finally, considering the customer willingness to use the ODRP service, the win-win-win situation between city, operator and customers is explored. The results show that the type of ODRP system (restrictive, normal, flexible) and the discount, for using the ODRP service compared to using the ODRH service, play an important role in determining the win-win-win situation. A total win-win-win can hardly be achieved for a restrictive ODRP system, albeit this system can be attractive for the customers. With higher ODRP system flexibility, the parameter space for which the win-win-win is possible increases. A discount of 30% can be desirable for customers, however it might not result in monetary benefits for the operator. Whereas a discount of 10% even though providing high profitability for the operator, might not be desirable for the customers, as the saving might not be high enough. As a result, it is anticipated that a win-win-win situation of all the three ODRP stakeholders can be achieved for higher parameter space when the ODRP system is flexible, and the discount parameter is between 25% and 20%.

**Key Takeaways – Evaluation and Results**

The models presented in this thesis capture quite well:

- the **shareability** that can be reached in an area for different SQP and vehicle routing optimization objectives,
- the **traffic impacts** of ODRP services for different penetration rates of the ODRP passenger demand,
- the **profitability** of ODRP services,
- under which framework conditions the **win-win-win** situation, considering the perspective of cities, operators, and customers, can be achieved.

# 6. Conclusion and Outlook

In this chapter, a summary of the motivation, the methodology, the results, and the most important contributions of the thesis are presented. The chapter will be concluded with an outlook and recommendations for future work.

## 6.1 Summary

This thesis analyzes the on-demand ride pooling (ODRP) service impact factors considering operator, city and customer perspectives. The main aim of the thesis is to determine the parameter space in which the win-win-win situation for all these three stakeholders is possible. In order to achieve the aim of this thesis, analytical models capturing the ODRP shareability impact factors, traffic efficiency, service profitability and attractiveness for customers are developed. The approach used to analyze the ODRP impacts is analytical modelling, as it does not require large amounts of input data, long computational times or expensive real-world pilots and the results are easily transferable to other cities. This would allow for a system-wide analysis of the ODRP impacts and would help to explore under which conditions a win-win-win situation in terms of customers, operators and cities can be achieved. Consequently, this model would assist in effective planning and implementation of ODRP services.

Initially, the factors influencing the percentage of shared trips in an area or shareability are explored. Two analytical models which capture the impact of city parameters, SQP and network modelling details on shareability are developed for two types of ODRP service distinguished by the ODRP booking procedure used. The first one is an instant booking system, where the passengers are served instantly, and the second one is called a short-term prebooked system, where the passengers have to reserve their trip a short time in advance. The SQP considered are maximum waiting time, detour time, boarding/disembarking time and reservation time. The analytical model of the instant booking system is validated by means of an agent-based simulation, where an ODRP service is modelled in different levels of detail and the model complexity is increased step by step. Consequently, the influence of network modelling details, such as the optimization objective, the network topology, the trip distribution patterns and the homogeneity of the average velocity, are also investigated.

Secondly, an analytical model is developed to estimate the traffic impacts of an ODRP service based on the previously mentioned shareability model and the macroscopic fundamental diagram (MFD) for a city. Thus, depending on the chances to find shareable trips in an area, an analytical model to determine the reduction of vehicle trips in the network due to trip pooling is developed and then a relation of the average velocity in a city and the generated number of vehicle trips is derived by using the benefits of the MFD. Additionally, as an ODRP service is expected to reduce the number of vehicles on the streets and thus improve the average velocity, this increase in average velocity leads to higher chances to find shareable trips in an area. This occurs as for the same detour time the vehicles can reach a larger area and consequently have higher chances to find shareable trips. Therefore, the second order effect that the velocity has on shareability (called the modified shareability model) is also analytically derived. The traffic impact model and the modified shareability model are tested via microscopic traffic simulations.

Finally, a general analytical model capturing the benefits of the ODRP service from city, operator and customer perspective is built. Firstly, the traffic impact model is extended to take into account the additional VKT due to the detour distance. Secondly, an analytical model to estimate the monetary profitability of an ODRP service is developed based on the shareability model and the traffic impact model. These models provide information about the VKT by the ODRP service and thereby present an estimation of the ODRP operation costs. The revenue is calculated based on the pricing strategy, which could be distance-based, time-based, or a combination of both. Thirdly, the attractiveness for customers to use an ODRP service is determined by the willingness of the customers to accept a certain detour time if they are offered a cheaper price compared to ODRH.

A combination of these models in a general analytical model provides information about the existence of a win-win-win situation for the three main ODRP stakeholders and determines under which type of the ODRP system and ODRP parameter space (maximum waiting time, detour time, ODRP passenger demand) this is possible.

## 6.2 Key Findings and Contributions

The key findings and the contributions of the analytical models developed in this thesis (and summarized in the previous section) will be provided in this part. Therefore, the research questions presented at the beginning of the thesis in *Section 1.3* will be given answers, which contribute to filling the research gaps identified in *Section 1.2*.

The three main research questions and their answers are provided below:

1. How do SQP, such as detour time, maximum waiting time, short-term reservation time and boarding/disembarking time, network modelling details and vehicle routing

optimization objectives, impact the percentage of possible shared trips in an area? (Addressing RG 1.a and RG 1.b → Model: *Section 3.1*; Results: *Section 5.1*)

**Analytical modelling of shareability impact factors, such as service quality attributes and network modelling details** (RG 1.a and RG 1.b) is used to answer the first research question. The analytical shareability models are developed to investigate the influence of service quality parameter, such as detour time, maximum waiting time, boarding/disembarking time and reservation time, on the percentage of shared trips in an area and are tested by means of agent-based simulations. These shareability models offer new insights about the influence that SQP, modelling details and vehicle routing optimization objectives have on shareability. The main findings are summarized below:

- The analytical model with a Euclidian topology, homogeneous average velocity and an optimization objective that aims to maximize the percentage of shared trips is able to estimate the theoretical shareability values from the agent-based simulation without needing any fitting. This is an important result as it proves that the complex properties of an ODRP service can be represented by an analytical model without requiring any fitting and thereby the results can be easily transferable to other operation areas.
- An increase (decrease) of the detour time and maximum waiting time directly translates to higher (lower) shareability/shared rides values. This happens as longer (shorter) maximum waiting times and detour times increase (decrease) the chances to find shareable trips in an area. The boarding time parameter is showed to have the same influence on the results as the detour time.
- It is shown that the percentage of shared trips depends on the way the ODRP system is modelled. Higher realism of the model, represented by increased modelling details, contributes to lower shareability/shared rides values than the ones estimated by the analytical model.
- The optimization objective is depicted to have the largest impact on the percentage of shared trips, compared to network topology and an inhomogeneous velocity distribution (which impacts are quite small). The optimization objective of minimizing the VKT decreases the percentage of shared rides up to 50% compared to the optimization objective of maximizing the percentage of shared trips – an indicator that the operator has to cautiously

choose the optimization objective in order to maximize the benefits of the ODRP service.

2. What are the traffic impacts of ODRP services and how does the change in average velocity due to ride pooling effect the possibility to find shareable trips? (Addressing RG 2.a, RG 2.b and RG 2.c → Model*: Section 3.2*; Results: *Section 5.2*)

   **Analytical modelling of the ODRP traffic impacts and the additional effect that changes in average velocity due to shared trips have on shareability** (RG 2.a, RG 2.b and RG 2.c) is used to answer the second research question. The shareability model of *Section 3.1* and the MFD of a city are used to analytically develop the model of the ODRP traffic impacts, which is then tested via microscopic traffic simulations. The main findings are summarized below:

   - The traffic impact model validation shows that the analytical model can predict the traffic impacts of an ODRP service for the free flow regime. This model contributes to the literature as it provides a quick way to explore the traffic impacts of an ODRP service for a wide range of system parameters, while considering not only the ODRP vehicle fleet but also the other vehicles in the network, which are currently not considered in the literature.
   - When substituting private vehicle trips with ODRP trips, it is shown that the benefits of the ODRP service are significant only during the peak hours. The improvement of the average velocity increases with higher penetration rates. Therefore, the average velocity in the city increases by up to 20% for a 100% replacement rate of the ODRP service. However, the change in average velocity in Munich is not significant for an ODRP penetration rate of 5%, implying that the benefits of the ODRP in traffic efficiency will require a higher penetration rate than 5%.
   - The second order effect of an increased average velocity on the shareability due to trip pooling is modelled analytically and tested by simulations. The results show that by the introduction of an ODRP service, not only the traffic impact will improve, but also the shareability will further increase. However, for this case study in Munich the alteration is limited as the average velocity was already high in the base scenario, yet more prominent influences of average velocity on shareability are expected in cities with higher level of congestion.

3. Under which framework conditions a win-win-win situation can be achieved, corresponding to an ODRP service that is beneficial in terms of improvement of traffic efficiency, operators' profitability, and customers' attractiveness? (Addressing RG 3.a and RG 3.b → Model: *Section 3.3*; Results: *Section 5.3*)

   **Analytical modelling of the ODRP traffic efficiency, operator's profitability and customer attractiveness** (RG 3.a and RG 3.b) is used to answer the third research question. The shareability model (*Section 3.1*) and the traffic impact model (*Section 3.2*) are combined and extended to examine the ODRP services in terms of traffic efficiency, service profitability and attractiveness for the customer to use the service. The general ODRP model offers novel insights in finding the parameter space where the win-win-win situation between all ODRP stakeholders can be reached. The main findings are summarized below:

   - The results of the ODRP system's traffic efficiency show that the ODRP passenger demand and the detour time value are key influencing factors in determining the improvement on the average velocity in the network, whereas the maximum waiting time is shown to have lower impact on the results. For low penetration rate of the ODRP service there is no significant improvement in average velocity in the city. Defining an optimum detour time, which corresponds to the lowest ODRP passenger demand where the average velocity in the network shows improvement, is important for a better planning of the SQP for an efficient ODRP system.
   - The ODRP system's profitability results depend on the selected SQP and the ODRP price. A restrictive ODRP system is in most of the cases unprofitable, even when the discount values are small. Higher system flexibility, for normal and flexible ODRP systems, influences higher ODRP system profitability due to higher achieved shareability. As expected, profitability increases with decreasing the discount (i.e., the ODRP price increases). The determination of an optimum detour time in this case (corresponding to the lowest ODRP passenger demand for which the ODRP system starts to be profitable), could help the operators better plan the SQP they want to offer to the customers, while having high chances to be profitable.
   - The results show that careful consideration should be given to the selection of the set of SQP, as in some cases rising ODRP passenger demand levels do not contribute to the ODRP system profitability. In these cases, the contrary

happens, because the monetary losses of the ODRP system increase with increasing ODRP passenger demand, as a result of higher loss in revenue or higher cost.

- The existence of a win-win-win situation between city, operator and customers depends on the kind of ODRP system (restrictive, normal or flexible) and the ODRP price. For a restrictive ODRP system could be attractive for the customers, however the win-win-win is difficult to be achieved, as the win for the operator is hardly reached. On the other side, a flexible ODRP system might not be attractive for the customer, but it offers higher chances to reach the win-win-win, as the operator has more chances to be profitable. The ODRP price plays an important role here as well, as a high discount compared to ODRH price can be attractive for the customers, but it might restrict the profitability of the operator. In the opposite, for a low discount the service is profitable, however the ODRP system might not be desirable for the customers. The results show that a flexible ODRP system, for which the price discount is between 20% and 25%, has higher possibility to attain a win-win-win situation for all the three ODRP stakeholders.

## 6.3 Planning and Policy Implications

One of the main contributions of this thesis is the ability to represent the complex impacts of the ODRP service by analytical modelling. This allows the swift examination of the influence of various ODRP influencing parameters and the impacts of a wide range of SQP, without being restricted to a scenario-based analysis. Therefore, these models are easily transferable to other ODRP operation areas and can be used for a better system-wide planning and implementation of an ODRP service, without the need of computationally expensive simulations, which require a huge amount of input data, or real-world pilots.

Hence, the main stakeholders which can benefit from the results of this thesis are service operators and cities or policy makers. The potential of these models is shortly summarized below. They could be used to quickly estimate:

1. **the shareability** that can be achieved in an area when offering different qualities of service to the customers and thus providing the operators the ability to explore in which areas offering an ODRP service is feasible,

2. **the traffic impacts** of varying ODRP passenger demand penetration rates and thereby giving the cities or policy makers the chance to explore the system-wide impact of such a service,
3. **the profitability** of an ODRP service and thus providing the service operators the opportunity to investigate in which conditions an ODRP service can be profitable,
4. **the ODRP win-win-win** situation for cities, operators, and customers, and thereby specifying the framework settings when an ODRP service can be beneficial for all three ODRP stakeholders.

## 6.4 Limitations and Future Work

The contributions of this thesis fill the identified research gaps; however, they also have some limitations and thus in this part additional topics for future investigation are identified and recommended.

Firstly, the analytical shareability model is valid only for the optimization objective of maximizing the percentage of shared trips. In order to derive the percentage of shared trips for the optimization objective of maximizing the saved VKT, a prediction model is developed. Even though this model provides good estimation of the results, it is based on data fitting for one simulation scenario. Therefore, the following topics could be further investigated in future work:

- The fitting parameters could be examined if they are valid also for other operation areas, except of Munich. If these fitting parameters are valid for other operation areas, they could be used to analytically derive the shareability for the optimization objective of minimizing the VKT, without the need of data fitting for a base simulation scenario.
- However, if these fitting parameters are only specific to Munich, the full potential of analytical modeling cannot be exploited, albeit the saving in computational time for an investigation of a wide range of SQP. Thus, an interesting future topic would be to derive a pure analytical model which could estimate the percentage of shared trips for the optimization objective of minimizing the VKT.

Secondly, the traffic impact model is validated by using a microscopic traffic simulation based on OD matrix reduction. This approach uses an analytical model to derive the number of reduced vehicle trips. However, this model assumes similar origins and destinations of the trips, which rarely happens. Additionally, by using only a microscopic traffic simulation the exact ODRP vehicle fleet operation is not possible to be considered. Furthermore, the model is tested only for the free flow regime, due to the limited amount of data for the congestion regime, and the analysis is performed only for the city of Munich. Thus, the following topics are interesting as future work:

- The vehicle trip reduction model could be further extended to also include the impact of partially shared trips, their dependence on the vehicle routing optimization objective. Additionally, the impact of empty vehicle trips due to customer pick-ups or reallocation methods. These extensions could increase the realism of the model.
- The extended traffic impact model could be tested with a microscopic traffic simulation model coupled with an ODRP agent-based simulation, where the traffic dynamism and the exact ODRP vehicle fleet operations are both represented.
- The traffic model validation could be extended for the congestion regime as well, allowing additional examination whether the used parabolic MFD functional form is valid for the congestion regime or if it should be adapted to a skewed or an asymmetric parabola.
- It would also be interesting to check the validity of the traffic impact model for other cities, especially for cities with high levels of congestion, where the second order effect of the velocity on the shareability could be more prominent.

Thirdly, the profitability model assumes a very simple cost calculation, based on the cost per kilometer, and revenue, based only on one pricing strategy which depends on direct travel distance. Future topics for further investigation in this regard could be:

- Cost calculation could be based on more realistic cost functions [Bösch et al., 2018; Negro et al., 2021], where for instance the fleet size could be explicitly considered. This could provide more realistic results for the total cost calculation.
- In addition, the experienced detour time is assumed to be half of the maximum detour time and as this directly influences the vehicle kilometers travelled and thus the total costs of the system, it should be further investigated the dependency of the experienced detour time and the maximum detour time parameter for different optimization objectives.
- Calculation of the revenue for other pricing strategies such as, time based, or a combination of distance and time based, could be a future topic. The effect of surge pricing could be another interesting future topic.

Lastly, the model could be extended to include a flexible passenger demand model (e.g., similar to the one used by Kucharski & Cats [2020]) depending on the service quality parameters, pricing, value of time or discomfort of pooling. In addition, it could be interesting to investigate the influence of induced demand coming from other transportation modes as a result of improved average velocity due to ride pooling.

## Publications

This thesis is based on the publications provided below:

| Publication | Description | Section |
|---|---|---|
| A. Bilali, F. Dandl, U. Fastenrath, and K. Bogenberger, "Impact of service quality factors on ride sharing in urban areas," in *2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, Cracow, Poland, Jun. 2019 - Jun. 2019, pp. 1–8. | **Shareability model**<br><br>for instant booking system | **Section 3.1** |
| A. Bilali, F. Dandl, U. Fastenrath, and K. Bogenberger, "An Analytical Model for On-Demand Ride Sharing to Evaluate the Impact of Reservation, Detour and Maximum Waiting Time," in *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, Auckland, New Zealand, Oct. 2019 - Oct. 2019, pp. 1715–1720. | **Shareability model**<br><br>for short-term prebooking system | **Section 3.1** |
| A. Bilali, R. Engelhardt, F. Dandl, U. Fastenrath, and K. Bogenberger, "Analytical and Agent-Based Model to Evaluate Ride-Pooling Impact Factors," *Transportation Research Record*, vol. 2674, no. 6, pp. 1–12, 2020, doi: 10.1177/0361198120917666. | **Shareability model evaluation** | **Section 5.1** |
| A. Bilali, M. A. A. Rathore, U. Fastenrath, and K. Bogenberger, "Analytical Model to Evaluate Traffic Impacts of On-Demand Ride Pooling," in *2020 IEEE Intelligent Transportation Systems Conference (ITSC)*, Rhodes, Greece (Online), Sep. 2020 - Sep. 2020. | **Traffic impact model** | **Section 3.2** |
| A. Bilali, U. Fastenrath, and K. Bogenberger, "An Analytical Model to Estimate Ride Pooling Traffic Impacts by Using the Macroscopic Fundamental Diagram," In *100th Annual Meeting of Transportation Research Board (TRB)*, 21-29 January 2021, Washington DC, US (Online). | **Traffic impact model & evaluation** | **Section 3.2 & Section 5.2** |

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## List of Abbreviations

| | |
|---|---|
| OD | Origin-destination |
| ODRH | On-demand ride hailing service |
| ODRP | On-demand ride pooling service |
| RG | Research gap |
| RQ | Research question |
| SQP | Service quality parameters |
| V2RB | Vehicle-To-Request-Bundle |
| VKT | Vehicle kilometers travelled |

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