Demand responsive transport to replace a fixed-line bus service

A case study in Voorne-Putten Rozenburg

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Preface

As this thesis has come to an end, I would like to express my gratitude towards my supervisors. The topic and goal of this thesis remained unclear for a long time. The first few meetings consisted mostly of brainstorming about all kinds of poorly thought out research ideas. I want to express my appreciation for their patience and support during these meetings and throughout the rest of the project.

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I hope you enjoy reading this thesis!

Laurens Krudde
Delft, October 2024

Abstract

Conventional fixed-line bus services are ineffective and costly in areas of low demand. Bus operators are motivated to scale down their service to reduce costs. Consequently, many rural areas in the Netherlands suffer from diminishing accessibility to jobs, hospitals, and education using public transport. Demand responsive transport (DRT) systems can offer a solution, but have been struggling in adoption by travellers because the need to make a reservation is perceived as an obstacle. Furthermore, the performance of DRT systems is complex and requires evaluation before implementation. In this context, this thesis considers the replacement of three low-demand bus lines by a DRT system in Voorne-Putten Rozenburg, Netherlands. Two scenarios are formulated: the replacement of a single bus line and the replacement of all three low-demand bus lines. The objective of this thesis is to evaluate the performance of a DRT system in serving the travel demand currently served by the bus lines. To obtain the travel demand, individual trips from the existing bus line were generated from aggregated data on boarding and alighting in 2023. The travel demand in a DRT system was evaluated using an agent-based simulation approach. To address the perceived obstacle of making reservations, the DRT system also considered on-demand requests and a proposed stop-based request where the user can request the DRT service physically at the bus stop with the consequence that the DRT system initially only knows the users' origin and not the destination. The main results suggest that a DRT system is an improvement over fixed-line buses in terms of waiting time and travel time, and $\mathrm{CO_2}$ emissions when considering current travel demand in both scenarios. However, the costs are comparable. In the case that travel demand increases more than twofold, fixed-line buses are to be preferred. Considering the different request methods, only a small difference in user times was observed. This thesis concludes that replacing the bus lines with a DRT system can lead to an increase in accessibility. The proposed stop-based request method was shown to be a feasible alternative to the request methods that require the use of an app or phone call and could potentially lower the obstacle to using DRT.

Contents

Preface i

Abstract ii

1 Introduction 1
1.1 Background 1
1.2 Research problem 2
1.3 Research objectives 2
1.4 Research question 3
1.5 Structure 3

2 Background and related work 4
2.1 Introduction to Demand Responsive Transport (DRT) 4
2.1.1 Historical background and origins 4
2.1.2 Challenges and success factors 4
2.2 Modelling approaches for DRT systems 5
2.2.1 Agent-based models 5
2.2.2 Microsimulation models 6
2.2.3 Analytical models 6
2.3 Simulation frameworks for DRT systems 6
2.4 Traveller generation methods 7
2.4.1 OD matrix estimation using boarding and alighting counts 8
2.5 Dispatching algorithms 8
2.5.1 Dial A Ride Problem 8
2.5.2 Solution methods 9
2.6 Recent simulation studies on DRT 10
2.7 Conclusion 11

3 Methodology 12
3.1 Overview 12
3.2 Data processing steps 13
3.3 Individual passenger trip generation 14
3.4 Simulation framework 15
3.5 Network creation 15
3.6 DRT service definition 16
3.6.1 Fleet size 16
3.6.2 Request types 16
3.6.3 Dispatching algorithm 17
3.6.4 Objective function 17
3.6.5 Time windows 18
3.7 Evaluation 18

4 Results 20
4.1 Generated individual trips 20
4.1.1 The original aggregated data 20
4.1.2 Sampling error 20
4.1.3 The generated data 21
4.2 Scenario 1: replacement of a single bus line 21
4.2.1 Scenario definition 23
4.2.2 Simulation results 23
4.2.3 Tipping point 23

4.3 Scenario 2: replacement of all regional bus lines . . . 26
  4.3.1 Scenario definition . . . 26
  4.3.2 Simulation results . . . 26
  4.3.3 Tipping point . . . 27
4.4 Comparing Scenario 1 and Scenario 2 . . . 27

5 Discussion **30**
5.1 Summary . . . 30
5.2 Implications and relation to literature . . . 30
5.3 Limitations . . . 31
  5.3.1 Generated travel demand . . . 31
  5.3.2 Simplifications in the simulation . . . 32
5.4 Recommendations . . . 32
  5.4.1 Recommendations for future research . . . 32
  5.4.2 Recommendations for practical implementation . . . 33

6 Conclusion **34**

References **36**

A Supplementary results **42**
A.1 Served users for different fleet sizes . . . 42
A.2 Results for different number of travellers . . . 43
A.3 Comparing insertion vs optimisation . . . 44
A.4 Objective function for bus stop requests . . . 45
A.5 Results for different fleet sizes . . . 46
  A.5.1 Scenario 1: replacement of a single bus line . . . 46
  A.5.2 Scenario 2: replacement of all regional bus lines . . . 47
A.6 Maximum waiting time . . . 48
A.7 Results variance due to sample size . . . 49

B Cost and $\mathrm{CO_2}$ emission calculation **50**

C Example of the OD matrix derivation **51**

D Visualisation of bus line data **53**

E Example of a bus schedule **55**

1

Introduction

In this chapter, the introduction of this research is described. First, background on demand responsive transport systems is given in Section 1.1. The research problem of this thesis is described in Section 1.2 and the research objectives are given in Section 1.3. The research questions are stated in Section 1.4. Finally, the structure of the thesis is given in Section 1.5.

1.1. Background

Public bus operators are continually faced with the challenge of implementing the most suitable transportation services to satisfy the travel demand in their area of operation. For areas with high travel demand, conventional transit services, such as fixed-line bus services, are a suitable solution [1]. High demand justifies frequent service and high bus stop density, resulting in reduced waiting and travel times for travellers. However, areas with low demand, often rural areas, are a pain point for public bus transport planners. Low demand trivially results in low revenue and makes it costly to operate a frequent fixed-line bus service. As a result, public bus operators are motivated to save costs by operating less frequently or reducing the number of bus stops. This reduces the service quality and causes even lower demand. One can see a negative spiral unfold. As a result, there are many areas in the Netherlands where the accessibility of jobs, hospitals, education and supermarkets using public transport is diminishing [2].

A potential solution to provide public transportation for low-demand areas is to offer a flexible bus system that does not operate on fixed routes or by using timetables and is able to respond to the demand. These systems are called demand-responsive transport (DRT) systems. DRT can be seen as an intermediate form of public transport, filling the gap between conventional fixed-line bus services and highly personalised transport services offered by taxis [3]. DRT as defined by the KFH Group:

> “DRT is a transit mode comprised of passenger cars, vans or small buses operating in response to calls from passengers or their agents to the transit operator, who then dispatches a vehicle to pick up the passengers and transport them to their destinations. A DRT operation is characterised by the following:
>
> 1. The vehicles do not operate over a fixed route or on a fixed schedule, except, perhaps, on a temporary basis to satisfy a special need, and
> 2. Typically, the vehicle may be dispatched to pick up several passengers at different pick-up points before taking them to their respective destinations and may even be interrupted en route to these destinations to pick up other passengers.” [4]

Replacing a fixed-line bus system by a DRT system has recently been the topic of various simulation studies in different cities and mostly concluded potential benefits [5, 6, 7, 8, 9]. Specifically in areas of low demand, it could save costs for the operator and improve traveller experience by reducing waiting and travel times [10]. Furthermore, as indicated by [11], DRT reduces $\mathrm{CO_2}$ emissions and is considered an environmentally sustainable alternative to existing local public transport systems.

However, DRT implementations tend to struggle in practice and many fail within a few years [12, 13]. Both travellers and operators experience problems with DRT. On the one hand, most travellers are unfamiliar with the service and require some time before using it. It also requires a little more digital literacy, which can be an obstacle for certain population groups. Furthermore, the need to make a reservation in advance is often perceived as an obstacle [14]. On the other hand, acceptance from transport operators is held back by the lack of insight in the performance of DRT systems.

Vansteenwegen et al. [15] note that there is a gap between theory and practice: ”Of the DRT systems that are proposed in the literature, only a small fraction are also implemented in practice. At the same time, more and more DRT systems are becoming available in practice without a link to scientific papers.” It is important to evaluate a DRT system in a new area before implementation. The complexity and flexibility of DRT systems make it difficult to generalise their performance. Moreover, it is even advised against duplicating a successful DRT system in another area without considering its new conditions [16, 13].

1.2. Research problem

The implementation of a DRT system requires not only the necessary vehicles and drivers but also a software solution to enable users to request the DRT service and manage the vehicle planning. It is often the case that bus operators have the vehicles and drivers, but do not have the software to implement a DRT system. Hence, a partnership between a bus operator and a software provider is required to implement a DRT system. This thesis is in collaboration with Siemens Mobility, who have a DRT software solution that is currently used in France. The software solution can be used to implement a DRT system in the Netherlands to improve an existing bus system.

To identify an existing bus system in the Netherlands that is struggling with low demand, contact with a Dutch bus operator, EBS, was initiated. The area of Voorne-Putten Rozenburg was selected because it contains several bus lines that are experiencing low demand, with one bus line having considerably low demand. A DRT system could potentially be an improvement, but is it not known what the performance of a DRT system will be in serving the demand that is currently served with the existing fixed-line bus system.

1.3. Research objectives

This thesis aims to evaluate the partial replacement of the current fixed-line bus system in Voorne-Putten Rozenburg with a DRT system. The existing bus system in the area consists of several bus lines. Some bus lines are operating at high frequency due to high demand and others operate less frequently due to lower demand. EBS, the bus operator of the area, noted that one of the bus lines had considerably low demand. The operator considers removing this bus line and serving the demand with a DRT system. The first goal of this research is to evaluate this scenario. The hypothesis is that the DRT will be an improvement compared to the existing bus system. Recent studies concluded that a DRT system is more efficient when operated on a large enough scale, as this would allow for more rides being shared such that vehicles are used more efficiently [17, 15, 14]. Therefore, the second goal of this research is to evaluate the replacement of all low-frequency bus lines with a DRT system and to evaluate whether the DRT system is in this case more efficient. This second scenario includes the bus line from the first scenario plus two additional low-frequency bus lines.

Considering the barrier that people experience when accessing a DRT service, this thesis focuses on three different methods of requesting the DRT service that are presumably increasingly easier to use, but consequently provide less information to the operator. The first method requires the user to make a reservation in advance, typically 30 minutes or an hour beforehand, and is what most DRT system in the Netherlands use [18]. This requires planning from the user side and prevents users from using the service spontaneously, but it gives the operator more time for planning and possibly ensure that a vehicle is available at the right time. The second method allows the user to request the DRT service on demand, allowing users to request the service whenever they need it. However, this makes planning more difficult for the operator, as they will need to dispatch a vehicle as quickly as possible to accommodate the user’s request. In both cases, the user is still required to request the service via an app or a phone call. The third method, as proposed in this thesis, considers a physical method to request the DRT service, where it is assumed that the DRT service can be requested at the bus stop through a simple interaction, such as pressing a button or checking in with a smart card, and thus no digital literacy is required. This simplification for users has the consequence for the operator that it initially only knows the pickup location of the user and the dropoff location is unknown. Once the traveller is picked up, the dropoff location is provided and can be added to the planning. The reservation, on-demand, and stop-based requests, in that order, are increasingly easier to use for users. Simultaneously, in the same order, they provide progressively less information to the operator. This thesis aims to evaluate the effect on the performance of the DRT system due to the reduced information to the operator.

To compare a DRT system with the existing bus service, this thesis assesses the performance of the DRT system in transporting individual trips that were transported by the existing bus service. As individual trip data could not be shared due to privacy concerns, this thesis generates individual trips from aggregated historical data of the existing bus system from 2023. An agent-based simulation approach is used to simulate how a DRT system performs in serving individual trips. Performance indicators considering the user, the operator and the environment are used to evaluate the results.

1.4. Research question

This thesis aims to answer the following research question:

> What is the feasibility of replacing the low-demand bus lines in Voorne-Putten Rozenburg with a demand responsive transport system?

With the following sub-questions:

1. How can individual passenger trips be generated from aggregated boarding and alighting data?
2. How does a DRT system perform compared to the existing bus system considering current travel demand?
3. What increase in travel demand results in a tipping point where the existing bus system becomes more efficient than the DRT system?
4. Does increasing the scale of the DRT system increase its efficiency?

The questions consider both the scenario of replacing a single bus line and the scenario of replacing all regional bus lines; three low-demand bus lines. Furthermore, a DRT system is evaluated in terms of reservation, on-demand and stop-based requests.

1.5. Structure

This thesis is structured as follows. Background and related work on DRT systems and simulation techniques are covered in Chapter 2. The methodology of this thesis is explained in Chapter 3. The results are presented in Chapter 4. The discussion of the results, limitations and recommendations is given in Chapter 5. Finally, a conclusion is drawn in Chapter 6.

2

Background and related work

This chapter discusses existing research related to DRT systems. Firstly, the origins of DRT and its challenges and success factors are highlighted in Section 2.1. Secondly, different approaches to modelling DRT systems are given in Section 2.2. Third, existing simulation frameworks that can be used to simulate DRT systems are shown in Section 2.3. The next two sections highlight two important components of DRT systems: traveller generation methods in Section 2.4 and dispatching algorithms in Section 2.5. The results of recent simulation studies on DRT systems are summarised in Section 2.6. Lastly, an overview of the discussed topics and the implications to this this is given in Section 2.7.

2.1. Introduction to Demand Responsive Transport (DRT)

This section introduces demand responsive transport (DRT). First, the historical background and the current state of DRT is given in Subsection 2.1.1. Then, the challenges and success factors of existing and previous DRT systems are identified in Subsection 2.1.2.

2.1.1. Historical background and origins

The concept of DRT is relatively old. The first formal and documented experiment was performed in 1916 in Atlantic City. It was a public jitney service that operated on a fixed route but picked up and dropped off passengers according to their requests [19, 20]. The 1960s and 1970s saw demand-responsive systems that were operated using cars or minibuses, mainly to overcome transportation problems in rural areas in North America and the UK [21, 22]. The Netherlands saw its first DRT service in 1989 in the Rotterdam neighbourhood Hillegersberg-Schiebroek. These DRT systems were often specifically targeted at specific user groups such as elderly or disabled people and are also known as paratransit. Serving the general public was infeasible due to the technological difficulties of operating a DRT system; requests were made by calling the operator and the vehicle allocation process was typically a labour intensive task that required specialist scheduling and local knowledge [22, 23].

In the 2000s, the rise of the internet and smartphones gave new possibilities to request the DRT service more conveniently. In addition, more advanced planning methods and automated vehicle scheduling allowed for larger number of users. Due to these technological advances, DRT has received more attention and has been implemented to serve the general population as a public transportation service. These DRT implementations over the past 20 years have varied in terms of success.

2.1.2. Challenges and success factors

Coutinho et al. [21] studied a DRT pilot in a rural area in Amsterdam Noord where two fixed-line buses were replaced by a DRT system. Most notably, despite being free of charge, the ridership of the DRT system was about 72% lower than the fixed line buses, dropping from 78 passengers per day to 16. The study notes the long time frame of 15 min around the desired departure time as a potential reason for the drop in ridership. This is supported by a big drop in user satisfaction for rides that were not on time, while on-time rides were perceived as highly satisfactory. It can be concluded that punctuality is an important factor for user satisfaction. However, because the total distance travelled by the DRT system was 89% less than that of the fixed line system, the study concluded that the DRT system was more efficient.

Laws et al. [24] investigated DRT schemes as a result of increased government funding in England and Wales. Most of the DRT systems were based in rural areas and were established as innovative transport solution to improve accessibility. The main lessons learned were that DRT must have sufficient time invested at the planning stage and that the design must not be over-complicated. The common problems that were found included generating sufficient demand and overcoming psychological barriers of prospective users who were lacking confidence in something new or needed time to grasp the concept.

Similarly, Currie et al. [12] concluded that simpler service design resulted in higher success rates based on 120 DRT schemes of the past 40 years. Furthermore, the study finds that lower costs and specialist services, i.e. paratransit, are strong contexts to develop successful DRT systems. However, the study concludes that DRT systems are prone to failure, with 50% of the considered DRT systems failing within 7 years. The failure of DRT systems was found to have a strong link with higher costs.

A recent study by Berenschot [14] investigated successful DRT systems, mainly in Germany, and concluded that DRT is more effective when implemented on a large enough scale. Other success factors included on-demand booking, easy booking and payment, and no fixed routes.

Jain et al. [25] looked into the demographic and trip characteristics that are susceptible to using DRT. Various parameters are identified to correlate with DRT usage, including shopping and social trips, short waiting and walking time.

In conclusion, there have been numerous DRT pilots with varying success. Failure factors included high costs, generating sufficient demand and too flexible systems. Success factors include punctuality, low costs, simple design and large enough scale. Furthermore, most studies highlight the importance of careful planning of the proposed DRT system, pointing to the importance of modelling and simulating proposed DRT systems to evaluate their performance and costs in advance.

2.2. Modelling approaches for DRT systems

There are a few ways in which a DRT system can be modelled and evaluated. The model used mostly depends on the research goal of the study. This section highlights common modelling frameworks used in modelling DRT systems, namely agent-based models, microsimulation models and analytical models.

2.2.1. Agent-based models

In traditional (simulation) modelling, a system is modelled by describing the system's behaviour directly based on input parameters. The assumption is that knowledge of the system as a whole is known and can be analytically described. This is a top-down approach. In many complex systems, the system's behaviour cannot be described directly. Agent-based modelling assumes that the system's behaviour is the result of many small interactions between the system's components or entities, called agents. The agents are of simpler nature, and their behaviour in the system can be modelled. The system's behaviour and its emergent properties are observed by simulating the modelled agents in an environment. There is no desired behaviour or task to be achieved, instead the idea of agent-based modelling is to merely describe the agents and observing how they interact to explore the system's possible states [26]. Borshchev et al. [27] describes the advantage of ABMs with respect to other approaches:

> "Agent Based approach is more general and powerful because it enables to capture more complex structures and dynamics. The other important advantage is that it provides for construction of models in the absence of the knowledge about the global interdependencies: you may know nothing or very little about how things affect each other at the aggregate level, or what is the global sequence of operations, etc., but if you have some perception of how the individual participants of the process behave, you can construct the agent-based model and then obtain the global behaviour."

DRT systems have been recognised as being notoriously complex [28]. However, the components in a DRT system, travellers, vehicles and an operator, can be described relatively easily. Indeed, the behaviour of a traveller in DRT system consists of making a request to the operator and deciding whether to accept the received offer or opt out. The operator managing the assignment and routing of vehicles, while not simple, can be described using an algorithm. ABMs have been widely used to simulate DRT systems and their results are described in Section 2.6.

2.2.2. Microsimulation models

Microsimulation, also called individual simulation, is a tool to analyse a system by modelling at the level of individual units, such as people or vehicles. In a microsimulation, individuals have a simple stochastic or rule-based structure. While similar to ABMs, the difference is that in this case the behaviour of the individual agents is not modelled. Therefore, microsimulation is suitable when this degree of detail is unnecessary. Several studies used microsimulation to develop dispatching algorithms for DRT. As the goal is to find the optimal algorithm, details on the behaviour of travellers and their interaction with the DRT service are not relevant.

Di Maria et al. [29] proposes a discrete event simulation model specifically targeted towards testing and developing dispatching algorithms for autonomous DRT. Winter et al. [30] formulated an iterative procedure for assigning vehicles to passenger requests. The model was used in an event-based simulation that progresses over stochastically generated passenger requests, where new requests trigger the dispatching algorithm.

2.2.3. Analytical models

Analytical models have been developed to research specific aspects of a DRT system. Although not able to evaluate the whole system, these analytical models can provide useful insights without the resources needed to simulate the whole DRT system.

To find the demand density at which fixed-line transport (FLT) becomes more effective than demand responsive transit, Quadrifoglio et al. [31] adopted an analytical approach to derive the critical demand density (the tipping point) between the two feeder services based on utility functions. The closed form expression of the critical demand density is a function of the geometry of the service area, the vehicle speed and the weights assigned to the terms contributing to the utility function; walking time, waiting time and riding time. This allows transport operators to choose between DRT and FLT without expensive modelling and simulation efforts. The case for one or two demand responsive buses are worked out. One big assumption is made however, which is the no-backtracking assumption. That means that the vehicle will cover the area by travelling in a sort of circle. This assumption is necessary to derive an analytical expression, but is not necessarily true in practice.

Santi et al. [32] quantifies the benefit of sharing rides in large scale taxi services and evaluates its effect on individual passenger discomfort. The study proposes a mathematical framework for the tradeoff between the benefits and passenger discomfort. The optimal sharing strategy can effectively be computed using this framework.

Vazifeh et al. [33] addresses the minimum fleet problem: given a collection of trips (specified by origin, destination and start time), how to determine the minimum number of vehicles needed to serve all the trips without incurring any delay to the passengers.

2.3. Simulation frameworks for DRT systems

Several simulation frameworks have been created for the purpose of simulating DRT systems. Nguyen et al. [34] and Huang et al. [35] reviewed existing agent-based approaches to general traffic simulations and elaborated how and where these simulators can be used. The frameworks include both commercial frameworks and open-source frameworks. Only a few of these software packages include functionality for DRT systems.

The commercial traffic simulation frameworks that allow for the simulation of DRT systems include Aimsun and PTV. Aimsun [36] includes a fleet management module ”Aimsun Ride” [37] that allows for the modelling and simulation of DRT systems. PTV group [38] offers a REST API that allows for the planning (VISUM) and the simulation (VISSIM) of different transportation modes and their impact on travel times, accessibility and cost of operation.

The open-source traffic simulation frameworks that allow for the simulation of DRT systems include MATSim, Polaris, SimMobility, SUMO, and TRANSIMS. MATSim [39] is an agent-based transportation simulation framework with numerous extensions, including the AMODEUS extension [40] that models DRT systems. It also includes an activity-based demand model to generate travellers. Polaris [41] is another agent-based simulation framework with an integrated activity-based travel demand model. Polaris also contains dynamic network travel times. SimMobility [42] is also an agent-based traffic simulation framework. SimMobility consists of three connected components: long-term, mid-term and short-term simulation. The multi-level approach is interesting when different levels of detail are to be considered. SUMO [43] is a microscopic traffic simulation framework with a similar activity-based demand model for the generation of travellers. SUMO in combination with Jade [44] allows the modelling of DRT systems. TRANSIMS [45] is another microscopic simulation framework with an activity-based travel demand model.

There also exist open-source simulation frameworks that have been created explicitly for DRT simulation. These include FleetPy, MaaSSim, and AMoDSim. FleetPy [46] is an agent-based framework made to model the detailed interactions of users with operators. It has a modular structure that ensures transferability of previously developed elements and the selection of the appropriate level of simulation detail. MaaSSim [47] is an agent-based simulator that focuses on the interaction between travellers and vehicles. The travel demand must be specified as input. MaaSSim is a relatively simple framework. AMoDSim [29] is a discrete event simulator for Autonomous Mobility on Demand. The focus of AMoDSim is on evaluating the dispatching algorithms that are used in DRT systems. The level of detail present in agent-based approaches is intentionally left out as it causes unnecessary overhead.

Table 2.1 highlights the existing software packages in which DRT systems can be simulated.

Name	Programming Language	Main purpose	Agent-based	Open-source
Aimsun	-	Traffic condition in road networks		
PTV	-	Traffic planning		
MATSim	Java	Traffic simulation	✓	✓
Polaris	C++	Traffic simulation	✓	✓
SimMobility	C++	Traffic simulation	✓	✓
SUMO	Java	Traffic simulation		✓
TRANSIMS	C++ / Python	Traffic simulation		✓
FleetPy	Python	DRT simulation	✓	✓
MaaSSim	Python	DRT simulation	✓	✓
AMoDSim	C++	Dispatching algorithms		✓

Table 2.1: Overview of existing simulation frameworks

2.4. Traveller generation methods

One of the most crucial input factors in simulating a DRT system is the travel demand. An accurate evaluation of a potential DRT system can only be achieved if an accurate representation of the travel demand is used. However, generating travel demand for DRT is a challenge, as it is difficult to predict how many travellers will adopt DRT once it is introduced in a new area. Since DRT is a relatively new mode, the behaviour of travellers towards it is uncertain. While the mode choice of traditional public transport, such as trains and buses, is well explored, this is not the case for DRT. A need for realistic travel demand data sets for DRT is present [15].

There are different ways in which existing studies generated travel demand for their proposed DRT system [15]:

1. Synthetic demand data
2. Demand data from existing public transport
3. Demand data from taxi's

4. Demand data from semi-flexible systems
5. Demand data from actual field tests or existing DRT systems

The method that was chosen to generate travel demand depends on the data that was available and the goal of the DRT system. This thesis considers a DRT system as a replacement of existing public transport (current fixed-line bus). Therefore, it is appropriate to use existing public transport demand data.

2.4.1. OD matrix estimation using boarding and alighting counts

The data available for this thesis are the average number of passengers boarding and alighting at bus stops. However, the input to the simulation must be a list of origins and destinations, from which the number of travellers between origin and destination pairs are unknown. Several methods have been proposed to estimate the probabilities of origin and destination pairs based on boarding and alighting counts. The result is an OD matrix from which origin-destination pairs can be sampled, which can be used in the simulation.

Iterative proportional fitting

Lamond et al. [48] and Ben et al. [49] used iterative proportional fitting, also known as the balancing method or the biproportional method. The balancing method starts with an initial matrix with the same size as the OD matrix, called the seed matrix. The seed matrix is iteratively scaled to match known row and column totals, which are the number of passengers boarding and alighting at each stop. The method will converge to the optimal solution [49] if an appropriate seed matrix is chosen.

Recursive methods

Tsygalnitsky [50] proposed a simple recursive method. The method iterates over the stops and distributes the alightings at each stop over the origin stops in proportion to the number of people from each origin stop who are eligible to alight. An eligible passenger has travelled a minimum distance and has not yet alighted previously. Li et al. [51] extended the recursive method to include the distinction between major and minor stops. It can be shown that the recursive method is a special case of the iterative proportional fitting method [52].

Blum et al. [53] proposes an improvement on the recursive method by using household survey data together with boarding and alighting data. The so-called hybrid demand estimation algorithm is shown to produce a more accurate demand estimation.

Maximum likelihood approaches

The relation between the OD matrix and the number of boarding and alighting at each stop can be expressed in the form of a system of linear equations. Furthermore, an assumption can be made about the distribution of boarding and alighting counts. The trip rates in the OD matrix can then be estimated using a maximum likelihood approach. However, this approach requires an enumeration of feasible sets of origin-destination pairs that result in the boarding and alighting data. The difficulty is that this enumeration quickly becomes extremely large even for moderately large OD matrices. As a solution, Hazelton [54] adopts a Bayesian sampling approach. Chen et al. [55] improves this approach by allowing uncertainty quantification.

2.5. Dispatching algorithms

This section covers dispatching algorithms in DRT systems. The dispatching algorithm is solving a problem called the Dial-A-Ride Problem (DARP). First, the DARP is introduced and some important aspects are highlighted. Then, different solution methods to the DARP are given, which are dispatching algorithms.

2.5.1. Dial A Ride Problem

A commonly studied aspect of DRT systems is the dispatching algorithm. The dispatching algorithm assigns incoming requests to vehicles and creates routes for each vehicle. The problem that the dispatching algorithm is solving is the Dial A Ride Problem (DARP). The DARP is the problem of scheduling the vehicle routes of m vehicles for n users, who each specify a pick-up and drop-off location. Furthermore, multiple users can share (a part of) their trip with another user [56]. The difficulty of the DARP is that the number of possibilities to assign requests to vehicles grows exponentially: $O(mn^{\mu})$, where μ is the maximum number of requests per vehicle [57].

Ho et al. [58] and Molenbruch et al. [59] conducted reviews on DARP systems. The DARP is most often formulated as an integer programming problem. Different formulations arise from different constraints that are required in different problem contexts. A basic formulation mathematical formulation of the DARP is given by Cordeau [60], which has been studied extensively by other authors and has formed the basis for other problem extensions.

Objective function

The objective of the dispatching algorithm is to minimise a cost function. The cost function often consists of a weighted sum of user and/or operator metrics [58]. User metrics include such as the number of served users, user waiting time and user travel time. Operator metrics include vehicle-driven distance and costs.

Constraints

DRT systems often include additional constraints imposed by the user or the operator. On the one hand, users might be able to specify an earliest pick-up time, a latest pick-up time, or a latest drop-off time. On the one hand, the operator might determine a maximum waiting time or maximum detour time to ensure a certain quality of service. Both constraints formally lead to time windows in which the traveller must get picked up or dropped off. The benefit of such constraints is that they greatly diminish the space of feasible assignments, which is beneficial from a computational point of view. However, the consequence of the constraints is that a request can be declined if the request cannot be added to the current schedule while adhering to all constraints.

Static or dynamic

It is important to note the difference between a static and a dynamic DARP. In a static setting, all requests are known in advance, typically a day ahead. In this case, the problem can be solved before the vehicles go into operation and the planning only has to be executed. In the dynamic DARP, not all requests are known in advance, and new requests are revealed over time while the vehicles are in operation. The vehicle routes need to be adjusted in real time to account for new incoming demand. The problem instances in a dynamic setting are naturally smaller than in a static setting, but the solution is required quickly and therefore the computational time of the solution method is important. This thesis considers the dynamic DARP.

2.5.2. Solution methods

In general, solution methods can be categorised in exact methods and heuristic methods.

Exact methods

Most of the exact methods for the DARP are based on a branch and bound (B&B) framework [58]. B&B enumerates all solutions for the problem and the computational time of a B%B procedure can be exponential in the worst case. The bounds for the optimal objective value have been improved by the use of cutting planes. Furthermore, preprocessing and branching rules have a considerable impact on the speed of a B&B framework. Recently, Alonso-Mora et al. [61] proposed an algorithm for high-capacity dynamic DARP. An implementation of this algorithm [57] in FleetPy is used in this thesis.

Heuristic methods

Exact methods are only able to solve small problem instances. Even for small instances, the computational time can exceed the available time in a dynamic setting of the DARP. The focus of much research has therefore been on (meta)heuristic methods.

Commonly used heuristic methods are insertion heuristic algorithms. These are mainly inspired by the greedy insertion heuristic proposed by Jaw et al. [62]. Here, each request is sequentially assigned to the position in the vehicle route that minimises the objective function. This thesis also uses a heuristic algorithm implemented in FleetPy [57].

Ho et al. [58] gives an overview of other heuristic methods. These include tabu search, simulated annealing, variable neighbourhood search, large neighbourhood search, genetic algorithms, and hybrid algorithms. Furthermore, an ant colony optimisation approach is used by Calabrò et al. [63].

2.6. Recent simulation studies on DRT

Calabrò et al. [64] compared demand responsive transport with schedule based transport as feeder service to a metro station in Catania (Italy) using an agent-based model. The feeder service transports people from and to a terminal where they start or end the rest of their public transport journey, meaning that the demand follows a one-to-many pattern. The other part of the O-D pair is based on socio-demographic data (population density). Travellers only choose between walking and transit, which follows from a certain distribution based on the walking distance. In a follow-up study, Calabrò et al. [5] extended their previous research, being a many-to-one (feeder) service, to a many-to-many service. The case study is done in the small city Vittoria (Italy) where there is currently no public transportation service available. Demand is generated from zone to zone with probability proportional to the number of employees. Again, travellers only choose between walking and transit. The results highlight the benefits of using a DRT system compared to a fixed-line service. The benefits include reduced detours, waiting times and walking distances experience by travellers while increasing shareability and efficiency of the service.

Calabrò et al. [65] adopted the parametric environment proposed by Quadrifoglio et al. [31] and used an ABM model to evaluate a feeder service in a demand responsive and a fixed line setting. The performance of a DRT system and a fixed line bus system were evaluated with respect to different parametric environments. The results show that DRT is to be preferred when the demand is spatially concentrated close to the station or when the station spacing is quite high. A fixed line system is preferred when the operation area is stretched out and during peak hours.

Martinez et al. [66] simulated a shared-taxi system in Lisbon, where they proposed a new organisational design and pricing scheme (discounting shared-rides) such that the current taxi capacity can be used more efficiently. The agent-based model was implemented on the road network of Lisbon and the trip requests are simulated based on a Lisbon taxi trip dataset. There is a simple choice model; the agent automatically accepts an offer unless it has to wait too long, then it has a probability of leaving the system. Results show the proposed system can lead to significant fare and travel time savings to travellers, while only slightly decreasing the taxi revenues.

Oh et al. [67] made an agent-based simulation for automated mobility on-demand (AMOD) in Singapore. Demand is generated using an activity-based model based on household survey data, while supply is handled by an insertion heuristic. The AMOD system is simulated together with all other known transportation modes to observe the market share of the proposed system. The AMOD shared minibuses result in a reduction of vehicle kilometres travelled compared to shared taxi's.

Inturri et al. [8] made an agent-based simulation to evaluate different values for the number and capacity of DRT vehicles and different dispatching strategies. The case study is done for Ragusa (Italy). To evaluate the performance, indicators for both the traveller and the operator are considered. The results show that many low capacity vehicles is better for travellers, but expensive for the operator. Few large capacity vehicles is cheaper for the operator, but less efficient for travellers. A follow-up study in Ragusa compares DRT services with taxi services [68]. The results showed that taxi services are more advantageous when transport demand is low, but DRT services are more efficient when demand is high. Between high and low demand there is a balance between taxi and DRT and requires further investigation of the area to get the optimal transportation service.

Giuffrida et al. [6] applied the ABM proposed by Inturri et al. [8] to one district of the city of Dubai. Different configurations of the DRT system are evaluated, taking both the traveller and the operator into account. The results suggest that the dispatching algorithm is important in finding a balance between operator and user costs. The DRT system can satisfy the travel demand with limited total costs compared to other transportation services.

Armellini et al. [7] analysed a potential DRT service in a peri-urban area near the city of Brunswick (Germany). An agent-based model was used to simulate the proposed solution, where there is a single (mass rapid) bus line and multiple DRT services serving as feeder service to the bus stops. The proposed solution reduced travel times with 30-45%.

Most DRT studies consider a door-to-door service. Although convenient for travellers, it is a factor that increases the costs of a DRT system. Operating on a limited number of stops means that travellers have to walk to the stop, but it causes consolidation of travellers and potentially lowers costs. Araldo et al. [69] evaluated the density of the stops. The results show that by decreasing the stop density, the travellers are more consolidated and the system capacity is increase; more travellers can be served with the same number of vehicles, thus lowering the costs per traveller.

In conclusion, the results of the simulation studies show many potential benefits of a DRT system as opposed to existing public transportation. The main benefit being lower travel times for travellers. The costs of a DRT system are not always lower. The costs-effectiveness of a DRT system depends on several factors; fleet size, vehicle capacity, dispatching algorithm, demand concentration and stop density. In contrast, the studies show that fixed-line transportation is still preferred in situations with steady demand or during peak hours, particularly in highly populated urban areas.

2.7. Conclusion

This chapter discussed the background of DRT systems, the work related to the simulation of DRT systems, and the results of recent simulation studies on proposed DRT systems.

First, the background on DRT systems was given by considering previous and existing implementations and highlighted the success and failure factors. The main success factors of previous and existing DRT implementation are low costs, low waiting time, punctuality, simple design and large enough scale. The failure factors are high costs, generating sufficient demand and too flexible systems. These points are considered in the following way. Costs, waiting time and punctuality are included in the evaluation of the DRT system. Simple design is addressed by considering an aspect of the design, namely the request method. Different request methods are evaluated with different levels of simplicity. The scale is evaluated through the two scenarios. The flexibility is reduced by transporting travellers from bus stop to bus stop instead of door-to-door. Generating sufficient demand is not in the scope of this thesis; the current existing bus demand is assumed.

Second, to evaluate a DRT system, the common methods of agent-based modelling, microsimulation and analytical models were discussed. An agent-based model approach can be concluded as suitable for this thesis, as it aligns with the goal of observing the behaviour of the system under different scenarios. Existing simulation frameworks in which DRT can be simulation were highlighted, and FleetPy can be concluded as most appropriate, as it uses agent-based modelling and is the more complete framework of the frameworks that specialise in DRT. Furthermore, two important components of the simulation were discussed: the method of generating travellers and the dispatching algorithm used by the DRT system. Various methods were formulated to generate travellers from aggregated data. In this thesis, a recursive method is adopted due to its simplicity, as generating travellers is not the primary focus. Dispatching algorithms were categorised into exact methods and heuristic methods. Exact methods find an optimal solution but are computationally expensive. Heuristic methods often have low computational time but only find near-optimal solutions. Both will be considered in this thesis.

Third, several simulation studies were explored that evaluated proposed DRT systems. The simulation studies mainly show potential benefits of a DRT system. The main benefit was the low travel times for travellers. The costs of the DRT system varied across the studies, and the cost-effectiveness a DRT system depends on several factors, such as the fleet size, dispatching algorithm, and demand density. When comparing DRT systems with fixed-line buses, it was found that DRT is preferred in areas with low demand. However, fixed-line buses are preferred when the demand is high and concentrated. As the demand in the scenarios in this thesis is low, it is evaluated at what point the fixed-line bus is preferred.

3

Methodology

This chapter is structured as follows. First, an overview of the research methodology is given in Section 3.1. Second, the steps taken to process the available data are explained in Section 3.2. Third, the method to generate individual trips based on data from the existing bus system is presented in Section 3.3. Then, the chosen simulation framework is elaborated in Section 3.4. The creation of the road network as the simulation environment is shown in Section 3.5 and the DRT system is defined in Section 3.6. Lastly, the evaluation metrics are given in Section 3.7.

3.1. Overview

The objective of this thesis is to evaluate the performance of a DRT system in Voorne-Putten Rozenburg as a replacement for the existing bus service. In other words, the objective is to evaluate the performance of the DRT system in transporting all individual passenger trips currently transported by the existing bus service. A list of individual trips for a single day was generated from the aggregated boarding and alighting data. Since travel patterns vary daily, multiple days of trips were generated. These trips were evaluated in the existing bus system using the timetable (and thus assuming that the existing bus perfectly adheres to it), which led to the results for the existing bus. To evaluate the trips in a DRT system, they were defined as DRT requests; as reservation, on-demand and stop-based request. For each of the request types, a simulation was run to evaluate how the DRT system performs considering that request type. The agent-based simulation framework FleetPy [46] was used. Additional input to the simulations were the road network, from which travel times were calculated, and the DRT configurations, which defined the DRT system through various parameters. The same set of individual trips was thus assessed four times; when presented as reservation, on-demand, and stop-based requests within a DRT system, and in the current bus system. An overview of the methodology is given in Figure 3.1.

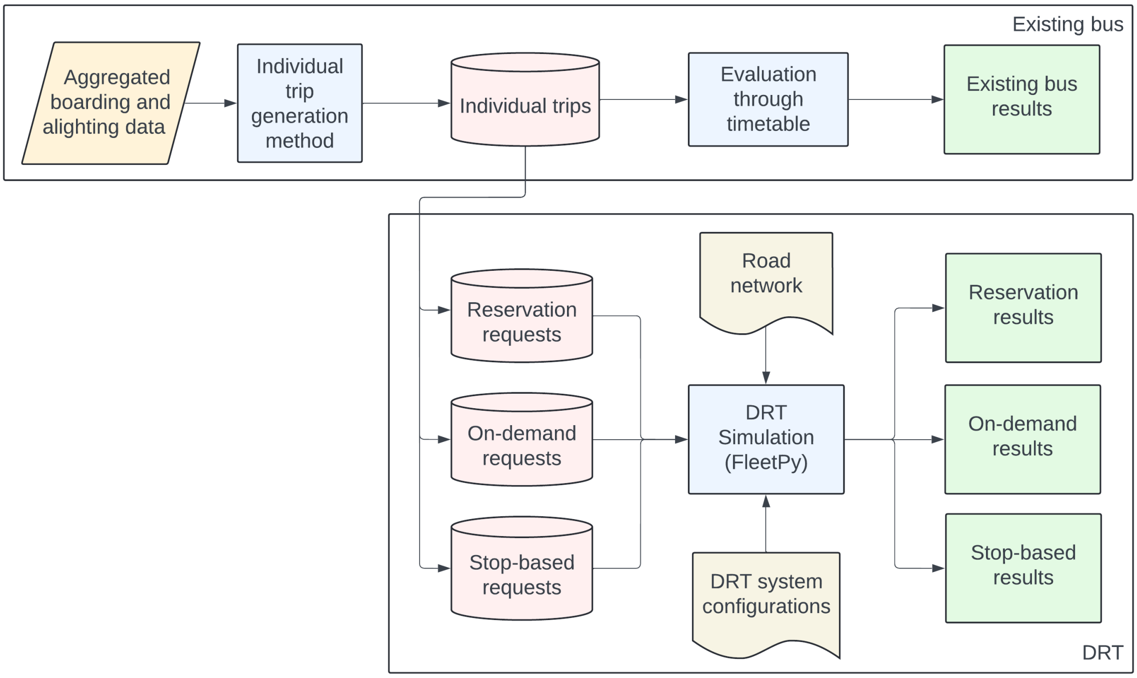


Figure 3.1: Overview of the methodology.

3.2. Data processing steps

Historic data of individual trips made with the existing bus system during weekdays in 2023 were aggregated to boarding and alighting counts. This was done separately for each of the bus lines in each of its two directions. Thus, for each of the entries in the bus schedules, the total number of passengers boarding and alighting in 2023 were available. The bus schedule for bus line 91, as an example, can be found in Appendix E. Some steps were taken to process the data and account for inconsistencies.

First, the data included some bus stops that were not on the schedule. This data was ignored and the data was filtered so that only the data corresponding to the schedule was selected.

Second, due to privacy concerns, all entries that were equal to 1 up to 5 were labelled "≤ 5". This means that no more than five counts were observed during 2023. These entries are replaced by 3, as this is the average of the possible values it could have taken. If no counts were observed, then the data entry contained a NaN value (not a number), which was replaced by 0.

Third, the boarding and alighting counts per bus trip were not always equal. This is likely the result of the entries labelled "≤ 5". As a solution, the data was scaled so that the boarding and alighting counts were equal.

Lastly, the average number of passengers boarding and alighting was derived by dividing the data by the number of weekdays in 2023. The final format of the processed data for a single bus line in one of its directions is illustrated in Table 3.1, where t is the time of departure, u is the average number of passengers boarding and v is the average number of passengers alighting.

	Trip number T				
Stop number S	1	2	3	$\cdots$	N
1	(t_{11}, u_{11}, v_{11})	(t_{12}, u_{12}, v_{12})	(t_{13}, u_{13}, v_{13})	$\cdots$	(t_{1N}, u_{1N}, v_{1N})
2	(t_{21}, u_{21}, v_{21})	(t_{22}, u_{22}, v_{22})	(t_{23}, u_{23}, v_{23})	$\cdots$	(t_{2N}, u_{2N}, v_{2N})
3	(t_{31}, u_{31}, v_{31})	(t_{32}, u_{32}, v_{32})	(t_{33}, u_{33}, v_{33})	$\cdots$	(t_{3N}, u_{3N}, v_{3N})
$\cdots$	$\cdots$	$\cdots$	$\cdots$		$\cdots$
M	(t_{M1}, u_{M1}, v_{M1})	(t_{M2}, u_{M2}, v_{M2})	(t_{M3}, u_{M3}, v_{M3})	$\cdots$	(t_{MN}, u_{MN}, v_{MN})

Table 3.1: Illustration of the available data of a single bus line in one of its two directions. t is the time of departure, u is the average number of passengers boarding and v is the average number of passengers alighting.

3.3. Individual passenger trip generation

The average number of individual passenger trips per day is the sum of the average number of passengers boarding (or alighting) at all stops: $P = \sum_{i=1}^{M} \sum_{j=1}^{N} u_{ij}$. As such, P passenger trips are considered per day. A passenger trip is generated by first sampling one of the bus trips from the bus schedule. A bus trip is a column in Table 3.1 and is not to be confused with a passenger trip, which is a person who boards and alights at two stops during a bus trip. The bus stops at which a passenger boards (origin) and alights (destination) are sampled based on the boarding and alighting data for that specific bus trip, so one of the columns in Table 3.1. This is done by deriving an origin-destination (OD) matrix for the bus trip.

The probability of a bus trip is the average number of passengers on that bus trip divided by the total number of passengers per day.

$$\mathrm{P}(T = k) = \frac{\sum_{i=1}^{M} u_{ik}}{\sum_{i=1}^{M} \sum_{j=1}^{N} u_{ij}} \tag{3.1}$$

Once a bus trip is sampled, the origin and destination of the passenger trip need to be generated. This is done by deriving an OD matrix for the bus trip. The following OD matrix derivation is based on the recursive method proposed by Tsygalnitsky [50].

Consider a single bus trip, a column from Table 3.1. The subscript for the bus trip will be neglected in the following. Let **u** $= (u_1, u_2, \ldots, u_N)^T$ denote the number of passengers boarding at each stop and let **v** $= (v_1, v_2, \ldots, v_N)^T$ denote the number of passengers alighting at each stop. We assume that no passengers alight at the first stop and no passengers board at the last stop, such that $v_0 = u_N = 0$. We are interested in the number of passengers travelling between any two stops. That is, we are interested in the travel rate $\lambda_{i,j}$ between stop i and stop j. Figure 3.2 illustrates the boarding and alighting counts together with the travel rates.

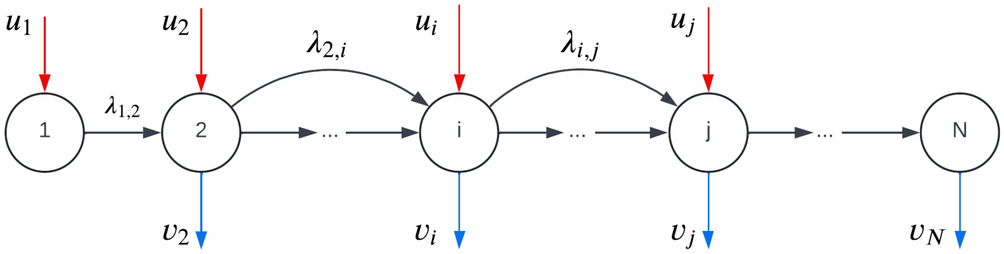


Figure 3.2: Illustration of passengers boarding and alighting on a bus line.

The travel rates λ_{ij} are recursively defined over the stops. Consider the number of passengers alighting at stop 2. It is clear that these passengers boarded at stop 1. We say that the probability $\mathrm{P}(O = 1 | D =$

2), denoted by $p_{1,2}$, that stop 1 is the origin given that stop 2 is the destination is equal to 1. The travel rate $\lambda_{1,2}$ is then defined as $p_{1,2} * v_2$, which in this case is simply v_2. Now consider the number of passengers alighting at stop 3. In this case, we do not know the origins of these passengers. However, we can define the probability that the origin was stop 1 or 2 based on the number of passengers boarding at stops 1 and 2. For stop 1, we need to subtract the travel rate $\lambda_{1,2}$ of the passengers who travelled from stop 1 to stop 2. As these passengers have alighted at stop 2, they cannot alight at stop 3. In general, the remaining boarding count at stop i when considering stop j is equal to the original boarding count u_i minus the travel rates from stop i to the stops $i+1$ up to $j-1$. These are the passengers who boarded at stop i and alighted at one of the stops before j. Formally, we define the remaining boarding count at stop i when considering stop j as

$$u_i^j = u_i - \sum_{l=i+1}^{j-1} \lambda_{il} \tag{3.2}$$

The probability $p_{i,j}$ that stop i is the origin given that stop j is the destination is then the remaining boarding count at stop i divided by the total remaining boarding counts at stops 1 up to $j-1$.

$$p_{ij} = \frac{u_i^j}{\sum_{k=0}^{j-1} u_i^k} \tag{3.3}$$

The travel rate λ_{ij} between stop i and j, is then defined as:

$$\lambda_{ij} = p_{ij} * v_j \tag{3.4}$$

The recursive pattern can be seen when writing out the travel rate:

$$\lambda_{ij} = \frac{u_i - \sum_{l=i+1}^{j-1} \lambda_{il}}{\sum_{k=0}^{j-1} \left(u_i - \sum_{l=i+1}^{k-1} \lambda_{il} \right)} * v_j \tag{3.5}$$

This recursive method can be repeated to obtain the demand rates λ_{ij} for all pairs of origins i and destinations j, with $i < j$ since it is only possible to travel forward on the bus line. The result is the upper triangular OD matrix Λ. An example is given in Appendix C. An individual trip, i.e. an origin-destination pair, is sampled from the OD matrix.

3.4. Simulation framework

An agent-based simulation approach is used to evaluate the performance of a DRT system in serving the individual trips that are currently made with the existing bus, as generated by the method in the previous section. The agent-based approach is chosen as the most appropriate among the modelling approaches discussed in Section 2.2 because the goal is to obtain an accurate idea of the performance of the DRT system as a whole and the focus is not on a specific aspect. Furthermore, FleetPy is chosen among the existing agent-based simulation frameworks presented in Section 2.3. MATSim, Polaris, and SimMobility are very large frameworks due to being general traffic simulation frameworks and are too complex for the scope of this thesis. FleetPy is chosen over MaaSSim because it is more complete and modular.

3.5. Network creation

The network for the simulation consists of the road network and the bus stops. The road network of Voorne-Putten Rozenburg is extracted from OpenStreetMap (OSM) [70] using the Python package OSMnx [71]. The result is a directed graph where the edges have a weight equal to their length and additional properties such as the maximum driving speed. Furthermore, the coordinates of the bus stops are extracted from OSM using the Overpass API [72]. The coordinates of the bus stops are then assigned to a node in the extracted road network, because travellers can only get picked up or dropped off at nodes. However, the coordinates of the bus stops rarely correspond exactly to a node in the graph; they often lie on an edge in the graph. To address this issue, the nearest node connected to the edge is selected as the bus stop node. The graph representation of Voorne-Putten Rozenburg together with the bus stops of bus line 91, 105 and 106 is shown in Figure 3.3.

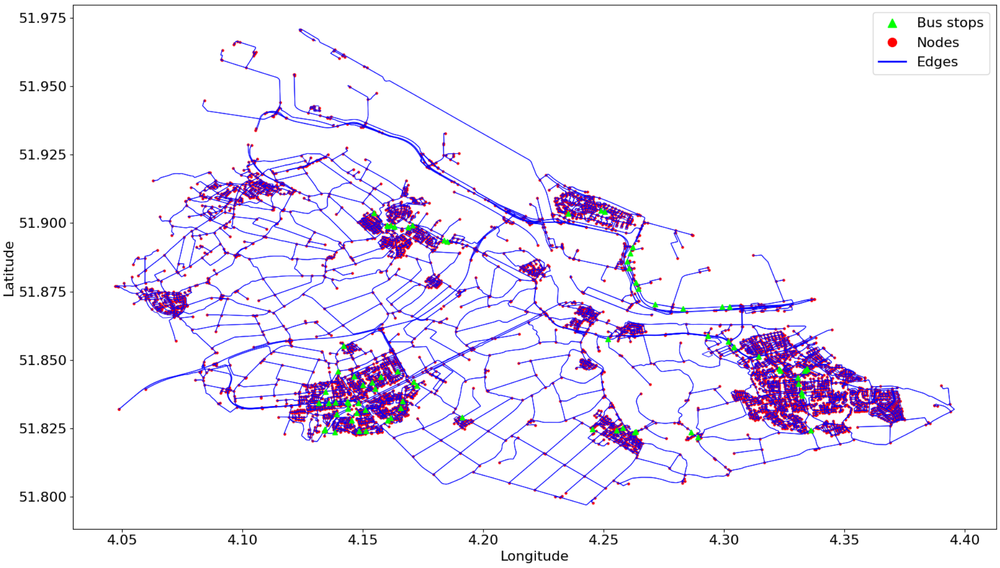


Figure 3.3: Graph representation of the road network of the Voorne-Putten Rozenburg area. Additionally shows the bus stops of bus lines 91, 105 and 106. Both are extracted from OSM [70].

3.6. DRT service definition

This section defines the simulated DRT system and its parameters. The DRT system consists of a fleet of vehicles, which is described in Subsection 3.6.1. The vehicles do not adhere to any fixed routes or schedules. The routes and schedules are created and updated dynamically based on the requests of travellers. Requests are made from and to existing bus stops. Three different request types are considered and are explained in Subsection 3.6.2. The requests are processed by a dispatching algorithm that tries to find the best match between requests and vehicles. The dispatching algorithms are highlighted in Subsection 3.6.3. A dispatching algorithm minimises an objective function, as defined in Subsection 3.6.4, while adhering to time windows, as defined in Subsection 3.6.5. If no feasible match is found, the request is declined and the traveller is not served. If a feasible match is found, the traveller receives an offer with the planned pickup and dropoff time. The traveller always accepts the received offer.

3.6.1. Fleet size

The DRT service consist of a number of vehicles n. The vehicles are assumed to have the same capacity c, the maximum number of travellers that can fit into the vehicle. The time it takes for travellers to board or alight the vehicle is taken to be 30 seconds. The costs of operating a vehicle is split in hourly fixed costs of 20.81 euro and variable costs of 0.30 euro per kilometre. The CO_2 emissions of an 8 person minibus is taken to be 206 gram per kilometre. The derivation of these numbers can be found in Appendix B

3.6.2. Request types

An individual traveller who wants to access the DRT service does so by submitting a request to the operator. Three ways in which travellers can access the DRT service are considered: reservation, on-demand, and stop-based requests.

- **Reservation** requests are made ahead of time. The user specifies a time in the future when they desire to use the DRT service. This means that there is a window between the time of the request and the earliest pickup time. This window is called the lead time, and the minimum lead time is defined by the operator.
- **On-demand** requests can be served immediately. In this case, the earliest pickup time is equal to the time of the request and the lead time is zero.
- **Stop-based** requests are on-demand requests that can be requested physically at the bus stop by a simple interaction such as pressing a button or checking in with a smart card. This simplification has the consequence that the dropoff location is initially unknown and is revealed once the user is picked up.

The requests correspond to the individual passenger trips made with the existing bus system, as generated by the method in Section 3.3. An individual passenger trip from the existing bus system consists of an origin stop i, a destination stop j, the departure time t_i at the origin and the arrival time t_j at destination. The request for the DRT system is then defined using the same origin and destination as pickup and dropoff location respectively. The earliest pickup time (EPT) of the request is t_i for all three request types. The time that the request is made (RQT) is different per request type. For reservation requests, the RQT is random, but at least 30 minutes before the EPT. A minimum lead time of 30 minutes is chosen because it is most common in Dutch DRT systems [18]. For on-demand and stop-based requests, the RQT is equal to the EPT.

3.6.3. Dispatching algorithm

FleetPy considers three dispatching algorithms: an insertion heuristic algorithm, a batch optimisation algorithm, and an insertion algorithm with periodic optimisation. The dispatching algorithms in FleetPy consider that the origin and destination of the request is given, as is the case with reservation and on-demand requests. To dispatch stop-based requests, an additional simple insertion algorithm was implemented.

Insertion heuristic algorithm

The insertion heuristic algorithm sequentially adds new requests to the current planning. The insertion of the request's pickup and dropoff is evaluated at all possible places in the current plan of each of the vehicles. Each insertion is assessed with respect to the objective function, and the insertion that yields the minimum value of the objective function is selected. Heuristics are applied to reduce the number of insertions that are evaluated.

In the case of stop-based requests, only the pickup off the request is planned. Once the traveller is picked up, then the dropoff is inserted.

Batch optimisation

The batch optimisation algorithm handles requests in batches at a periodic time trigger. New requests are considered together with active requests; requests that have not yet been dropped off. The time interval at which batch optimisation is performed is taken to be one minute. As this was deemed appropriate as this is also the time that a user potentially has to wait for an offer. The batch optimisation algorithm uses an exact method from Engelhardt et al. [57].

Insertion with batch optimisation

The insertion algorithm is also combined with periodic batch optimisation. Requests entering the system are inserted into the current planning using the insertion heuristic algorithm. Then, at certain time intervals, the planning is re-optimised by the batch optimisation algorithm. Note that the insertion algorithm is always performed first when a new request comes in. Therefore, a new request that potentially fits into the planning using batch optimisation might get declined if no feasible insertion is found by the insertion algorithm.

3.6.4. Objective function

The objective function that is minimised by the dispatching algorithm is defined as the weighted sum of the total user time and the total distance driven by the operator. This is deemed appropriate for this thesis, as it considers the users through the user time and the operator and the environment through the driven distance. These are the three stakeholders considered in the evaluation, which will be explained in Section 3.7. The objective function is given in Equation 3.6.

$$\min \quad w_{tut} * \text{TUT} + w_{tdd} * \text{TDD} - w_{T_s} * T_s \tag{3.6}$$

The total user time (TUT) is the sum of the waiting time and the travel time for each of the requests in the schedule and is weighted by w_{tut}. The total distance driven (TDD) by the operator is the sum of the distances driven by all vehicles to complete the schedule and is weighted by w_{tdd}. For this thesis, the weights are chosen to reflect the monetary cost. The weight for the total user time is the value of time and is equal to 0.45 cents per second [73]. The weight for the total distance driven by the operator is the costs per kilometre for a minibus for 8 people and is equal to 0.30 euro per kilometre, as calculated in Appendix B. The last term in the objective function in Equation 3.6 is a large reward (w_{T_s}) that is given for each traveller included in the schedule. The number of travellers served is denoted by T_s. The reward is taken large enough to ensure that only the schedules with the maximum number of travellers are considered. Serving as many users as possible and preferably all users reflects the goal of a public bus operator.

3.6.5. Time windows

The RQT and the EPT for a request have been defined in Subsection 3.6.2. In addition, a request can also have a latest pickup time (LPT) and a latest dropoff time (LDT). The LPT depends on the maximum waiting time (MWT) and is defined by LPT $=$ EPT $+$ MWT. This thesis uses a maximum waiting time of 15 minutes as it is most commonly used in existing DRT systems in the Netherlands [18]. An example to illustrate what happens when the maximum waiting time is increased can be found in Section A.6. The EPT and LPT formulate a time window for the pickup of the request. The LDT depends on the maximum relative detour time factor (MRD) with respect to the direct travel time (DTT) between the origin and destination. The LDT with respect to the planned pickup time (PT) is defined by LDT $=$ PT $+$ DTT $* (1 +$ MRD$)$. This thesis uses a maximum detour time factor of 0.75. The PT and LDT formulate a time window for the dropoff of the request. Figure 3.4 illustrates the time windows. In the case of on-demand and stop-based requests, the lead time equals zero.

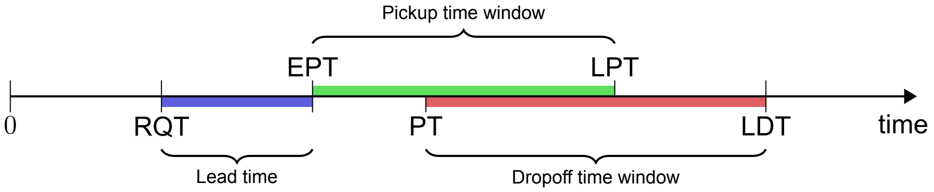


Figure 3.4: Illustration of time windows for requests showing the request time (RQT), the earliest pickup time (EPT), the planned pickup time (PT), the latest pickup time (LPT) and the latest dropoff time (LDT).

3.7. Evaluation

Key performance indicators are chosen to reflect the objectives and interests of the stakeholders in the system: travellers, bus operators, and the community. Firstly, travellers are interested in the quality of service which is characterised by the waiting time and the travel time. Secondly, the bus operator aims to minimise the costs per user. As we are considering a public bus operator, the goal should always be to serve all users. If this is not achieved, then this is a very strong indicator that the DRT service is not sufficient. Lastly, the community is interested in reducing air pollution by reducing CO_2 emissions.

Besides the key performance indicators, additional indicators are considered to further explain the results. For the waiting time, a distinction is made between the offered waiting time and the extra waiting time to show the punctuality of the DRT system. The travel time is compared with the direct travel time, i.e. taking the fastest route from origin to destination. Deviating from the fastest route occurs when another user has to be picked up or dropped off. This results in a detour time. The total cost is also given and a distinction is made between driver costs and gas costs. The effectiveness

Indicator	Description
Served users [%]	The percentage of users that are served with respect to the total amount of users
Avg waiting time [min]	Average time that a traveller waits from the earliest pickup time to pickup
Avg travel time [min]	Average time that a user spends on board of a vehicle
Total unit cost [euro/user]	The total costs for the operator divided by the number of served users
$\mathrm{CO_2}$ emission [kg]	The total $\mathrm{CO_2}$ emissions from all vehicles
Avg user time [min]	Average time that a traveller spends from earliest pickup time to dropoff time. Equal to the sum of the avg waiting time and avg travel time.
Average offered waiting time [min]	The time from the earliest pickup time to the offered pickup time
Average extra waiting time [min]	The time from the offered pickup time to the actual pickup time
Average direct travel time [min]	The average fastest travel time from origin to destination
Average detour time [min]	The difference between the direct travel time and the actual travel time
Total driven distance [km]	The distance driven by all vehicles
Gas costs [€]	The gas costs summed for all vehicles
Driver costs [€]	The driver costs summed for all vehicles
Total costs [€]	The sum of driver and gas costs
Empty vehicle km [%]	The distance driven by all vehicles with zero travellers on board
Fleet utilisation [%]	The percentage of active vehicles averaged over time.
Shared rides [%]	The percentage of travellers that shared a part of their ride with another traveller
Average occupancy	The average number of travellers on board while driving
$\mathrm{CO_2}$ emissions [g / pax km]	The $\mathrm{CO_2}$ emissions divided by the total kilometres driven for all travellers. When two travellers are sharing a ride, then those kilometres count twice.

Table 3.2: The performance indicators. The first five are the key performance indicators. The remaining are additional performance indicators.

of the transportation system can be further derived from the total driven distance, the empty vehicle kilometres, the percentage of shared rides and the $\mathrm{CO_2}$ emissions per passenger kilometre.

An overview of the key performance indicators and additional indicators is given in Table 3.2.

The indicators for the existing bus system are calculated from the timetable; the existing bus is not simulated. This assumes that the existing bus perfectly follows the timetable and thus has no delays. Also, to calculate the distance driven, the fastest route from bus stop to bus stop is used. The indicators for the DRT systems are calculated from the simulation results. The calculations are given in Appendix B.

4

Results

This section presents the results. First, results of the individual trip generation method from Section 3.3 are presented in Section 4.1. Second, the results for Scenario 1 considering the replacement of a single bus line are presented in Section 4.2. Third, the results for Scenario 2 considering the replacing all regional bus lines are presented in Section 4.3. The scale of DRT system is evaluated by making a comparison between the two scenarios in Section 4.4.

4.1. Generated individual trips

This section aims at answering sub-question 1: “How can individual passenger trips be generated from aggregated boarding and alighting data?” This is done by presenting the results of generating individual trips from the boarding and alighting data based on the method explained in Section 3.3. First, the original data is shown. Second, the error between the generated data and the original data is evaluated. Lastly, the resulting generated data is presented.

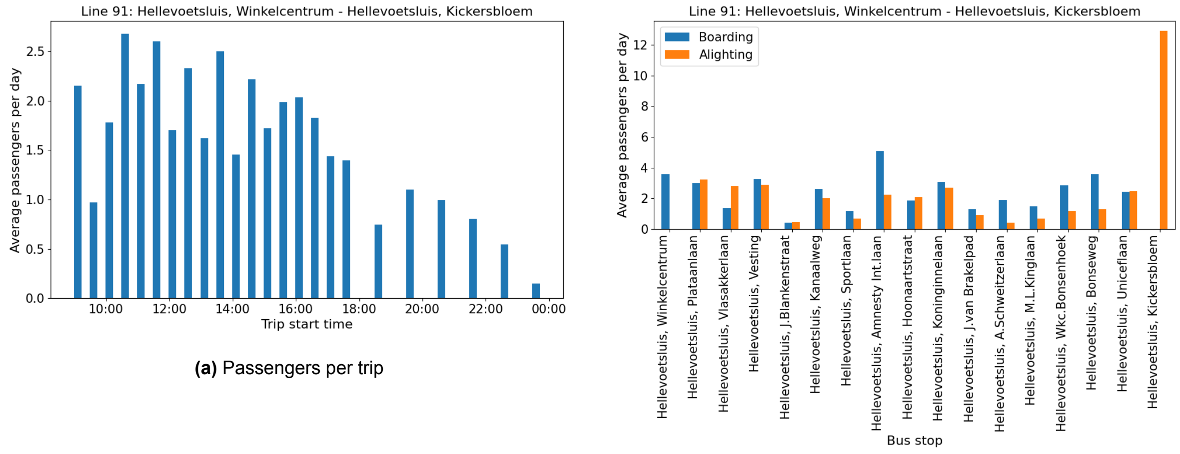
4.1.1. The original aggregated data

Three bus lines are considered. Each of these bus lines has two directions. The individual trips made during weekdays in 2023 are aggregated to boarding and alighting counts for each bus line and each direction separately, totalling six datasets. Figure 4.1 shows one of these datasets after the processing steps from Section 3.2. Figure 4.1a shows the average number of passengers summed for each bus trip. The trips are plotted on the starting time of the bus trip. One can note the extremely low number of passengers per bus trip. Moreover, there are no clear morning or afternoon peaks. Figure 4.1b shows the average number of passengers boarding and alighting summed for each bus stop. The usage of the bus stops is fairly evenly distributed over the bus stops except for the bus stop ’Hellevoetsluis, Kickersbloem’. This bus stop is near a business premises and is also the bus stop where one can transfer to a different bus line.

Similar figures for the other direction of line 91 and for bus lines 105 and 106 can be found in Appendix D.

4.1.2. Sampling error

To evaluate the method of generating individual trips, they are compared to the original data. This was done by aggregating the generated individual trips to boarding and alighting counts and then computing the root mean squared error (RMSE) with the original boarding and alighting counts. A single day of generated individual trips is what will be called a sample. Figure 4.2 shows the RMSE between the original data and the samples for bus line 91 in one directions. The number of samples up to 250 were considered, which is roughly the number of weekdays in a year. Each of the sample sizes is created multiple times to compute the mean RMSE for that sample size. As one day of trips is not representative for a whole year, the error for small sample sizes is expected. It can be seen that the error quickly decreases when the sample size is increased to 10. However, the error does not get close to zero when the sample size is increased to 250.



(a) Passengers per trip

(b) Passengers per stop

Figure 4.1: Data from EBS bus line 91, direction Winkelcentrum to Kickersbloem.

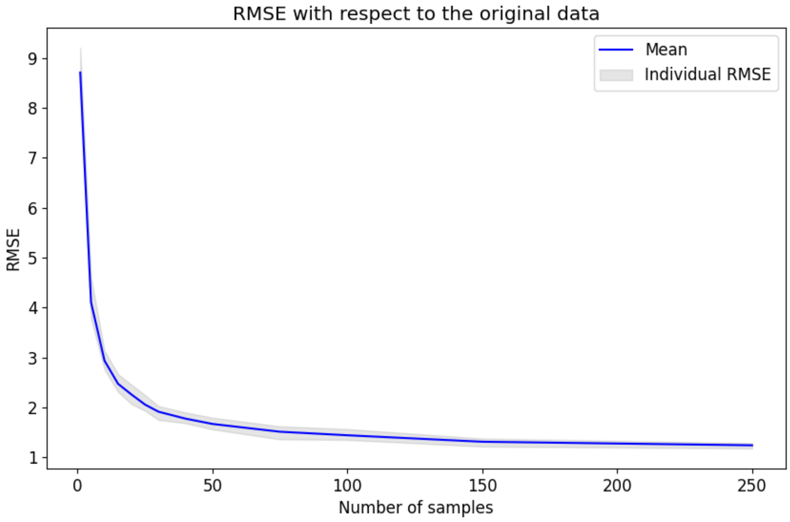


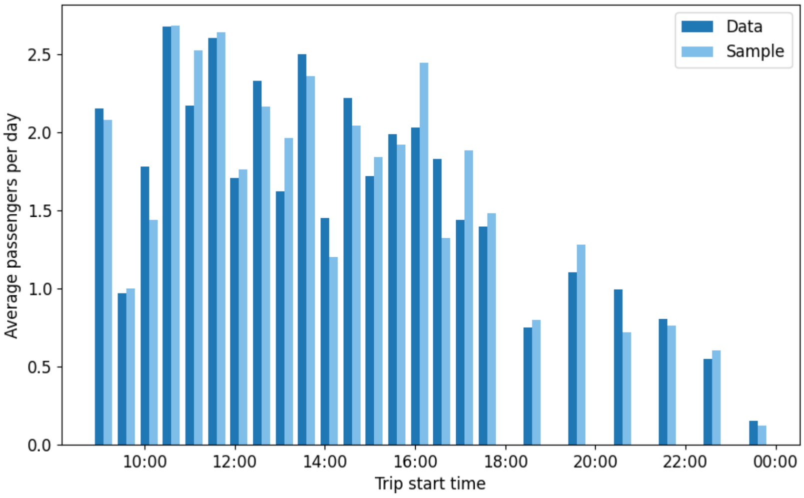
Figure 4.2: RMSE between the data and samples for line 91a.

4.1.3. The generated data

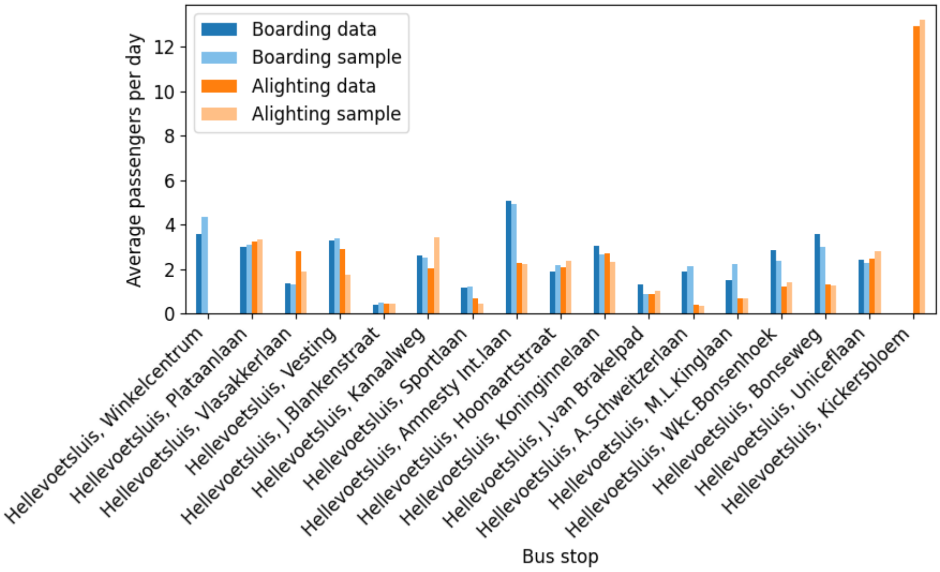
The error shown in the previous section starts to decrease more slowly after 25 samples. Furthermore, the variance in the simulation results due to the sample size was shown to be stable after 10 samples (see Section A.7). Similar results were found for the other bus lines. For this reason and considering the computational expense of running the DRT simulations, a sample size of 25 was chosen. This means that 25 days of individual trips are used to evaluate a DRT system in the scenarios. Figure 4.3 shows the aggregation of the 25 samples from one direction of bus line 91 next to the original data.

4.2. Scenario 1: replacement of a single bus line

This section aims at answering sub-question 2: “How does a DRT system perform compared to the existing bus system considering current travel demand?” and sub-question 3: “What increase in travel demand results in a tipping point where the existing bus system becomes more efficient than the DRT system?” for Scenario 1: replacement of a single bus line. First, the scenario is defined by describing the current bus system and the considered DRT system. Second, the results considering the current travel demand are presented to answer sub-question 2 for this scenario. Third, the travel demand is



(a) Passengers per trip



(b) Passengers per stop

Figure 4.3: 25 samples from EBS bus line 91

increased to find a tipping point to answer sub-question 3 for this scenario.

4.2.1. Scenario definition

Scenario 1 considers the replacement of bus line 91 with a DRT system. Figure 4.4 shows the map of the bus lines in Voorne-Putten Rozenburg and bus line 91 operates in the south-east part. Bus line 91 has a travel demand of 73 passengers per day on average. The bus line makes 48 trips per day, which means that it on average only transports 1.5 travellers when driving from start to end stop. Due to low demand, the bus line operates with minibuses of capacity 8 passengers. The aggregated data of line 91 was used to generate travel data for 25 days, each with 73 individual passenger trips.

The generated individual passenger trips were also formulated as reservation, on-demand and stop-based requests, with each request type evaluated in a separate simulation. The DRT system consisted of two vehicles, which was selected because it was the minimum number of vehicles necessary to service all requests (see Table A.1). The DRT vehicles also had a capacity of 8, as this is standard in DRT systems and it was shown that a larger capacity did not improve the DRT systems (see Figure A.5). In the simulations of the reservation requests, the insertion heuristic with periodic batch optimisation was used as the dispatching algorithm. The simulations of on-demand and on-demand-stop requests used the insertion heuristic algorithm as no sufficient improvement was gained from the use of batch optimisation (see Section A.3).

4.2.2. Simulation results

The key performance indicators are shown in Figure 4.5 and the full results are given in Table 4.1. Figure 4.5a shows that the average waiting times in the DRT system, for all three request types, were much lower than for the existing bus. Surprisingly, the waiting time for stop-based requests was lower than for on-demand requests. However, stop-based requests have a longer travel time, resulting in a longer total user time (see Table 4.1). Furthermore, the extra waiting time was negligible in the DRT systems, indicating its punctuality. Figure 4.5b shows a large reduction in travel time compared to the existing bus. In addition, it can be seen that the detour time was quite low. This is related to the low number of shared rides of 10-20% (see Table 4.1). In the reservation and on-demand simulations, around 90% of travellers were directly driven from their origin to their destination. Figure 4.5c shows that the costs were similar. It can be seen that driver costs made up the largest part of the costs and were equal due to operating the same number of vehicles throughout the day. The higher gas costs for the existing bus system were caused by the existing bus driving more than twice the kilometres (see Table 4.1). The ineffectiveness of the existing bus can also be seen in the fact that about 73% of the distance was driven with no travellers on board. Figure 4.5d shows that CO_2 emissions were much lower for the DRT systems, which is also the result of the driven distance (see Table 4.1).

Although the variation in the number of travellers was unknown, the results for slight increases and decreases in the number of travellers were also explored and can be found in Section A.2.

4.2.3. Tipping point

The previous sections showed that the DRT system performs better in terms of all KPIs when considering the average number of travellers that currently use the existing bus. However, fixed-line buses were found to be more efficient when demand is higher, as stated in Section 2.6. To identify the tipping point where the fixed-line becomes preferred for Scenario 1, we simulate up to ten times the average number of travellers. At higher demands, DRT's constraints on waiting and travel times can cause declined requests, preventing a fair comparison with buses as they would then not be serving the same number of travellers. Therefore, the maximum waiting time is increased to ensure that the DRT system serves all requests. The DRT system with reservation request is not included due to computational time.

Figure 4.6a shows the result in terms of average user time. It can be seen that the tipping point for stop-based requests is around 500 daily travellers, a little over seven times the current demand. For the on-demand requests, the tipping point is at around 700 travellers, over nine times the current demand. Figure 4.6b shows the result in terms of the total unit cost. A tipping point for on-demand and stop-based requests is seen around 150 travellers or two times the current demand. However, the costs are very similar for all demand levels.

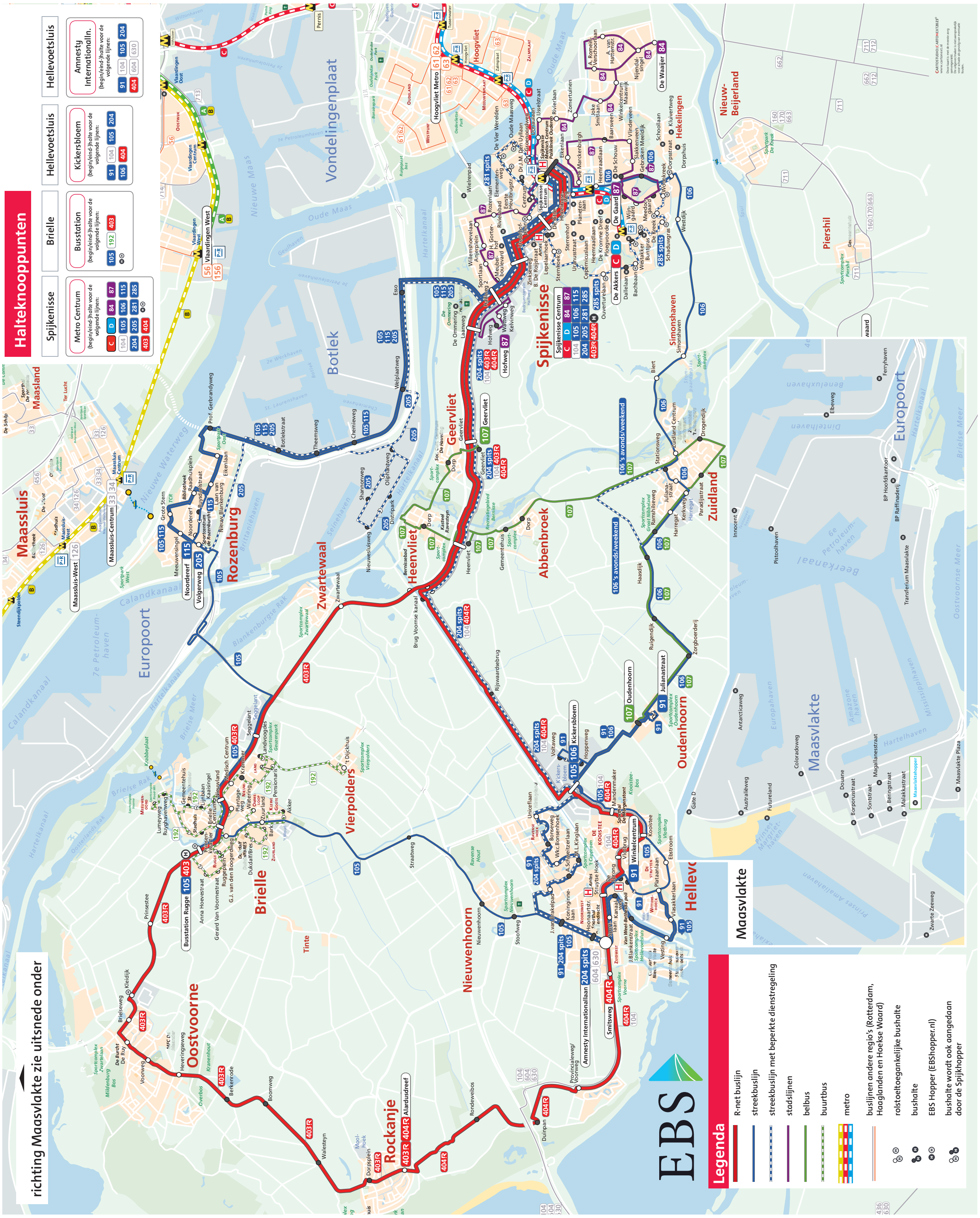
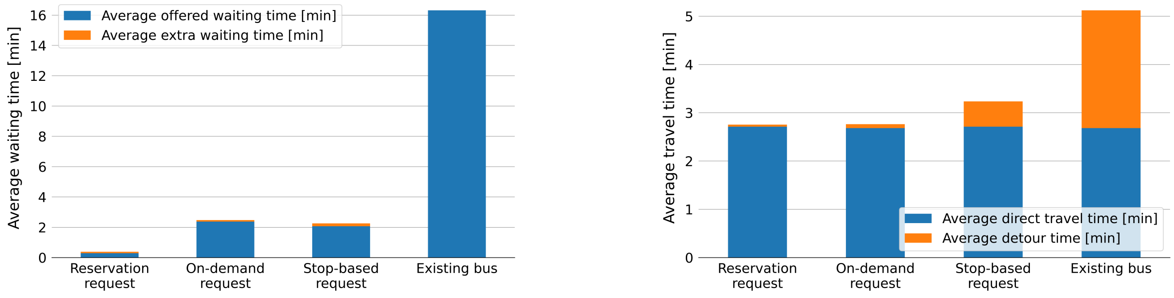
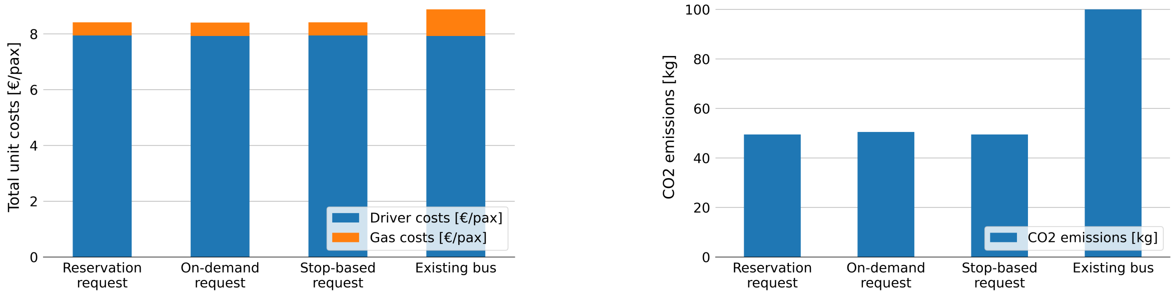


Figure 4.4: EBS operating area Voorne-Putten Rozenburg [74]. Bus lines 91, 105 and 106, shown in blue, are considered in this thesis.



(a) Average waiting time

(b) Average travel time



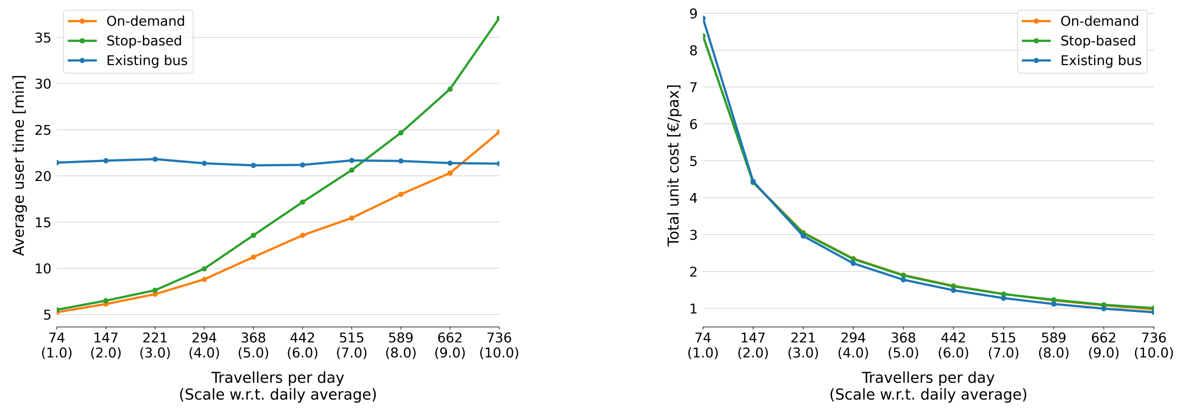
(c) Total unit cost

(d) CO_2 emissions

Figure 4.5: Key performance indicators comparing the DRT system with reservation, on-demand, and stop-based requests with the existing bus in scenario 1: replacing a single bus line. The results are based on 25 simulations.

	Mean (± std)							
	Reservation		On-demand		Stop-based		Existing bus	
Served users [%]	100.0	(±0.0)	100.0	(±0.0)	100.0	(±0.0)	100.0	(±0.0)
Average waiting time [min]	0.4	(±0.2)	2.5	(±0.2)	2.3	(±0.1)	16.3	(±0.5)
Average travel time [min]	2.8	(±0.2)	2.8	(±0.1)	3.2	(±0.3)	5.1	(±0.5)
Total unit cost [€/pax]	8.4	(±0.1)	8.4	(±0.1)	8.4	(±0.1)	8.9	(±0.1)
CO2 emissions [kg]	49.5	(±3.3)	50.5	(±2.7)	49.5	(±2.6)	100.0	(±0.0)
Average user time [min]	3.1	(±0.2)	5.2	(±0.3)	5.5	(±0.3)	21.4	(±0.6)
Average offered waiting time [min]	0.3	(±0.1)	2.4	(±0.2)	2.1	(±0.1)	16.3	(±0.5)
Average extra waiting time [min]	0.1	(±0.1)	0.1	(±0.1)	0.2	(±0.1)	0.0	(±0.0)
Average direct travel time [min]	2.7	(±0.1)	2.7	(±0.1)	2.7	(±0.1)	2.7	(±0.1)
Average detour time [min]	0.0	(±0.0)	0.1	(±0.1)	0.5	(±0.1)	2.4	(±0.4)
Gas costs [€]	34.6	(±2.3)	35.3	(±1.9)	34.6	(±1.8)	70.0	(±0.0)
Driver costs [€]	582.2	(±0.0)	582.2	(±0.0)	582.2	(±0.0)	582.4	(±0.0)
Total costs [€]	616.8	(±2.3)	617.5	(±1.9)	616.8	(±1.8)	652.4	(±0.0)
Total driven distance [km]	235.6	(±15.7)	240.4	(±12.9)	235.6	(±12.5)	476.3	(±0.0)
Empty vehicle km [%]	46.9	(±2.8)	48.0	(±2.2)	44.2	(±3.1)	72.9	(±2.5)
Fleet utilization [%]	72.0	(±3.1)	21.9	(±0.9)	21.5	(±0.8)		-
Shared rides [%]	10.0	(±4.6)	11.6	(±6.1)	20.4	(±8.1)	53.0	(±6.5)
Average occupancy	0.6	(±0.0)	0.5	(±0.0)	0.6	(±0.1)	0.4	(±0.0)
CO2 emissions [g / pax km]	0.4	(±0.0)	0.4	(±0.0)	0.3	(±0.0)	0.6	(±0.1)

Table 4.1: Full results for Scenario 1: replacement of a single bus line. The simulations included the daily average of 73 daily passengers. The results are from 25 simulations.



(a) Average user time **(b)** Total unit cost

Figure 4.6: Results of simulation with higher demand level to find a tipping point where the existing bus becomes the preferred option in scenario 2: replacing all regional lines. The results are based on 25 simulations.

4.3. Scenario 2: replacement of all regional bus lines

This section aims at answering sub-question 2: “How does a DRT system perform compared to the existing bus system considering current travel demand?” and sub-question 3: “What increase in travel demand results in a tipping point where the existing bus system becomes more efficient than the DRT system?” for Scenario 2: replacement of all regional bus lines. First, the scenario is defined by describing the current bus system and the considered DRT system. Second, the results considering the current travel demand are presented to answer sub-question 2 for this scenario. Third, the travel demand is increased to find a tipping point to answer sub-question 3 for this scenario.

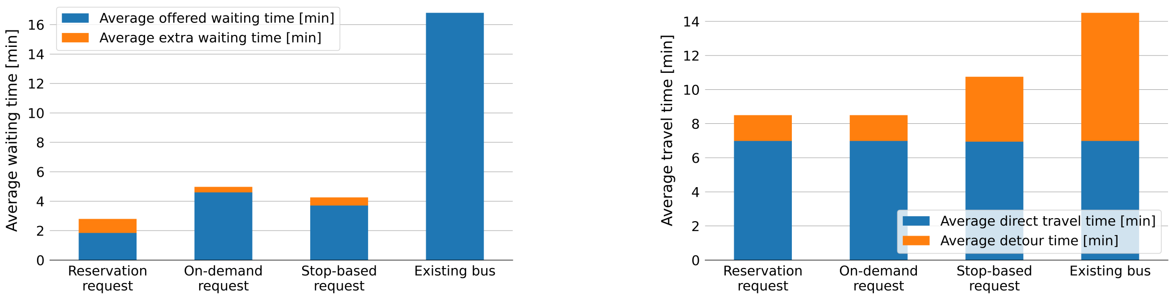
4.3.1. Scenario definition

Scenario 2 considers the replacement of all regional bus lines in Voorne-Putten Rozenburg with a DRT system. In Figure 4.4, the regional bus lines are shown in blue. This includes bus line 91 from Scenario 1 and the bus lines 105 and 106. The three bus lines together transport 359 travellers per day on average, while making 142 trips. Thus, 2.5 travellers are transported on average per bus trip. The buses on line 105 and 106 operate with regular city buses with a capacity of around 30 to 40 passengers. The data of the three bus lines was used to generate travel data for 25 days, each with 359 individual passenger trips.

As in Scenario 1, the generated individual passenger trips were formulated as reservation, on-demand and stop-based requests and the DRT system was evaluated through simulation. The DRT system consisted of seven vehicles because it was the minimum at which all travellers were served (see Table A.2). In the simulation of all three request types, the insertion heuristic algorithm was used as the dispatching algorithm. Batch optimisation was no longer included for reservation requests due to computational time.

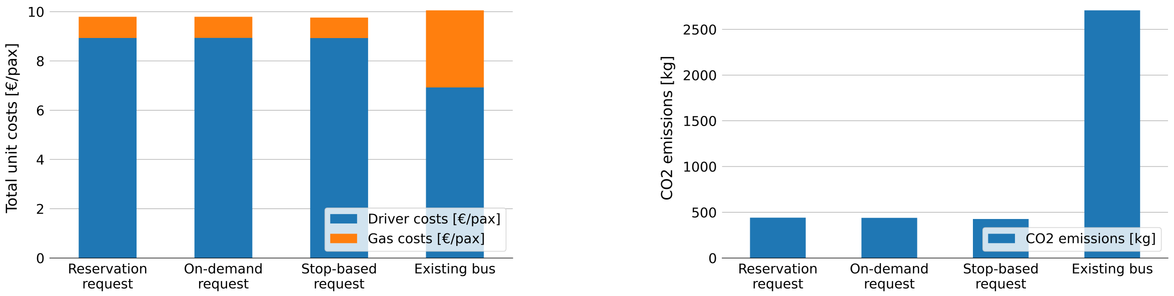
4.3.2. Simulation results

The key performance indicators are shown in Figure 4.7 and the full results are given in Table 4.2. The results look similar to the results of Scenario 1 (see Figure 4.5); the DRT systems performed better than the existing bus for all indicators. However, there are some points worth noting. From Figure 4.7a, it can be seen that the average extra waiting time for reservation requests was higher than the other request types. This is because the insertion heuristic was used instead of the optimisation. The problem is that requests are added to the schedule far before they need to be picked up. In the meantime, new requests are added to the schedule, which can affect the planned pickup of the first request, resulting in extra waiting time. This shows that the insertion heuristic is not suitable in the case of reservations. However, the extra waiting time was still not more than one minute. Figure 4.7b shows relatively longer detour times, as in this scenario more than 60% of the rides were shared (see Table 4.2). In Figure 4.7c, it can be noted that the driver costs for the DRT system were higher than the existing bus. This is because



(a) Average waiting time

(b) Average travel time



(c) Total unit cost

(d) CO_2 emissions

Figure 4.7: Key performance indicators comparing the DRT system with reservation, on-demand, and stop-based requests with the existing bus in scenario 2: replacing all regional lines. The results are based on 25 simulations.

a relatively large number of vehicles was necessary to serve all travellers during busy hours. A large part of the vehicles were idle during less busy times, as can be seen from the fact that the utilisation of the fleet was not more than 25% (Table 4.2). Figure 4.7c shows that the gas costs were significantly higher for the existing bus because the existing bus system operates with larger buses that use more gas. This can also be seen in Figure 4.7d, which shows a large difference in CO_2 emissions.

The results of simulations with different numbers of travellers can be found in Section A.2.

4.3.3. Tipping point

The previous sections showed that, also for Scenario 2, the DRT system performed better in terms of all KPIs when considering the average number of travellers that currently use the existing bus. To find the tipping point in Scenario 2, the demand was increased up to 5 times the current demand. The reservation requests were again excluded due to computational time.

Figure 4.8a shows the result in terms of average user time. It can be seen that the tipping point for stop-based requests was relatively close at twice the current number of travellers. For the on-demand requests, the tipping point was around three times the current demand. When considering the total unit cost, Figure 4.8b shows that the tipping point again shows that the total unit costs are similar, but a tipping point can be seen at twice the current demand.

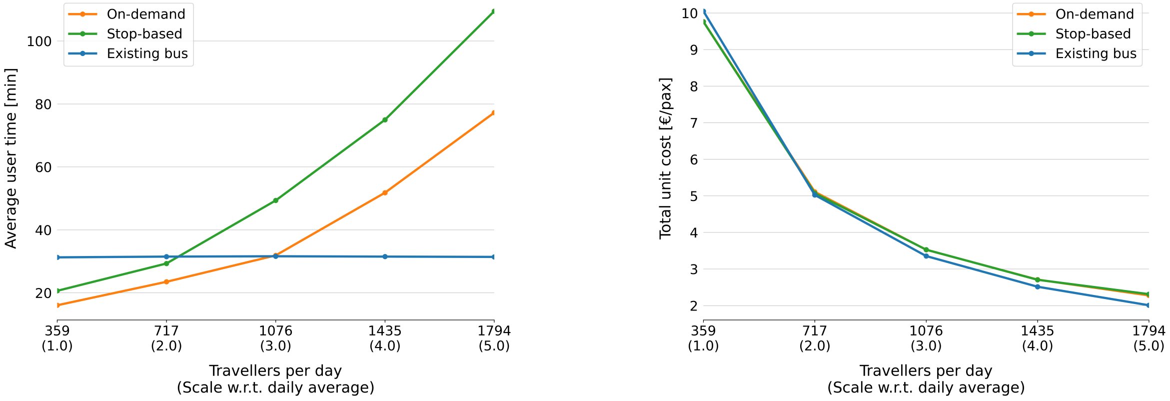
4.4. Comparing Scenario 1 and Scenario 2

This section aims at answering sub-question 4: ”Does increasing the scale of the DRT system increase its efficiency?”. In this section, a comparison is made between the results of the smaller Scenario 1 and the larger Scenario 2. The scale of the DRT system is larger in Scenario 2 as there are more travellers and more DRT vehicles, but the vehicles also have a larger area to cover, as can be seen in Table 4.3.

Referring back to Table 4.1 and Table 4.2, it can be seen that Scenario 2 had more shared rides: 60 to 75% compared to 10 to 20% in Scenario 1. Furthermore, the occupancy is also larger on average, meaning that vehicles transported more travellers per distance travelled. The fleet utilisation was low in both scenarios: around 22% in Scenario 1 and around 24% in Scenario 2.

	Mean (± std)			
	Reservation	On-demand	Stop-based	Existing bus
Served users [%]	100.0 (±0.0)	100.0 (±0.0)	100.0 (±0.0)	100.0 (±0.0)
Average waiting time [min]	2.8 (±0.2)	5.0 (±0.3)	4.3 (±0.3)	16.8 (±0.3)
Average travel time [min]	8.5 (±0.3)	8.5 (±0.3)	10.8 (±0.5)	14.5 (±0.5)
Total unit cost [€/pax]	9.8 (±0.1)	9.8 (±0.1)	9.8 (±0.1)	10.1 (±0.0)
CO2 emissions [kg]	440.5 (±16.6)	439.3 (±17.2)	426.0 (±16.6)	2707.6 (±0.0)
Average user time [min]	11.3 (±0.4)	13.5 (±0.5)	15.0 (±0.7)	31.3 (±0.5)
Average offered waiting time [min]	1.8 (±0.2)	4.6 (±0.3)	3.7 (±0.2)	16.8 (±0.3)
Average extra waiting time [min]	1.0 (±0.1)	0.4 (±0.1)	0.6 (±0.1)	0.0 (±0.0)
Average direct travel time [min]	7.0 (±0.2)	7.0 (±0.2)	6.9 (±0.2)	7.0 (±0.2)
Average detour time [min]	1.5 (±0.1)	1.5 (±0.1)	3.8 (±0.4)	7.5 (±0.3)
Gas costs [€]	308.3 (±11.6)	307.5 (±12.0)	298.2 (±11.6)	1122.1 (±0.0)
Driver costs [€]	3203.2 (±0.0)	3203.2 (±0.0)	3203.2 (±0.0)	2482.4 (±0.0)
Total costs [€]	3511.5 (±11.6)	3510.7 (±12.0)	3501.4 (±11.6)	3604.5 (±0.0)
Total driven distance [km]	2097.5 (±79.1)	2091.9 (±81.9)	2028.4 (±79.0)	2461.4 (±0.0)
Empty vehicle km [%]	28.4 (±1.8)	26.0 (±1.8)	17.1 (±2.1)	67.9 (±1.7)
Fleet utilization [%]	44.8 (±1.8)	24.7 (±0.8)	24.2 (±0.8)	-
Shared rides [%]	60.1 (±2.6)	61.5 (±3.5)	74.8 (±4.9)	80.6 (±2.2)
Average occupancy	1.4 (±0.1)	1.4 (±0.1)	1.7 (±0.1)	1.1 (±0.0)
CO2 emissions [g / pax km]	0.1 (±0.0)	0.1 (±0.0)	0.1 (±0.0)	0.2 (±0.0)

Table 4.2: Full results for Scenario 2: replacement of all regional transport. The simulations included the daily average of 359 daily passengers. The results are from 25 simulations.



(a) Average user time

(b) Total unit cost

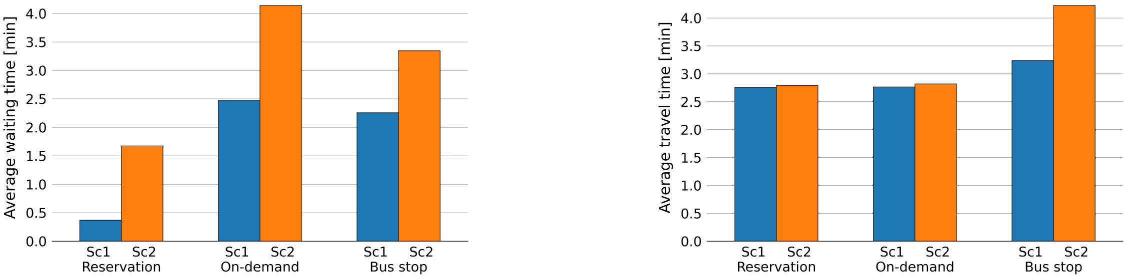
Figure 4.8: Results of simulation with higher demand level to find a tipping point where the existing bus becomes the preferred option in scenario 2: replacing all regional lines. The results are based on 25 simulations.

Parameter	Scenario 1	Scenario 2
Average number of passengers per day	73	359
Average number of passenger per hour	4.1	16.3
Area size [km^2]	25	180
Average demand density [pax/h km^2]	0.16	0.09
Number of bus stops	16	57
Stop density [stops/km^2]	0.64	0.32
Average distance between adjacent stops [km]	0.62	1.14

Table 4.3: Characteristics of the two considered scenarios.

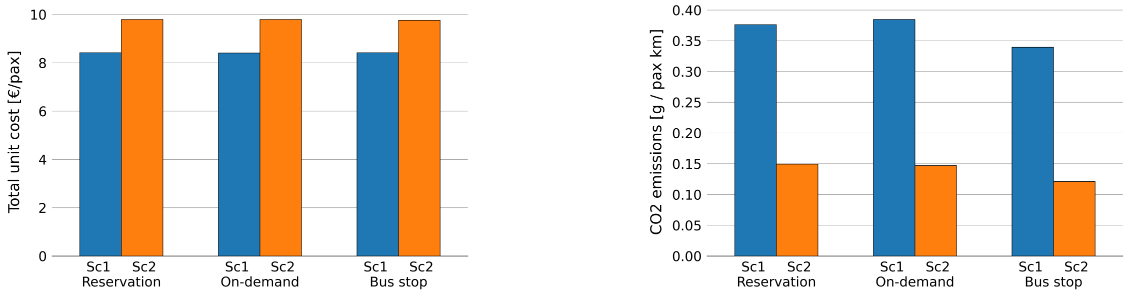
The results of the two scenarios were also compared in terms of the key performance indicators considered in this thesis. To compare the waiting time and the travel time, only requests originating from bus line 91 were considered in Scenario 2 because these requests occur in both scenarios. This means that we compare whether these requests are better served using fewer vehicles dedicated to them or using more vehicles but that also serve other requests. Figure 4.9a shows that the average waiting times increased in Scenario 2. This can be explained by the fact that the vehicles cover a larger area (see Table 4.3) and the nearest vehicle is potentially further away. In fact, it can even be seen that the demand density is lower in Scenario 2. Figure 4.9b shows that the travel times are approximately equal, except for the stop-based requests, which had a notable increase in travel time.

From an operator point of view, the comparison was made for all the demand and the total unit cost was used to compare whether a larger scale lowers the costs per traveller. Figure 4.9c shows that this was not the case in these scenarios. From an environmental perspective, the comparison was also made for all demand, but the $\mathrm{CO_2}$ emissions per user kilometre were considered instead of the total $\mathrm{CO_2}$ emissions. This is because there are a different number of travellers in the scenarios. Figure 4.9d shows that the larger scenario was more efficient in terms of $\mathrm{CO_2}$ emissions, which can be explained by the higher occupancy and the larger number of shared rides, as stated earlier.



(a) Average waiting time

(b) Average travel time



(c) Total unit cost

(d) $\mathrm{CO_2}$ emissions per user kilometer

Figure 4.9: Comparison of the DRT between scenario 1 and 2.

5

Discussion

5.1. Summary

The aim of this thesis was to evaluate whether serving the travel demand in Voorne-Putten Rozenburg with a DRT system is an improvement to the existing fixed-line bus system. Two scenarios were formulated: 1) the replacement of a single bus line that had extremely low demand and 2) the replacement of all low-demand bus lines in the area, resulting in a total of three bus lines. Furthermore, the focus was on three methods of requesting the DRT service: i) reservations made in advance, ii) requesting the service on-demand, and iii) a stop-based request where a physical request method is present at the bus stop showing only the pickup location to the operator. The request methods, in the given order, were presumed to be increasingly easy to use for users but provided a decreasing amount of information to the operator. To evaluate the scenarios, individual trips from the existing bus system were generated from aggregated data and defined as requests for the DRT service. The performance of the DRT system in serving these requests was assessed using an agent-based simulation. The performance of the existing bus was assessed by looking up the trips in the bus timetable. The results considering the current travel demand showed that the DRT system is mainly an improvement for the user in terms of waiting time and travel time, and for the environment in terms of $\mathrm{CO_2}$ emissions. For the operator, the costs of operating a DRT system that serves all users are comparable to the costs of the existing bus system. Increasing travel demand to more than twice the current demand led to a tipping point after which the fixed-line bus is preferred. Considering the different methods to request the DRT service, it was shown that the methods that were easier for the user only showed a small reduction in the evaluation metrics due to the decrease in information to the operator. The first results for the proposed stop-based request method showed that it is a feasible alternative. The expected increase in efficiency of the larger scenario was not confirmed.

5.2. Implications and relation to literature

The results of the DRT system proposed in this thesis can be compared to the challenges and success factors of existing DRT systems stated in Subsection 2.1.2. In addition, the results can also be compared to the results of other simulation studies that were stated in Section 2.6. Lastly, some practical implications are stated with respect to other DRT systems in the Netherlands.

First, considering the challenges and success factors of DRT systems, one of the main challenges for existing DRT systems is the cost. High costs were often the reason for the failure of DRT systems. The scenarios considered in this thesis showed that the costs of the DRT system are comparable with the existing fixed-line bus system. However, only driver and gas costs were considered. Additional costs for the operator of a DRT system, such as the necessary software solutions, could make DRT a more expensive alternative. This is in line with the high costs of existing DRT systems. In contrast, one of the success factors of existing DRT systems; implementation on a large enough scale, is not evident from the simulation results in this thesis. Although a large reduction in $\mathrm{CO_2}$ emissions per passenger was observed, waiting times and costs were higher in the larger scenario. The idea of operating on a larger scale is that more demand could lead to more shared rides and provide the revenue to use more vehicles, which was expected to result in a more efficient operation than with one or two vehicles. The problem in the larger scenario in this thesis might be that the area of operation also increased significantly. In fact, the demand density was shown to be lower in the larger scenario. This could be the reason why the larger scenario was not more efficient.

Second, looking at the results of other DRT simulation studies, the main improvement when using a DRT system was lower waiting and travel times. The results in this thesis are in line with these results, as waiting and travel times showed quite a large decrease in all scenarios with respect to the existing bus system. Furthermore, considering the dispatching algorithm, several simulation studies noted that insertion heuristic algorithms obtain near-optimal performance with respect to exact methods while being computationally much less expensive. The results showed a similar conclusion, since the exact method used in this thesis also showed little improvement in terms of served users and user time. Furthermore, the exact method often took excessive time, sometimes several hours. In an on-demand setting, this is not feasible, as the user is waiting during this time.

Lastly, in the Netherlands, most DRT systems require reservations in advance to reduce waiting times and improve planning. However, a simple design was also noted as one of the success factors for DRT systems. This thesis focused on request methods for accessing DRT services, which is an aspect of the design. The findings indicate that reservations only decrease waiting time by approximately two minutes compared to on-demand requests, with negligible benefits in terms of cost and $\mathrm{CO_2}$The simple physical stop-based requests slightly reduced performance compared to on-demand, but they were still an improvement over the existing bus system. These results could be an indication for bus operators to experiment with simpler request methods. Especially in a small scenario like Scenario 1, where waiting times are low, a stop-based request method could be implemented as an effort to lower the obstacle of using DRT and potentially increasing adoption.

5.3. Limitations

Some limitations of this research have been identified. They concern the generation of travel demand and simplifications in the simulation.

5.3.1. Generated travel demand

There are some limitations to the generation of individual trips from the aggregated boarding and alighting data. The method used resulted in individual trips that, when aggregated, resembled the original aggregated data. However, this does not mean that the generated individual trips are similar to the original individual trips. It is not known what the difference is, as the original individual trips are unavailable. The RMSE was also shown to not converge to zero for the sample sizes considered, indicating that the method is not able to recover the exact individual trips.

Furthermore, the average number of passengers per day is considered in the simulations, as the variance of the number of passengers per day was not given. However, it can be expected that the number of passengers differs from day to day and there might be typical busy, or typical slow days, for which different DRT fleet sizes might be more appropriate. More detailed demand data would enable the formulation and simulation of more specific scenarios and should eliminate such uncertainties.

In addition, the generation of individual trips considers each bus line separately and does not take into account transfers. This means that if a person transferred from one bus line to another to make a longer trip, then this is considered as two separate trips. This results in two requests for the DRT service, while this should result in one request. Therefore, the method might generate slightly more and shorter trips.

Lastly, only requests for a single person are simulated. In reality, a request can also be made for a group of multiple travellers, for example, a group of friends or a family. Taking groups into account in the generation of travel demand could be done using a gravitational distribution [64] or a geometric distribution [65]. The performance of the DRT system is expected to improve if group requests were included, because the same number of users would be considered but a few of those users are already bundled. The only problem that could occur is when the capacity of the vehicles is reached, but in the cases studied in this thesis this was seldom reached.

5.3.2. Simplifications in the simulation

The simulation also contains some simplifications that should be noted. The maximum driving speed is used to calculate the driving time. Furthermore, potential delays due, for example, to traffic lights or traffic jams are not considered. Driving speed is therefore overestimated, resulting in an underestimation of travel and waiting times. On the other hand, the existing bus was evaluated based on its timetable, thus also not considering delays.

The costs only consider the salary of the driver and the variable costs per kilometre. There might be additional costs that could increase either or both systems. Specifically, a DRT system potentially requires additional software and hardware that allow users to request the service and drivers to see the routing. Furthermore, the driver costs of the current bus were based on the times that there were active buses in the timetable, but it was unknown how many hours the drivers are getting paid. Drivers are likely compensated for additional hours beyond the timetable, as their work likely extends beyond just the scheduled times. Thus, both the costs of the DRT system and the current bus system could be higher than what was considered in this thesis.

The reservation requests posed computational problems for the exact method in the larger scenario. Because requests are known ahead of time, the dispatching algorithm has a larger set of requests to create a schedule for. Due to computational limitations, the insertion algorithm was used. However, an insertion algorithm is more suitable for on-demand requests and not so much for reservation requests. Note that the smaller scenario used the exact method for reservations.

In a realistic setting, the different request methods are available simultaneously. However, this raises the question of what the ratio between the different request types would be. As no answer was available and because the aim was to show their difference, such scenarios were left out.

5.4. Recommendations

This section provides recommendations for future research and for practical implementations.

5.4.1. Recommendations for future research

The recommendations for future research are divided into recommendations to address the previously stated limitations and ideas for possible extensions.

Addressing limitations

Several limitations on the generated travel demand were noted. Although they are mainly due to the little information contained in the aggregated data, there are possible improvements in the derivation of the OD matrix. Household survey data, for example data from the Netherlands Mobility Panel data [75], could be used to obtain a more accurate OD matrix [53]. Furthermore, inspiration could be taken from similar but more advanced statistical methods [55, 54, 51].

The limitations of the simulation that were noted in the previous section are in part the result of the chosen simulation framework FleetPy. A more complex traffic simulation framework such as MATSim [39] or SUMO [43] could be used to obtain more accurate results in travel time and therefore waiting time. Furthermore, a thorough analysis of the costs of DRT and conventional bus systems can be used to obtain a more accurate comparison [76]. The problem of the dispatching algorithms for reservation could be addressed by using more computational resources or by implementing a dispatching algorithm that is faster than exact methods but better than the insertion algorithm. Ho et al. [58] provides an extensive overview of the solution methods for the DARP, of which hybrid algorithms might be suitable for this case.

Possible extensions

In addition to the recommendations to address the limitations, some recommendations are given to extend the research.

The insertion algorithm used for the stop-based request is simple, but could easily be extended. For example, the destination of new requests could be predicted, which could improve the insertion. The probabilities are readily available from the OD matrix that was derived from the aggregated data. Moreover, existing bus stops have two sides for the different directions, which can be used to gain information about the direction of the request.

This thesis only considered the trip from bus stop to bus stop. An exact starting and end location for requests could be approximated using, for example, population density data which is available in the Netherlands [77]. In that case, the walking time can be included. Furthermore, this allows for the evaluation of the locations of the bus stops, and they can be optimised [78]. These stops do not necessarily need a physical stop, but can be what is called ”virtual stops”, a concept already known in DRT implementations. Moreover, serving users door-to-door could be evaluated. While stop-to-stop is more efficient with high demand, door-to-door could be feasible in the case of low demand [69]. The functionality to simulate this can be a good extension to the simulation framework FleetPy that was used in this thesis.

Additional extensions can also be considered if found applicable. For example, the connection with other public transport was not considered in this thesis. Alonso-González et al. [79] found that large accessibility improvements were gained from an existing DRT system in the Netherlands that was used as a complement to other public transport services. Furthermore, other extensions include repositioning strategies, the use of electric vehicles with appropriate charging strategies, automated vehicles, pricing strategies, or parcel delivery.

5.4.2. Recommendations for practical implementation

This thesis does not consider how many people will actually use DRT. The number of people who use the DRT system is even likely to deviate from the number of people who currently use the existing bus. To gain insight into the number of users for the DRT system, a survey study could be carried out among existing bus users. Furthermore, other citizens who currently use the car can be surveyed to determine if they would use public transport if a DRT system is available with lower travel times. The survey study results in an estimate of the number of users for the DRT system and an idea of the DRT system performance can then be obtained from the results in this thesis.

In a real setting, reservation, on-demand, and physical stop-based requests are likely to be combined. This thesis does not consider what request method is preferred and what the ratio between the different methods will be. Using the same survey as mentioned above to ask what the preferred request method is, an indication of the ratio can be obtained. The ratios can then be simulated using the approach in this thesis to get a more realistic idea of the DRT system performance when allowing multiple request types.

In this thesis, the number of vehicles is assumed to be constant throughout the day. However, the number of requests fluctuates hourly. This results in some vehicles being only needed during peak hours and leaving them idle during off-peak times. Despite being idle, drivers are still compensated, leading to high costs. A potential solution is to use idle vehicles for services such as paratransit or general taxi operations. Alternatively, a smaller fleet size could be maintained with the flexibility to hire additional taxis when needed during peak hours. Such solutions could lead to a large reduction in the costs of the DRT system.

6

Conclusion

To conclude this thesis, the research questions are answered.

1. "How can single traveller's origin and destination be generated from aggregated boarding and alighting data?"

A recursive method was formulated that derives the travel rates between all origins and destination based on the aggregated data. The resulting OD matrix was used to sample individual passenger trips. It was shown that when enough individual passenger trips were generated, the aggregation of the generated trips started to align with the original aggregated data, but there is room for improvement.

2. "How does a DRT system perform compared to the existing bus system considering current travel demand?"

The generated individual trips were evaluated on the existing fixed-line bus and on the DRT system. The existing fixed-line bus was evaluated through its timetable and the DRT system was evaluated using an agent-based simulation that considered the trips as requests to a DRT system. This was done for a Scenario 1 that considered replacing a single bus line and for a Scenario 2 that considering replacing three regional bus lines. The travel demand in both scenarios was relatively low, and therefore the expectation was that the DRT system would be an improvement. This expectation was confirmed in both scenarios, as the KPIs considering the travellers and the environment showed a large improvement in the case of the DRT system. Considering the operator, a slight improvement in costs was observed in both scenarios. This shows that for roughly the same costs, the travellers are served more efficiently when allowing the buses to be flexible in transporting the travellers than when letting the buses adhere to a fixed-line timetable. Distinguishing between the two scenarios, the improvements were relatively higher in Scenario 1. When comparing the different request types, it was shown that reservation, on-demand and stop-based requests, in that order, showed increasing user times (the sum of waiting and travel time). As was expected due to the decreasing amount of information that the operator could use for planning. However, the difference was quite small when considering the improvement compared to the existing fixed-line bus. This shows that the proposed stop-based request is a feasible alternative to on-demand and reservation requests when considering the implementation of a DRT system. It can be concluded that a DRT system can be an improvement to the existing bus by increasing accessibility and reducing $\mathrm{CO_2}$ emissions.

3. "What increase in travel demand results in a tipping point where the existing bus system becomes more efficient than the DRT system?"

The previous question concluded that the DRT system is an improvement compared to the existing bus system for the current number of travellers. When demand is higher, the fixed-line bus system was expected to become more efficient. To evaluate at what point this is the case for the scenarios in this thesis, additional simulations were run where the number of travellers per day was increased and evaluated in terms of the user times and the total unit costs. In both Scenario 1 and Scenario 2, there was no convincing tipping point in terms of total unit costs, as they were roughly equal across the various numbers of travellers. In terms of user times, it was shown that the tipping point for Scenario 1 may be higher than what can realistically be experienced: the tipping point occurred after more than seven times the current number of travellers. This strongly indicates that a DRT is preferred over the existing bus and that there is minimal concern that the tipping point will be reached in practice. For Scenario 2, the tipping point was observed at two to three times the current demand.

4. “Does increasing the scale of the DRT system increase its efficiency?”

The DRT systems in Scenario 1 and Scenario 2 were compared to evaluate efficiency. The DRT system was expected to be more efficient in Scenario 2, the larger scenario, because more travellers would lead to more shared rides, which means that vehicles are used more efficiently. In line with expectations, the percentage of shared rides was higher in Scenario 2 and, consequently, the emissions of $\mathrm{CO_2}$per traveller kilometre decreased. However, the waiting time and the total unit costs were higher in Scenario 2. Thus, the results of the two scenarios studied in this thesis do not fully support the notion that DRT is more efficient on a larger scale.

The main research question of this thesis was:

> *“What is the feasibility of replacing the low-demand bus lines in Voorne-Putten Rozenburg with a demand responsive transport system?”*

Combining the answers of the sub-questions and taking into account the discussion, a main conclusion can be drawn. Using a DRT system to serve the current travel demand of the existing fixed-line bus in Voorne-Putten Rozenburg is an improvement in terms of the key performance indicators for both the scenario of replacing one bus line and the scenario of replacing all three low-demand bus lines in Voorne-Putten Rozenburg. For both scenarios, the costs of operating a DRT system are only slightly lower than the existing bus system. Although this is only a small improvement from an operator perspective, it was shown that the DRT systems were a great improvement for users and the environment. The combined waiting and travel time was more than twice as low in the DRT system. This means that a great improvement can be expected in terms of accessibility which addresses the problem of decreased accessibility of public transport in the Netherlands. Furthermore, the results show a large reduction in $\mathrm{CO_2}$ emissions. The benefits decrease if demand gets higher and fixed-line buses become favourable if the travel demand more than doubles. However, a decrease in demand might be more realistic as this was experienced in real-world DRT implementations that replaced a fixed-line, partly due to the perceived obstacle of having to make a reservation. On-demand requests, which might lower this obstacle, only showed a small increase in waiting time compared to reservations. Furthermore, the physical stop-based request was shown to have a user time similar to that of the on-demand request. Although the stop-based request might benefit from further research to refine its dispatching algorithm, it is shown to be a feasible alternative to the other request methods and can potentially help increase the adoption of DRT.

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A

Supplementary results

A.1. Served users for different fleet sizes

To chose an appropriate fleet size for the scenarios, it was evaluated how many vehicles were necessary to serve all travellers. The results for Scenario 1 can be found in Table A.1 and the results for Scenario 2 in Table A.2.

Number of vehicles Demand scale w.r.t. daily average	1.0	2.0	3.0
0.25	100.0	100.0	100.0
0.50	100.0	100.0	100.0
0.75	99.8	100.0	100.0
1.00	98.2	100.0	100.0
1.25	98.2	100.0	100.0
1.50	94.2	99.9	100.0
1.75	92.5	100.0	100.0
2.00	88.9	99.7	100.0

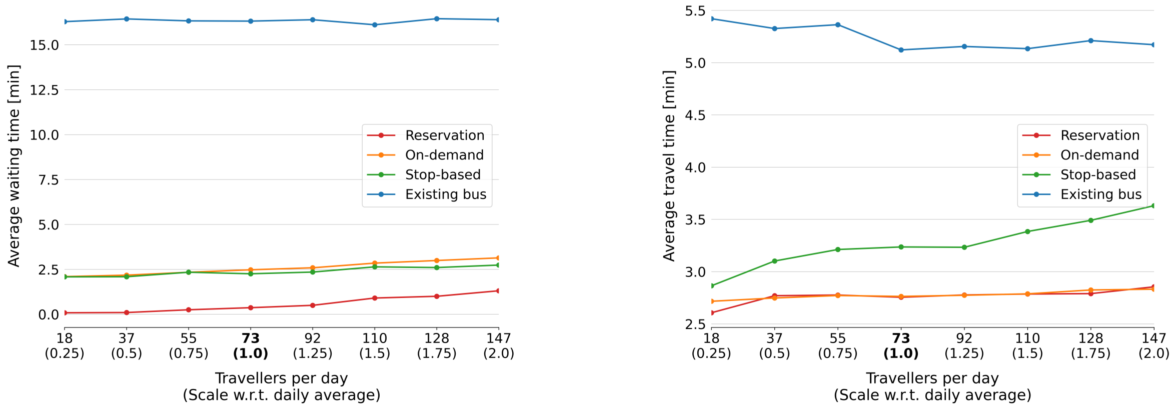
Table A.1: The percentage of served users for Scenario 1: replacement of a single bus line in Voorne-Putten Rozenburg. The table shows the percentage of served users with respect to different fleet sizes and different demand scale. The results are based on 25 simulation, each with a different set of generated requests.

Number of vehicles Demand scale w.r.t. daily average	4.0	5.0	6.0	7.0	8.0	9.0	10.0
0.25	100.0	100.0	100.0	100.0	100.0	100.0	100.0
0.50	99.8	100.0	100.0	100.0	100.0	100.0	100.0
0.75	98.5	99.9	100.0	100.0	100.0	100.0	100.0
1.00	96.0	99.2	99.9	100.0	100.0	100.0	100.0
1.25	92.6	97.7	99.7	100.0	100.0	100.0	100.0
1.50	88.3	95.2	98.7	99.8	99.9	100.0	100.0
1.75	83.7	92.8	97.2	99.2	99.8	100.0	100.0
2.00	78.7	89.3	95.0	98.4	99.5	99.9	100.0

Table A.2: The percentage of served users for Scenario 2: replacement of all regional transport in Voorne-Putten Rozenburg. The table shows the number of served users with respect to different fleet sizes and different number of travellers. The results are based on 25 simulation, each with a different set of generated requests.

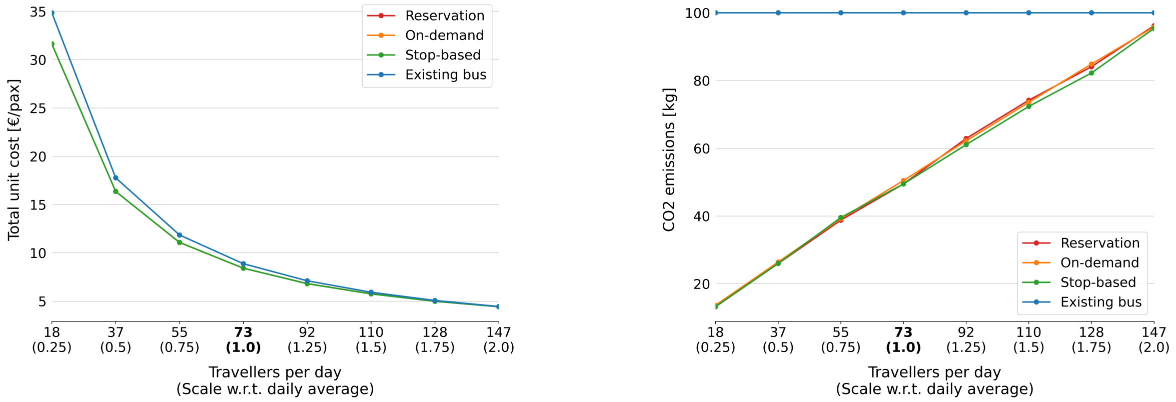
A.2. Results for different number of travellers

Figure A.1 shows the results when the number of travellers per day was changed. It can quickly be seen that the waiting time (Figure A.1a) and the travel time (Figure A.1b) are mainly unaffected by slightly higher or lower demands, while still serving (almost) all demand (see Table A.1). Figure A.1c) shows that the total unit costs remained similar. Figure A.1d shows a clear trend of increasing CO2 emissions for the DRT systems. Similar results were observed for Scenario 2 (see Figure A.2). The full results for Scenario 1 and Scenario 2 can be found in **??** and **??** respectively.



(a) Average waiting time

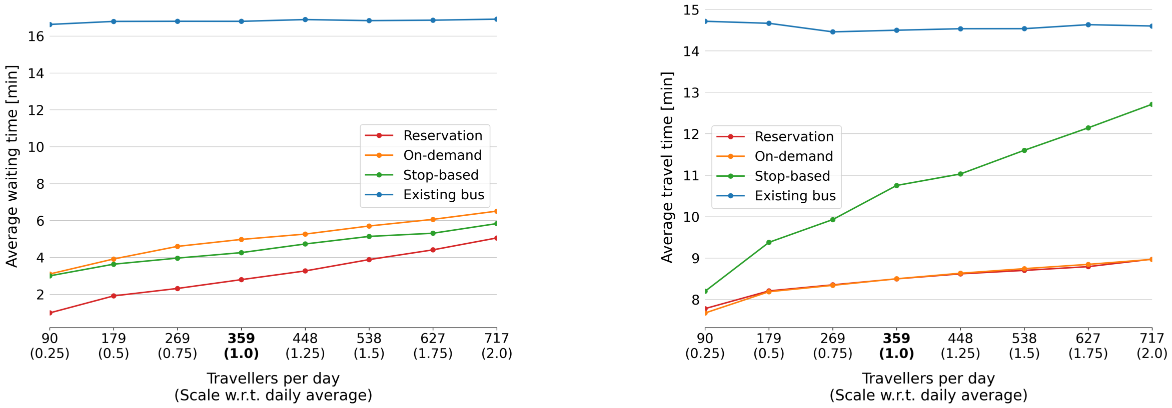
(b) Average travel time



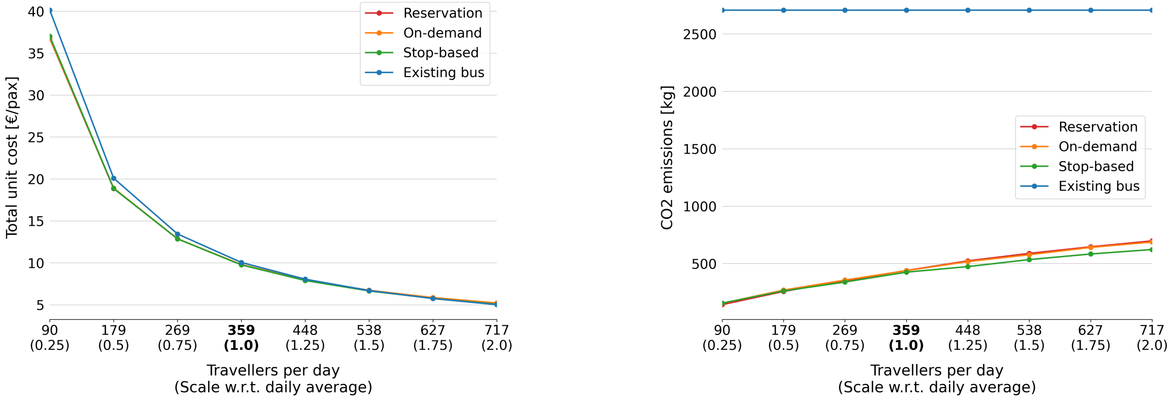
(c) Total unit cost

(d) CO2 emissions

Figure A.1: Key performance indicators comparing the DRT system with reservation, on-demand, and bus stop requests with the existing bus in scenario 1: replacing a single bus line. The results are based on 25 simulations.



(a) Average waiting time **(b)** Average travel time



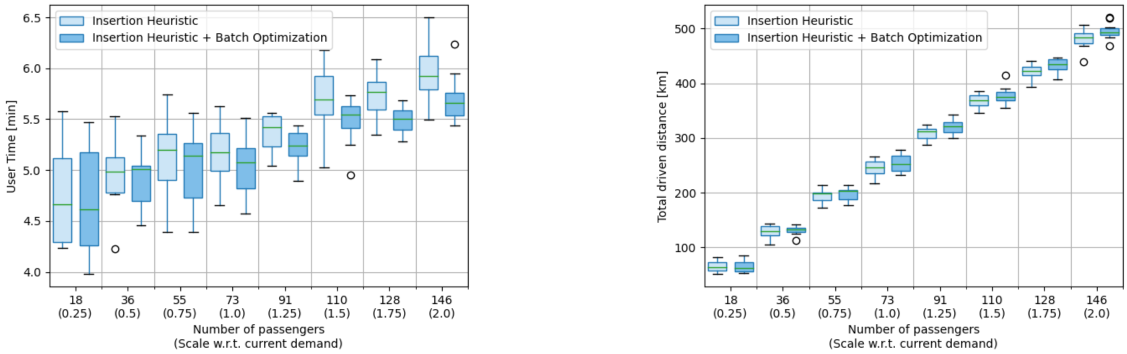
(c) Total unit cost **(d)** CO2 emissions

Figure A.2: Key performance indicators comparing the DRT system with reservation, on-demand, and bus stop requests with the existing bus in scenario 2: replacing all regional lines. The results are based on 25 simulations.

A.3. Comparing insertion vs optimisation

It was evaluated what the improvement was when using periodic batch optimisation in the case of an on-demand system. It is common for on-demand systems to use an insertion heuristic algorithm due to computational efficiency and near optimal performance [65]. While batch optimisation allows to find the global optimum, it is possible for the computational time to exceed real time. Therefore, it was evaluated whether this extra use in resources weighs up against the improvement in performance. The improvement is assessed in terms of user times and driven distance as the objective function is a weighted sum thereof.

Figure A.3 shows that only a small improvement is observed in terms of user times when demand is higher, but the difference is rather small. They are similar in terms of driven distance. It was concluded that the extra computational time did not lead to sufficient improvement.



(a) Average user time

(b) Total driven distance

Figure A.3: Performance of two DRT vehicles serving on-demand requests using an insertion heuristic algorithm and a batch optimisation algorithm.

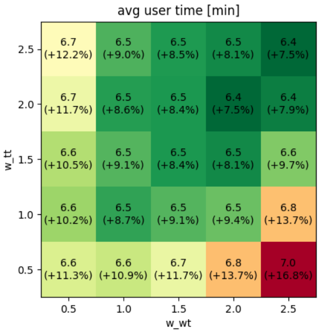
A.4. Objective function for bus stop requests

The results of the bus stop requests showed shorter waiting times and longer travel times than the on-demand requests. This means that new travellers are often picked up before in-vehicle travellers are dropped off, causing longer travel times for in-vehicle travellers. Whether a shorter waiting time or a shorter in-vehicle time is more desirable, we will leave the middle. However, we aim to explore different weights for waiting and travel times to see their effect on the results. **??** shows the result of the sensitivity analysis. Figure A.4c shows that similar user times can be achieved with different waiting and travel time weights. For example, $w_{tt} = 2$ and $w_{wt} = 1$ has the same user time as $w_{tt} = 1$ and $w_{wt} = 1$, but the waiting and travel time are closer to what is seen in the on-demand case.

One might note the improvement in user time as both weights are increased. This is explained by the fact that the objective is still the weighted sum of distance and user times. Therefore, increasing both w_{tt} and w_{wt} results in a higher weight for the user time, resulting in the user time improvement seen in Figure A.4c.

(a) Average waiting time

(b) Average travel time



(c) Average user time

Figure A.4: Sensitivity to different weights for the waiting time and travel time. The percentage show the change with respect to the on-demand DRT system.

A.5. Results for different fleet sizes

This section explores the sensitivity of the KPI's with respect to various number of vehicles and capacities.

A.5.1. Scenario 1: replacement of a single bus line

The results showed that the base case with a fleet of two DRT vehicles is capable of handling the current demand. Figure A.5 explores various DRT fleets in terms of number of vehicles and capacity. It can be seen that the KPIs are highly dependent on the number of vehicles. Furthermore, it is shown that the vehicle capacity of larger than four has negligible influence, which means that it had not occurred that more than four travellers needed to share a vehicle.

(a) Average waiting time

(b) Average travel time

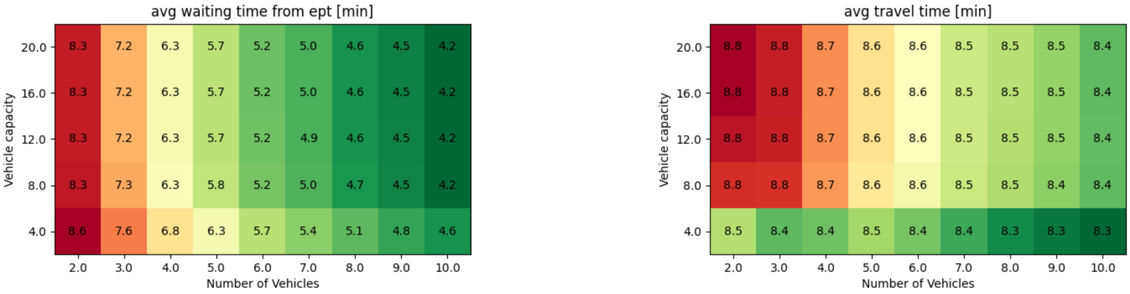
(c) Total unit cost

(d) CO2 emissions

Figure A.5: Sensitivity to different vehicle capacity and number of vehicles for scenario 1.

A.5.2. Scenario 2: replacement of all regional bus lines

In Scenario 2, the results showed that the base case of 7 DRT vehicles is capable of handling the current demand. In Figure A.6, we aim to explore the influence of different fleet sizes in terms of number of vehicles and capacity. The main relation that can be observed is that increasing the number of vehicles leads to lower waiting and travel time, but increases the total unit costs. And vice versa when the number of vehicles is reduced. Importantly, figures A.6a and A.6b show that increasing the vehicle capacity above 8 does not produce an improvement. A vehicle capacity greater than 8 would only be beneficial if at a certain point in time more than 8 users need to travel in roughly the same direction. These results indicate that this is not often the case. In Figure A.6b one can also note a decrease in travel times for vehicles of the lowest capacity. This can be explained by the fact that a detour is less likely when there are fewer other passengers in the same vehicle.



avg waiting time from ept [min]

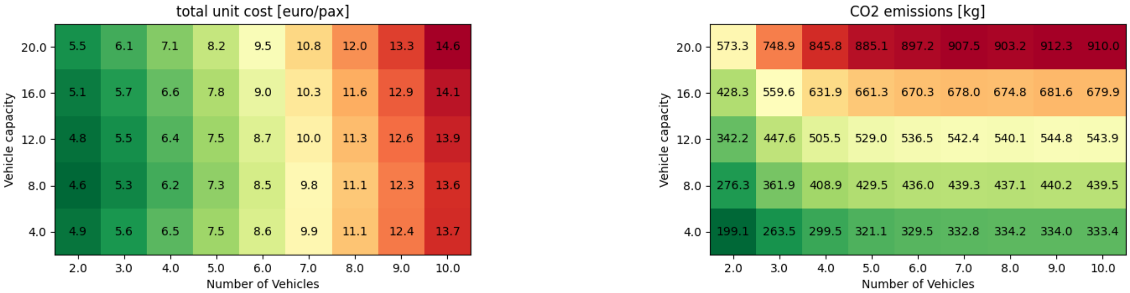
	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0
20.0	8.3	7.2	6.3	5.7	5.2	5.0	4.6	4.5	4.2
16.0	8.3	7.2	6.3	5.7	5.2	5.0	4.6	4.5	4.2
12.0	8.3	7.2	6.3	5.7	5.2	4.9	4.6	4.5	4.2
8.0	8.3	7.3	6.3	5.8	5.2	5.0	4.7	4.5	4.2
4.0	8.6	7.6	6.8	6.3	5.7	5.4	5.1	4.8	4.6

avg travel time [min]

	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0
20.0	8.8	8.8	8.7	8.6	8.6	8.5	8.5	8.5	8.4
16.0	8.8	8.8	8.7	8.6	8.6	8.5	8.5	8.5	8.4
12.0	8.8	8.8	8.7	8.6	8.6	8.5	8.5	8.5	8.4
8.0	8.8	8.8	8.7	8.6	8.6	8.5	8.5	8.4	8.4
4.0	8.5	8.4	8.4	8.5	8.4	8.4	8.3	8.3	8.3

(a) Average waiting time

(b) Average travel time



total unit cost [euro/pax]

	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0
20.0	5.5	6.1	7.1	8.2	9.5	10.8	12.0	13.3	14.6
16.0	5.1	5.7	6.6	7.8	9.0	10.3	11.6	12.9	14.1
12.0	4.8	5.5	6.4	7.5	8.7	10.0	11.3	12.6	13.9
8.0	4.6	5.3	6.2	7.3	8.5	9.8	11.1	12.3	13.6
4.0	4.9	5.6	6.5	7.5	8.6	9.9	11.1	12.4	13.7

CO2 emissions [kg]

	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0
20.0	573.3	748.9	845.8	885.1	897.2	907.5	903.2	912.3	910.0
16.0	428.3	559.6	631.9	661.3	670.3	678.0	674.8	681.6	679.9
12.0	342.2	447.6	505.5	529.0	536.5	542.4	540.1	544.8	543.9
8.0	276.3	361.9	408.9	429.5	436.0	439.3	437.1	440.2	439.5
4.0	199.1	263.5	299.5	321.1	329.5	332.8	334.2	334.0	333.4

(c) Total unit cost

(d) CO2 emissions

Figure A.6: Sensitivity to different vehicle capacity and number of vehicles for scenario 2.

A.6. Maximum waiting time

In this thesis, the maximum waiting time was set to 15 minutes. This makes sure that users have to wait at most 15 minutes, but the consequence is that user can get declined if they do not fit into the schedule within 15 minutes. One might consider increasing the maximum waiting. After all, the objective function makes sure that the user time (and thus also waiting time) is minimised.

It is important to note that the objective function considers the sum of all user times (and thus waiting times). Figure A.7 shows the waiting time of two identical on-demand simulations, only changing the maximum waiting time. Surprisingly, setting the maximum waiting time higher (7200 seconds) led to a lower average waiting time. What happened is that some users had to wait much longer to let more users wait shorter. Probably, users who have such long waiting will not accept the offer.

It can be debated whether is it better to ensure a certain service quality, with the risk of declining a few users, or giving every user an offer, with the risk of offering high waiting times which could be rejected. In this thesis it was chosen to ensure good service quality (maximum of 15 minutes waiting) and only considering a fleet size that is able to provide this service.

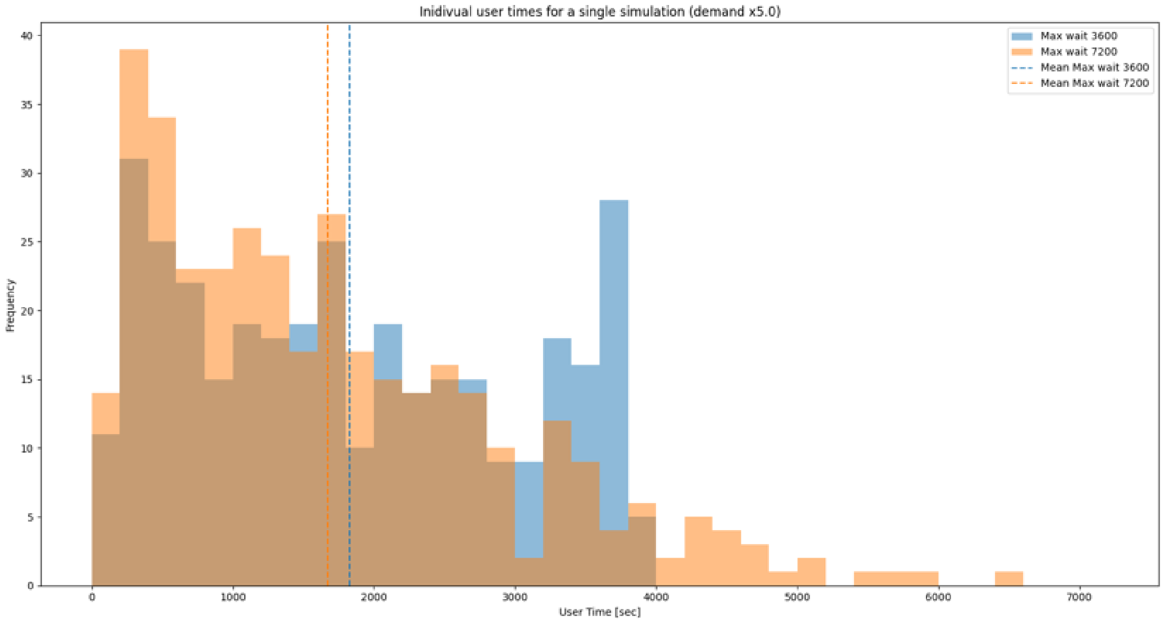


Figure A.7: The individual waiting times of two identical simulations. Only the maximum waiting time is changed.

A.7. Results variance due to sample size

The RMSE between the original data and the sampled data was shown to decline. Figure A.8 shows the effect on the simulation results. Recall that a sample is a list of individual travellers for a single day. The figure shows the travel and waiting time of all individual users in all samples. This means that the sample size of 1 contains 73 users, which is why there is already variance for a sample size of 1, and 10 samples contains 730 users, etc. It can be seen that the variance is the results quickly decreases, and is approximately stable after a sample size of 10.

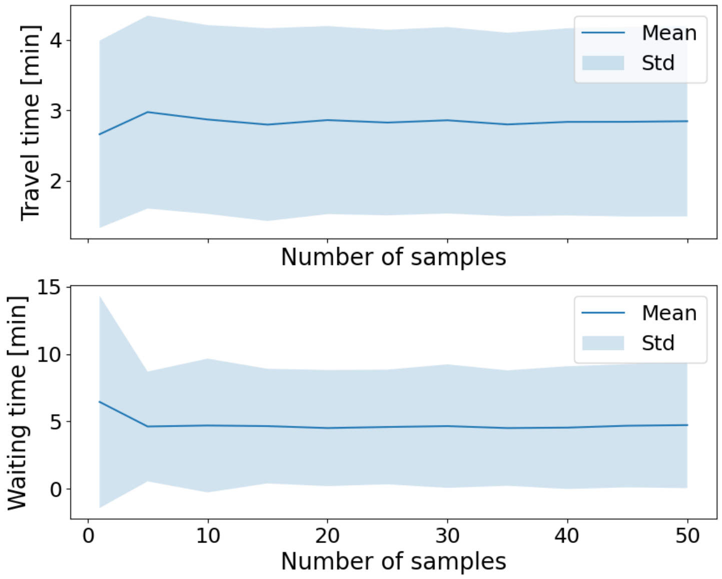


Figure A.8: The variance in the travel and waiting time considering various number of samples (days) for Scenario 1.

B

Cost and CO_2 emission calculation

The average gross salary of a bus driver in the Netherlands is 2770 per month[1]. On average, the total costs for an employer are 130% of the gross income[2]. This results in an hourly cost of 20.81 euro.

The 8-person minibuses used by the DRT system drive 12.5 kilometres per litre[3]. The cost of diesel are 1.88 per litre[4]. The variable cost of a vehicle are roughly 2.0 times the gas costs[5]. This results in a cost per kilometre of 0.30 euro.

The average CO_2 emissions per litre are 2606 gram[6]. This results in an average CO_2 emission of 206 gram per kilometre for the DRT vehicles.

The regular buses of capacity 30-40 drive 3 kilometres per litre[7]. Resulting in a variable cost per kilometre of 1.06 euro. The CO_2 emissions of the bus are 1100 gram per kilometre[8].

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[1] https://www.werkzoeken.nl/salaris/buschauffeur/

[2] https://www.sazas.nl/kennisbank/financieel/wat-kost-personeel-dit-zijn-de-personeelskosten-voor-u-als-werkgever/

[3] https://voorraad.autodatawheelerdelta.nl/renault/trafic/passenger-16-dci-8-pers-l2h1-inclbpm-btw-vrij-navi-ac-cruise-pdc-mf-stuur/occ18091798-35de5

[4] https://www.nu.nl/brandstof

[5] https://www.nibud.nl/onderwerpen/uitgaven/autokosten/

[6] https://www.anwb.nl/auto/brandstof/uitstoot

[7] https://waterstofgate.nl/Praktijk/Businesscase-Bussen-verbruik/Businesscase-Bussen-CO2-uitstoot

[8] https://www.mobiliteit.nl/ov/bus/2022/12/09/hoe-vervuilend-zijn-dieselbussen-in-het-openbaar-vervoer/

C

Example of the OD matrix derivation

A small example is given to illustrate the derivation of an OD matrix from boarding and alighting counts as defined above. Let two passengers board at the first stop and one passenger board at the second stop, so that $u_1 = 2$ and $u_2 = 1$. Now, if two passengers alight at the third stop, such that $v_3 = 2$, then it is not clear at which stop these passengers boarded the bus. Furthermore, one passenger boards at stop 3 and two passengers alight at stop 4, such that $u_3 = 1$ and $v_4 = 1$. The example is illustrated in Figure C.1.

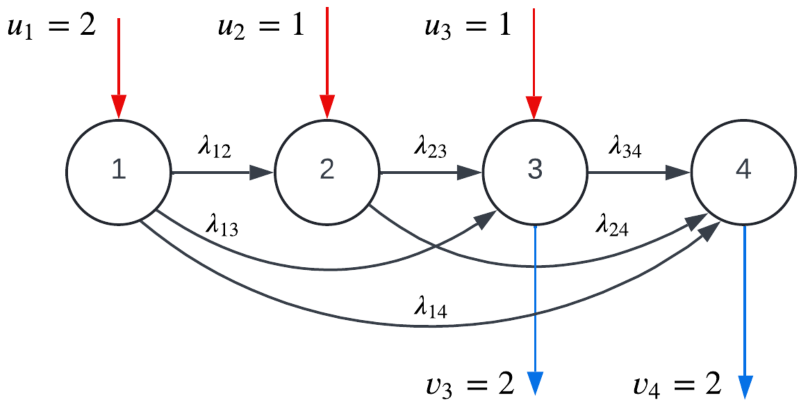


Figure C.1: Illustration of running example.

Consider stop 3. The alighting passengers at stop 3 have a probability of $\frac{2}{3}$ of having boarded at stop 1 and a probability of $\frac{1}{3}$ of having boarded at stop 2, such that $p_{1,3} = \frac{2}{3}$ and $p_{2,3} = \frac{1}{3}$. The travel rates are then $\lambda_{1,3} = \frac{2}{3} * 2 = \frac{4}{3}$ and $\lambda_{2,3} = \frac{1}{3} * 2 = \frac{2}{3}$.

Now, consider stop 4. The travel rates $\lambda_{1,3}$ and $\lambda_{2,3}$ should be subtracted from u_1 and u_2. The remaining boarding counts when we consider stop 4 are $u_1^4 = \frac{2}{3}$ and $u_2^4 = \frac{1}{3}$.

The probabilities of the origins are $p_{1,4} = \frac{1}{3}$, $p_{2,4} = \frac{1}{6}$, and $p_{3,4} = \frac{1}{2}$. The travel rates are then $\lambda_{1,4} = \frac{2}{3}$, $\lambda_{2,4} = \frac{1}{3}$ and $\lambda_{3,4} = 1$. As one would expected, they are equal to the remaining boarding counts, since this was the last stop.

In this example, we obtain the OD matrix:

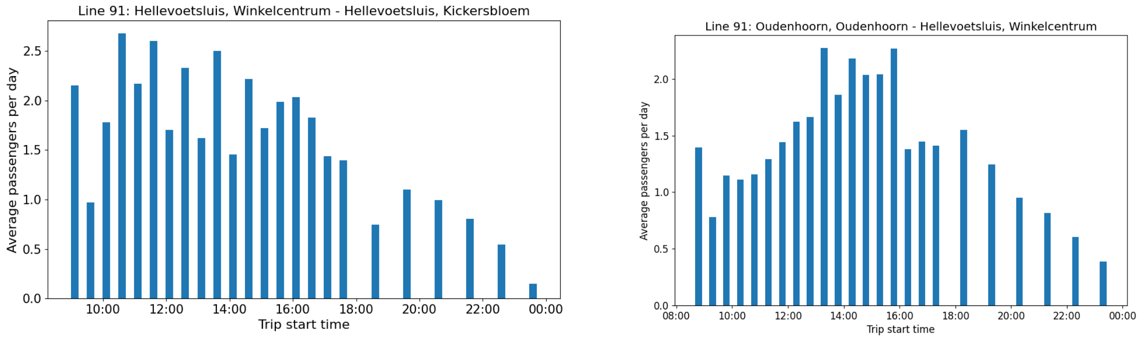
$$\Lambda = \begin{bmatrix} 0 & 0 & \frac{4}{3} & \frac{2}{3} \\ 0 & 0 & \frac{2}{3} & \frac{1}{3} \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{C.1}$$

It can be seen that the rows in Λ sum to the boarding counts and the columns sum to the alighting counts.

D

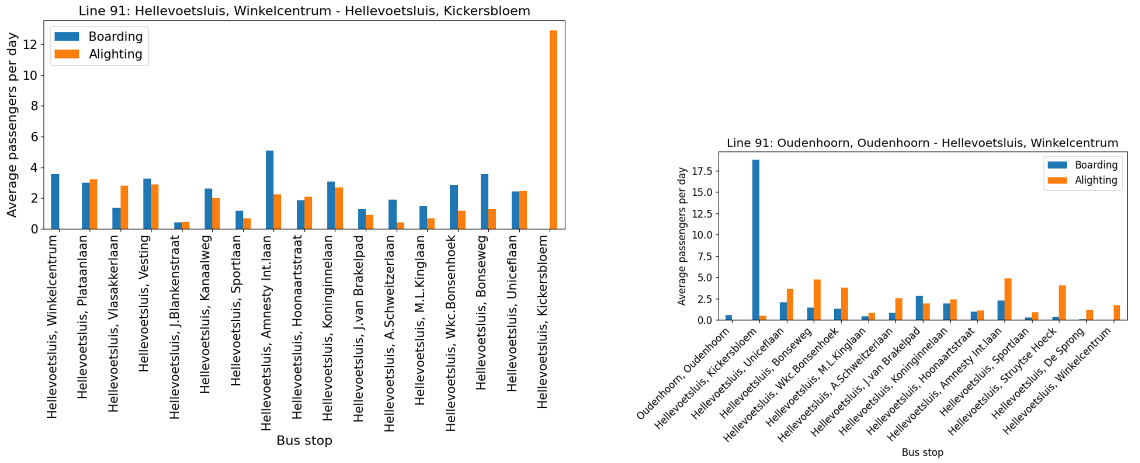
Visualisation of bus line data

This chapter contains more figures of the boarding and alighting distributions of bus lines 91, 105 and 106.



(a) Passengers per trip

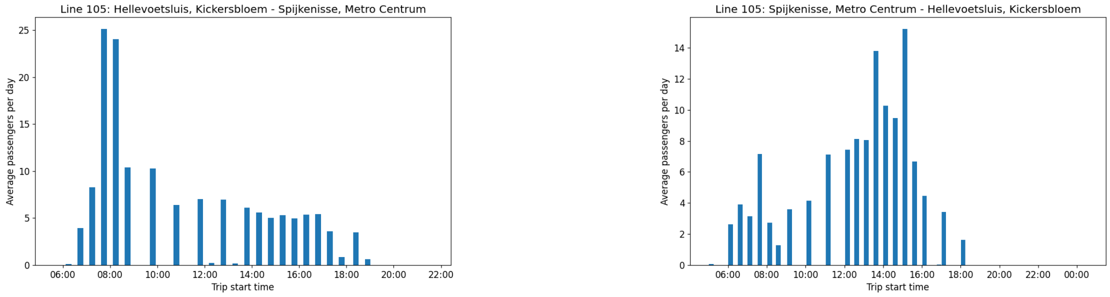
(b) Passengers per stop



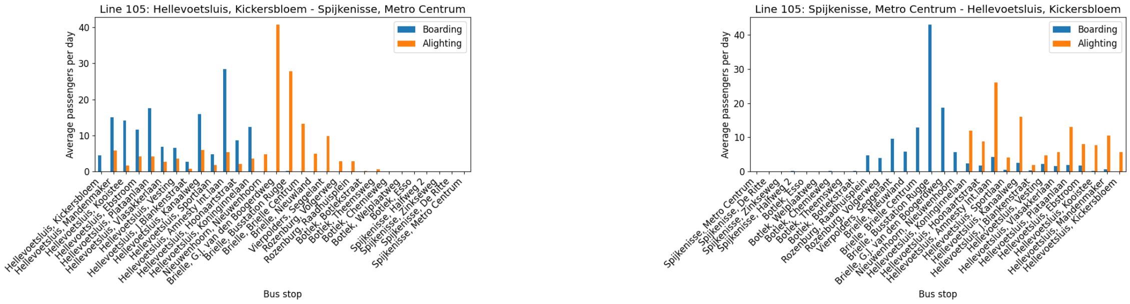
(c) Passengers per trip

(d) Passengers per stop

Figure D.1: Data from EBS bus line 91.

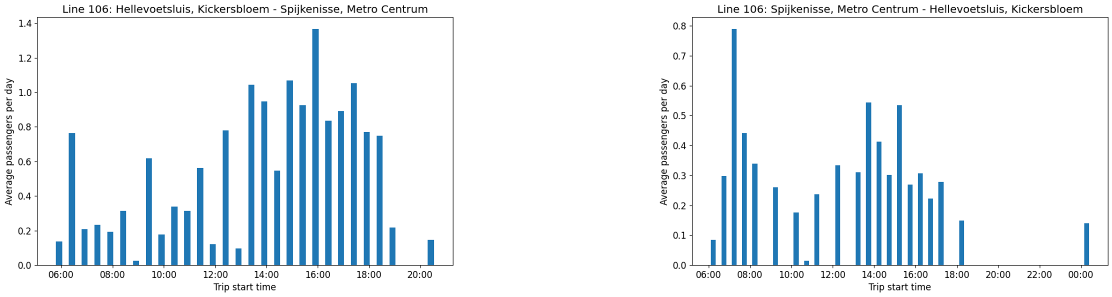


(a) Passengers per trip **(b)** Passengers per trip

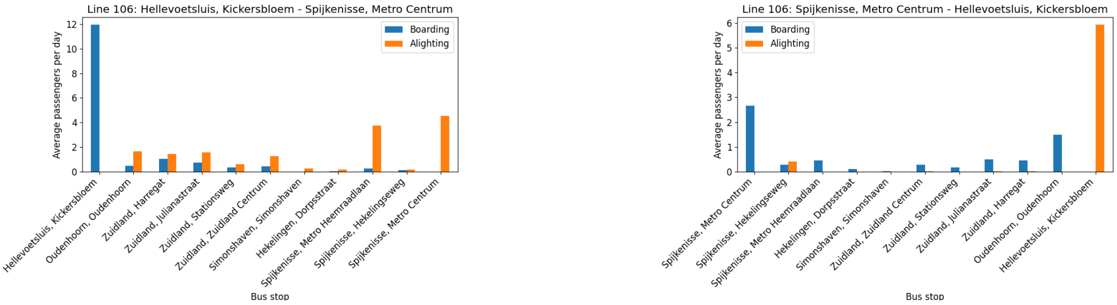


(c) Passengers per stop **(d)** Passengers per stop

Figure D.2: Data from EBS bus line 105



(a) Passengers per trip **(b)** Passengers per trip

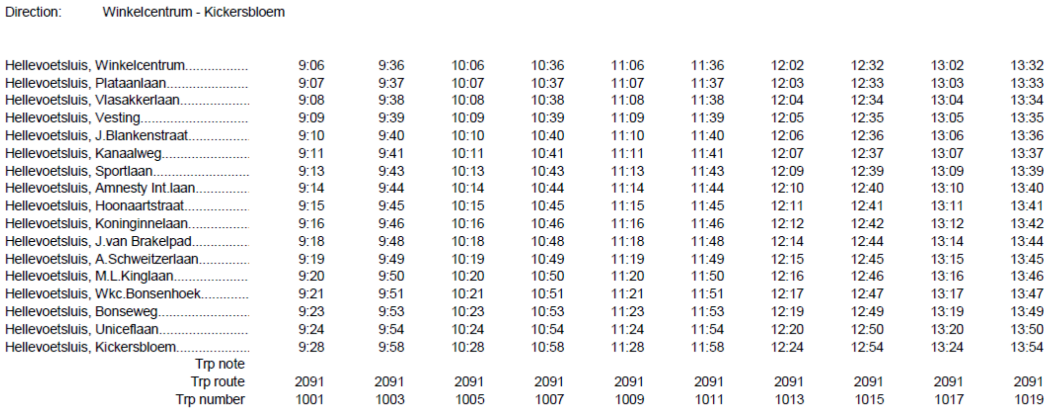


(c) Passengers per stop **(d)** Passengers per stop

Figure D.3: Data from EBS bus line 106

E

Example of a bus schedule



Direction: Winkelcentrum - Kickersbloem

Hellevoetsluis, Winkelcentrum	9:06	9:36	10:06	10:36	11:06	11:36	12:02	12:32	13:02	13:32
Hellevoetsluis, Plataanlaan	9:07	9:37	10:07	10:37	11:07	11:37	12:03	12:33	13:03	13:33
Hellevoetsluis, Vlasakkerlaan	9:08	9:38	10:08	10:38	11:08	11:38	12:04	12:34	13:04	13:34
Hellevoetsluis, Vesting	9:09	9:39	10:09	10:39	11:09	11:39	12:05	12:35	13:05	13:35
Hellevoetsluis, J.Blankenstraat	9:10	9:40	10:10	10:40	11:10	11:40	12:06	12:36	13:06	13:36
Hellevoetsluis, Kanaalweg	9:11	9:41	10:11	10:41	11:11	11:41	12:07	12:37	13:07	13:37
Hellevoetsluis, Sportlaan	9:13	9:43	10:13	10:43	11:13	11:43	12:09	12:39	13:09	13:39
Hellevoetsluis, Amnesty Int.laan	9:14	9:44	10:14	10:44	11:14	11:44	12:10	12:40	13:10	13:40
Hellevoetsluis, Hoonaartstraat	9:15	9:45	10:15	10:45	11:15	11:45	12:11	12:41	13:11	13:41
Hellevoetsluis, Koninginnelaan	9:16	9:46	10:16	10:46	11:16	11:46	12:12	12:42	13:12	13:42
Hellevoetsluis, J.van Brakelpad	9:18	9:48	10:18	10:48	11:18	11:48	12:14	12:44	13:14	13:44
Hellevoetsluis, A.Schweitzerlaan	9:19	9:49	10:19	10:49	11:19	11:49	12:15	12:45	13:15	13:45
Hellevoetsluis, M.L.Kinglaan	9:20	9:50	10:20	10:50	11:20	11:50	12:16	12:46	13:16	13:46
Hellevoetsluis, Wkc.Bonsenhoek	9:21	9:51	10:21	10:51	11:21	11:51	12:17	12:47	13:17	13:47
Hellevoetsluis, Bonseweg	9:23	9:53	10:23	10:53	11:23	11:53	12:19	12:49	13:19	13:49
Hellevoetsluis, Uniceflaan	9:24	9:54	10:24	10:54	11:24	11:54	12:20	12:50	13:20	13:50
Hellevoetsluis, Kickersbloem	9:28	9:58	10:28	10:58	11:28	11:58	12:24	12:54	13:24	13:54
Trp note										
Trp route	2091	2091	2091	2091	2091	2091	2091	2091	2091	2091
Trp number	1001	1003	1005	1007	1009	1011	1013	1015	1017	1019

Figure E.1: A part of the time schedule for week days of line 91 in the direction Winkelcentrum - Kickersbloem.