Network effects of activity based departure time choice with automated vehicles

A case study in the 'Haaglanden' region

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by

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An electronic version of this thesis is available at `http://repository.tudelft.nl/`.

Preface

Before you lies the thesis document: “Network effect of activity based departure time choice with automated vehicles”. This thesis has been written to fulfil the graduation requirements of the MSc Transport, Infrastructure and Logistics at the Delft University of Technology. I was engaged in researching and writing this thesis from June to December 2020.

The project comprised investigation of future network effects with automated vehicles. Being able to really contribute to a field of a new developing technology was something that energised me throughout the project. Even though it has been a challenging process at times, especially during the COVID-19 crisis and the associated limitations, I can honestly say that I am proud of the final result.

This research has been conducted as a combined internship at DAT.Mobility. This provided me with supervision from Klaas Friso and Luc Wismans from DAT.Mobility and Goudappel Coffeng, respectively. I would like to thank both for their availability and willingness to guide me during the project. Without their supervision, I would not have been able to overcome some of the challenging modelling issues and arrive at this final document.

Furthermore, the results would not have been achieved without the thesis committee. First of all, I would like to thank Baiba Pudāne, whose work served as a starting point for this project and who really helped me with the scoping during the first part of this research. I would like to thank Adam Pel and Sander van Cranenburgh for their availability and guidance with any questions I had on the content as well as the overall structure of the report. Lastly, I also wish to thank Bart van Arem for his time to chair this committee and provide me with clear feedback on the methodology, structure and presentation of the research.

I am grateful for the support I had from my friends and roommates who helped me to keep motivated if I ever lost interest throughout the project. My parents deserve a particular note of thanks: your counsel and kind words have, as always, served me well.

I hope you enjoy your reading.

Floris Hooft
December 8, 2020

Summary

Over the past years, more and more human tasks have been computerised and replaced by machines. One of these developments involves the substitution of the driving task from human to machine with the introduction of the automated vehicle (AV). These vehicles bring the possibility to engage in on-board activities and be productive during travel. This increased on-board productivity implies that people will show less aversion to longer travel times (i.e. congestion). The commonly adopted approach to capture this effect is to reduce the 'penalty' associated with travel time. This leads to travellers prioritising their arrival time close to the preferred arrival time and thus, increase the peak congestion.

However, a distinction should be made between the type of performed activity, since this could likely affect the departure time preferences and thus have an impact on the congestion pattern. If we consider commuting travellers this on-board productivity can either be related to home or work activities. For instance, a businessman might use an AV to prepare meetings during his commuting trip. Therefore he might choose to depart later since he has already been productive regarding his work. Contrarily, a person who uses the extra time to sleep, might choose to depart earlier since this is an activity related to the home end.

A person will try to schedule the departure at such a moment that he/she loses the least value of being at home or at work. One way to model this trade-off is with the use of the $\alpha - \beta - \gamma$ scheduling preferences. These scheduling preferences basically say that our departure time choice is determined by our value of being at home or at work at a given point in time. Pudāne (2019) extended this model to account for in-vehicle productivity and differentiated between home and work activities. Theoretical closed-form results showed that travellers with automated vehicles in which home activities could better be performed, preferred to arrive early in the peak, i.e. depart earlier, and conversely travellers with automated vehicles in which work activities could better be performed, preferred to arrive later in the peak, i.e. depart later. In addition, the results suggested that automated vehicles could likely increase severe congestion in the future (Pudāne, 2019 Yu, van den Berg, & Verhoef, 2019).

However, these studies were based on a theoretical bottleneck model with one origin and destination. Up to this point we do not yet know the effect of activity-based departure time choice on peak congestion for real-life networks: settings with multiple origins/destinations and where travellers also choose their routes. Therefore this study aims to investigate these network effects based on the following research question:

"How will activity based departure time choice affect peak congestion within a network in the automated vehicle era?"

To answer this question, the extended $\alpha - \beta - \gamma$ model has been integrated in an existing modelling framework of a traffic simulation model. This model has been used on a case study area of the 'Haaglanden' region. The main focus of this research are the congestion effects related to the departure time choice. Furthermore route choice is assessed and the relation to external effects (traffic safety and emissions) is evaluated.

To differentiate between the type of activity, we adopted the same differentiation of AV types as used in the closed-form setup to enable analysis for the type of activities: Home, Universal and Work AV (Pudāne, 2019). Home AVs are vehicles in which home activities can best be performed. Universal AVs are suited for both home and work activities. Work AVs are vehicles in which work activities can best be performed. In addition, the conventional car (non-AV) has been defined to be used as a reference scenario. For each of these vehicles (modes) we can describe the utilities for a person's morning period. To implement these utilities within the modelling framework, they had to be rewritten as disutilities. This mathematical deduction of the extended $\alpha - \beta - \gamma$ model calls for the definition of three distinct departure/arrival time scenarios per mode. The resulting disutility functions of this mathematical derivation are listed in Table 1.

Table 1: Mathematically derived disutility functions per mode per departure/arrival scenario

Travel scenario	Disutility function
Non-AV 1	$\alpha T(t) + \beta(t^* - (t + T(t)))$
Non-AV 2	$\alpha T(t) + \gamma((t + T(t)) - t^*)$
Non-AV 3	$\alpha T(t) + \gamma((t + T(t)) - t^*)$
Home AV 1	$\alpha(1 - e_h)T(t) + \beta(t^* - (t + T(t)))$
Home AV 2	$\alpha(1 - e_h)T(t) + \gamma((t + T(t)) - t^*)$
Home AV 3	$\alpha(1 - e_h)T(t) + \gamma((t + T(t)) - t^*)$
Universal AV 1	$\alpha(1 - e_h)T(t) + \beta(t^* - (t + T(t)))$
Universal AV 2	$\alpha T(t) + \gamma((t + T(t)) - t^*) - e_h\alpha(t^* - t) - e_w(\alpha + \gamma)((t + T(t)) - t^*)$
Universal AV 3	$\alpha T(t) + \gamma((t + T(t)) - t^*) - e_w(\alpha + \gamma)T(t)$
Work AV 1	$\alpha(t^* - t) - e_w(\alpha - \beta)T(t) - (\alpha - \beta)(t^* - (t + T(t)))$
Work AV 1	$\alpha T(t) + \gamma((t + T(t)) - t^*) - e_w(\alpha - \beta)(t^* - t) - e_w(\alpha + \gamma)((t + T(t)) - t^*)$
Work AV 1	$\alpha T(t) + \gamma((t + T(t)) - t^*) - e_w(\alpha + \gamma)T(t)$

These disutilities were implemented in the departure time choice module of the overall modelling framework as build by van Amelsfort (2009). This model uses macroscopic dynamic traffic assignment (DTA) model INDY. This DTA was used to assign the traffic flows of the specific modes within the road network of the case study region ‘Haaglanden’. Figure 1 shows the network model of the ‘Haaglanden’ region.

Figure 1: Network model of the ‘Haaglanden’ region in OmniTRANS

This region is located in the western part of the Netherlands and is part of the metropolitan area of Rotterdam and The Hague. It is small enough to prevent tedious model running times while it is also large enough to incorporate many real-life choice options. The network area contains 168 origins and destinations with a total traffic demand of 473,868 vehicles during the morning period 6:00 - 11:00 AM. Within this network, differentiation was made between the following three road types: motorways, provincial/distributor roads and urban roads.

The model results showed that congestion slightly increased when AVs were assigned to the network and that based on the type of AV, the departure time shifted either to the beginning (Home AV), the middle (Universal AV) or to the end of the morning period (Work AV). Figure 2 shows the departure time profiles obtained in the Haaglanden network for each of the four modes.

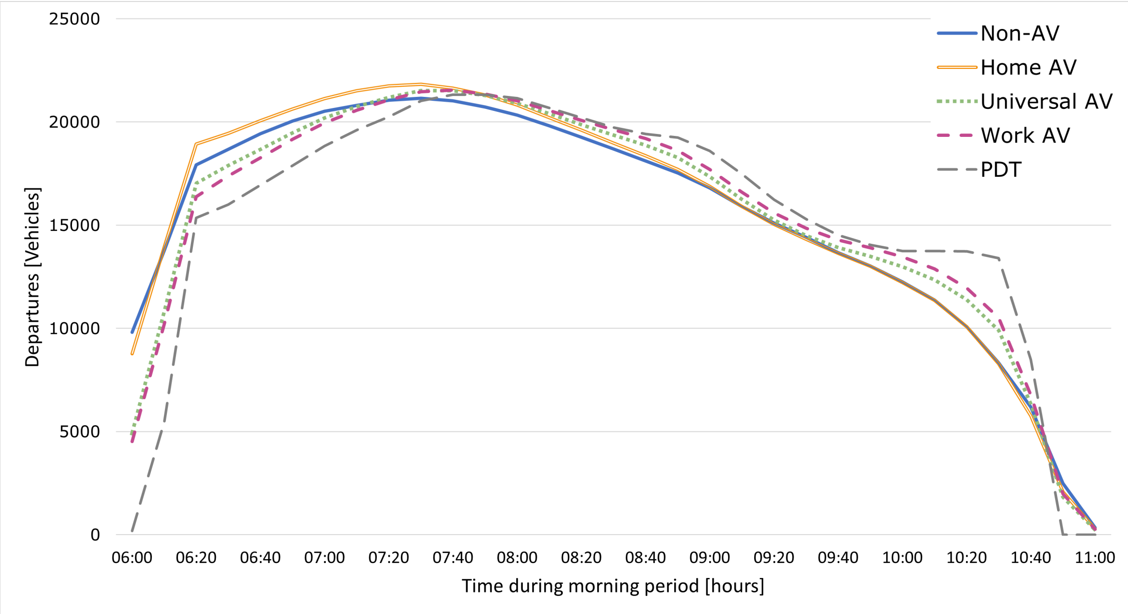


Figure 2: Departure time profiles for each mode in the Haaglanden network

It must be noted that Home AVs and non-AVs showed a more similar profile. Likewise, similarities could be observed regarding Universal and Work AVs. This can be explained by the fact that Home AV will always loses utility from the home side during travel. Since this home utility (α) is significantly lower than the utility associated with work ($\alpha + \gamma$) Home AVs show a relatively high aversion to late arrivals compared to Universal and Work AVs in which, after the PAT, utilities are lost from the work side. This leads to the belief that in mixed traffic situations, Home AVs would compete the most with non-AVs.

Regarding the travel times, results indicated that Universal AVs will increase travel times and related delays the most. Although the observed changes were relatively small and could in some cases be considered insignificant, the direction of the effects was visible. Table 2 shows the (relative) changes regarding travel times and delays.

Table 2: Maximum, minimum and mean travel times including delays and relative changes per mode for the Haaglanden network. Note that due to rounding, some absolute values might be the same while their corresponding relative changes are not.

	Non-AV	**Home AV**		**Universal AV**		**Work AV**	
Max. travel time [min]	13.69	13.72	*0.17%*	13.71	*0.13%*	13.67	*-0.19%*
Min. travel time [min]	7.83	7.93	*1.31%*	7.89	*0.74%*	7.98	*1.89%*
Mean travel time [min]	11.91	11.92	*0.03%*	11.96	*0.38%*	11.92	*0.05%*
Mean delay [min]	4.10	4.11	*0.08%*	4.15	*1.11%*	4.11	*0.14%*

Considering route choice, results showed that with the introduction of AVs in the network, there was an observed increase of vehicle-kilometres (VKM) on the underlying road network. This means a more intense usage of urban and provincial/distributor roads, which is usually associated with a negative impact on traffic safety and an increase in emission levels. Although one might argue that future AVs will be associated with better safety levels and more eco-friendly driving. Table 3 shows the absolute Vehicle Kilometres (VKM) and the relative changes with the reference scenario per road type.

Table 3: Total vehicle kilometres (VKM) for each mode including difference with reference situations

Road category	**Non-AV**	**Home AV**		**Universal AV**		**Work AV**	
Motorway	2,642,545	2,636,128	*-0.24%*	2,637,689	*-0.18%*	2,637,351	*-0.20%*
Prov./dist. road	1,259,488	1,263,714	*0.34%*	1,263,291	*0.30%*	1,263,629	*0.33%*
Urban road	1,236,918	1,239,154	*0.18%*	1,237,602	*0.06%*	1,237,293	*0.03%*
Total	5,138,951	5,140,172	*0.02%*	5,139,582	*0.01%*	5,138,273	*-0.01%*

Though the direction of these effects could be observed, the size of some of them remained small and could in some cases even be considered insignificant. Three specific OD pairs with distinct characteristics were selected to investigate the effects on OD level. This showed that equilibrium was not yet reached for every relation. However, it was observed that specifically the relations which use primarily the main (congested) road network, are associated with bigger delays and to some extent a more widened departure time profile.

A sensitivity analysis was conducted to investigate the model's outcome to the input parameters and the influence of different penetration rates of AVs. The effect of penetration rates was analysed with Universal AVs compared to non-AV. Results showed that with increasing the share of AVs, non-AV users were 'forced' to shift their departures more to the beginning of the morning period. At the same time, their overall travel times decreased, which can be explained by the fact that they show a greater aversion to longer travel times than the share of AV users. This expulsion effect was already quite significant with a relatively low penetration rate (25%).

In addition, the sensitivity of the model's outcome to the model parameters has been assessed. This was based on different ratios of $\alpha - \beta - \gamma$ parameters and efficiency factors. The first shows that the more important/strict arriving at the preferred arrival time is, meaning the significance of β and γ, the more the departure times shift to the preferred departure times but the more travel times increase. The second shows that with increased efficiency of on-board activities, making the efficiency factors more extreme, less aversion was assigned to travel time and thus an increase in delays could be observed.

This study pointed out that with introducing fully AVs within larger road networks while accounting for the performed on-board activity, congestion might increase. This is a result of the ability to spend trip time productively which leads to less aversion to longer travel times. This may lead to an increase in congestion levels and VKM which is unfavourable with regard to emission levels. Furthermore a small but significant shift of VKM was identified from the main road network to the underlying road network. This is considered to be disadvantageous with regard to traffic safety. Considering emissions, the net effect of changes in CO_2 emissions remains questionable. However, the increase in VKM on urban/provincial roads leads to a negative impact towards noise and air pollution (NO_x and PM10) in these areas.

On the other hand, one might argue that one of the positive aspects associated with AVs is a better road/vehicle safety. But there is still a long way to go before all, or even a significant part, of the vehicles on the road will be (fully) AVs. And it is especially those mixed traffic situations, in which both non-AVs and AVs share the same road network, which might be the most hazardous. Another aspect to bear in mind is the trend towards more sustainability with modern (electrical) cars. This will reduce the negative impact of increased noise and air pollution.

Moreover, it was observed that with mixed traffic, non-AV users shifted their departure times more to the beginning of the morning period while AV users shifted the departures more to peak travel time moments. Since AV users have less aversion to longer travel times, they have the opportunity to arrive closer to their preferred arrival times. This implies that non-AV users will come out on the losing end when it comes to these mixed traffic situations.

One option to solve this to some extent can be to introduce designated lanes/routes for AVs, primarily on the main road network. This way the longer travel times are linked to the users that can better tolerate these. Furthermore, this will shift the increase in VKM towards the main road network which is beneficial regarding traffic safety and air/noise pollution in urban areas. At the same time more and more cities are prohibiting cars in the city centres. Another direction of alternatives could be the implementation of pricing systems. This can be done with respect to road types, charges for driving (AVs) on the underlying road networks, or with respect to time periods, charges for driving (AVs) during peak hours. We must however mention the current COVID-19 crisis which now partly solves the congestion problem. It remains uncertain to what extent this this phenomenon will remain. Furthermore, it might be that more and more people will work from home in the future which reduces traffic at peak moments.

This research aimed to contribute to the literature within the field of AVs. It presented some key insights on the network effects of activity based departure time choice and identified its relation to route choice, external effects and the impact on mixed traffic situations. Based on the assumptions and findings in this study it is recommended that further research is conducted to investigate the following aspects:

- Increased accurate dynamic modelling
  The model used in this study, was not able to capture blocking back effects, which resulted in underestimated delays. It is recommended to include this aspect in further studies, since this will provide more realistic results.
- Extended $\alpha - \beta - \gamma$ model parameters
  This research adopted the extended $\alpha - \beta - \gamma$ model parameters from previous work. It is recommended that further research is conducted to determine more substantiated values. This refers to our valuation of arrival times and the level of assumed on-board productivity.
- Capacity implications
  This research did not differentiate among road capacities between AV and non-AV users. Up to this point it remains questionable if introducing AVs will be beneficial towards this road capacity, particularly if they will not have the ability of cooperative driving. It is suggested that further research is conducted to assess the impact of differentiation between road capacities with AVs.
- Heterogeneity/endogeneity
  This research did not include heterogeneity among travellers' preferences but it might be that not all travellers wish to engage in on-board activities. In addition no endogeneity has been included. However, it would be interesting to investigate the effects if travellers could assign themselves to engage in a certain type of on-board activity. These elements require further investigation.
- Level of automation
  This study assumed full automation. Currently lower levels are already being implemented on a wider scale. The impact of including for instance an operational design domain (ODD) is important to study further since this affects route choice. It is suggested to further study the impact of including lower levels of automation.
- Valuation of travel time with route choice
  An important extension of this study would be to also differentiate in travel time valuation on the route choice level. Where this study used the same probabilities to choose a specific route for both AVs and non-AVs, it is recommended that further research will differentiate between AV- and non-AV users to capture the effect of on-board VTT with respect to route choice.

Abbreviations

AV Automated Vehicle. 1–5, 7, 9, 11–18, 20, 24, 27, 35, 37, 38, 42–46, 48–50, 52–54, 56–60, 63, 64, 66

DTA Dynamic Traffic Assignment. 9, 13, 14, 22–24, 26, 27, 53, 54, 59

KPIs Key Performance Indicators. 34, 38, 43, 54, 55

OD pair Origin-Destination pair. 21, 23, 24, 26, 31, 32, 34, 36, 43, 49–51, 58

ODD Operational Design Domain. 3, 4, 38, 60, 64, 66

PAT Preferred Arrival Time. 23, 24, 27–29, 34, 38, 45, 46, 53–57, 66

PDT Preferred Departure Time. 23, 27–30, 44

VKM Vehicle Kilometres. vii, 4, 5, 8, 12, 13, 35, 36, 46–48, 58–60, 64

VTT Value of Travel Time. 7, 12–14, 20, 46, 66

Contents

1 Introduction

Over the past years, more and more human tasks have been computerised and replaced by machines. One of these developments involves the substitution of the driving task from human to machine with the introduction of the automated vehicle (AV). Even though this innovation is still in its infancy, members of the IEEE anticipate that up to 75% of the vehicles on road could be fully automated by 2040 (IEEE, 2012). These self-driving cars could change our way of transportation and are expected to bring many positive effects, such as better road/vehicle safety, increased comfort and productivity due to the travel time being spend more effectively (Pudāne et al., 2019). On the other hand, they might also bring negative effects, such as an increase in congestion and more cut-through traffic.

If these presumed effects can be identified and the size of these effects determined, policy makers can create more effective tailor-made policies with the aim to deliver better service to all future - AV and non-AV - road users. For instance, implementing charges for the avoidable use of lower road categories or reduced charges for engaging in a trip outside of peak hours might counter the expected effects. Getting insight in these aspects is of key importance in taking effective measures.

However, there are still many uncertainties regarding the direction and extent of these effects. One extensively studied aspect is the impact on network congestion brought by the Automated Vehicle (AV)s (van den Berg & Verhoef, 2016; Wadud, MacKenzie, & Leiby, 2016; Milakis, Van Arem, & Van Wee, 2017; Simoni, Kockelman, Gurumurthy, & Bischoff, 2019). An important element in these studies is related to the expected change in travel behaviour. Nowadays, a person may choose public transport over a shorter car trip given that he/she is able to spend travel time more productively. However, as AVs bring the possibility to be 'productive' during travel, the disutility of a trip is reduced. With an increased level of productivity and comfort, the AV will become more attractive, which in turn may lead to a higher mode-share and therefore a probable increase in congestion levels and environmental costs. On the other hand these effects might be neutralised (to a certain extent) due to the AV's characteristics: improved energy consumption, shorter headways and lighter vehicles (Milakis et al., 2017).

The commonly accepted approach to capture the effect of increased on-board productivity is to reduce the 'penalty' associated with travel time. However, as described by Pudāne (2019), a distinction should be made between the type of on-board activities since this might directly affect the departure time preferences for making a trip. For instance, if a businessman engages in working activities during his morning commuting trip, he might prefer to depart later since he can already work, to some extent, during his trip. Another person may choose to sleep during his/her morning trip and prefers to depart earlier. Therefore the congestion patterns can, based on departure time preferences and in particular the type of performed activity, be affected differently than by using a single travel time penalty.

One way to model departure time preferences is using the $\alpha-\beta-\gamma$ model. This model entails the most widely used scheduling preferences (Vickrey, 1969; Small, 1982). It basically says that our departure time choice is determined by our value of being at home or at work. A person will try to schedule the departure at such a moment that he/she loses the least of being at these places, while including the necessity of travel. By means of a step-wise function, which describes our utility to be at home/work, we can derive optimum departure times.

With AVs individuals can be productive during travel and engage in either home or work activities. To include this on-board productivity, Pudāne (2019) extended the $\alpha - \beta - \gamma$ model with efficiency factors and defined three types of AVs to study the effects of the type of on-board activity (home/work). She distinguished Home, Universal and Work AVs. Home AVs are better suited to perform home related activities, Work AVs are better suited for engaging in work related activities. Universal AVs can be used for both home and work activities. By using this distinction, the activity based departure time choice and its effect on peak congestion has been investigated. Within a theoretical single link setting, also known as the bottleneck model, closed-form results were obtained which indicate that congestion might increase with AVs. Furthermore, if Home AVs are considered, users are likely to travel earlier in the peak. Conversely if Work AVs are considered, users are likely to travel later in the peak. Lastly, with Universal AVs in which both home and work activities are possible, the departure time might shift to the centre of the peak (Yu et al., 2019; Pudāne, 2019) This coincides with what we would expect given the example above: once an individual engages in work activities during the commuting trip, it is more likely that he/she will schedule his/her departure to later in the peak and vice versa.

However, the results in both studies were obtained with the use of the bottleneck model. This theoretical single link setting is extremely useful when investigating congestion effects in a closed-form but is restricted to have only one origin and one destination. This setup does not incorporate route choice (or trip making choice), whereas in real-life networks, people have the ability to reroute or decide not to make a trip. The effect that AVs will have on activity based departure time choice and the resulting peak congestion in more complex situations, has up to this point not yet been investigated. It might be that the inclusion of route choice will induce rerouting and increase congestion on the underlying road network. This may lead to a decrease in traffic safety and possibly an increase in emissions. On the other hand, AV are expected to be safer and drive more eco-friendly which may offset these outcomes. And what happens if we consider situations with mixed traffic, i.e. AV and non-AV users within the same network? Will AVs be predominantly using the peak moments and therefore shove the non-AV users outside of their preferred departures/arrival times. In short: “Who benefits and who loses?”

This document presents a study into the network effects of activity based departure time choice on peak congestion in the automated vehicle era. The purpose of this study is to determine if and, more importantly, how the implementation of AVs will affect peak congestion in a real city network. Since it is unable to investigate these effects on a wide scale in a real-life situation, a transportation model will be used on a case study area.

The report is structured as follows: It starts with the presented research question and related sub-questions in section 1.1. Section 1.2 describes the objectives and scope after which section 1.3 presents the approach to conduct this study and answer the research questions. Chapter 2 provides the literature review which addresses the relations between previous work and the proposed research. Hereafter, chapter 3 elaborates on the required theoretical background regarding the bottleneck model and the extended $\alpha - \beta - \gamma$ scheduling preferences. This is followed by chapter 4 in which the used methods: the traffic simulation model and the case study, are described. In chapter 5, the model results are presented and the observed effects are identified. Chapter 6 discusses the results, presents policy-relevant insights and relates them to the assumptions and broader perspective of this study. Finally, chapter 7 gives the overall conclusions and provides recommendations for further research.

1.1. Research questions

From the above, it can be concluded that there has been some research conducted on the departure time preferences' effect on peak congestion with AVs. However, the activity based perspective and the effects within a network have not yet been investigated. The direction and size of these effects on a larger network remain unclear. This leads to the following research question:

"How will activity based departure time choice affect peak congestion within a network in the automated vehicle era?"

Hypothesis

The expectation is that with the introduction of AVs in real-life networks, an increase in congestion can be observed similar to the theoretical insights obtained in a single link setting such as the bottleneck model. However, in a network with multiple links and the ability of rerouting, this may lead to more cut-through traffic. Additionally, it is expected that the underlying road network will be used more intensively as congestion increases due to the reduced aversion to longer travel times by AV owners. On the other hand it might be that the inclusion of multiple routes reduces the increase in congestion at certain bottlenecks since traffic can disperse. Moreover it is the belief that non-AV users will have to deviate more from their preferred departure times as they show a greater aversion to longer travel times. Based on previous work it is expected that Home AVs will shift the congestion more to the beginning of the peak and Work AVs more the end of the peak. These effects are assumed to be dependent on the penetration rate of AVs. It is the belief that the higher this penetration rate, the more congestion will increase and the more non-AV users will have to deviate from their preferred departure times.

To incorporate all aspects within the context of this study and to answer this question in a structured way, the following sub-questions have been formulated:

1. What should be the parameters associated with the extended $\alpha - \beta - \gamma$ model?
2. How can the extended $\alpha - \beta - \gamma$ model with on-board activities be incorporated in a traffic simulation model?
3. What will be impact of changing scheduling preferences regarding departure time choice?
4. How sensitive are the simulation outputs to the model parameters and penetration rates of AVs?

1.2. Research objectives & scope

The overall objective of this research is twofold. First, the aim is to integrate the extended $\alpha - \beta - \gamma$ model within an existing framework of a traffic simulation model. Second, the goal is to use the adapted framework on a case study area to assess the network effects. The main contribution this research aims to bring is providing key insights in network effects of AVs resulting from activity based departure time choice.

The main focus of this research are the effects related to the departure time choice. Therefore the only differentiation between vehicle types is the mathematical formulation of the scheduling preferences. This means that no heterogeneity amongst travellers is included. Furthermore, all commuting travellers use the same network characteristics.

This research only looks at full automation (L5 SAE). Although this is a far stretch from reality and it would be interesting to investigate the effects with a lower level: high automation (L4 SAE), there are some associated difficulties with implementation and analysis of this type of automation. When considering high automation, an Operational Design Domain (ODD) will have to be defined. This means defining which part of the trip the vehicle is able to autonomously perform the driving task and thus the user is able to perform on-board activities. For instance, one might suggest that the middle 80% of the trip can be assigned to on-board activities and within the first and last 10% the user takes control. Or it could be that only the main road network is suited for these vehicles to drive autonomously. This implies more complexity within the model and since the research already focuses on a quite specific domain, including an ODD results in a less generalised case.

In addition, incorporating an ODD will result in changes in route choice. It is often desired to have a consecutive ODD, which enables the possibility to perform on-board activities without any interruptions. Therefore, this type of AV might choose to use the main road network as long as possible which implies a change in route choice. Thus, including the ODD results in a possible change in route choice, which is actually an indicator we are interested in based on presumed change the departure time choice. The analyses of the results, especially with regard to route choice, will become less justifiable.

Moreover, the aim of this research is not to look in to the effects of lower levels of automation, such as a presumed change in route choice associated with the ODD. However, the objective is to investigate the effects of on-board activities and associated change in departure time on network congestion patterns. Thus, this research will only include full automation since the incorporation of lower levels of automation will result in more complexity, less generalised and ambiguous results and does not necessarily serve the aim of this research, except for the more realistic aspect.

This research uses a case study area which means focusing on a specific road network with its own characteristics and limitations. This must be regarded when assessing the level of generalisability of this study's outcome. A detailed description of this network and related assumptions will be given in 4.2.1.

Now that the objective and scope have been defined, the next section will elaborate on which key elements this research aims to assess.

1.2.1. Assessment framework

In order to conduct this research in a manageable amount of time, while at the same time preserve a level of generalisability, an assessment framework is defined. This section presents the set of elements which will be investigated in this research. Within the assessment framework, a distinction is made between behavioural, network and external effects. It must be noted that most of these indicators require a distinction between the type of road and AV/non-AV users. This is done to relate this research to the policy perspective: who benefits and who loses? Note that with AV users, a distinction is also made per AV type (Home, Universal, Work).

Behavioural effects
Behavioural effects are those effects which relate to the choices that individuals make. This means a person may select a specific time and route for making his trip. This choice may differ if the individual can use an AV. The following elements have been identified:

- **Departure time choice**
  This indicator provides insight in peoples preferences to departure time and the change in behaviour to depart earlier or later is captured. On an aggregate level the resulting departure time profiles are analysed. A distinction is made between AV and non-AV users.

- **Route choice**
  This indicator is used to assess the route choice between AV and non-AV-users. The route choice is investigated on road type level. AV users might experience less aversion to congested routes whereas non-AV users might prefer the less popular uncongested routes. Based on the VKM per road type, this choice and the observed differences with a reference scenario are assessed. A distinction is made between road types and between AV and non-AV users.

Network effects
Besides the behavioural changes, the simulation brings insight in the effects on the network outputs. These network effects follow from the behavioural effects and the associated choices that people make. The following elements have been identified:

- **Travel time**
  This indicator which will be used to explore the difference between total network travel times of AV and non-AV users. It is expected that AV users will spend more time in the system but the extent to which is unknown. In addition, the delays will be investigated since these give a better understanding and more nuanced result of congestion increase. A distinction is made between AV and non-AV users.

- **Traffic flows**
  This indicator shows the increase or decrease of traffic flows on certain areas within the network. It provides insight in the popularity of certain link types and shows if congestion will increase or decrease at certain locations. A distinction is made between AV and non-AV users.

External effects
External effects relate to those effects which are a presumed consequence of the direction and size of the behavioural and network effects. For this research they will not be quantified. However, their relation to the simulation results will be discussed since they are important indicators for improvement or deterioration. The following external effects have been selected:

- **Traffic safety**
  Traffic safety is often related to exposure and risk. It depends on the total VKM on certain link types (i.e. main road network or underlying network). More traffic on the urban road network and equal or less on the motorways often means more risk and therefore less traffic safety. Vice versa, more traffic on the main roads and less on underlying road network is often associated with a better traffic safety (Poppe, 1996; Janssen, 2005). The traffic safety will therefore be related to the VKM per road type. A distinction is made between the motorways, provincial/distributor and urban roads. In addition, a different level of safety may be associated with AVs (on certain road types). Therefore a distinction will be made between AV and non-AV users.

- **Emissions**
  Emissions is an element which is considered of great importance these days. Although this research will not provide exact numbers on the amount of produced CO_2, NO_X or PM10, it is aimed at assessing their relation to the resulting network effects. Air emissions are often determined by a general formula which is a multiplication of an emission factor with VKM (Wismans, van den Brink, Brederode, Zantema, & van Berkum, 2013). This means that more VKM results in an increase in emissions. But also, more congestion often means an increase in emissions. This indicator depends on the VKM and congestion per road type. A distinction will be made between the main road network and the underlying road network. In addition, roads within urban areas will be selected to investigate the number of VKM and congestion and relate this to an increase or decrease in noise pollution. Lastly, it might be that AVs may adopt an eco-driving system in congested situations. Therefore, a distinction will be made between AV and non-AV users.

1.3. Research approach & methodology

Based on the research questions and objectives, we can design the methodology. This section presents the methodology used to carry out this research. This study primarily uses two methods: a traffic simulation model and a case study approach. As stated by Dooley (2002), simulation enables studying more complex systems because it creates observations by “moving forward” into the future. Effects or phenomenons have not (yet) occurred can be captured with the use of the right models and simulation tools. That is why using a traffic simulation model as a method is perfectly suited for studying the congestion patterns in the AV era, of which the effects are *a priori* unclear. In addition, a case study approach is chosen to assess the congestion effects within a representative and as much as possible real-life environment. This section starts with a description of the research steps and relations between them in 1.3.1. Hereafter, the two main methods: the traffic simulation model and the case study, will be described more in-depth in section 1.3.2 and 1.3.3 respectively.

1.3.1. Approach per sub-question

This section will discuss the overall methodology of this research. A schematic overview of the methodology approach is given in Figure 1.1 in which the elements have been related to the chapters within this document. In the figure, the steps related to the sub-questions have been depicted with light blue boxes. The arrows in between boxes are used to show the consecutive relations between process steps. The dotted horizontal lines are used to indicate the research phases.

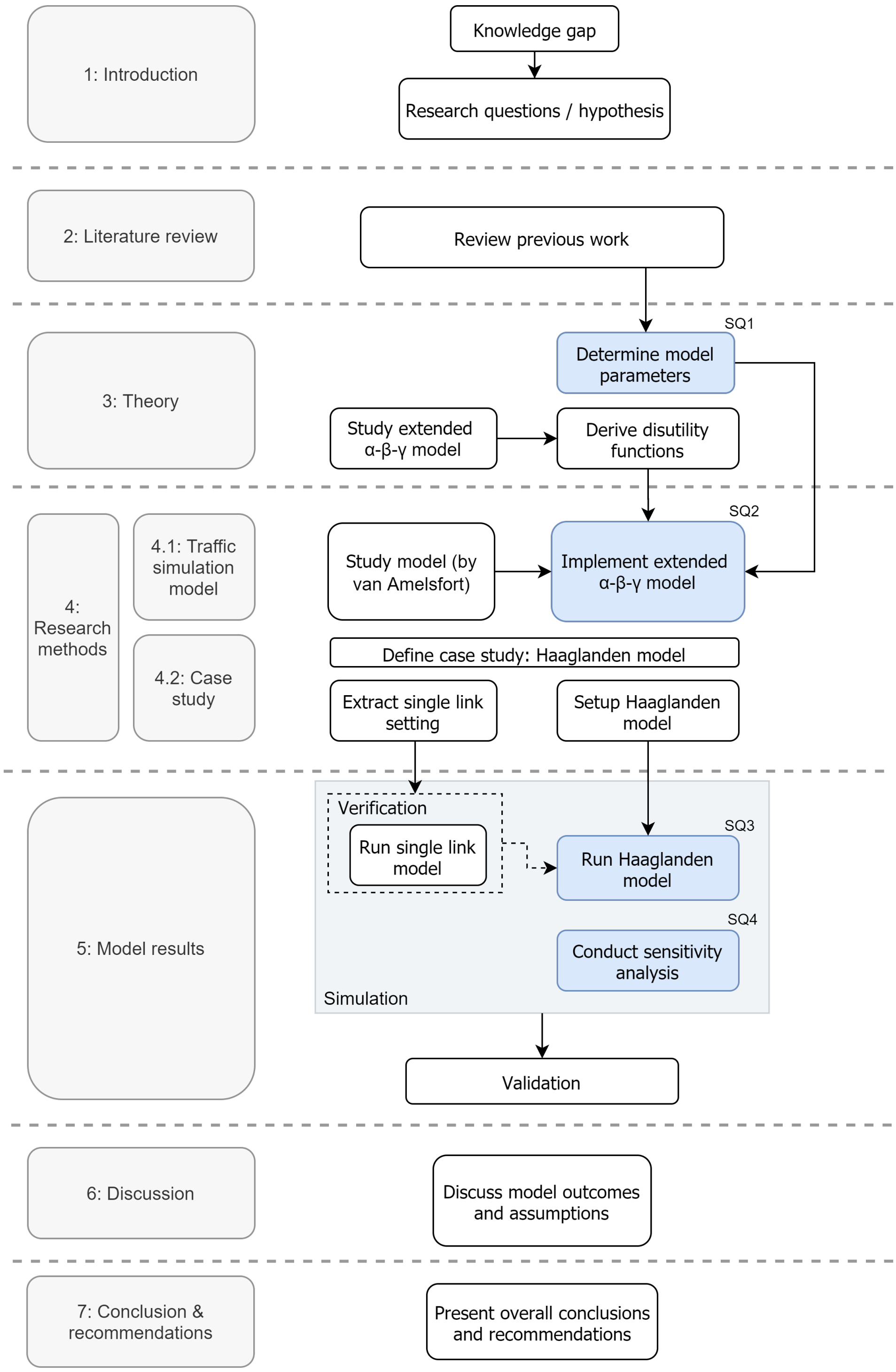


Figure 1.1: Schematic overview of methodology and research steps

The first phase of this research comprises of identifying the research gap and define the research questions as presented in 1.1. This is followed by a literature review in chapter 2 to present the findings of previous and relate this research to the existing literature. The aim of this literature review is to elaborate on which theories and methods have been used in relation to this topic.

The next step comprises studying the theory of the $\alpha - \beta - \gamma$ model, presented in chapter 3. This provides the required insights for implementation within the simulation model. Furthermore it briefly reviews the model parameters used in other studies, which relates to the first sub-question.

SQ1. What should be the parameters associated with the extended $\alpha - \beta - \gamma$ model?

These parameters are determined using previous work from, among others, Pudāne (2019) but also research on the Value of Travel Time (VTT) in relation to on-board activities in AVs to arrive at substantiated values for both the $\alpha - \beta - \gamma$ parameters as well as the efficiency factors e_h and e_w. It is important to notice that there is not one single correct set of parameter values to adopt. The focus of this research is not to obtain the most correct parameter values. However, investigation of the parameters with previous work is important as the margins in which these parameters are determined will define an upper and lower bound for the sensitivity analysis. Even though this can be seen as part of the literature review, it is placed within theory chapter (section 3.3), to logically follow from the theoretical background.

Hereafter, a detailed study of the traffic simulation model is needed. The model which is used during this study uses the existing framework build by van Amelsfort (2009). A detailed description of this model can be found in chapter 4. To get acquainted with the modelling architecture, the thesis document by Zantema (2007) and the PhD report by van Amelsfort (2009) is used. Getting insight in the modelling framework provides an understanding of the possibilities and limitations regarding the integration of the extended $\alpha - \beta - \gamma$ model within his model. This relates to the first sub-question:

SQ2. How can the extended $\alpha - \beta - \gamma$ model with on-board activities be incorporated in a traffic simulation model

To successfully reconcile the extended $\alpha - \beta - \gamma$ model within the existing framework, a mathematical integration is needed. A detailed description of this integration is provided in section 4.1.4. Following from this mathematical formulation, the modifications to the existing departure time module can be made. This means incorporating the obtained results from rewriting the extended $\alpha - \beta - \gamma$ within the modelling framework. This entails the adjustments of some of the existing programming scripts within the departure time module. This way the effect of on-board activities can be included with the mathematically rewritten $\alpha - \beta - \gamma$ scheduling preferences. A schematic overview of the modelling framework can be found in section 4.1.

After having successfully adjusted the departure time choice module, the network(s) on which the simulation model is used can be defined. Before jumping into a 'bigger network', first a small toy network is used to enable early analyses and verification of correct implementation of the model. Initially this network is restricted to only follow a single link setting, i.e. one origin, one destination and one link with a certain capacity. This is done to assess if the theoretical closed-form results of flow rates and travel times, as obtained by Pudāne (2019) correspond to what can be observed from the simulation model. This way, correct integration can be verified before applying the model to the bigger network in which it is more difficult to figure out if the model is functioning properly. By using this single link setting, not only first analysis on the potential effects is provided. It also enables assessing the possibility of running different scenarios, and the implementation of user classes: Non-AV, Home AV, Universal AV and Work AV. The 'bigger network' refers to the case study area of the Haaglanden region which will be addressed in more detail in section 4.2.

The next phase comprises the actual simulation by executing the traffic simulation model. An overview of the experimental setup which presents all simulation scenarios and desired outputs, can be found in section 4.2.6, after which chapter 5 presents all simulation results. First, the single link network is run with the implemented $\alpha - \beta - \gamma$ preferences for each mode specific. These model outcomes are recorded and can be found in section 5.1. This verification step is carried out to check whether the simulation model is actually doing what is expected. This is executed in the toy network to enable a relatively straightforward analysis regarding right implementation of the extended $\alpha - \beta - \gamma$ model. This way any incorrect modelling can be eliminated. The verification step is depicted in Figure 1.1 with a dotted outlined box. Once the model is verified, the simulation is run on the network of the case study area. The simulation outputs regarding this network relate to sub-question 3:

SQ3. What will be impact of changing scheduling preferences regarding departure time choice?

This question is answered with the use of the assessment framework, as presented in the previous section. We distinguished three perspectives, namely behavioural effects, network effects and external effects. The behavioural effects are the underlying reason we can observe impacts on the network and they comprise the main elements of the above question: departure time and route choice.

The impact on departure time choice is the main focus of this research and is investigated primarily by looking into the departure time profiles outputted by the model. In addition, three different Origin-Destination pairs (OD pairs) are selected to study these profiles on OD level. This is done to enable a better understanding of the results on specific network levels/road types. The departure time profiles for the entire network gives an aggregated result which can make interpretation more difficult and incomplete. The selection of these OD pairs and their main characteristics will be discussed in section 4.2.1.

Route choice is investigated by looking into the change in VKM, especially regarding the different road network levels. As discussed, we can differentiate between a main road network and an underlying network. To investigate the impact regarding route choice we will distinguish three road types: motorways, provincial/distributor roads and urban roads. These types and their characteristics will be discussed in more detail in section 4.2.1.

To provide a broader context for interpretation of the results, we look into the second perspective of the assessment framework: network effects. Network effects are those effects which can be directly observed from the simulation outcome and are a result of the underlying behavioural changes. One of the most important elements we are interested in is the impact on congestion. This can be captured with observing changes in travel times but more importantly the experienced delays. Furthermore, the location of congested areas is important. Therefore we will look into traffic flows in the network, to identify congested links and observe changes.

Lastly, the model results will be related to the third perspective in the assessment framework: the external effects. These effects follow from changes in route choice and congestion patterns. Although we will not quantify the external effects, the outcomes with regard to route choice as well as some of the network KPIs, such as total travel time, will be linked to safety and emission aspects.

Lastly, it is important to assess the sensitivity of the model to (slight) changes in the parameters and some of the assumptions that are made. Therefore, a sensitivity analysis is carried out, which relates to the fourth sub-question:

SQ4. How sensitive are the simulation outputs to the model parameters and different penetration rates of AVs?

The most important set of parameters which requires a sensitivity analysis, are the $\alpha - \beta - \gamma$ parameters and the associated efficiency factors. By means of running multiple simulations with different parameter values between the explored margins and the analysis of the results, this question is answered. The (ratio of) efficiency factors e_h and e_w might even be more important than the $\alpha - \beta - \gamma$ parameters since less is known on this perspective (Personal communication B. Pudāne). Both will be investigated to assess their influence on the simulation results.

In addition, the simulation outcomes regarding the congestion pattern and its sensitivity to different penetration rates of AVs is assessed. Through running the simulation with several distinct penetration rates, this aspect is addressed, meaning the direction and size of adjustments to this parameter are explored. The sensitivity runs will comprise five levels of penetration rates, namely 0%, 25%, 50%, 75% and 100%. It might be that the effects will only occur in a certain range of this parameter. However, due to time limitations this region is not explored in more detail. Note that this sensitivity analysis will only be carried out with the Universal AV type, since we assume that it is more likely for these type of AVs to be present in the future rather than Home and Work AVs, which have mainly been defined to distinguish between the type of activities.

After the simulations have been run and the outputs retrieved, the model is validated. This “validation concerns whether the simulation is a good model of the target” (Gilbert & Troitzsch, 2005). During this stage the simulation outcomes will be validated to check whether these correspond (to a certain extent) with the the expected outcomes. Because this research focuses on future effects which are not yet detectable, we are unable to compare the results with real life situations. We have to rely on theory and the effects we do observe within the field of AVs. A face validity check is carried out to assess the hypothesis with the actual results and if they can provide validation to a certain extent. Validation is be done in consultation with supervision from DAT.Mobility. A critical view on the validation is required to identify the reasons for a successful (or not) validation.

Hereafter, the model results are discussed and related to the assumptions and broader perspective of this study in chapter 6. Lastly, chapter 7 gives the overall conclusions and recommendations for further research.

1.3.2. Traffic simulation model

For this study, a simulation model is used. These models are meant to answer questions related to topics which have a dynamic, quantitative and above all uncertain character. As this research entails investigation of such uncertain dynamic future events and the associated effects, a traffic simulation model is a suitable method. The model which is used work with OmniTRANS 4.2.35 and is provided by DAT.Mobility. This model combines departure time and route choices and operates using a Dynamic Traffic Assignment (DTA) module (INDY). The application cases can progress from simple toy networks to real networks (e.g., Haaglanden area), which are already modelled in the simulation tool. The traffic simulation model uses the modelling framework which builds on the work by van Amelsfort (2009). This is applied within the case study area on the basis of data from this area. With these data the simulation model should be able to calculate the traffic flows on network, link and OD level. Since a simulation model is used, several simplifications need to be made. These are listed in section 4.2.5. A more in-depth description of the working of the several modules can be found in section 4.1 on the modelling architecture.

1.3.3. Case study approach

In order to assess the effects of the implemented extended $\alpha - \beta - \gamma$ model, we will use a case study approach. This way we are able to investigate a situation which represents a real-life road network to test the effects of activity based departure time choice with AVs. The area of this cases study is the road network of the ‘Haaglanden’ region. Within this region the following three road types can be identified: Motorways, provincial/distributor roads and urban roads. Home zone streets are not included. Distinguishing between these different road categories is especially useful when analysing the results and assessing certain indicators in the assessment framework as described earlier. By using a specific area, the results will have a limited generalisability. Meaning that, once you observe effects in the ‘Haaglanden’ region, you can not simply draw conclusions for other regions as well. A critical view is required considering this aspect. Section 4.2 gives a more detailed elaboration on the case study area, its characteristics and limitations.

2 Literature review

This chapter presents a concise literature review of previous work. The aim of this chapter is to evaluate research within the field of AVs and departure time modelling using scheduling preferences. In addition it gives insight in how this topic has been researched in the past; which theories and tools such as transport modelling studies were used? Lastly, this chapter is helpful to indicate how earlier published work relates to this research and to identify the literature gap.

2.1. AVs and projected trends

Until not that long ago, driving has been something which was exclusively preserved for humans. However, over the past decades car manufactures have been actively engaged with developments of vehicle automation. The estimations and projected trends regarding the level of automation and penetration rates of AVs differ quite extensively. As projected by Lutin (2018), level 4 will be generally available by 2025 and level 5 (SAE International, 2018) in approximately 10 years. In addition, it was estimated that AVs would reach 9% of sales in 2035 and a penetration rate of 90% within 20 years that followed. A similar optimistic projection was given by members of the IEEE, who anticipated that up to 3 out of 4 vehicles could have full automation within the next 20 years (IEEE, 2012). However, there is also some restraint. Gomes (2014) stated that a significant number of experts present at the automated vehicle conference in 2014, did not expect to see level 4 until 2030 and some not until 2040 (Greenblatt & Shaheen, 2015). So there is some disagreement on when AVs will become generally available. An inquiry among Dutch car owners presented that only 17% of the respondents expects to use an AV and that 75% was not planning to drive an AV in the future (van Wijngaarden, 2020). However, there is no doubt that manufacturers will continue developing AVs, thus getting to higher levels of automation and indirectly increasing penetration rates. This trend stimulates research on the effects and associated impact of widespread AV implementation.

2.2. On-board activities

The rise of the AV may bring many opportunities. These self-driving cars could change our way of transportation and are expected to bring many positive effects, such as better road/vehicle safety, increased comfort and productivity due to the travel time being spend more effectively (Pudāne et al., 2019). On the other hand, they might also bring negative effects, such as an increase in congestion.

The ability to perform on-board activities is something which has not been associated with privately owned vehicles. Compared to public transport, in which more and more people use their phone or laptop to be more productive during their trip, driving privately owned vehicles does not (yet) offer this possibility. However, with AVs an individual can choose to perform on-board activities which reduces the disutility of his/her travel. This way, travelling can be, to a certain extent, spend productively other than just being a necessary transportation from one location to another.

Impacts on Value of Travel Time Savings

When discussing the disutility of travel in relation to on-board activities, most research has been focused on determining the reduction of the VTT. (Molin, Adjenughwure, de Bruyn, Cats, & Warffemius, 2020; Correia, Looff, van Cranenburgh, Snelder, & van Arem, 2019; Pudāne & Correia, 2020; Fosgerau, 2019) However, many research conducted in this field has been based on the conventional use of a single travel time penalty, in which it is assumed that the time spent during travel has a lower utility when on-board activities can be performed (Steck, Kolarova, Bahamonde-Birk, Trommer, & Lenz, 2018). This penalty is time-independent. However, these models neglect the fact that the possibility of performing on-board activities, will affect a traveller's daily program (Pudāne, Molin, Arentze, Maknoon, & Chorus, 2018). In addition, this penalty induces that no differentiation is made between the type of on-board activities (Pudāne et al., 2019). Although, some work has found varying changes in the VTT (or penalty) depending on various on-board activities (Molin et al., 2020). They found a reduction in VTT of 30% for commuters, in which they also differentiated among the type of activity and an even higher percentage (50%) reduction for leisure trips.

Moreover, a stated choice experiment has been conducted by Correia et al. (2019) especially designed for measuring the VTT and analysed with discrete choice modelling. They distinguished between AVs with office interior, leisure interior and a conventional car. It was found that the VTT with office interior turned out to be lower with a conventional car. However, the VTT of the leisure interior car did not decrease. Pudāne and Correia (2020) revisited the theoretical underpinnings of the reduced VTT and found that, in both work and home activity facilitating vehicles the VTT depends on the facilitation level.

In addition, we should be critical towards adopting a reduction in VTT associated with AVs and especially its source. As stated by Singleton (2019), many on-board activities may nowadays be more about dealing with the "burden" of commuting travel than spending travel time in a productive way. (Shaw, Malokin, Mokhtarian, & Circella, 2019) go even further by saying that "people might also experience disadvantages based on the fact that travel-based multitasking may not uniformly increase trip utility". This could imply a smaller reduction in VTT than anticipated. However, this study builds on the idea that the ability to perform in-vehicle activities covers a considerable part of the advantages associated with AVs. Although, in the form of $\alpha - \beta - \gamma$, a utility drop will be adopted to cover the reduction in VTT.

Impacts on travel behaviour

Besides the fact that the ability of performing on-board activities might reduce the disutility of travel time, many of the automation's potential effects can be assigned to a change in travel behaviour. However, how easily will behaviour be affected? The extent to which, for example mode choice, is subject to the level of productivity while travelling has been studied by Malokin, Circella, and Mokhtarian (2019). They looked into these changes with the use of revealed preferences and concluded that greater perceived multitask-ability of a mode increases that mode's utility which, if we relate this to vehicle automation, implies less aversion to longer and more trips.

Kim, Mokhtarian, and Circella (2020) did also look into the (short-term) effects on mode choice. They investigated impacts on activity patterns and the impacts on changes in behaviour with a focus group of residents in Georgia. It was found that some of the expected medium-tern effects (i.e. change in activity pattern) influenced the long-term changes.

However, with limited availability of empirical data, models and simulations are widely used to make assessments on the potential effects. Soteropoulos, Berger, and Ciari (2019) provided a comprehensive review of several modelling studies. They identified the main effects from two perspectives: impact on travel behaviour and impact on land use. Regarding travel behaviour, the results indicate that AVs will bring an increase in VKM, and shift in mode share from public transport and slow mode shares to AVs, which is associated with an assumed high reduction of VTT.

An attempt has been made to assess if these effects could also be observed on an empirical basis.

Harb, Xiao, Circella, Mokhtarian, and Walker (2018) mimed a situation in which people experienced possessing a privately owned AV by providing a free chauffeur service. This study provided key insights in the behavioural aspects and although it does not show the (net) effects of vehicle automation on a system, it resembles, as much as possible, the situation in which households do privately own self-driving cars. This experiment showed again an increase in VKM and number of trips (with a substantial portion of empty trips). Similar trends were observed by Milakis et al. (2017). They presented a literature review which explored, among other things, the potential change of these travel choices. Research showed that AVs could lead to "an increase of travel demand between 3% and 27%, due to longer trips and more trips and a modal shift from public transport and walking to car."

Several studies were also conducted to assess the shift in behaviour regarding route choice. Although it difficult to say how strong the effects are, it was found that AVs may bring less aversion to longer routes since individuals have the ability to be productive during the trip. A related increase in VKM has therefore been observed in multiple modelling studies (Childress, Nichols, Charlton, & Coe, 2015; Thakur, Kinghorn, & Grace, 2016; Correia & van Arem, 2016; Chen, Kockelman, & Hanna, 2016; Auld, Sokolov, & Stephens, 2017; Emberger & Pfaffenbichler, 2020). Many of these studies used transport models with a DTA to investigate network effects. However, they were based on a single time independent VTT reduction.

Impacts on congestion

The changes of travel behaviour indicate a reduction in aversion to long trips, i.e. people experience less disutility of travel time. This implies that individuals with self-driving cars might be less affected to (peak) congestion. As a consequence they adjust their scheduling preferences to arrive closer to their preferred arrival time - associated with longer travel times - resulting in increased congestion. However, the effects are highly dependent on exact penetration rates and the level of automation which is considered and more importantly, they depend on the assumed changes in travel behaviour which may or may not include a change in departure time. For instance, if commuters engage in working activities during their morning trip, they might prefer to depart later since they can be productive, to some extent, during their trip. Others may choose to sleep during their morning trip but therefore prefer to depart earlier. With the use of a single time-independent penalty for travel time, these changes in departure time preferences and their impact on congestion could not have been predicted.

Therefore, another approach has been used by van den Berg and Verhoef (2016) in which they let the utility during trip differentiate by means of the $\alpha - \beta - \gamma$ preferences within the bottleneck model. They assumed that any on-board activity contributes to a decreasing travel penalty and found that congestion is likely to be more severe with AVs than with conventional vehicles. However, they did not differentiate between the type of activity. Therefore, Pudāne (2019) proposes another approach in which she differentiates among on-board activities and uses the $\alpha - \beta - \gamma$ scheduling preferences to incorporate the utility reduction related to these activities within the bottleneck model (Vickrey, 1969). These $\alpha - \beta - \gamma$ preferences have also been used by Yu et al. (2019) to analyse congestion patterns with AVs. They distinguished vehicles in which home/leisure and work activities were more easily performed, similar to Pudāne (2019) who identified three types of AVs: Home, Work and Universal AVs. Home AVs are vehicles in which home activities can better be performed, Work AVs are vehicles in which work activities can better be performed and Universal AVs are vehicles which are best suited for both types of activities. Both theoretical studies (Yu et al., 2019; Pudāne, 2019) in this single link setting led to the following conclusions:

- If home activities can better be performed in (home) AVs, modelling shows that travellers may shift to the begin of the congestion peak, i.e. depart earlier. Vice versa, if travellers are able to better perform work activities, theoretical results show they might prefer to depart later.
- These results also indicate congestion could increase with the introduction of automated vehicles. Because travellers experience less aversion to longer travel times, due to on-board activities, they will prioritise arriving at or near the preferred arrival time over longer travel times, which increases

congestion.

- Lastly, if home, work and universal (home/work) AVs are available, work AVs would increase congestion the least in a single link setting.

Conclusion
Based on this literature review, it can be concluded that a lot of research has focused on the potential effects that self-driving cars will bring. Regarding the congestion effects, many modelling studies have used the VTT as a measure to relate (dis)utility of travel time to vehicle automation within real-life road networks (Childress et al., 2015; Thakur et al., 2016; Correia & van Arem, 2016; Chen et al., 2016; Auld et al., 2017; Emberger & Pfaffenbichler, 2020). However, this assumes a single time-independent travel time penalty. Several studies have therefore adopted other approaches using the $\alpha-\beta-\gamma$ preferences to incorporate the time varying (dis)utility and the effects on the associated departure time choice within a theoretical bottleneck setting (van den Berg & Verhoef, 2016; Pudāne, 2019; Yu et al., 2019). These effects however, remain unclear for bigger real-life networks. Specifically considering the inclusion of trip making choice and route choice which brings the possibility to assess congestion effects with a more real-life characteristic.

In conclusion, we know how differentiating between performed on-board activities may change people's departure time preferences and how these could affect congestion from a theoretical perspective. However, it remains unknown how this will play out in a larger region. As far as we know, up to this point no modelling study has used the element of activity based departure time choice for AVs. Therefore, this research aims to investigate the effects of changing departure time preferences with the use of extended $\alpha-\beta-\gamma$ model (Pudāne, 2019) within a transport model using a DTA. The next chapter will elaborate on the theoretical background of the $\alpha-\beta-\gamma$ model and its extension to include the element of on-board activities. Hereafter, chapter 4 discusses the modelling framework and the case study to which the model assigned.

3
Theory

This chapter presents some necessary and useful theoretical background to understand the perspective of congestion patterns and scheduling preferences. It starts with the basic concept of congestion patterns and a brief introduction to the bottleneck model. Hereafter, the scheduling preferences are discussed, with in particular the $\alpha - \beta - \gamma$ model, which will be used in this study. Lastly, the model parameters as used in other studies are discussed briefly.

3.1. Bottleneck model

Vickrey (1969) distinguishes six types of congested situations: “simple interaction, multiple interaction, bottleneck, triggerneck, network and control, and general density.” Although these situation often occur in various combinations, only the bottleneck situation will be discussed in more detail, since this was also used as the basis for the research of Pudāne (2019) which led to the theoretical results with the $\alpha - \beta - \gamma$ preferences.

As stated by Vickrey (1969), the pure bottleneck is a situation in which we have a fixed capacity on a short route segment which is considerably smaller, in relation to the traffic demand, than the previous and successive route segments. As long as the traffic flow is lower than the bottleneck capacity, there will be relatively little delay, except for the fact that small variations can occur due to the stochastic variations in the amount of traffic flow. However, when traffic flow continuously exceeds the capacity, delay will increase significantly. This will either stop if the traffic flow will be lower than the capacity for a certain period, if traffic disperses to other routes, if individuals opt to travel at other times (i.e. changing their departure time) or enough individuals choose not to make the trip at all.

When investigating possible congestion effects of on-board activities with AVs, the bottleneck model is particularly useful. Since the introduction of this model (Vickrey, 1969), it has been widely used to study various aspects which influence congestion (Small, 1982).

Although, the bottleneck situation in itself is not a perfect representation of the general congestion patterns, it does enable closed-form analyses which can be used to acquire knowledge on how congestion evolves. This can be used to assess disutilities in travelling at certain times via certain routes. For instance, when in a specific period the link capacity is lower than the traffic flow in that same period, not all travellers are able to arrive at their destinations at their preferred arrival times. Some of them will have to arrive earlier or later than preferred. However, these travellers will in general experience less time in the queue. The travellers arriving the closest to their preferred arrival times, will spend the most time in the queue. This trade-off between travel times and preferred departure/arrival times is captured with scheduling preferences.

3.2. Scheduling preferences

In the most general form, scheduling preferences can be described with utility functions of both home and work activities. Vickrey (1973) assumes that the utility of home activities can be described with a positive monotonously decreasing function and work activities with a positive monotonously increasing function. In the conventional way, the time between home and work (travel time) does not include any utility since one can not perform any activities or make the travel useful. However, once the individual can participate in activities during his/her trip, as with fully AVs, the situation become different. This way, the utility during trip time T is not zero but can be described as a loss in utility.

Within the bottleneck setting, a useful method to study the congestion effects has been the use of $\alpha - \beta - \gamma$ preferences. This model provides a conservative estimation for changes in congestion patterns. (Arnott, De Palma, & Lindsey, 1990) used these preferences to investigate the congested patterns for conventional vehicles. Arnott et al. (1990) assume a perfect balance between the penalty for departing early or late and the disutility associated with longer travel times. In the end these gained and lost utilities for all will cancel each other out and the total for all travellers is in balance. The $\alpha - \beta - \gamma$ scheduling preferences assure a closed-form solution which is suitable for analysing the equilibrium flow rates, i.e. the number of commuters which depart at given time moments as obtained by Arnott et al. (1990). Therefore, from now these scheduling preferences will be used for this study. For consistency reasons, a similar notation is used as in Pudāne (2019).

3.3. α-β-γ model

The $\alpha - \beta - \gamma$ model is a very fundamental, theoretical, economic framework. The model entails the most widely used scheduling preferences (Vickrey, 1969; Small, 1982). It basically says that, similar to the general scheduling preferences, the departure time choice is determined by our value of being at home or at work. A person will try to schedule the departure at such a moment that he/she loses the least value of being at these places. Pudāne (2019) states that, because individuals can do either home or work activities during travel, this directly enters this equation of how much we lose at every time during the morning by being on the way. If we lose more on the home activities or more on the work activities then we will find a different optimum time to depart. In the $\alpha - \beta - \gamma$ model we can specify the home utility rate $h[x]$ to be constant (eq. 3.1) while the work utility rate $w[x]$ follows a step function (eq. 3.2):

$$h[x] = \alpha \tag{3.1}$$

$$w[x] = \begin{cases} \alpha - \beta, & if x \leq t* \\ \alpha + \gamma, & if x > t* \end{cases} \tag{3.2}$$

In this formulation, α is the utility associated with performing activities at home. β and γ represent the utility differences with this home utility when performing work activities before or after the preferred arrival time t^* respectively. Meaning, prior to the preferred arrival time, the utility of work activities equals $\alpha - \beta$ and after the preferred arrival time the utility equals $\alpha + \gamma$. These parameters are constant and positive. Furthermore, we assume the following relationship: $\beta < \alpha$.

Extended α-β-γ model

If we take these preferences and use them for AVs, we need to include the possibility to be productive during trip. Therefore, the $\alpha - \beta - \gamma$ model has been extended with the use of efficiency factors (Pudāne, 2019). Figure 3.1 shows a schematic representation of the extended $\alpha - \beta - \gamma$ scheduling model and the associated utility functions. Note that this corresponds to a Universal AV, which will be explained in more detail in the next section.

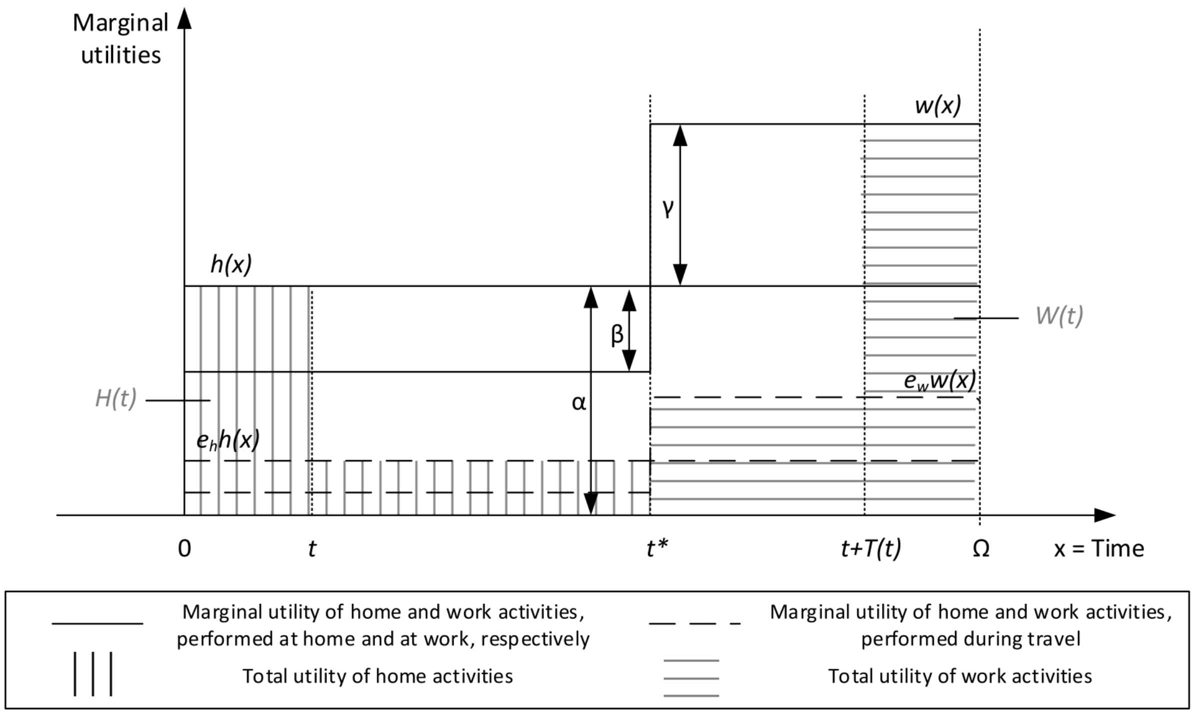


Figure 3.1: $\alpha - \beta - \gamma$ scheduling preferences utility functions with a Universal AV, retrieved from Pudāne (2019)

The figure shows the step-wise utility formulation as function of time x between interval $[0, \Omega]$. Within this interval, the departure time is given as t, preferred arrival time as t^*, the travel time as T and thus the arrival time with $t + T(t)$. The vertical and horizontal lined areas represent the total utilities associated with home and work activities respectively. It can be seen that prior to this person's departure time t, the home utility is equal to α. Once this person has left home, he/she can engage in on-board activities. This utility is however, assumed to be lower than the utility associated with performing the activity off-trip, due to the fact that the in-vehicle environment will not be as productively usable as at being at home or work. This loss is expressed with efficiency factors e_h and e_w for home and work activities respectively. As Pudāne (2019) states: "These factors are such that until t^* it would be optimal for one to engage in home activities and after time t^* it would be optimal to switch to work activities." This can be described as: $e_h h[x] > e_w w[x]$ for $x \leq t^*$ and $e_h h[x] < e_w w[x]$ for $x > t^*$. Figure 3.1 illustrates the efficiency factors and this loss of utility during trip. After departure time t^* the individual engages in on-board home activities and therefore his utility $h(x)$ drops from α to αe_h. In this case, the individual arrives at work after his/her preferred arrival time. Therefore the remaining part of the trip, after t^*, will be used to perform work activities. The utility $w(x)$ associated with these work activities during trip is $e_w(\alpha + \gamma)$. Once the individual has arrived the utility $w(x)$ becomes $\alpha + \gamma$. Note that in a conventional vehicle the utility during travel would drop to 0 - considering this $\alpha - \beta - \gamma$ setup - as travel time can not be used to perform other activities than driving.

3.3.1. Home, Work and Universal AVs

Figure 3.1 illustrated the case of a Universal AV in which both home and work activities could be performed during travel. However, with the $\alpha - \beta - \gamma$ set-up we can think of different types of vehicles in which solely home or work activities can be performed. This way, the effects of having different types of on-board activities can be investigated. B. Pudāne distinguishes three types of AVs: 'Home AV', 'Work AV' and 'Universal AV'. These AVs are vehicles in which activities related to home, work or both (home/work) can best be performed, respectively.

The definitions of these vehicles regarding the $\alpha - \beta - \gamma$ set-up are as follows:

$$\alpha e_h > (\alpha - \beta)e_w \qquad \text{Home AV} \tag{3.3}$$

$$\alpha e_h < (\alpha - \beta)e_w \qquad \text{Work AV} \tag{3.4}$$

$$H(t) = \begin{cases} \alpha e_h, & \text{if } t < x \leq t^* \\ (\alpha + \gamma)e_w, & \text{if } t^* < x \leq t + T(t) \end{cases} \qquad \text{Universal AV} \tag{3.5}$$

Equation 3.3 and 3.4 show that, irrespective of departure time t^*, it is optimal for the individual to engage in home or work activities respectively, during the entire trip. For the Universal AV, Equation 3.5 ensures that it would be optimal to engage in home activities before t^* but switch to work activities after t^* till the end of the trip.

The situation described in Figure 3.1, is one in which an individual uses a Universal AV and arrives at his work late, i.e. later than his/her preferred arrival time t^*. This means that he/she leaves home at t and first engages in on-board home activities until the preferred arrival time t^*. Since this person arrives late, he/she can engage in work activities till the end of the trip time $t + T(t)$ is reached. The total utility of this person is depicted by the vertical and horizontal lined areas. Regarding the integration within the modelling framework, we are interested in disutilities and therefore the mathematical formulation of the $\alpha - \beta - \gamma$ utilities is rewritten. In addition, there are other scenarios we can think of in which a person arrives before the preferred arrival time or even leave after his/her preferred arrival time. These cases are further described in section 4.1.4 and a full derivation regarding the different disutilities per AVs type and departure/arrival scenario is given in appendix A.

It must be noted that in real-life there is heterogeneity amongst people's scheduling preferences. Some people are able to more easily engage in work activities during their trip based on their profession. For instance, a construction worker might not be able to engage in any work activities during travel and therefore does not have the ability to arrive later at his work. On the other hand, a businessman might be able to perform several business calls during his trip and therefore his schedule preferences are more substitute to this ability. The model does not take these differences into account and the used preferences with associated parameters are an average to approximate the generalised effects. A drawback is that the model's outcome does not give insight in these individual preferences. However, by looking at the generalised effects, the net congestion impacts of road users in general can can be shown. Therefore we assume that scheduling preferences amongst travellers are homogeneous and follow the extended $\alpha - \beta - \gamma$ model.

3.3.2. The extended α-β-γ model parameters

The extended $\alpha - \beta - \gamma$ model entails several parameters. This section is aimed at finding common values of those parameters in literature and the associated margins in which they can be varied. Even though this could be seen as part of the literature review, this is done after the theory has been discussed. This way the explanation of the $\alpha - \beta - \gamma$ model and associated parameter values follows a logical structure.

For $\alpha - \beta - \gamma$ model, both the schedule delay parameters α, β, γ and the efficiency factors e_h and e_w need to be determined. Rather than looking at the absolute values, the ratio between $\alpha - \beta - \gamma$ is determined, since these are effectively what is used in the model for calculations. As common in literature, the schedule delay parameters are often based on the ratios established by Small (1982) (β/α = 39/64 and γ/α = 1521/640).

Hjorth, Börjesson, Engelson, and Fosgerau (2013) estimate the parameters regarding different types of scheduling preferences. They distinguish between travellers with fixed and flexible working times and found that for travellers with fixed working times, a constant-step function, as the $\alpha - \beta - \gamma$ model, provides a better fit than people with flexible working times. This is consistent with the idea that arriving a bit to early or late while having fixed working times, is associated with an immediate change in utility. They present the following values for travellers with fixed working times: α, β, γ = 0.542, 1.03, 1.70. Regarding flexible working times the following was presented: α, β, γ = 1.31, 0.381, 0.492. This leads to the ratios β/α = 1.90 and γ/α = 3.14 for fixed and β/α = 0.29 and γ/α = 0.38 for flexible.

A stated preference experiment was conducted by Börjesson, Eliasson, and Franklin (2012) which was aimed at valuating travel time variability. They presented parameter values for both the step model ($\alpha - \beta - \gamma$) and the slope model. Regarding the step model, the following ratios were found: β/α = 0.68 and γ/α = 0.63.

Table 3.1 shows the parameter ratios used in these several studies.

Table 3.1: Ratios of $\alpha - \beta - \gamma$ model found in literature.

	Ratios	
Literature	β/α	γ/α
Small (1982)	0.61	2.38
van den Berg and Verhoef (2016)	0.61	2.38
Yu et al. (2019)	0.61	2.38
Hjorth et al. (2013) (fixed)	1.90	3.14
Hjorth et al. (2013) (flexible)	0.29	0.38
Börjesson et al. (2012)	0.68	0.63
Pudāne (2019)	0.5	2.0

It must be noted that there is not one single correct ratio to adopt here. Initially we will use the same $\alpha - \beta - \gamma$ ratios as used by B. Pudāne since this study follows her research and extension of the $\alpha - \beta - \gamma$ model. That means that the following set will be used: α, β, γ = 2, 1, 4.

However, based on these ratios in Table 3.1 and some sensitivity analyses conducted in these studies, we can define an upper and lower bound for β/α and γ/α. The following margins have been defined:

$$0.29 \leq \beta/\alpha \leq 1.90$$
$$0.38 \leq \gamma/\alpha \leq 3.14$$

Since it is assumed that arriving too late is associated with a higher disutility than arriving too early, $\beta < \gamma$. Table 3.2 gives the parameter ratios that have been identified for the sensitivity analysis. Note that the first column corresponds to the values as adopted from Pudāne (2019). The last column corresponds to a scenario in which $\beta > \alpha$, meaning that arriving to early gives you a negative utility. In other words, once you arrive to early you can not engage in work activities at work, and since we assumed that individuals will not remain in his/her car, you will be losing time doing nothing. Therefore, in hindsight we will not use this selection of parameter values for the analysis. Recall that this corresponds with our earlier assumed relationship $\beta < \alpha$ in 3.3.

Table 3.2: Ratios of $\alpha - \beta - \gamma$ model used for the sensitivity analysis

Parameter (ratio)	**Value**			
α	*2*	4	2.5	2
β	*1*	1.5	2	3
γ	*4*	2	3	6
β/α	*0.5*	0.375	0.8	1.5
γ/α	*2*	0.5	1.2	3

In addition to the $\alpha - \beta - \gamma$ parameters, the efficiency factors will need to be determined. As this is something which has not yet been investigated extensively, we will primarily rely on the values used by Pudāne (2019) which corresponds to e_h = e_w = 0.3. Although we assume a level 5 AV, this only implies that 100% of the driving task is taken over by the vehicle. It does not tell us anything on the productivity/efficiency levels associated with certain on-board activities. Since it is not yet known how well the in-vehicle environment is suited to perform activities other than driving, we will have to assume initial values and carry out a sensitivity analysis to investigate the impact of these initial selected values.

However, we can, to some extent, relate these factors to the extensively used VTT and its reduction with autonomous driving. Although it is not one-to-one comparable, it gives us a direction in which we might investigate these parameters. Steck et al. (2018) for instance, showed that the VTT dropped with 31% if people were in possession of an AV. This indicates that instead of 'losing' 100% of the travel time, the individual feels like he/she has used 31% of the travel time productively. Emberger and Pfaffenbichler (2020) defined a range of values found in other studies to be 5% to 50% (Wadud et al., 2016). This suggests that adopting a value of 0.3 does not extremely differ from values associated with VTT reduction. Again, this is not the same as an efficiency factor. It is merely an indication of the size of these parameters.

Then, if we look at the extreme cases: e_h, e_w = 0 and e_h, e_w = 1, the first one corresponds to a conventional vehicle and the second one resembles an AV in which you could be 100% productive. The first case is already captured by incorporating a reference case with only conventional vehicles. The second one would imply a situation in which there is no difference in valuation of spending time in-vehicle or at your origin/destination. This case is assumed to be stretched too far from reality and since it neglects the travel time component entirely, we will not include this. Instead the efficiency factors used in the sensitivity analysis will have values 0.3, 0.5 and 0.8, as shown in Table 3.3.

Table 3.3: Efficiency factor values used for the sensitivity analysis

Efficiency factor	**Value**		
Home e_h	0.3	0.5	0.8
Work e_w	0.3	0.5	0.8

4

Research methods

The previous chapter presented the methodology to answer the research questions and described two main methods: Traffic simulation model and a case study approach. This chapter will elaborate on these methods. Section 4.1 will explain the simulation model and its modelling architecture after which section 4.2 gives a detailed description of the case study area and its characteristics.

4.1. Traffic simulation model

This section starts with the more generalised concept of the transport modelling framework and its relation to the model as used in this study in section 4.1.1. This presents the overall framework of the model, including its specific elements, their function within the model and how they are related. Hereafter, the separate modules are described in more detail in section 4.1.2 to 4.2.5. In addition, the adjustments and mathematical formulations to incorporate the extended $\alpha - \beta - \gamma$ model within the existing modelling framework will be addressed. Finally, some model assumptions and their presumed impacts on the outcome will be addressed.

4.1.1. Overall framework

Within traffic modelling, there is often made use of the 5 step transport modelling framework (Ortúzar & Willumsen, 2011). This framework is depicted in Figure 4.1. Within transport models we often assume sequential choices which lead to the network loading and travel times. These are the 'travel cost' which are then used as input via a feedback loop as they influence trip destination, mode choice, departure time choice and route choice.

Within these models, the aim is to arrive at an equilibrium between travel demand and network supply. To reach this equilibrium, models are usually equilibrated 'from the inside out' (Brederode, 2015). This means that they start from the choice closest to the actual trip: route choice. This choice is combined with the network loading model incorporated in the assignment model, as shown in Figure 4.2. The network loading model results in route travel times which are the input for the route choice model. This results in the route demand which is then again used in the network loading model. After several iterations, the route choice equilibrium is reached. These lead to travel times per Origin-Destination pair (OD pair) and are used within the departure time choice model. This does also include, again using the assignment model since the departure time model results in updated travel times and costs. When the departure time choice equilibrium is reached, the OD travel times are used to iteratively reach mode/destination choice equilibrium, again using the both previously used models via feedback loops. After mode/destination choice equilibrium is reached, the updated OD travel times are used as input for the Trip making Choice Model. This iterative process is schematically shown in Figure 4.2. In a similar way these feedback loops are shown in Figure 4.1, depicted as horizontal arrows from travel costs into trip distribution, modal split, period allocation and the assignment.

This sequential modelling approach is based on the assumed response time to changed circumstances.

Each choice within this framework has its own response time. For instance, trip frequency choice is often decided upon years in advance, whereas route choice could be changed minutes or even seconds before the trip.

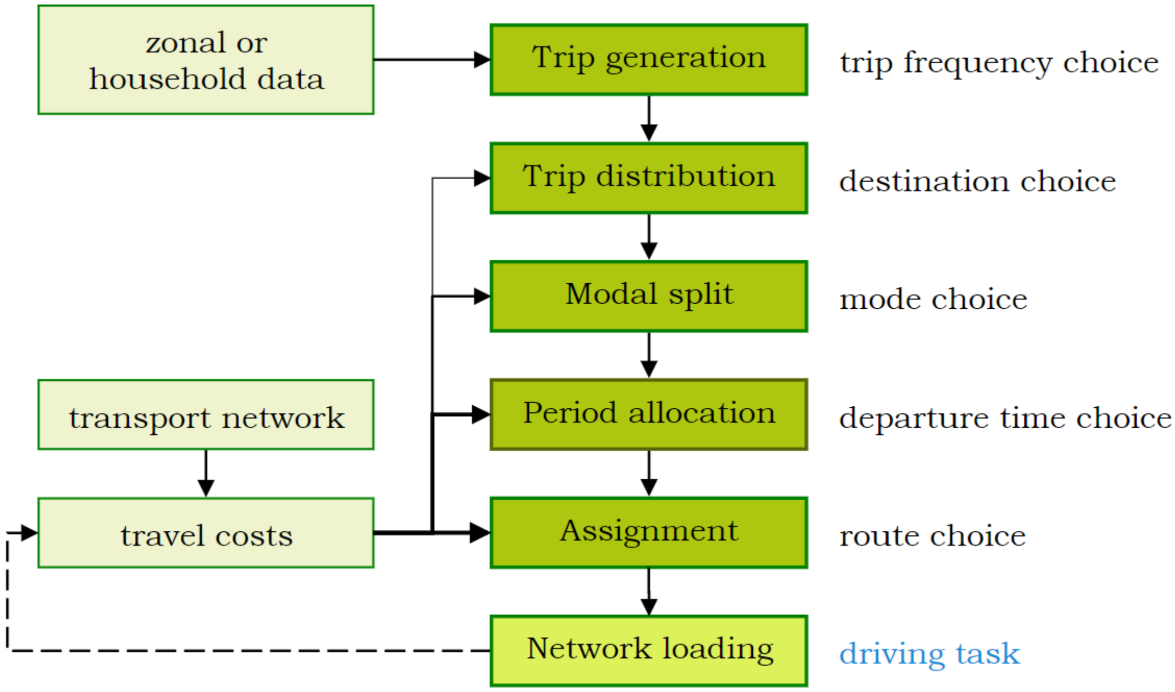


Figure 4.1: Transport modelling framework, retrieved from Pel (2019)

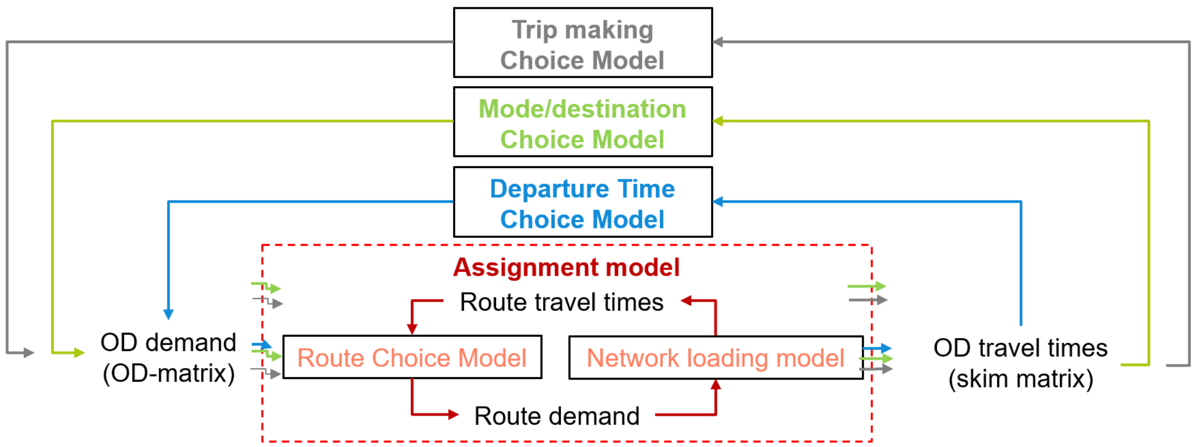


Figure 4.2: Feedback loops and iterations in strategic transport models. Retrieved from Brederode (2015)

The model used in this study has similarities with the general transport modelling framework and the feedback loops, shown in Figure 4.1 and 4.2. However, some conversions have been made to cope with the implementation as well as the scope of this research. An overview of the modelling framework is shown in Figure 4.3. It must be noted that for this study, we are only interested in car traffic. Therefore, mode choice is not incorporated within the framework. In addition, destination choice as well as trip making choice are not taken into account, since we assume that people will make the trip anyway. A more detailed description of neglecting this trip making choice (by car) will be given in section 4.2.5 in which the model assumptions are addressed. Section 4.1.3 and 4.1.4 will elaborate on the DTA and departure time choice module respectively.

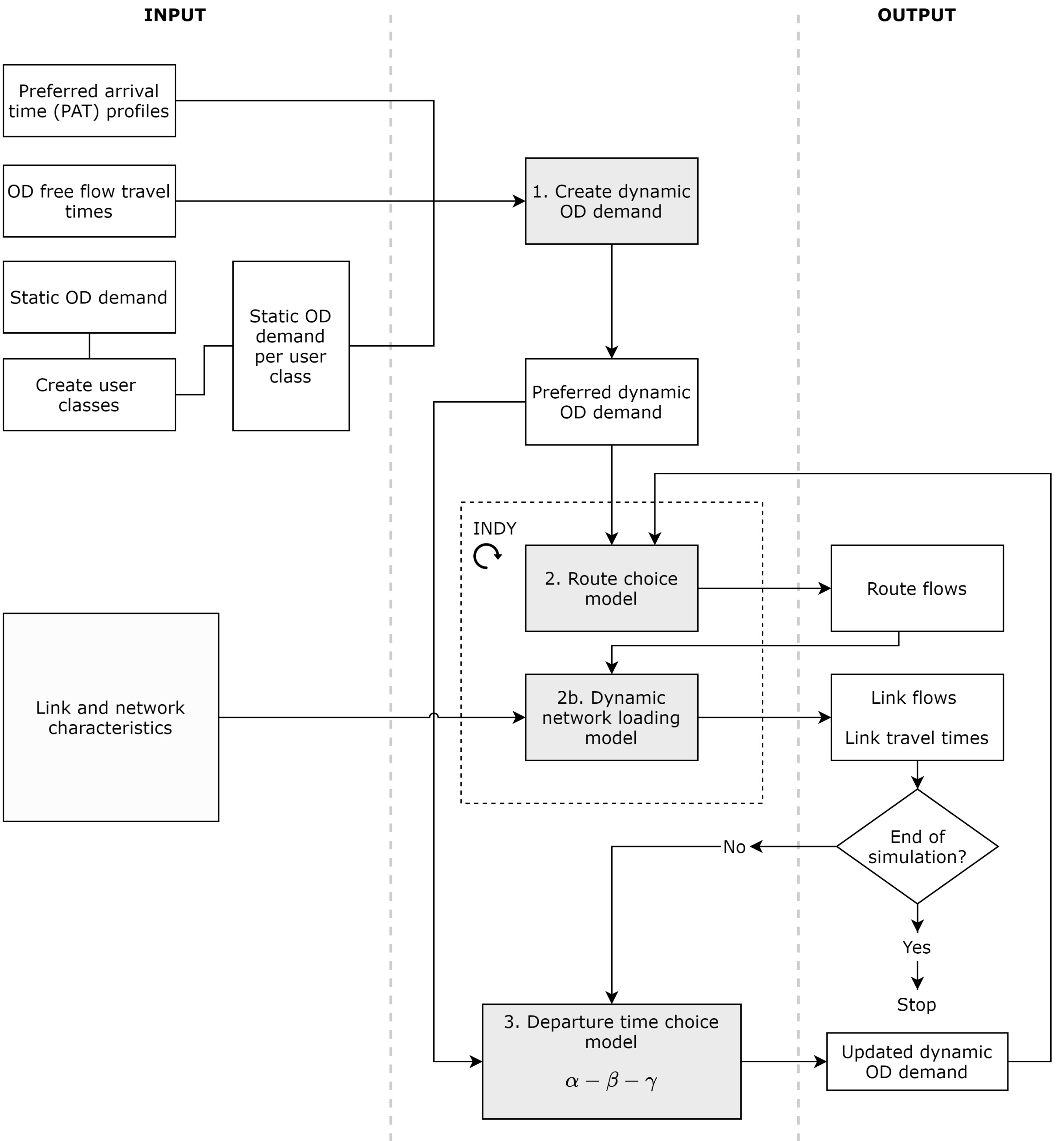


Figure 4.3: Overview modelling framework

Within the overall framework, three sub models can be distinguished. First, the initial dynamic OD demand is created, which is referred to as the Preferred Departure Time (PDT) profiles. These are constructed with the use of the Preferred Arrival Time (PAT) profiles, assuming that travel is a necessity to reach a certain destination at the PAT. I.e. the PAT minus the free flow travel times (FFTT) results in the PDT per OD pair. The FFTT are calculated at the beginning of each run, as the shortest path length divided by the sum of free flow speed associated with each link within this path. The obtained initial PDT profiles, dynamic OD demand, is used in the second sub model, the DTA, to determine initial travel times. Since all vehicles are now 'departing' at their PDT, the associated travel times will, during peak moments, be higher than in free flow travel conditions. This route choice model and DTA, are iteratively executed until no more route changing occurs and the dynamic traffic assignment has converged to a dynamic user 'equilibrium'. This is achieved by incorporating a stopping criterion for these INDY iterations.

The link travel times that follow from INDY are then used as input for third sub model, the departure time choice model which is a logit model. Based on the travel times, this model determines fractions of departing vehicles in a certain time period. This results in a new Dynamic OD Demand, or the 'Actual departures' associated with that outer loop iteration. This new distribution of departures is then used for the next iteration in the DTA to arrive at updated travel times and so on until a stopping criterion for these outer loop iterations is met. The model ends with the last link flows and travel times from the previous INDY iteration. This completes the simulation and the model has reached an 'equilibrium' departure time choice and route choice. Note that this equilibrium is not definitive and that it would take more iterations to approximate a more optimised solution.

It can be noted that the above follows the same iterative process as depicted in Figure 4.1 and 4.2. Although the model used in this study does not include trip making, destination and mode choice.

4.1.2. Creating user classes

To assess the effects of performing distinct types of activities during travel, three types of AVs have been defined in chapter 2: Home AV, Universal AV and Work AV. In addition, there is the conventional vehicle (Non-AV) which is used for the reference case. These four modes are implemented in the model with exactly the same PAT profiles and use the same network with the same characteristics. One could argue that AVs can have shorter headways and therefore they should be given an increased link capacity. However, to capture the net effects of changing scheduling preferences and the resulting effects on congestion, these have not been taken into account. Furthermore, there is also reason to believe that especially in mixed traffic conditions these higher capacities cannot be reached because of safety reasons. Therefore, in this study, the only difference between the modes is that they use different utility functions as will be explained in section 4.1.4.

To create the initial static OD demand for each mode specific, the following three parameters have been defined: ϕ_h, ϕ_u and ϕ_w. They represent the participation rates of Home, Universal and Work AVs respectively. Each can have a value between 0 and 1, while a summation of the three needs to add up to 1. For the conventional vehicle this leads to: 1 minus the sum of all AV participation parameters. For each possible penetration rate, a uniform is assumed. To clarify, the following example is given:

Consider the scenario with 50% Non-AV and 50% Home AV. This will use the following parameter values: $\phi_h = 0.5$, $\phi_u, \phi_w = 0$. These factors are multiplied with the total demand matrix and lead to one matrix assigned to Home AV with half of the total demand. Two empty matrices are assigned to Universal and Work AV. The Non-AV is assigned with the remaining half of the total demand through multiplication of the total demand matrix with factor: $1-(\phi_h+\phi_u+\phi_w) = 0.5$. This way we have ended up with half of the traffic demand being Non-AV and the other half being Home AV.

4.1.3. INDY

The second sub-model within the overall framework is INDY. INDY a DTA model (Bliemer, Versteegt, & Castenmiller, 2004) which has been developed by TNO together with the Delft University of Technology. It dynamically assigns traffic to the network while incorporating route choices. The INDY assignment consists of two models: a route choice model and a dynamic network loading model. An overview of the INDY module is depicted in Figure 4.4.

INDY starts with a the route set generation model. This needs the network characteristics and the Dynamic OD demand. Before the actual simulation the route set that drivers can choose from is generated. The most likely routes for each OD pair are added to the route set. Once a route has been chosen in the route choice model, the route flows are loaded in the dynamic network loading model. This model results in link flows, link speeds and related travel times, which can then be used to calculate the updated route cost for each OD pair.

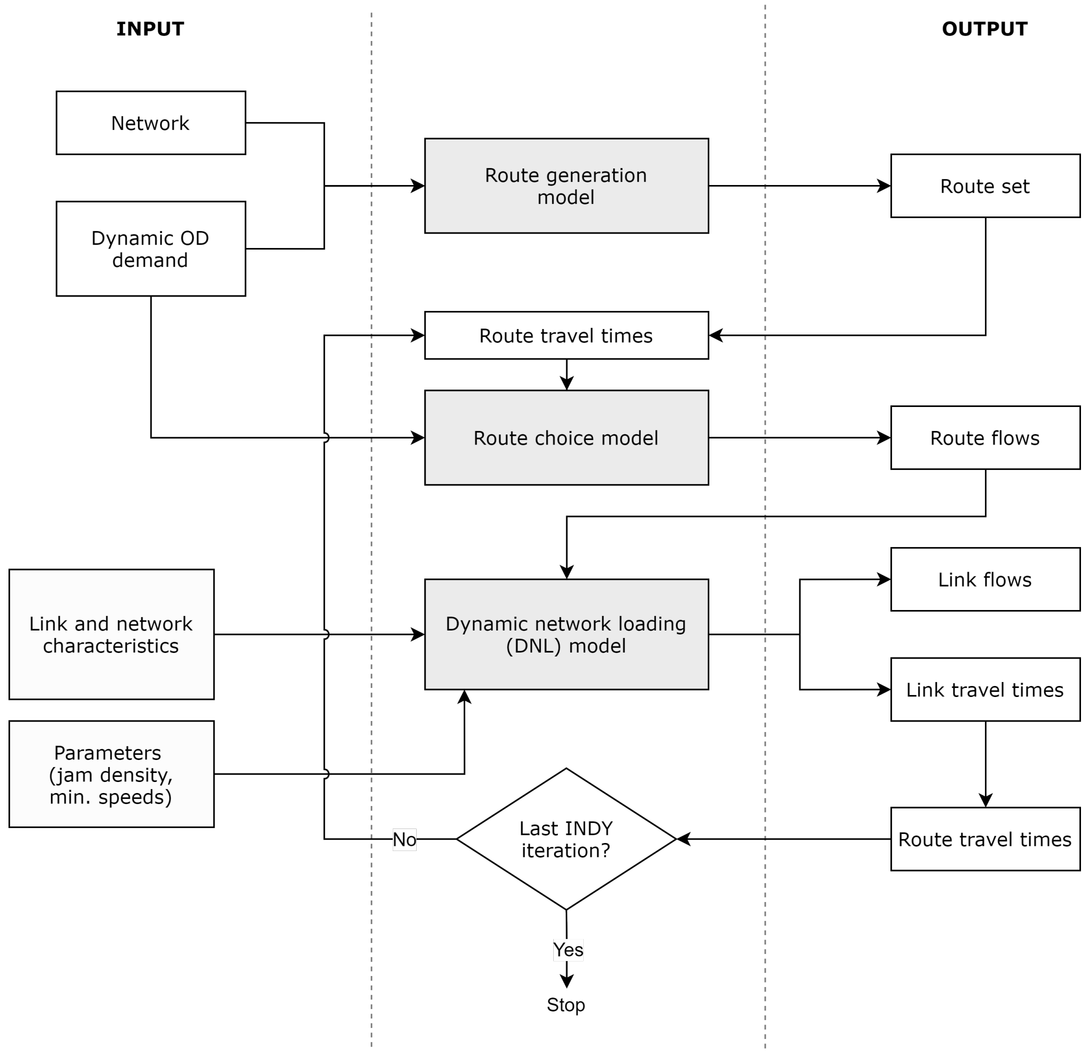


Figure 4.4: Overview INDY module

Route set generation model

Within INDY there are two approaches available to generate route sets: a static equilibrium and Monte Carlo simulation. Static equilibrium assignment uses addition of many routes with relatively small changes. This is useful for urban network in which multiple options with small detours are present. However, this approach leads to a large route set and results in long simulation times. For interurban networks this approach is not that convenient as the main importance is avoiding congestion. With Monte Carlo simulation route sets are generated based on the following set of criteria:

- Iterations: once more iterations are used, more routes are added.
- Spread: every new iteration the so-called spread is increased. This way deviation of routes from the shortest route increases until the final iteration is reached.
- Level of overlap: a maximum level of overlap in route length is set. The higher this percentage is set, the more routes are added.

By using these criteria, different settings are useful for different network types. Since this study uses both urban and interurban networks, we use two Monte Carlo simulations with different criterion values. For urban networks, we want many routes with small differences while we also ensure limited calculation time. Therefore the first Monte Carlo simulation is set with a high maximum overlap but few iterations. For the interurban networks, we want a small set of routes with low overlap, since this will have little effect on the congestion per OD pair. To include enough different routes, the iterations are set to a higher value regarding the interurban network settings. By combining the two strategies, each type of network is associated with the convenient settings. Urban networks have many routes with small differences, much overlap, while interurban networks have few routes with few overlap (Zantema, 2007)

Route choice model
The route choice model is based on assigning each route with a certain disutility based on route travel times. We will not elaborate on this model too much, since Zantema (2007) provides a detailed description of this process. However, based on the route disutilities trip fractions are calculated using the multinomial logit model (McFadden, 1973), as shown in Equation 4.1.

$$\Psi_{mr}^{o,d}(j) = \frac{e^{(-\mu_1 c_{mr}^{o,d}(j))}}{\sum_r e^{(-\mu_1 c_{mr}^{o,d}(j))}} \tag{4.1}$$

in which:

$\Psi_{mr}^{o,d}(j)$ = Trip fractions for route r, relation o,d and mode m at time j
$c_{mr}^{o,d}(j)$ = Disutility of route r, relation o,d and mode m at time j based on travel time
μ_1 = Scaling parameter

The disutilities are a calculated as a function of route travel times. These are an aggregated result of link travel times which depend on the allowed link speeds and lengths but also the possible congestion on those specific links.

By means of multiplying the obtained route fractions with the Dynamic OD demand, the route flows can be derived with Equation 4.2:

$$f_{mr}^{o,d}(j) = \Psi_{mr}^{o,d}(j) D_m^{o,d}(j) \tag{4.2}$$

in which:

$f_{mr}^{o,d}(j)$ = Route flows for route r, relation o,d and mode m at time j
$D_m^{o,d}(j)$ = Dynamic traffic demand for relation o,d and mode m at time j

However there is one final step needed to arrive at the demand that will be used in the next generation. Namely to achieve stable equilibrium conditions, the dynamic demand of iterations up to that point is averaged based on a method of successive averages (MSA) (van Amelsfort, 2009).

Dynamic Traffic Assignment (DTA) model
The DTA or Dynamic Network Loading model requires the route flows, link and network characteristics and several other parameters such as queue density and simulation time steps as input. It dynamically assigns the route flows to the network. While doing this, the maximum link capacities and speeds are taken into account. Its outputs are link flows (inflows, queue inflows, outflows and loads) and link travel times. These are again used as input for the route choice model in the subsequent INDY iteration. This is repeated until the INDY stopping criterion is reached and the resulting link flows and travel times are outputted. These are then used as input for the departure time choice model, except if the final iteration of the outer loop, as described in 4.1.1 and Figure 4.3, is considered. Then these resulting link flows and travel times are written of as final network loads & costs. Bliemer et al. (2004) provides a more detailed description of INDY and the DTA.

It must be noted that blocking back is not included in the model since this INDY version is not compatible with multiple user classes in combination with blocking back. This leads to a less accurate modelling of traffic jams and not all travel times will be correct. In addition, intersection delay is not included. This affects primarily provincial/distributor roads and urban roads in the way that travel times are underestimated (Zantema, 2007). A list of these parameters and other modelling assumptions is presented in section 4.2.4 and 4.2.5, respectively.

4.1.4. Departure time choice

The departure time choice module is the third module within the overall framework. It needs a previous INDY run in which the DTA has assigned all traffic through the network. The INDY output are route/link speeds and flows and resulting travel time skim matrices. These are used as input for the departure time choice module. Figure 4.5 schematically shows how the departure time choice module is build up. Basically, the model determines for every OD pair given a certain PAT interval (and associated PDT interval), the probability of departing in a certain time interval with an associated travel time. Based on these probabilities and the total demand the number of vehicles departing in a certain interval can be determined resulting in a new dynamic OD matrix.

Integration of α-β-γ scheduling preferences

The departure time choice module is mainly based on disutility calculations. Before jumping into the calculation process it is important to elaborate on how the $\alpha - \beta - \gamma$ preferences are incorporated in this module. As described in chapter 3, the $\alpha - \beta - \gamma$ scheduling preferences are used to calculate the total utility of one's morning period. However, the existing departure time choice model used the total disutility of travel time and associated penalties of departing and/or arriving early or late. In order to implement the extended $\alpha - \beta - \gamma$ model, the total utility of one's morning period has been rewritten to a total disutility.

In this research, three types of AVs have been identified (see section 3.3) next to the conventional car which is used for the reference case. This leads to the following four modes: Non-AV, Home AV, Universal AV and Work AV. In addition, the mathematical deduction of the $\alpha - \beta - \gamma$ model calls for the definition of three distinct situations which will be called travel time periods (TTP):

1. Departure and arrival time before PAT
2. Departure time before but arrival time after PAT
3. Departure and arrival time after PAT

For each type of vehicle and each TTP, the disutility function has been derived with the use of the equation 3.1 and 3.2 and their integrals over time period $[0, \Omega]$. In this section these cases will not be written out mathematically but the exact derivations can be found in appendix A. Table 4.1, 4.2, 4.3 and 4.4 provide the end results of the utility derivations for each TTP for Non-, Home, Universal and Work AV respectively.

Table 4.1: Utility functions per departure and arrival time for Non-AV

TTP	Disutility function
1	$U[t] = \alpha T(t) + \beta(t^* - (t + T(t)))$
2	$U[t] = \alpha T(t) + \gamma((t + T(t)) - t^*)$
3	$U[t] = \alpha T(t) + \gamma((t + T(t)) - t^*)$

Table 4.2: Utility functions per departure and arrival time for Home AV

TTP	Disutility function
1	$U[t] = \alpha(1 - e_h)T(t) + \beta(t^* - (t + T(t)))$
2	$U[t] = \alpha(1 - e_h)T(t) + \gamma((t + T(t)) - t^*)$
3	$U[t] = \alpha(1 - e_h)T(t) + \gamma((t + T(t)) - t^*)$

Table 4.3: Utility functions per departure and arrival time for Universal AV

TTP	Disutility function
1	$U[t] = \alpha(1 - e_h)T(t) + \beta(t^* - (t + T(t)))$
2	$U[t] = \alpha T(t) + \gamma((t + T(t)) - t^*) - e_h\alpha(t^* - t) - e_w(\alpha + \gamma)((t + T(t)) - t^*)$
3	$U[t] = \alpha T(t) + \gamma((t + T(t)) - t^*) - e_w(\alpha + \gamma)T(t)$

Table 4.4: Utility functions per departure and arrival time for Work AV

TTP	Disutility function
1	$U[t] = \alpha(t^* - t) - e_w(\alpha - \beta)T(t) - (\alpha - \beta)(t^* - (t + T(t)))$
2	$U[t] = \alpha T(t) + \gamma((t + T(t)) - t^*) - e_w(\alpha - \beta)(t^* - t) - e_w(\alpha + \gamma)((t + T(t)) - t^*)$
3	$U[t] = \alpha T(t) + \gamma((t + T(t)) - t^*) - e_w(\alpha + \gamma)T(t)$

A few notable things need to be addressed here. For Non-AV as well as for Home AV, the disutilities for TTP 2 and TTP 3 are the same. This logically follows from the fact that arriving after the PAT, irrespective of the departure time, these vehicles respond the same. You will lose on the Home side since you can not be productive regarding Work related activities. Another thing worth mentioning is the similarity between Universal AV TTP 1 and TTP 3 and Home AV TTP 1 and Work AV TTP 3 respectively. This can be explained by the fact that within a Universal AV arriving before the PAT, you will only engage in Home activities similar to Home AV. Vice versa in a Universal AV departing after the PAT, you will only engage in Work activities similar to Work AV.

These functions have been written in such a way that they could easily be implemented within the departure time choice module, meaning all variables can be acquired relatively easy from previous runs and/or existing data in matrices. The disutilities for a specific mode will only be used once that mode is being used in that specific run through if-statements. The full elaboration of these statements and the way they have been programmed within the module can be found in appendix B.

With regard to the disutility functions, the following variables are needed:

$$\begin{aligned} t^* &= \text{Preferred arrival time} \\ t &= \text{Departure time} \\ T(t) &= \text{Travel time, depending on departure time } t \\ t + T(t) &= \text{Actual arrival time, depending on departure time } t \end{aligned}$$

To further explain how these can be obtained within the model, it is important to address the fact that time intervals are used. The entire morning period between 6:00 - 11:00 AM is divided into 31 periods of 10 minutes. This means the first period considers time interval 6:00 - 6:10, the second period is 6:10 - 6:20 and so on. The last period corresponds to 11:00 - 11:10. For each possible departure time period, travel times per OD-pair can be obtained from the previous INDY run. In addition, the PDT profiles are given in these same time intervals. This means that for a given OD-pair at a given period in time, the number of vehicles that prefer to depart is known. These have been calculated within the first sub module in which the dynamic OD demand has been created, section 4.1.1.

Now that we know the PDT periods, the PAT periods, the free flow travel times (FFTT) and the travel times (from INDY), the TTP and the associated disutility functions can be described within the model.

We will use the following notation:

i = PDT period
j = Possible departure time period
TT[o,d][j] = Travel time for relation (o,d) and possible departure time period j
FFTT[o,d] = Free flow travel time for relation (o,d)
i + FFTT[o,d] = PAT period
j + TT[o,d][j] = Arrival time period when choosing departure time period j

Note that the travel time and FFTT are rounded off to fit the 10 minute time intervals. This is done for computational reasons.

By means of if-statements, the travel time periods as used in Table 4.1 to 4.4 are defined. Once an if statement is true, the associated disutility function will be used for further calculation. Further elaboration regarding the exact implementation can be found in appendix B in which the programming code is presented.

Figure 4.5 illustrates how the components within the module are related. It starts with the route flows obtained from the last INDY run. These result in travel times per time period for each OD-pair. The same goes for departure/arrival and preferred departure and arrival time profiles. With the use of the existing departure time profiles and free flow travel times, the PAT periods are determined. These enter the disutility calculation for a specific mode and a specific travel time period. By calculating the disutility for all departure alternatives j, the probabilities associated with departing in these alternative periods j, are calculated.

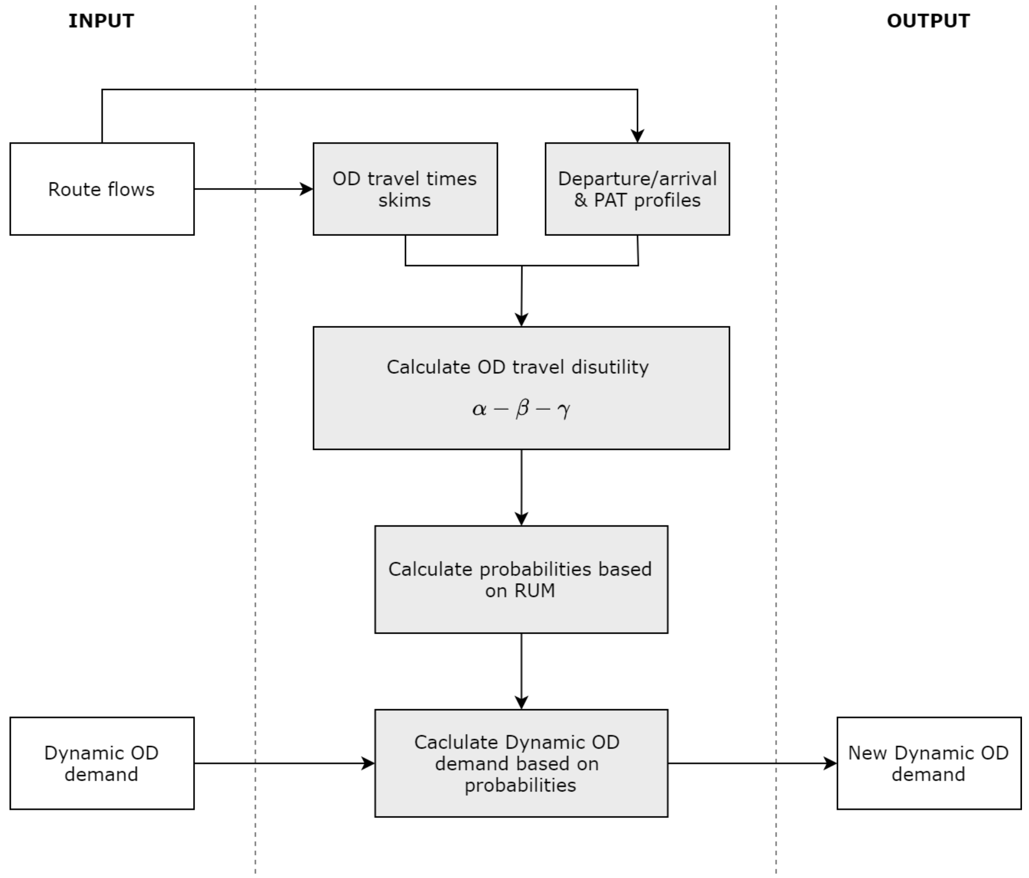


Figure 4.5: Overview departure time choice module including the extended $\alpha - \beta - \gamma$ model

Similar to the derivation of route fractions in section 4.1.3, the calculation of probabilities is based on Random Utility Maximization (RUM) with the multinomial logit function (McFadden, 1973). These calculated probabilities correspond to the fraction of vehicles with PDT period i choosing departure time period j and is given by:

$$\Phi_{mi}^{o,d}(j) = \frac{e^{(-\mu_2 U_{mi}^{o,d}(j))}}{\sum_{j=1}^{31} e^{(-\mu_2 U_{mi}^{o,d}(j))}} \tag{4.3}$$

in which:

$\Phi_{mi}^{o,d}(j)$ = Fraction of vehicles choosing departure time j given PDT i for mode m and relation o,d

$U_{mi}^{o,d}(j)$ = Disutility associated with choosing departure time j given PDT i for mode m and relation o,d

μ_2 = Scaling parameter

Within equation 4.3, μ_2 is used to reflect the imperfect knowledge of drivers and therefore divide the fractions a bit more continuously. In our model μ_2 is set to 0.5. Based on the fractions as determined with equation 4.3 and the previous dynamic OD demand - the PDT during the first iteration - the new dynamic OD demand that results from this iteration can be calculated. However similar to the route choice, there is one final step needed to arrive at the demand that will be used in the next generation. Namely to achieve stable equilibrium conditions, the dynamic demand of iterations up to that point is averaged based on a method of successive averages (MSA) (van Amelsfort, 2009). This completes the departure time choice module and the updated dynamic OD demand can be used for the following iteration.

4.2. Case study

In order to assess the effects of changing departure time preferences within a network, a representative and as much as possible real-life environment is required. Therefore, a case study approach has been chosen. The previous section discussed the modelling framework and how the separate modules are related. This section will elaborate on the case study in which the framework will be applied. First, a network description is given in 4.2.1. This also comprises a description of the selected OD pairs. Hereafter, the single link setting will be discussed in section 4.2.2. The reference situation will be discussed in section 4.2.3 after which the model parameters and assumptions will be addressed in 4.2.4 and 4.2.5. Lastly, the experimental setup will be presented in 4.2.6. This comprises which simulation runs will be executed for specific scenarios to acquire the desired results. Chapter 5 will present all results for the single link, the Haaglanden network, the selected OD pairs and the sensitivity analysis.

Figure 4.6: Case study area with The Hague, Delft and Zoetermeer, retrieved from Google (2020)

4.2.1. Network description

The case study area is located in the western part of the Netherlands and includes the road network of the region ‘Haaglanden’. This is part of the metropolitan area of Rotterdam and The Hague. Within this region the cities of The Hague, Zoetermeer and Delft can be found see Figure 4.6. This region is chosen, in consultation with L. Wismans & K. Friso (personal communication, 2020), because of its convenient size. The region is small enough to prevent tedious model running times while it is also large enough to incorporate many real-life choice options. In this area, drivers will have multiple route options of different road categories. In addition, this area includes congestion during peak hours, which makes it perfectly suited for this research in which the change of these congestion patterns is being investigated. Finally, this region is chosen for the fact that Zantema (2007) has used the same case study which induces a relatively simple adoption of the same model.

Figure 4.7: Haaglanden region with OmniTRANS network overlay

Figure 4.7 shows the Haaglanden area including an overlay of the road network which is used by the model. It can be observed that the network stops outside of the aforementioned cities. The in- and outflows of the outer zones can therefore be seen as flows that would continue to either Rotterdam (South), Leiden (North) and Gouda (East). All the main road have been incorporated in the model. These include the main motorways: A4, A12 and A13, all provincial/distributor roads and most of the urban roads. Figure 4.8 shows the different road types and their location within the network. Although today the A4, West from Delft, has been extended towards Rotterdam in the southeast, this ‘old’ network situation is still useful for this study, since it was a realistic case (L. Wismans & K. Friso, personal communication, 2020). Because we are only interested in the extent to which congestion and route choice are affected, the fact that the network is not up-to-date is not a problem, as long as the system is calibrated.

Every road in the network is build up from network links which require a description of its characteristics: maximum speed, capacity, number of lanes, etc. Every road type has a specific set of those characteristics. Regarding the nodes in the network, no information is needed, as delays at intersections are not taken into account. The centroids which correspond to origins and destinations require the number of trips departing between each centroid. This is provided in the OD-matrix for this specific network. An extracted figure from this OmniTRANS network is shown in Figure 4.9. All nodes are depicted with small dots and connected through links, depicted as lines. Within this network, there are 168 zones. This leads to a total of 28.224 (168 $\times$ 168) OD pairs.

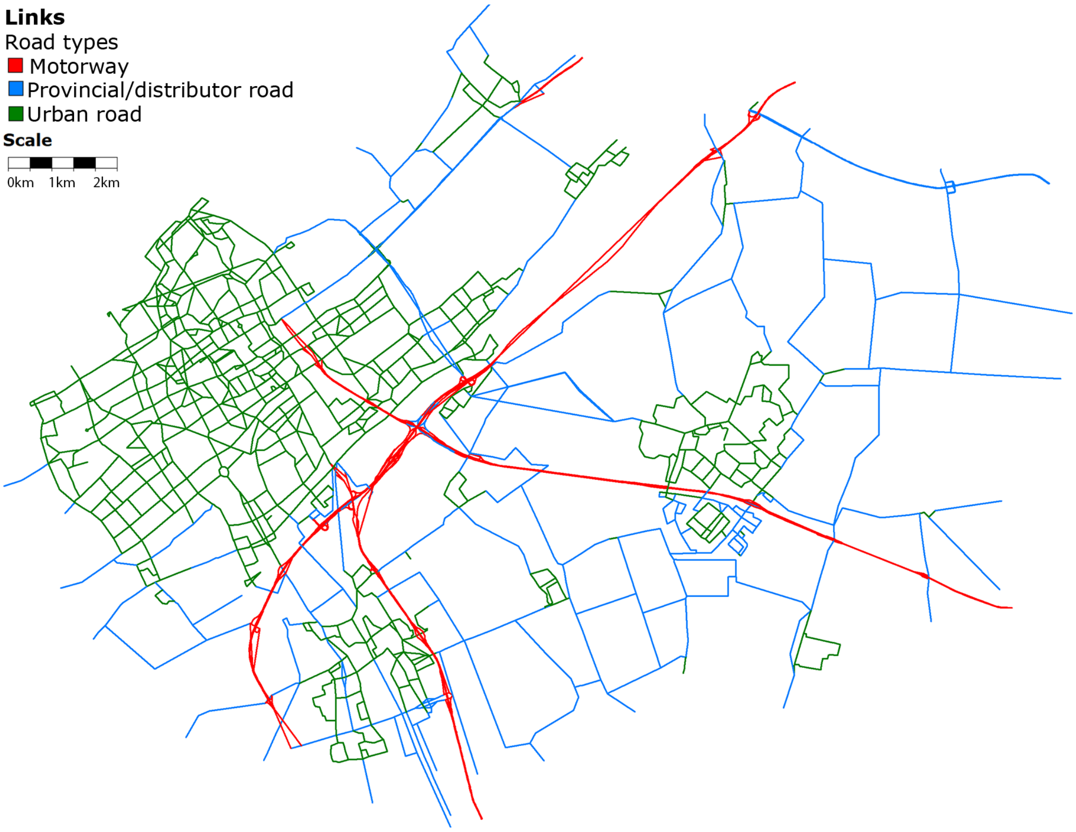


Figure 4.8: Haaglanden network with different road types displayed

Figure 4.9: Haaglanden network in OmniTRANS model including all 168 zones

Description of selected OD pairs

In section 1.3 it was explained that the Key Performance Indicators (KPIs) for the entire network give aggregated results and that, for interpretation needs, several origin-destination relations should be investigated in more detail. This section presents the three selected OD pairs and substantiates this choice. The OD pairs have been selected based on the following criteria:

- At least a static demand of 100 trips
- At least 2 OD pairs with a free flow travel time > 10 minutes
- At least a significant delay, i.e. max. travel time is significantly larger than free flow travel time
- At least 1 route that uses the motorway for a large part of the trip
- At least 1 route that does not use the motorway
- At least 1 route that uses the congested motorway from 'Prins Clausplein' into the Hague

Based on these requirements the following OD pairs have been selected, shown in Table 5.5 and Figure 4.10:

Table 4.5: Selected OD pairs and their characteristics in which delays correspond to the reference scenario (non-AV)

Origin	Destination	Demand [veh]	Distance [km]	FFTT [min]	Mean delay [min]
10	156	183	13.92	12.09	3.31
23	26	4060	26.3	13.99	5.8
157	127	107	12.37	7.26	6.8

(a) OD 10-156 (North to South) (b) OD 23-156 (South to North) (c) OD 157-127 (East to West)

Figure 4.10: Selected OD pairs: locations and shortest paths within the Haaglanden network

The first relation, 10-156 from 'Leiden' to 'Zoetermeer', uses no motorways, has a demand of 183 during the morning period, a free flow travel time of over 12 minutes and a maximum travel time of 18 minutes. The second relation, 23-26 from 'Rotterdam' to 'Leiden', uses only motorways and is also the one with the highest demand in the network: 4060 vehicles. In addition it has a relatively long distance and a delay of about ten minutes. Lastly, relation, 157-127 from 'Zoetermeer' to 'the Hague', has the lowest demand but the largest (relative) delay. These characteristics per OD pair should be regarded when interpreting the results.

4.2.2. Single link setting

The single link setting is used as a first verification. The single link is created with an extraction of two zones from the Haaglanden network. These zones are 42 'Oud-Clingendaal' and 128 'van Hoytemastraat e.o.' in the Northeast area of The Hague. They are connected to the network by two connector links and consist of 7 consecutive links in between. Only traffic going from zone 42 to zone 128 is assigned to the model. This static OD-demand is set to 11,0000 vehicles between 6:00 AM and 11:00 AM. By means of the same PAT profile as used in the Haaglanden case, this static OD-demand has been divided over the 31 time periods. To create congestion, the second-last link has been given a capacity restriction of 2,000 veh/h to ensure that during the morning peak, more traffic is flowing in than out and thus congestion is building up. Figure 4.11 shows the single link setting between zone 42 and 128 at 8:00 AM for Non-AV.

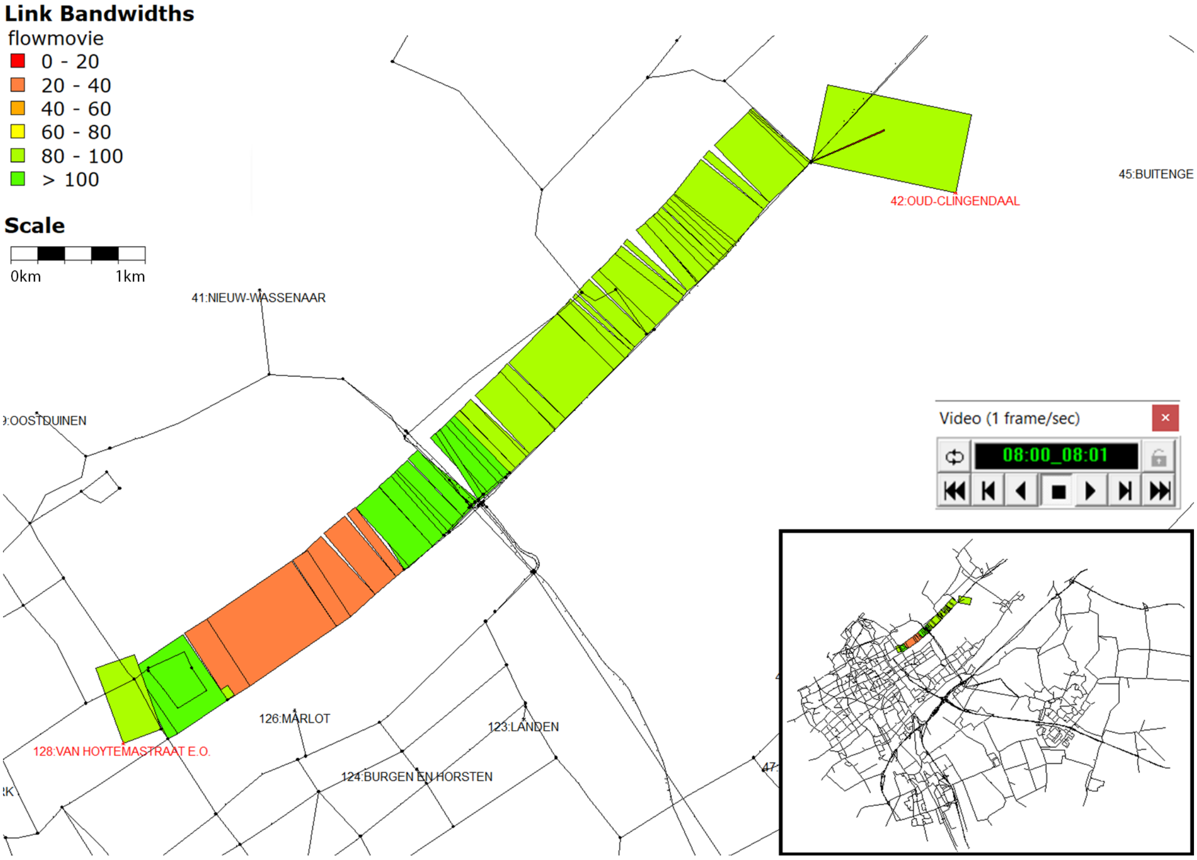


Figure 4.11: Single link configuration at 8:00 AM in OmniTRANS

4.2.3. Reference situation

To compare the model results and be able to profoundly say something about the effects of changing departure time preferences with AVs, a reference situation has been defined. In this situation, 100% of the total demand is assigned to the conventional car (Non-AV). This means a departure time choice based on the $\alpha - \beta - \gamma$ preferences without the efficiency factors, Table 4.1.

Figure 4.12 shows the reference case during the morning peak at 8:00 AM. In this figure, congestion can be observed on the A4 towards Leiden, the N44 from Wassenaar to the Hague, on the A12 close to Zoetermeer, at the junction Prins Clausplein and on the A13 East of Delft. One important indicator which is evaluated are the number of VKM per road type. These are presented in Table 4.6. In addition, the accessibility of the network can be assessed with several other network indicators. These are used in the analysis and compared to this reference situation. They include: total travel time, total number of vehicle kilometres, the mean travel time and the mean travel distance. Table 4.7 presents the indicators and their values for the reference situation.

Table 4.6: Total vehicle kilomtres (VKM) in the reference situation: 100% Non-AV

Road category	Motorway	Provincial/distributor road	Urban road	Total
Total vehicle kilometres	2,642,545	1,259,488	1,236,918	5,138,951

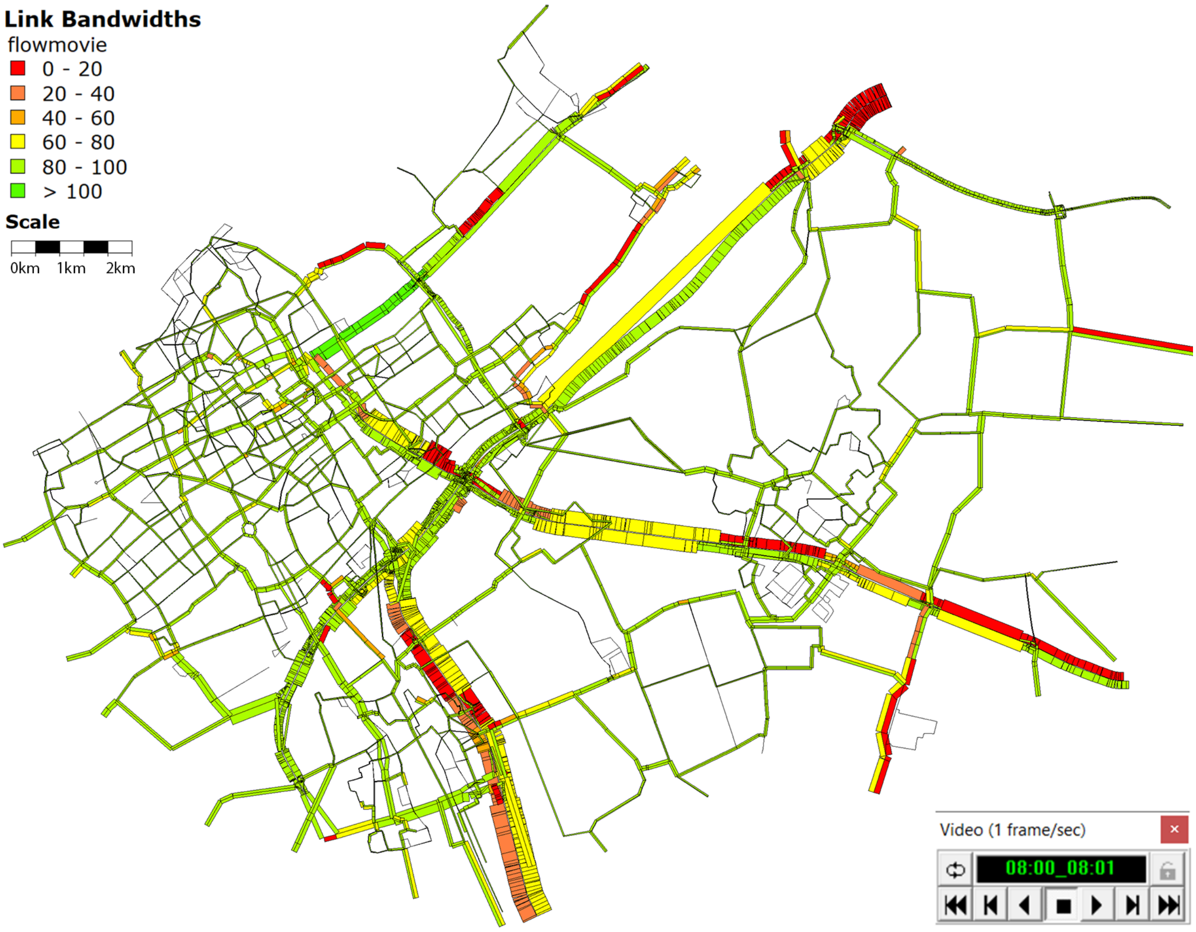


Figure 4.12: Morning peak congestion at 8:00 AM in Haaglanden network in OmniTRANS

Table 4.7: Network indicators reference situation: 100% Non-AV

Indicator	Value
Total travel time spent [min]	94,097
Total number of kilometres travelled	5,340,399
Total number of vehicles put on the network	473,868
Mean speed in the network [km/hour]	56.75
Mean travel time [min]	11.91
Mean travel distance [km]	11.27
Mean free flow travel time [min]	7.81

It can be noted that the total VKM in Table 4.7 deviate from the ones presented in Table 4.6. This is due to the fact that they have been obtained differently. The total VKM in Table 4.6 is a summation over all traffic flows times the associated link lengths and time steps for each link. It even adds two extra time periods to account for any remaining vehicles in the depletion time of the network. It has been checked that after these extra periods no flows are present at any of the links. This gives the exact number of VKM travelled. The second derivation (Table 4.7), is based on a multiplication of skim matrices. This means the distances for each time period between all OD pair is multiplied with the demand for each specific OD pair at that point in time. These are aggregated results and therefore not as exact as the first derivation.

4.2.4. Model parameters

Within the model and network there are certain initial conditions and parameters which have been set. Besides the parameters from the $\alpha - \beta - \gamma$ model and the link characteristics there are several other network wide parameters which have been used (for INDY). The following parameters have been applied:

- *Aggregation*
  Aggregation specifies the aggregation level of the link output data in minutes. In our case INDY will produce average link output data for each 5 minutes' period.
- *Time step*
  Time step is the time step of INDY's dynamic assignment in seconds that is used during simulation in which traffic is distributed within the network. In our model this value has been set to 2 seconds.
- *Spread (route choice)*
  Spread reflects the imperfect knowledge of the driver for taking the fastest route. It represents the inverse of the scale parameter of the logit model for route choice and is a degree of spread of vehicles over different routes between OD-pairs. For our model spread has been set to 0.07.
- *Jam density*
  Jam density is the maximum number of vehicles per kilometre in the network and is used to calculate speed from flow. This parameter is set to 130 veh/km.
- *Jam speed*
  Jam speed the minimum speed on each road. When a link reaches its jam density, new drivers will have this speed. In our model this equals 14 km/h.
- μ_1 *(route choice)*
  μ_1 is the spread parameter related to the route choice model. It indicates the imperfect knowledge of the drivers. In this model, μ_1 is set to 0.7.
- μ_2 *(departure time choice)*
  μ_2 is the spread parameter related to the departure time choice model. It indicates the imperfect knowledge of the drivers. In this model, μ_2 is set to 0.5.
- *Blocking back*
  Blocking back refers to the blocking back effects of traffic jams. If blocking back is turned on, queues will spill back on upstream links. This will thus model jams more accurately, at the cost of increased run times and memory usages. However, the INDY version used within this study is not able to use blocking back with multiple user classes. Therefore this parameter is switched off.

4.2.5. Assumptions

In the model, some assumptions have been made. These will have to be regarded when interpreting the results. The assumptions can be categorised in two groups: general assumptions and transportation model assumptions. This section lists these assumptions and briefly discusses the most important ones.

General assumptions

- No individual cars are identified. This means that differentiation is limited to the user groups, i.e. four modes, that are defined within the model.
- Only the mode car is taken into account, meaning no public transport, bicycles or even freight traffic is considered.
- No differentiation is made between the types of vehicles with regard to the network characteristics. This means that both the three AV types as well as the conventional car, use the same speeds,

capacities (headways), densities and junction modelling. It is expected that future AVs might cooperate and can therefore smoothen traffic flow which reduces traffic congestion. Some of these characteristics could be included in the model by setting different road type settings for specific AV and non-AV users. For instance, increase the capacity for AVs to mimic shorter headways. However, since the size of this effect is assumed to be small and we are interested in the net congestion effects by the implementation of the extended of the $\alpha - \beta - \gamma$ model, these are not taken into account.

- No operational design domain (ODD) is included. This relates to chapter 2 in which was discussed that this study only focuses on fully AVs (level 5). The option to include an ODD has been rejected since this will also influence route choice. As route choice is one of the KPIs we are interested in, an ODD is not be included. This means that AVs considered in this study can operate during the entire trip, even though it might be a far stretch from reality at this point.
- The model makes use of certain preferred arrival time (PAT) profiles. These have profiles have been calibrated within the existing model and included for each zone. This means that each of the 168 zones incorporated in the model, has a specific preferred arrival time profile. It should be noted that nowadays people might be less and less restricted to certain specific arrival times, due to the technological progress which enables the possibility to perform several working tasks from home. However, this study focuses on the effects of shifting departure time choice due to on-board activities (home/work). This implies looking at the commuting travellers and thus investigation of the morning peak. Moreover, the $\alpha - \beta - \gamma$ model is able to incorporate cases in which an individual departs after the PAT. However, the extreme cases in which one would arrive for instance 5 hours too late are not included.
- The morning period is split up in 31 periods of 10 minutes, as discussed in section 4.1.4. This affects the departure time choice since the disutility functions are based on travel times and differences between preferred and actual departure and arrival times. By rounding off these differences, the probability distribution is affected. For instance, if a car departs at a certain departure time and therefore arrives 2 minutes too late, the arrival time will be one period too late. This will be used in the disutilities and, based on the $\alpha - \beta - \gamma$ preferences, results in aggregated probability distributions.

Transportation model assumptions

- Due to calculation times, a limited number of iterations is executed, both for INDY as well as the outer loop, described in 4.1.1. It is assumed that equilibrium is reached. Within the single link setting the INDY iterations are always set to 1, since no route choice is incorporated.
- Delays at intersections are not taken into account which results in an underestimation of travel times, primarily on urban and provincial/distributor roads which will makes taking these roads more attractive.
- No elastic demand is taken into account even though it would be available in this model. Elasticity mimics the effect of a change in demand due to increased or decreased congestion, i.e. more or less disutility. An individual may choose not make the trip by car anymore due to increased congestion. This can either mean that they shift to other modes, or that they decide not to make the trip at all. If we recall the 5-steps in transportation modelling, elasticity can be seen as a simplification of the mode and trip making choice to cover the realistic situation in which travel times become extremely long and individuals no longer take the car. However, this study focuses solely on cars and is interested in the net effects Therefore this step is not taken into account.
- Blocking back is turned off since the INDY version was not compatible with multiple user classes and the use of blocking back simultaneously. Therefore blocking back is not incorporated. On the one hand this avoids the possible presence of gridlocks, in which the system comes to a

full standstill. However, it is a simplification which means that when the link density exceeds the maximum jam density (130 veh/km) queues will not spill back on upstream links. Traffic jams will be modelled less accurately.

4.2.6. Experimental setup

This section presents the setup to carry out the required simulation runs and obtain results. It is divided in the simulations for the single link, the Haaglanden network (including the OD pairs) and the sensitivity analysis.

Single link setting

The single link merely serves as a first verification and since no route choice is included, the desired outcomes will only comprise of departure time choice profiles and travel times. These will be plotted for the entire morning period. The number of simulation runs will be restricted to four: one for each mode (non-, Home, Universal and Work AV). This means no scenarios with mixed traffic will be run for the single link setting. Table 4.8 shows the scenarios and the desired output.

Table 4.8: Simulation runs for single link scenarios

Variant	Description	Output
1	100% non-AV	Departure time profiles Travel times/delays
2	100% Home AV	
3	100% Universal AV	
4	100% Work AV	

Case study

Similar to the single link, the case study network will be run with four different scenarios which correspond to each of the four modes. In addition to the departure time choice and travel time differences, for the Haaglanden network we are also interested in route choice. This will be captured with the vehicle kilometres while differentiating between road types. The results regarding route choice can then be used in relation to the assessment of external effects. Furthermore, investigation of traffic flows is desired. This will be captured by network plots with link outflows in bandwidths. Table 4.9 shows the scenarios and desired output.

Table 4.9: Simulation runs for Haaglanden network scenarios

Variant	Description	Output
1	100% non-AV	Departure time profiles
2	100% Home AV	Travel times/delays
3	100% Universal AV	VKM (per road type)
4	100% Work AV	Traffic flows

As discussed in 4.2.1, three OD relations have been selected. These will not require additional simulation runs. The results associated with these relations can be retrieved directly from the simulation runs of the Haaglanden network. For these relations we will restrict the outputs to departure time profiles, travel time profiles and the minimum and maximum travel time differences.

Sensitivity analysis

In the approach to obtain results for the sensitivity analysis, we distinguish between the analysis regarding penetration rates and the $\alpha - \beta - \gamma$ model parameters. Regarding the penetration rates we will use different ratios of Universal AVs and non-AVs in the Haaglanden network. Table 4.10 shows the variants with increasing percentages of Universal AVs. Note that variant 1 and 5 correspond to the variants which have already been obtained for the case study, 100% non-AV (reference scenario) and 100% Universal AV.

Table 4.10: Variants with AV penetration rates as used in the sensitivity analysis

Variant	Non-AV	Universal AV
1	100%	0%
2	75%	25%
3	50%	50%
4	25%	75%
5	0%	100

For this analysis we are interested in the (summed) departure time profiles per increased ratio of AVs. Additionally, to investigate the effects of AV dominance in peak moments, relative changes in departures of non-AVs for increasing ratios of Universal AVs will be retrieved from the simulation outputs. Furthermore, insight in travel times is required. This comprises the total and mean travel times for both modes as well as a differentiation between AV and non-AV. Together with the departure time results these can bring a better understanding of the observed impact of varying penetration rates. Since modes do not respond differently to route choice, this aspect has been neglected.

The analysis regarding the extended $\alpha - \beta - \gamma$ model parameters will also use simulations in the Haaglanden network. Since this analysis comprises altering the extended model parameters, the chosen reference scenario is 100% Universal AV. This way both home and work activities are incorporated and the efficiency factors are also included. Table 4.11 and 4.12 show the variants with different $\alpha - \beta - \gamma$ parameters and efficiency factors respectively. Note that in both tables, the second column, 'Reference', corresponds to the previously obtained results of Universal AV, with using the adopted parameters values $\alpha - \beta - \gamma$ (2,4,1) and efficiency factors e_h and e_w (= 0.3).

Table 4.11: Variants with $\alpha - \beta - \gamma$ model parameters as used in the sensitivity analysis

Parameter (ratio)	Reference	α-β-γ 1	α-β-γ 2
β/α	0.5	0.375	0.8
γ/α	2	0.5	1.2
e_h, e_w	0.3	0.3	0.3

Table 4.12: Variants with efficiency factors as used in the sensitivity analysis

Parameter (ratio)	Reference	Eff 1	Eff 2
β/α	0.5	0.5	0.5
γ/α	2	2	2
e_h, e_w	0.3	0.5	0.8

For these analyses we are interested in the effect on departure time choice and changes in travel times. Therefore the simulation results which will be presented comprise the departure time profiles per variant and tables with (relative) changes in total and mean travel times. Route choice is regarded as irrelevant since it is only dependent on changes in travel times. Nevertheless we will report total vehicle kilometres to assess if we can observe any significant impacts from this perspective as well.

The next chapter will present the results following the experimental setup as presented in this section.

5 Model results

This chapter presents the results for both the single link setting, Haaglanden case and the sensitivity analysis in section 5.1, 5.2 and 5.3 respectively. The data and figures have all been obtained through several simulation runs in OmniTRANS and follow the network setup as described in chapter 4.

5.1. Single link setting

With regard to the single link setting, the following results are presented: the departure time profiles per mode in Figure 5.1, the travel time profile and the mean travel times in Figure 5.2 and Table 5.1 respectively.

Departure time choice

Figure 5.1 shows the actual departures in the morning period 6:00 - 11:00. The graphs represent each of the four modes: Non-AV (blue), Home AV (orange), Universal AV (green), Work AV (purple) after three iterations within the model. In addition, the preferred departure time (PDT) has been included as a dashed grey line. The x-axis corresponds to the time during the morning period. The y-axis corresponds to the number of vehicles with actual departure time for that period.

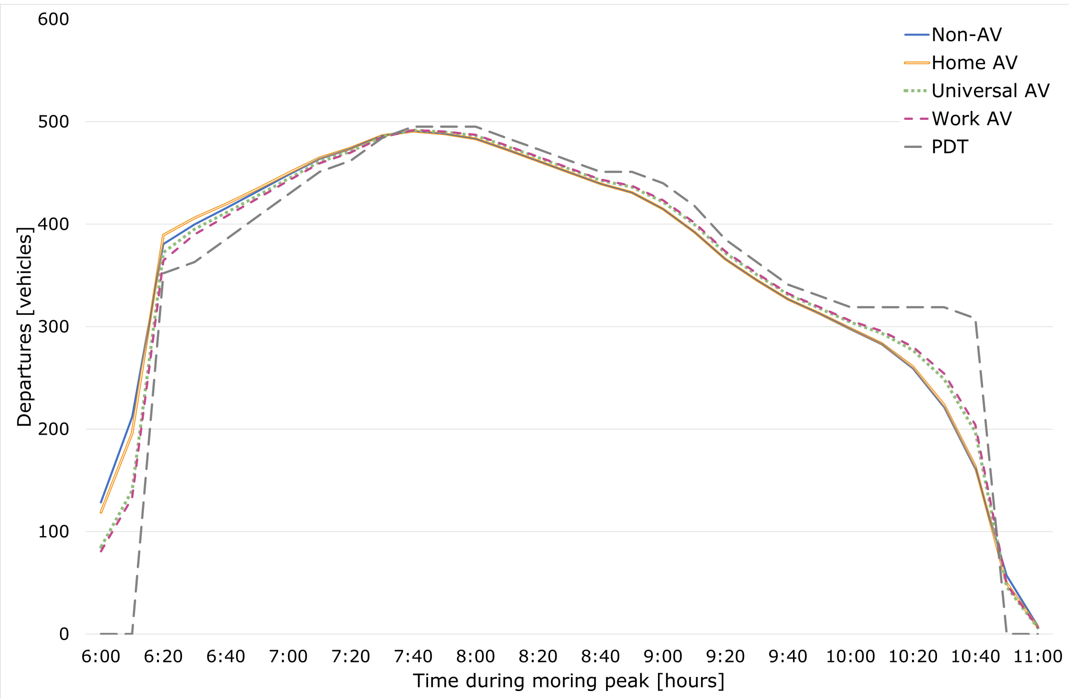


Figure 5.1: Departure time profiles for each mode in the single link setting

It can be observed that for each mode most of the actual departures seem to lie before the preferred departures. This might be assigned to the fact that time intervals of 10 minutes are used. This means that even a relatively small delay can result in an arrival of an entire time period later. Given the parameter values of the $\alpha - \beta - \gamma$ model and the resulting disutility of arriving 10 minutes too late compared to a longer travel time, will in most cases result in the choice to depart earlier. Note that the figure represents the aggregated departure time profiles. This means that even though all departures seem to lie before the preferred departures, this is not the case for every single vehicle. Due to the use of the logit function in the choice model, even the smallest fractions are assigned to the period associated with that probability. The graphs show a resultant of all departing vehicles at that point in time and therefore the resulting departure times are mostly depicted before the preferred departure times. In this observation, we also need to be aware of the spreading factor μ_2, since this parameter also disperses the distribution of the fractions.

Furthermore, the differences between the modes seem relatively small. However, we do observe the following: in the first part of the morning period Home AVs depart the most, followed by Non-AVs, Universal AVs and lastly Work AVs. After the departure peak, around 8:00 AM, the opposite effect can be identified to some extent. Although Home AVs and Non-AVs follow more or less the same profile, there is a notable gap with Universal and Work AVs, of which Work AVs even show slightly later departures than Universal AVs. Despite the fact that these differences seem small, the direction corresponds with what has been obtained by Pudāne (2019).

Travel times

Figure 5.2 shows the travel times for the single link for each given 10 minute time interval during the morning period. The graphs represent each of the four modes: Non-AV (blue), Home AV (orange), Universal AV (green), Work AV (purple) after three iterations within the model. The x-axis corresponds to the time intervals during the morning period. The y-axis corresponds to the number of vehicles with actual departure time for that period times the corresponding travel time at that moment. The free flow travel time is equal to 4.58 minutes.

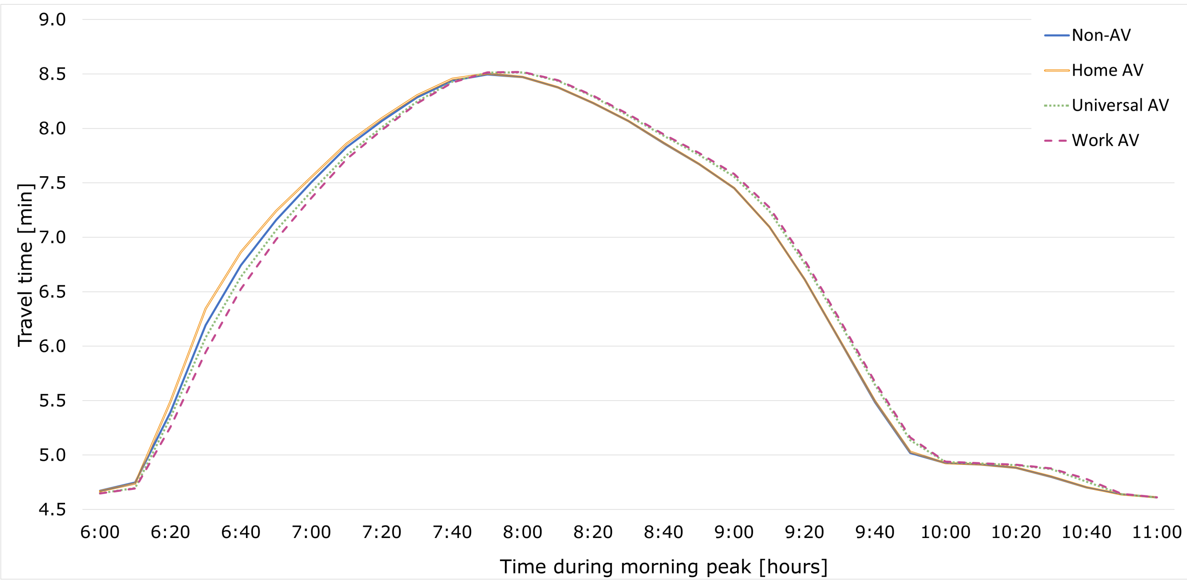


Figure 5.2: Travel time profiles for each mode in the single link setting

Similar to what has been observed from Figure 5.1, the travel times profiles show that in the first half of the morning period the longer travel times are associated with Home AVs, followed by Non-AVs, Universal AVs and lastly Work AVs. Later in the morning period, these longer travel times correspond to Universal and Work AVs. Again, these differences seem small but the direction is visible.

Table 5.1 gives the maximum, minimum and mean travel times and the relative changes per mode over all vehicles during the morning period. In addition, the mean delays and the relative changes with non-AV are shown.

Table 5.1: Maximum, minimum and mean travel times including delays and relative changes per mode for the single link setting

	Non-AV	**Home AV**		**Universal AV**		**Work AV**	
Max. travel time [min]	8.49	8.50	*0.09%*	8.51	*0.23%*	8.52	*0.28%*
Min. travel time [min]	4.61	4.61	*-0.01%*	4.61	*-0.02%*	4.61	*-0.01%*
Mean travel time [min]	6.56	6.58	*0.31%*	6.58	*0.34%*	6.57	*0.20%*
Mean delay [min]	1.98	2.00	*1.04%*	2.00	*1.12%*	1.99	*0.65%*

It can be seen that each AV is associated with a slight increase in travel times and delays. Although this direction of changes can be observed, these differences are considered small. We tried to increase these effects by making the congestion more extreme. However, with the model parameters and assumptions described in section 4.2.4, such as minimum link speeds, jam density etc., it was unable to further increase these changes on the single link. We will need to assess other indicators and OD pairs to make substantiated claims regarding the impact of AVs on a network.

Based on the observed effects within this single link setting, and the fact that the direction corresponds to the direction of the theoretical results as obtained by Pudāne (2019) - Home AVs skew more to the beginning, Universal AVs in both directions and Work AVs more to the end of the peak - the implementation of the $\alpha - \beta - \gamma$ scheduling preferences is considered correct. Although in our case Universal AVs show a slightly bigger increase in delay than Home AV, Work AV increase congestion the least which corresponds to the findings in previous work. The next section presents the results of the simulation outcomes regarding the case study area.

5.2. Case study

This section presents the model results which are related to simulations in the case study area. This refers to the KPIs, the departure time profiles and the route choice for the entire network in section 5.2.1. In addition, the results for the three selected OD pairs, as described earlier, are presented in section 5.2.2.

5.2.1. Haaglanden network

Table 5.2 gives the most important indicators for each mode. The column 'Non-AV' contains the same values as presented in section 4.2.3, in which the reference situation with 100% Non-AV was described. The other columns give the values for the AV types. In addition the relative differences with the Non-AV scenario are given.

Table 5.2: Key performance indicators for the entire Haaglanden network per mode

KPI	**Non-AV**	**Home AV**		**Universal AV**		**Work AV**	
Travel time [hours]	94.097	94.123	*0.03%*	94.455	*0.38%*	94.143	*0.05%*
Travel distance [km]	5.340.399	5.339.824	*-0.01%*	5.341.167	*0.01%*	5.339.755	*-0.01%*
Mean speed [km/h]	56.75	56.73	*-0.04%*	56.55	*-0.36%*	56.72	*-0.06%*
Mean travel time [min]	11.91	11.92	*0.03%*	11.96	*0.38%*	11.92	*0.05%*
Mean distance [km]	11.270	11.269	*-0.01%*	11.271	*0.01%*	11.268	*-0.01%*

Although we can identify changes with the reference scenario, these effects are relatively small and are considered insignificant. Although we can observe significantly larger differences with the Universal AV. This might be explained by the fact that other than Home and Work AVs, Universal AVs widen the departure profile from both the home and work end. This makes investigation of distinctive OD pairs even more interesting.

Departure time choice

Figure 5.3 shows the departure time profiles for all modes in the Haaglanden network. The PDT is depicted as a dashed line in grey, similar to the single link results.

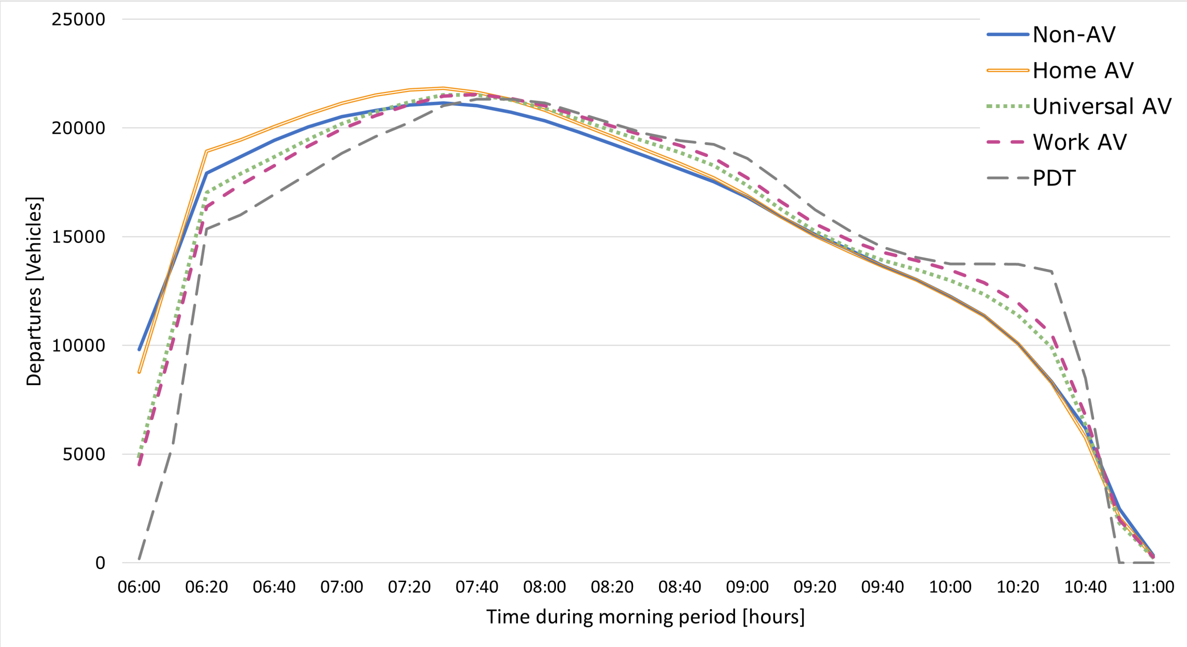


Figure 5.3: Aggregated departure time profiles for each mode in the Haaglanden network

Even though the changes are small, the following can be observed:

- The profiles show similarities with the obtained results from the single link setting.
- In the first possible departure time period, there is already a significant part of departures visible.
- There seem to be almost no departures after the PDT except for the last two time periods.
- Compared to the Non-AVs, Home AVs shift the departure time profile peak more to the beginning of the morning period. Universal AVs shift the peak more to the centre and end of the morning period, while Work AVs show a shift to the end of the morning period.

With interpreting these results, we need to keep in mind that these profiles show an aggregated result, not only of the entire network but also of the departures itself. Similar to the explanation for the single link, we need to mention the time periods of ten minutes. These leads to the fact that even the smallest delay results in an arrival of 10 minutes later than preferred. This brings high disutilities to depart in that specific preferred departure period compared to a period earlier. Therefore, the associated probabilities with departing a period earlier are significantly higher than departing in the preferred departure time period. So only a small ratio, which does not necessarily have to be zero, is assigned to the later time period. The graph however only shows an aggregated result of the departures and therefore we see the profiles as depicted above. Moreover, the scaling factor μ_2, used to mimic imperfect knowledge, makes that the graph is widened as can be observed especially at the beginning and end of the profiles. With the above explanation in mind, we can still observe the direction of the shifted departure profile peak. This corresponds with the hypothesis: Home AV users choose to departure earlier, Work AV users choose to depart later. Universal AV users shift their departure times more to the end of the morning period, compared to the Non-AV users.

Travel times

Regarding travel times, Figure 5.4 shows the aggregated travel time profiles for each mode. In addition, Table 5.3 gives the maximum, minimum and mean travel times for all modes. The average free flow travel time for the Haaglanden network is equal to 7.81 minutes. We need to regard that these results represent aggregated travel times over all departing traffic for every period.

Table 5.3: Maximum, minimum and mean travel times including delays and relative changes per mode for the Haaglanden network. Note that due to rounding, some absolute values are the same while their corresponding relative changes are not.

	Non-AV	Home AV		Universal AV		Work AV	
Max. travel time [min]	13.69	13.72	*0.17%*	13.71	*0.13%*	13.67	*-0.19%*
Min. travel time [min]	7.83	7.93	*1.31%*	7.89	*0.74%*	7.98	*1.89%*
Mean travel time [min]	11.91	11.92	*0.03%*	11.96	*0.38%*	11.92	*0.05%*
Mean delay [min]	4.10	4.11	*0.08%*	4.15	*1.11%*	4.11	*0.14%*

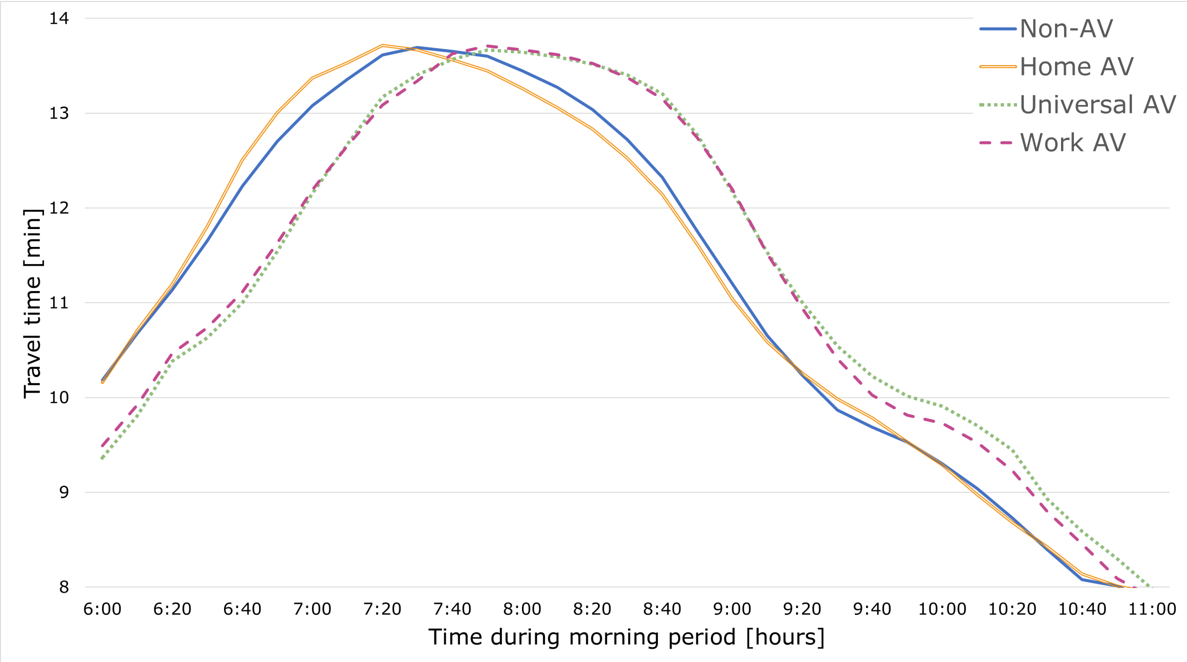


Figure 5.4: Aggregated travel time profiles for each mode in the Haaglanden network

The following can be observed from the figure and table:

- Within the first period, travel times are already significantly higher than those associated with free flow conditions.
- Regarding the AVs, Home AV shows the closest travel time profile to Non-AV.
- Universal and Work AVs show similar profiles which do significantly differ from Home AV.
- Universal AV shows the biggest increase in travel times and delays.

The fact that the travel times are already significantly high in the beginning, i.e. immediate delay, can be related to the departure time profiles. It could be observed that at 6:00 AM there was a already a substantial amount of departing vehicles, which was primarily due to the scaling factor μ_2.

The profile of Home AVs lies significantly different within the morning period than Universal and Work AVs. This can be assigned to the possible utility loss of Home AVs when arriving after the PAT. If we recall the mathematical formulation, a Home AV will always loses utility from the home side during travel. Since this home utility (α) is significantly lower than the utility associated with work ($\alpha+\gamma$), Home AVs show a relatively high aversion to late arrivals compared to Universal and Work AVs in which, after the PAT, utilities are lost from the work side. This explains the shifted profiles and the similarities between Universal and Work AVs. To some extent this could also be observed in the departure time profiles (Figure 5.3) This observed shift in profiles might be even more extreme and discrete due to the assignment per 10 minute time intervals.

Even though relative changes in delays are small, we observe an increase for every AV type compared to non-AV. This will be interesting when assessing mixed traffic situations by means of increasing penetration rates, as presented in 5.3.1

Route choice
Regarding route choice in the total network area, we focus on the VKM per mode and road type. Table 5.4 presents these.

Table 5.4: Total vehicle kilometres (VKM) for each mode including difference with reference situations

Road category	Non-AV	Home AV		Universal AV		Work AV	
Motorway	2,642,545	2,636,128	*-0.24%*	2,637,689	*-0.18%*	2,637,351	*-0.20%*
Prov./dist. road	1,259,488	1,263,714	*0.34%*	1,263,291	*0.30%*	1,263,629	*0.33%*
Urban road	1,236,918	1,239,154	*0.18%*	1,237,602	*0.06%*	1,237,293	*0.03%*
Total	5,138,951	5,140,172	*0.02%*	5,139,582	*0.01%*	5,138,273	*-0.01%*

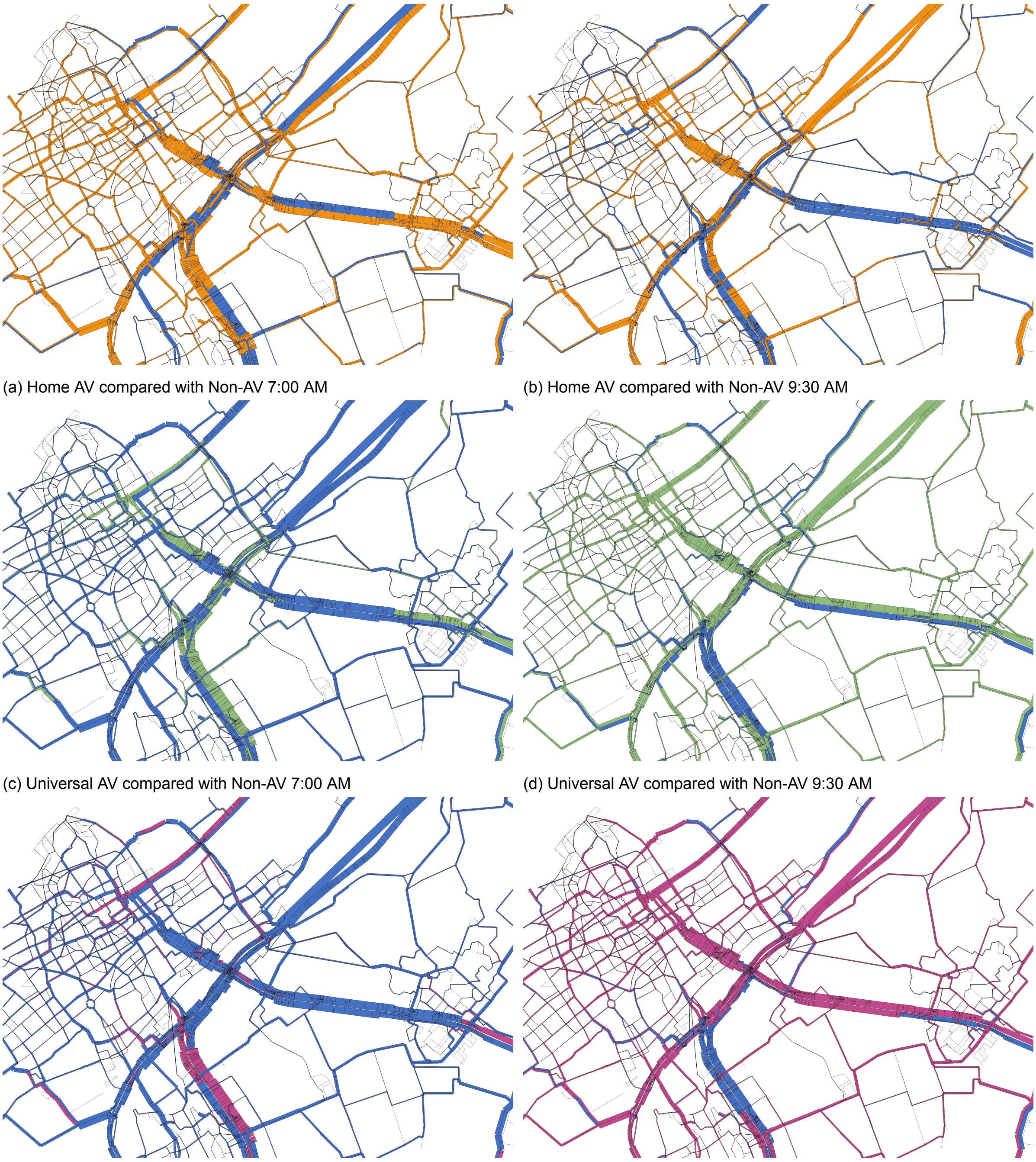
The following can be observed from the table:

- Differences are relatively small and might be considered insignificant, especially the network totals.
- Scenarios in which AVs are considered show a slight decrease in VKM on motorways and a slight increase on the underlying road networks.

We must regard the fact that these are again aggregated results for the entire network during the entire morning period. Therefore the relative differences are small and might be considered insignificant. However, if we were to extrapolate these results, we can deduce that AVs show less aversion to longer distances, i.e. longer travel times, which can primarily be assigned to the lower valuation of travel time by inclusion of the efficiency factors within the $\alpha - \beta - \gamma$ model. Note that no differentiation was made in VTT regarding the route choice model and that observed differences in VKM can be assigned to the VTT changes in the departure time choice module. The increase VKM on the underlying road network is important to regard when discussing the external effects.

Traffic flows
Since the differences in the OmniTRANS network outflows are relatively small, the presented traffic flows represent absolute differences between AV types and the Non-AV. They are given for two time periods, 7:00 and 9:30, with the main focus at intersection 'Prins Clausplein' and the urban road network of the Hague. Figure 5.5a to 5.5f present the compared flows at those times.

Within these figures the same colours are used as in previous figures, namely Non-AV (blue), Home AV (orange), Universal AV (green), Work AV (purple). It must be noted that once a link is depicted with a certain colour, this means that the associated vehicle type has the largest flow on this link. So an orange link means a higher share of Home AV compared to Non-AV at that point in time. Therefore, these figures show the dominant presence of a specific mode rather than that they provide insight in congested locations. We observe that at 7:00 AM, more Home AV than non-AV is present, especially on the underlying road network of the Hague, compared to the other variants, which have a dominant share at 9:30 AM.



(a) Home AV compared with Non-AV 7:00 AM

(b) Home AV compared with Non-AV 9:30 AM

(c) Universal AV compared with Non-AV 7:00 AM

(d) Universal AV compared with Non-AV 9:30 AM

(e) Work AV compared with Non-AV 7:00 AM

(f) Work AV compared with Non-AV 9:30 AM

Figure 5.5: Summed traffic flow for each AV compared to Non-AV at 7:00 and 9:30 AM, Prins Clausplein

External effects

As described in the assessment framework, the third perspective, namely the external effects are evaluated. This includes a global assessment of the impact on traffic safety and emissions based on the results associated with route choice, as presented above. The most important element to consider when assessing traffic safety and emission levels is the change in total VKM as well as congestion, i.e. level of service on road segments. With regard to investigating traffic safety it is required to differentiate between road categories since we can identify significant differences in safety levels per road type (Poppe, 1996; Janssen, 2005).

An observed increase in overall VKM can be directly related to a negative impact on traffic safety. Even though the changes in total VKM seem small and might even be considered insignificant, the direction with differentiation to road types gives a decrease of VKM on motorways and an increase mostly on provincial/distributor roads. The latter is considered the least safe type of road, i.e. the one with the highest associated risk factor (Janssen, 2005). If we recall that the number of accidents can be written in its most generic form as: VKM (per road type) $\times$ risk factor (per road type), this increase in VKM on provincial/distributor roads is considered unfavourable with respect to the overall traffic safety. However, one might argue that AVs are expected to be safer. On the other hand, mixed traffic situations might not be associated with safer conditions.

Respecting emissions, VKM changes with differentiation to road type showed an increase primarily observed on provincial/distributor roads which is regarded as beneficial. Since these roads are often associated with relatively lower emission levels of CO_2 due to more eco-friendly driving (speeds). On the other hand, when we assess the air (NO_x, *PM10*) and especially noise pollution, increase of VKM on the underlying roads, meaning more cut-through traffic, is seen as a negative impact. It must be noted that traffic flows did not significantly change: bottlenecks remained the same and thus the location of congested areas did not change. Though, there might be some small increases in queue lengths which can be related to a slight increase in mean travel times. Therefore, congestion probably did increase a little which directly results in an increase of emissions and is thus considered negative. However, the change in VKM on provincial/distributor roads might counter this effect. So an overall increase of emissions and the net effect this has remains questionable. Especially when regarding the fact that more and more future cars are expected to be electrical.

5.2.2. Selected OD relations

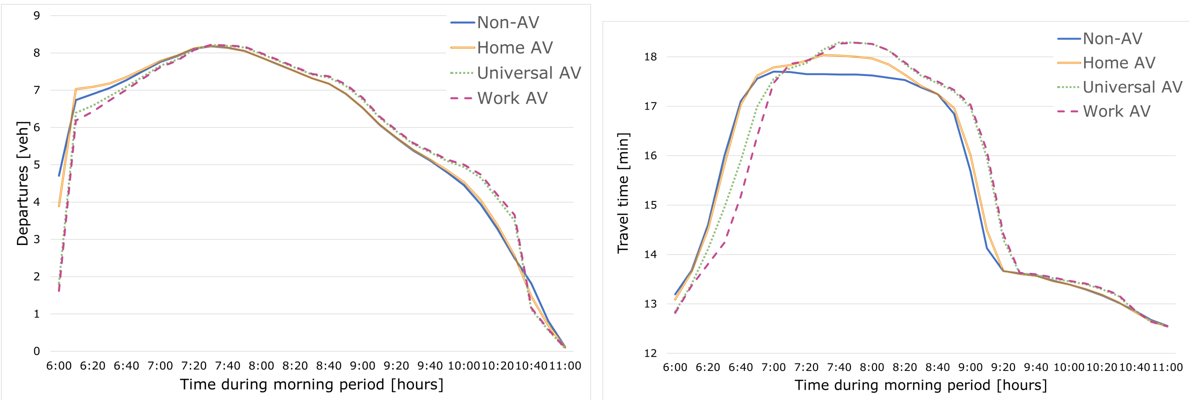
The results of the selected OD pairs will be discussed per OD pair in order from lowest to highest origin. To recapitulate, the OD relations and their key values, as presented in section 4.2.1, have been added in Table 5.5.

Table 5.5: Selected OD pairs and their characteristics in which delays correspond to the reference scenario (non-AV)

Origin	Destination	Demand [veh]	Distance [km]	FFTT [min]	Mean delay [min]
10	156	183	13.92	12.09	3.31
23	26	4060	26.3	13.99	5.8
157	127	107	12.37	7.26	6.8

OD pair 10-156 (Leiden to Zoetermeer)

Based on the departure time profile for relation 10-156 (Figure 5.6a), it seems that an equilibrium has been reached. This assumption is based on the absence of sudden irregularities in the graphs. As for the size and direction of these departure time differences, effects are again small. However, it can be seen that Home AVs have shifted the departures to the beginning and Universal and Work AVs more to the end of the morning period. Regarding travel time and related delay differences, we present both Figure 5.6b and Table 5.6. The figure implies that for this specific relation, all AV types are associated with an increase in travel time whereas for Universal and Work AVs travel time increases the most. If we investigate the relative changes in delay, Universal shows the biggest increase. Similar to the 'Haaglanden' network this can be explained by the fact that, other than Home and Work AVs, Universal AVs use both the home and work end which widens the departure profile in the middle of the peak. This in turn increases travel times and delays the most.



(a) Departure time profile OD pair 10-156

(b) Travel time profile OD pair 10-156

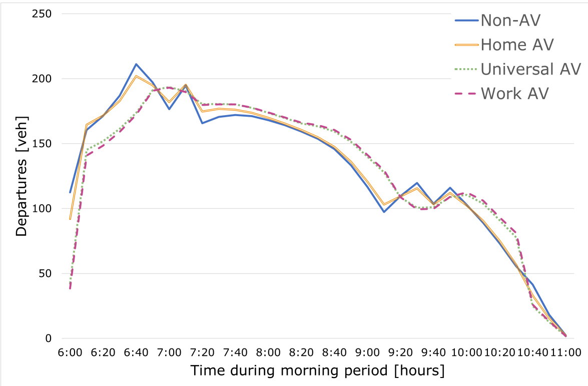
Figure 5.6: Departure time and travel time profiles OD 10-156

Table 5.6: Maximum, minimum and mean travel times including delays and relative changes per mode for OD pair 10-156

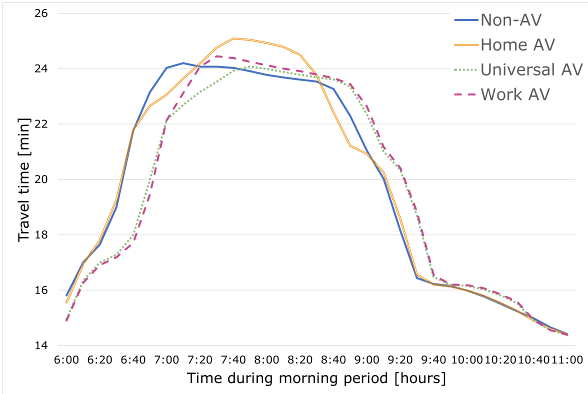
	Non-AV	Home AV		Universal AV		Work AV	
Max. travel time [min]	17.70	18.04	*1.9%*	18.29	*3.3%*	18.28	*3.3%*
Min. travel time [min]	12.56	12.55	*0.0%*	12.54	*-0.1%*	12.55	*-0.1%*
Mean travel time [min]	15.40	15.49	*0.6%*	15.55	*1.0%*	15.49	*0.6%*
Mean delay [min]	3.31	3.40	*2.7%*	3.46	*4.5%*	3.40	*2.7%*

OD pair 23-26 (Rotterdam to Leiden)

Based on the departure time profile for relation 23-26, we must conclude that no equilibrium with respect to the departure time choice has been reached. This is based on the irregular jumps within the graphs, although least observable for Universal and Work AVs. This assumption was confirmed by looking into previous iterations in which these jumps showed an alternating behaviour. With this in mind, analysis becomes more difficult but we do see Non- and Home AVs departures more to the beginning and Universal and Work AVs more to the end of the morning period. Regarding travel time differences, we present both Figure 5.7b and Table 5.7. The figure implies that for this specific relation, not all AV types are associated with an increase in travel times and delays. The mean travel times and delays for both Universal and Work AVs are even smaller than those corresponding to the Non-AV. Now, we need to regard the fact that this OD pair uses predominantly motorways and, as seen in the route preferences for the entire network, this road type is more associated with Non-AV users than with AV users. That still does not explain the highest travel time corresponding to Home AV and that its peak is observed later than both Universal and Work AV. However, we indicated that equilibrium was not yet reached. Therefore these results should be regarded with caution.



(a) Departure time profile OD pair 23-26



(b) Travel time profile OD pair 23-26

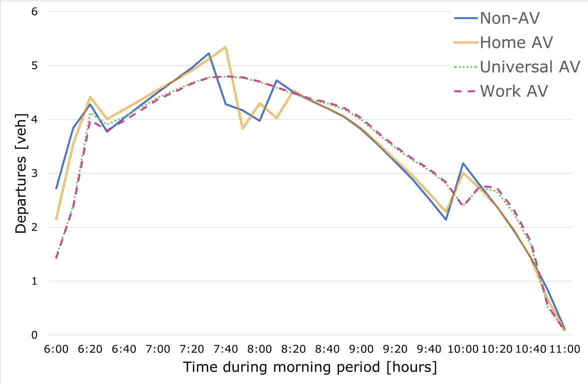
Figure 5.7: Departure time and travel time profiles OD 23-26

Table 5.7: Maximum, minimum and mean travel times including delays and relative changes per mode for OD pair 23-26

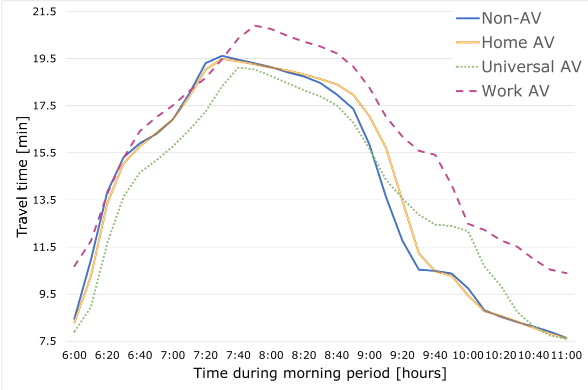
	Non-AV	Home AV		Universal AV		Work AV	
Max. travel time [min]	24.20	25.09	*3.7%*	24.08	*-0.5%*	24.44	*1.0%*
Min. travel time [min]	14.41	14.40	*-0.1%*	14.39	*-0.2%*	14.39	*-0.2%*
Mean travel time [min]	19.79	19.89	*0.5%*	19.61	*-0.9%*	19.71	*-0.4%*
Mean delay	5.80	5.90	*1.7%*	5.62	*-3.2%*	5.72	*-1.3%*

OD pair 157-127 (Zoetermeer to the Hague)

Similar to the previous OD relation, the departure time profile show irregular jumps within the graphs, although it should be noted that we are looking on a different scale here. The y-axis is more ‘zoomed in’, meaning that the difference between one departing vehicle is depicted with a relatively big jump. This aside we can not assume that equilibrium was reached regarding the departure time choice. This assumption was confirmed by looking into previous iterations in which these jumps showed an alternating behaviour. Regarding travel time differences, we present both Figure 5.8b and Table 5.8. The figure implies that for this specific relation, not all AV types are associated with an increase in travel time and/or delay. The mean travel and delay time for Universal is even smaller than those corresponding to the Non-AV. Only Work AVs show a significant increase in travel times and delays. Now, we need to regard the fact that this OD pair uses predominantly motorways and the congested intersection 'Prins Clausplein' which is used by many other routes, which may also be the reason for not yet having reached departure time choice equilibrium. With this last in mind, these results should be regarded with caution.



(a) Departure time profile OD pair 157-126



(b) Travel time profile OD pair 157-127

Figure 5.8: Departure time and travel time profiles OD 157-127

Table 5.8: Maximum, minimum and mean travel times including delays and relative changes per mode for OD pair 157-127

	Non-AV	**Home AV**		**Universal AV**		**Work AV**	
Max. travel time [min]	19.62	19.49	*-0.7%*	19.13	*-2.5%*	20.90	*6.5%*
Min. travel time [min]	7.64	7.62	*-0.3%*	7.60	*-0.5%*	10.39	*36.0%*
Mean travel time [min]	14.06	14.19	*0.9%*	13.93	*-0.9%*	16.03	*14.0%*
Mean delay [min]	6.80	6.93	*1.9%*	6.67	*-1.9%*	8.77	*29.0%*

To conclude on the results of the selected OD pairS, similar changes in departure time choice and travel times were observed as for the entire network. Since these results were shown on OD level, they were less aggregated. However, it was observed that equilibrium was not yet reached for every OD pair which led to some irregular jumps in departure time choice profiles and difficulty to explain the results such as travel time and delay differences. This was the case for both OD pair 23-26 and 157-127. An explanation may be that these two relations use routes that are widely used by other OD pairs as well. Other than OD pair 10-156, which does not have to share its route with many other OD pairs. To investigate this further and make substantiated claims on the effects on these OD pairs, more iterations should have been added. Moreover, we need to regard the μ_2. The higher we would have set this scaling parameter, the more discrete the probabilities are distributed and the profiles might become even more irregular. Lastly, a slightly wider profile could be observed for OD pairs 23-26 and 157-127 which use predominantly (congested) motorways and are associated with relatively bigger delays. Although we need to be aware that it was these relations in particular, that had not yet reached equilibrium.

5.3. Sensitivity Analysis

This section presents the results from the sensitivity analysis. A distinction is made between the analysis regarding the penetration rates (section 5.3.1) and the analysis of sensitivity to the model parameters (section 5.3.2).

5.3.1. Penetration rates

This section presents the results of the sensitivity regarding different penetration rates of Universal AVs and Non-AVs. Figure 5.9 gives the departure time profiles for each chosen penetration rate of Universal AVs and non-AV.

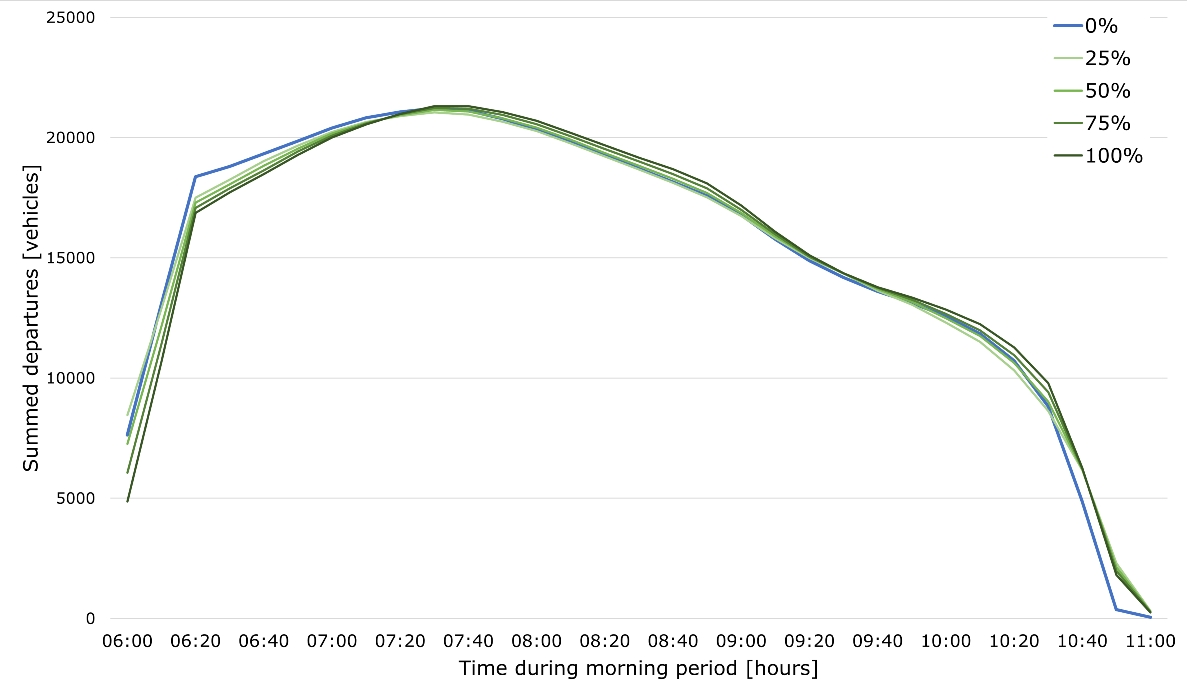


Figure 5.9: Summed departure time choice profiles for increasing penetration rates of Universal AVs

The above figure shows the summed departure time profiles for each of the chosen penetration rates. This means that the profile associated with 25% shows the summation of 75% Non-AV departures and 25% Universal AV departures. It can be observed that with increasing Universal AV penetration rates, the overall departure times shift to follow the profile of the scenario with 100% Universal AVs. What stands out is the differences between the variant with 0% Universal AV and the other variants. This is significantly larger than the differences between variants with a percentage of AVs. This might be explained by the expulsion effect. This means that 25% Universal AV does already take a significant dominance in the congestion peak periods and the 75% non-AV is not able to compensate enough to counter this effect. The following rates show less extreme effects since the major shift has already taken place at or before the 25% penetration rate.

Table 5.9 presents the relative change in departures per hour for the non-AV users. The percentages show the relative change in number of departing non-AVs per hour compared to the reference scenario (100% non-AV). It can be observed that with increasing the penetration rate, the first two hours correspond to an increase in number of departing non-AVs. The later hours of the morning period are associated with a decreasing number of departing non-AVs when a higher share of Universal AV is present. Thus, as a result of (Universal) AV, non-AV users have to depart earlier to reach their destination in time, because non-AV users are more sensitive for delay compared to AV users. This coincides with the hypothesis that AVs show less aversion to longer travel times, will increase congestion and thus have an adverse effect on non-AV users. They are the ones that are 'forced' to reschedule their departure times, in this case to more early. It would be interesting to investigate the scenarios with increasing penetration rates of Home AV and see if non-AV users were to reschedule their departure to later. Due to time limitations this has not been investigated in this study.

Table 5.9: Relative changes per hour in number of departing non-AVs as a result of increasing penetration rates

Time period	25% Universal AV	50% Universal AV	75% Universal AV
6:00 - 7:00 AM	11.1%	11.2%	11.3%
7:00 - 8:00 AM	0.1%	0.4%	1.2%
8:00 - 9:00 AM	-2.2%	-2.4%	-2.7%
9:00 - 10:00 AM	-0.9%	-1.1%	-1.3%
10:00 - 11:00 AM	-20.3%	-20.3%	-20.3%

We only present results related to departure time choice and not to route choice since no differentiation between vehicle types is made in the DTA. Which means that route choice is only based on travel times and the choice to take a certain route does not differ among AV and non-AV, however the valuation of travel time does. So, even though there could be differences with respect to road type usage, this is more due to the fact that proportions (AV/non-AV) vary over time. These differences are probably limited since route choice within a time period does not differ between non-AV and Universal AV.

Table 5.10: Travel times for the entire network with increasing penetration rates of Universal AVs

KPI	0%	25%	50%	75%	100%
Total travel time Non-AV [hours]	94,097	69,801	46,510	23,152	-
Total number of vehicles Non-AV	473,868	355,401	236,934	118,467	-
Mean travel time Non-AV [min]	11.91	11.78	11.78	11.73	-
Total travel time Universal AV [hours]	-	23,408	46,829	70,648	94,455
Total number of vehicles Universal AV	-	118,467	236,934	355,401	473,868
Mean travel time Universal-AV [min]	-	11.86	11.86	11.93	11.96
Total summed travel time [hours]	94,097	93,209	93,339	93,800	94,455

It can be observed that the mean travel times decrease for Non-AV users with increasing the share of Universal AVs. This seems positive, however the underlying reason for this effect is that non-AV users are forced to depart earlier with an increase of AV penetration rates. They do then obtain shorter travel times but this is due to the fact that departing later would give a higher disutility, considering the Non-AV users' preferences. The opposite is happening for Universal AVs. With increasing their share, the longer their mean travel times become. However, based on their preferences given the ability to be productive during travel, they show less aversion to longer travel times and therefore prioritise the PAT.

Based on these findings and (departure time) results presented for the case study area, it would have been appropriate to also study penetration rate effects with Home and Work AVs. However, due to time limitations this was not possible.

5.3.2. Extended α-β-γ model parameters

The sensitivity regarding different parameter values is assessed based on the scenario with a demand of 100% Universal AVs. This demand remained unchanged during the different runs and was equal to the previously used 473,868 vehicles. First, the results of changing $\alpha - \beta - \gamma$ parameters are presented followed by the results of varying the efficiency factors. Table 4.11 and 4.12 showed the parameters per variant that have been selected for analyses with $\alpha - \beta - \gamma$ parameters and efficiency factors, respectively.

α-β-γ parameters

Table 5.11: Key performance indicators for Universal AV in the Haaglanden network with varying α-β-γ parameter ratios

KPI	Reference	α-β-γ 1		α-β-γ 2	
Total travel time [hours]	94,455	92,921	*-1.62%*	96,371	*2.03%*
Total travel distance [km]	5,341,167	5,341,577	*0.01%*	5,341,355	*0.00%*
Mean speed [km/hour]	56.55	57.48	*1.66%*	55.42	*-1.98%*
Mean travel time [min]	11.96	11.77	*-1.62%*	12.20	*2.03%*
Mean delay [min]	4.15	3.96	*-4.58%*	4.39	*5.78%*

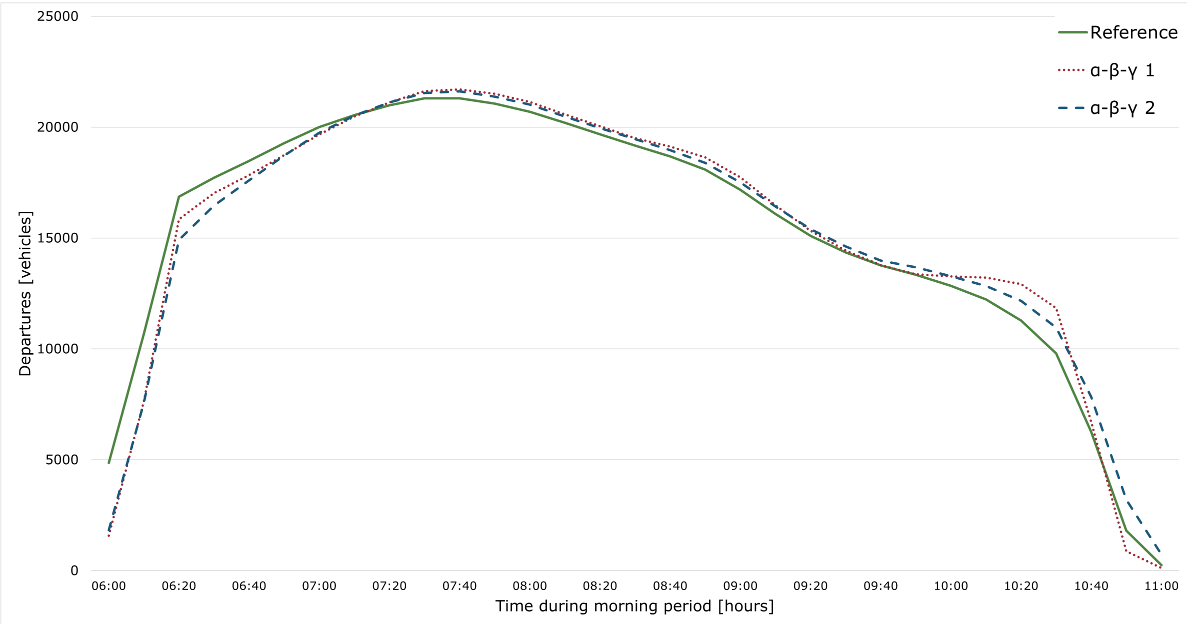


Figure 5.10: Departure time profiles for varying α-β-γ model parameters

Table 5.11 shows the relevant KPIs associated with this sensitivity analysis. Figure 5.10 gives the departure time profiles for the variants with different α-β-γ parameters, including the profile associated with the reference scenario (green). It can be observed that the total travel time more importantly the mean delays are significantly dependent on the selected ratios of the parameters. With an increase in β/α and γ/α, travel times and delays increase. In other words, a higher 'penalty' associated with deviation from arriving at the PAT means that people accept longer travel times to minimise this deviation which results in more congestion (increase in delays). As expected, the total travel distance is not that sensitive to these changes as this is a result of a change in route choice. This route choice is barely affected by the increase in travel times since no differentiation is made within the DTA between different runs. Furthermore it can be seen that the departure time profile associated with a high β/α and γ/α (α-β-γ-2), i.e. high penalty for arriving early or late, shift towards the right in direction of the PAT. Vice versa, the departure time profile associated with a lower β/α and γ/α

(α-β-γ-1) widens the profile which corresponds to prioritising low travel times over the PAT. Lastly, the green ‘Reference’ profile shows the variant with the highest penalty of arriving to late ($\gamma = 4$) compared to a relatively low penalty of arriving early ($\beta = 1$). This explains why this graph is depicted more to the left (earlier departures), where one could initially have thought it should be positioned in the middle, based solely on the comparison of β/α and γ/α.

Efficiency factors

Table 5.12: Key performance indicators for Universal AV in the Haaglanden network with increasing efficiency factors e_h and e_w

KPI	Reference	Eff 1		Eff 2	
Total travel time [hours]	94,455	95,450	*1.05%*	96,307	*1.96%*
Total travel distance [km]	5,341,167	5,341,502	*0.01%*	5,341,436	*0.01%*
Mean speed [km/hour]	56.55	55.96	*-1.04%*	55.46	*-1.92%*
Mean travel trime [min]	11.96	12.09	*1.05%*	12.19	*1.96%*
Mean delay [min]	4.15	4.28	*3.13%*	4.38	*5.54%*

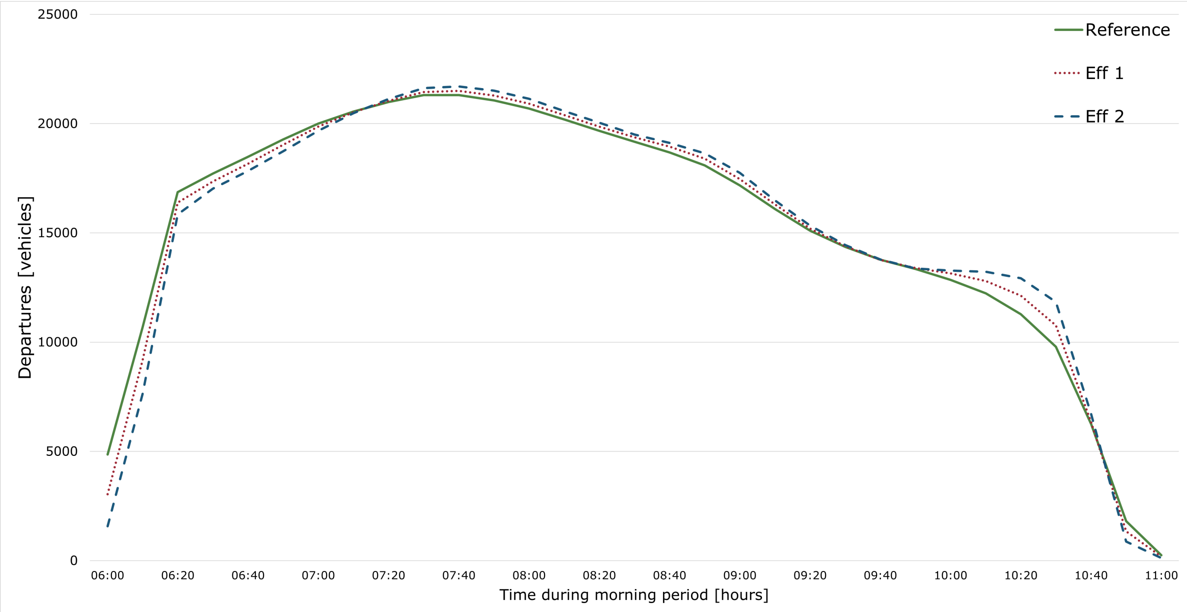


Figure 5.11: Departure time profiles for increasing efficiency factors

Table 4.12 shows the relevant KPIs associated with this sensitivity analysis. Figure 5.11 gives the departure time profiles for the variants with different efficiency factors, including the profile associated with the reference scenario (green). Similar to the results associated with $\alpha - \beta - \gamma$ sensitivity analysis, we can observe an increase in total travel time and mean delays. As expected, the total travel distance has not changed much as this is a result of route choice which is barely affected by the increase in travel time.

Furthermore it can be observed that the departure time profiles, with increasing efficiency factors, move more towards the right, in direction of the PAT. This can be explained since a lower valuation of your travel time, by increased productivity, is associated with less aversion to longer travel times and therefore a relatively stronger preference to arrive at or near the PAT

Validation
Based on the above sections we can conclude that the model outcomes are in line with what was expected. Results indicate that introducing AVs in real-life city network may cause an increase in congestion levels (delays), travel times and vehicle kilometres. Home AVs shift their departure more the beginning and Work AV more to the end of the peak. This can be compared to what we would expect in real-life situations with simple deduction of what changes activity based departure time choice brings. A businessman who is more likely to engage in on-board work activities, will probably shift his departure time to later in the morning period. Then he might arrive a little later than preferred but has already been doing some work while travelling. This corresponds with (the direction of) the model results. The increase in vehicle kilometres can also be explained based on the reduced aversion to longer travel times. If that same businessman was not able to carry out any work during his trip, he would show a greater value to having a shorter travel time, which is often associated with taking a shorter route.

If we consider the penetration rates, an expulsion effect could be observed meaning that non-AV users were ‘forced’ to reschedule their departure times outside of peak moments. This is in line with the expected deviation from their preferred departure times. Vice versa, AV users show less aversion to longer travel times and therefore prioritise their PAT, something that logically can be deduced for real-life situations, based on their preferences.

6 Discussion

The previous chapter presented the model results and identified the main effects that could be observed. This chapter discusses these results with regard to policy-relevant insights and aims to relate the outcomes to the broader perspective in which this study was conducted. In addition, the outcomes are discussed based on the assumptions that were made. Similar to section 4.2.5, assumptions can be divided in general assumptions and model assumptions.

Policy-relevant insights

The main objective of this research has been to investigate the effect of activity based departure time choice with AVs within a real-life city network. The results showed that with the extended $\alpha-\beta-\gamma$ setup, vehicles in which home activities can best be performed will depart earlier, vehicles in which both home and work activities are possible depart in the middle of the peak and vehicles which are best suited for work activities will depart later in the peak. However, given the initial set of $\alpha-\beta-\gamma$ model parameters, vehicles in which it is possible to engage in work activities (Universal and Work AVs), showed similar behaviour to late arrivals, as they loose less utility during travel after the PAT compared to vehicles in which only home related activities can be performed (Home AV).

Furthermore, the departure time profiles of Home AV users were closer to the profiles of non-AV users. This indicates that if we would have future mixed traffic situations with non-AV users and AV users which engage primarily in home activities, these will compete for the same departure times. As shown in the sensitivity analysis, it is likely that the non-AV users will then have to reschedule to less preferred departure times. This effect may even be stronger than competing with vehicles in which travellers can also engage in work related activities. So the competition for the same departure times of non-AVs seems stronger with Home AVs than Universal and Work AVs. This leads to the expectation that regarding increased delays and related change in route choice, this effect is strongest with mixed traffic situations which include Home AVs. The vehicle type that shows the biggest departure time profile shift compared to non-AV is the Work AV. This implies that it would be best to have mixed traffic situations with conventional car users and AV users which engage in work related activities since they will have to compete the least for the same departure times and corresponding network usage.

If we consider the selected OD pairs and generalise the outcomes, results indicate that OD pairs with routes primarily using the main road network, widen the departure time profiles. These routes are often associated with traffic from other OD pairs. This generally corresponds to congested locations. In addition the OD pairs with these kind of routes, often have little route choice options other than to stick with these main arteries. This means that due to congestion on these routes, more departures can be observed in the beginning as well as in the end of the peak, i.e. more travellers deviate from their preferred departures and shift to early or late departure times. On the other hand, if we consider OD relations with routes only using the lower road networks, results indicate that travellers do not have to deviate much from there preferred departure times. This can be explained by the fact that they use roads which are less congested and have more routes to choose from. So, if a route is congested, they will have the possibility to reroute with a slight, however acceptable, increase in travel time. Therefore, observable changes between vehicle types are small compared to routes which use the main road network. This means that the departure time choice for OD pairs in urban areas are less affected by what type of activity travellers engage in. However, given the explanation above, this does also imply that with mixed traffic situations competition for departure times increases which probably leads to a bigger disadvantage for non-AV users.

Overall the outcomes suggest that the effects towards departure time shifts are strongest if we would have mixed traffic situations with non-AV and Home AV. Similarly it is expected that these are less with vehicles in which work activities can be performed. Regarding the distinction towards road types, more deviation from preferred departures was observed for routes which use the main road network. On the urban and provincial road network this effect was less extreme. This would imply that for mixed traffic situations on those roads, competition is higher and non-AV users will be negatively affected more. Furthermore there has been an overall observed increase in VKM for these underlying road networks which may be linked to a decrease in traffic safety. One might argue that one aspect of AVs is increased safety levels. However, before we will have 100% penetration rate of fully AVs, there will be a period which includes mixed traffic. This may cause even more dangerous traffic situations, decreasing the overall traffic safety. It remains difficult to assess the net effect considering CO_2 emissions since the increase in overall VKM is small. However, it must be noted that the emissions regarding noise and air pollution have a negative impact due to the traffic increase on the underlying road network. More noise pollution as well as an increase in NO_x or *PM10* within urban areas is considered undesirable. Then again, it is expected that more cars will be electrical and have a more sustainable way of driving which might reduce these effects.

Model assumptions

Several model assumptions were made to cope with the computational complexity. Still, with these simplifications and aggregations such as time steps, time intervals etc., the duration of a single simulation run was somewhere in between 45-60 minutes for the single link model, which was considered manageable. However simulation running times lasted 10-12 hours for the 'Haaglanden' network. Especially with mixed traffic simulation runs, calculation times increased significantly. OmniTRANS 4.2.35 was run on single core which could not be adapted to multi-core usage. This restricted the minimisation of simulation times. Although, we need to be aware that with the size of this network: the dynamic demand and 28,224 OD pairs - especially considering multi-user class assignments - calculation times will often increase significantly.

Due to these calculation times and the desired number of scenarios, a limited number of 3 iterations has been set for both INDY as well as the outer loop. This is regarded as relatively few considering the number of zones and total number of trips. The results per OD pair showed that equilibrium in departure time choice was not yet reached for all relations and thus, the observed effects were not yet definitive. Although we did visually observe converging behaviour, the size of the exact end results could have shifted a little. However, the direction of the departure time profiles on network level is considered to be definitive and valid.

Within the model, no demand elasticity was taken into account, meaning that the demand was assumed to be fixed. This has been neglected to observe the net effects to departure time changes and increase or decrease in congestion patterns. In reality there is a possibility that people not to make the trip anymore or switch modes due to a significant increase in delays. Or vice versa, when delays decrease, more people might consider to make a trip (and/or switch modes). Although we do need to mention that this elasticity might have reduced the observed effects, the direction remains unchanged and considering the size of obtained model results (i.e. limited changes in delays), the influence of including elasticity is considered relatively small. Especially considering the high degree of habitual behaviour of people in terms of mode and trip choice. Normally these choices are only affected by substantial differences in travel (dis)utility.

During this modelling study, several model parameters were set. Two of these are of main importance when discussing the travel times calculations: the maximum jam density of 130 veh/km and by use of travel time functions not able to model blocking back phenomena. Once a link has reached its maximum density, travel times will not increase further as well as no blocking of other routes not travelling via this bottleneck. This may have underestimated the derived travel times and therefore route delays. To check if this assumption was justified, the number of exceeding densities were retrieved from the link database. This led to 1,149 of the total 233,703 links over all periods which had a jam density greater than 130 veh/km. It was investigated where these links were located, how severe the exceedance was and for how long. We found that predominantly short exit ramps near congested motorway sections gave high jam densities. For the links which exceeded this density the most, this was often significantly higher and for more than 10 consecutive time periods (100 minutes). So even though the total number of links with exceeding the maximum jam density over all periods is less than 0.5%, for the ones where this exceedance occurs, this was severe. Therefore we need to be aware that the effect of not incorporating blocking back, might not be as small as initially thought. Not all travel times and delays can be assumed 'realistic' and it is likely that these are underestimated. We need to keep in mind that it is precisely the increase in delays which is a key indicator associated with introducing AVs. This effect is thus probably slightly flattened by this assumption.

Furthermore, intersection delays have not been incorporated which might have resulted in underestimating travel times and route delays on the underlying road networks, especially the urban road network. This might have lead to an underestimation of disutilities for those routes and therefore an overestimation of VKM on those roads. Even though, this does affect the absolute VKM per road type, this study did not differentiate within the DTA among vehicle types and resulting route choice. So, intersection delays are the same for all types and thus the size and direction of the effects is still meaningful.

Regarding the departure time choice results, two elements need to be addressed here. The model works with a morning period divided in 31 time intervals of 10 minutes. Therefore the level at which departures could be assigned was also on these 10 minute periods. This leads to the fact that even the slightest delay may result in a departure 10 minutes later. Based on the sensitivity of the model to the $\alpha - \beta - \gamma$ parameters and the relatively high penalty associated with arriving to late (i.e. $\gamma > \alpha > \beta$), predominantly higher disutilities were assigned to arriving (a period) too late. Although due to the use of the multinomial logit function, there are some probabilities which assigned demand later periods, the departure time profiles showed a resultant of the departing vehicles and thus followed a profile which mostly gives departures before the preferred departure time. In addition, the scaling parameter μ_2 needs to be regarded when interpreting the results. This parameter mimics the imperfect knowledge of travellers and distributes the probabilities of demands per time interval less discrete. This parameter therefore reduces the effect described above. However, selecting the value of this parameter is highly arbitrary. If this value would have been increased, probabilities would be distributed more discrete and the departure time profiles would follow the preferred departures, or earlier, even more.

Conclusively we can state that using a dynamic traffic simulation model is useful to study the network effect with AVs, since it was able to capture key indicators to investigate departure time choice, delays and route choice. However, using this specific version of the modelling software (OmniTRANS 4.2.35) and the DTA (INDY 1.02.03), did lead to some restrictions in computational power and dynamic modelling options. The main limitation which is referred to was not being able to include blocking back effects. This reduced the net effect of increasing delays (congestion) which in turn affects departure time choice, route choice and the related external effects.

General assumptions

One of the most important simplifications has been the level of differentiation. This study did not differentiate between the characteristics of user classes, other than the formulation of scheduling preferences per vehicle type. This means that homogeneity in preferences among all commuting travellers has been assumed. I.e. the $\alpha - \beta - \gamma$ scheduling preferences as well as efficiency factors, which describe valuation of being at home or work and the level of on-board productivity, are the same for all users. In reality, these vary among individuals. A businessman might already engage in several on-board work related activities, such as preparing meetings or making calls while a construction worker does not have this ability and is 'restricted' to spend the time on leisure activities. At the same time some of the on-board work related activities can already be performed in non-AVs today and thus the advantages might be reduced. Regarding the model results this means that we should be cautious with making hard claims on the size of the direction of Home and Work AVs and their departure time preferences, since these effects could be overestimated.

In addition, no differentiation was made regarding network characteristics per mode. I.e. each vehicle type uses the same speeds, capacities and densities etc. This is especially relevant when we assess the route choice and related external effects. The results showed an increase in VKM on the underlying road network. However, this was based on the increase in travel times. With AVs the possibility of shorter headways, increased link capacities and therefore reduced increases in travel times might diminish the effects. However, the opposite could also be true if AVs will not have the ability of cooperative driving. Furthermore, mixed traffic situation are usually considered to have a lower road capacity. These phenomena become interesting if designated lanes/routes will be available for AVs.

The adoption of the extended $\alpha - \beta - \gamma$ model parameters needs to be discussed as well. Since this study builds on previous work of among others (Pudāne, 2019), the extended $\alpha - \beta - \gamma$ model has been adopted. However, the sensitivity analysis showed that the model outcomes are significantly sensitive to these input parameters, especially the ratio of $\alpha - \beta - \gamma$ parameters. This means that the penalty for arriving too late or too early, influences the total travel time in the network. This can be related to the difference between flexible or strict working times where a higher γ/α and β/α ratio corresponds to the more strict working times. As stated by Pudāne (2019), the utility function of Home AV is actually not that different from a single travel time penalty due to the constant home utility. Therefore other options to model departure time preferences would be interesting as well. For instance the more generalised form of scheduling functions as based on Vickrey (1973). This model assumes monotonously decreasing and increasing utilities for home and work. This replaces the step-wise character of the $\alpha - \beta - \gamma$ model and enables analysis for slight increases in departure time periods. Other recent studies derived the so-called slope model or the exponential scheduling preferences to model this aspect (Fosgerau & Engelson, 2011; Hjorth et al., 2013).

It is important to discuss the level of suitability of the $\alpha - \beta - \gamma$ scheduling preferences to model departure time choice of non-AV versus AV users. This model is based on the assumption that there is a drop in utility due to the necessity of travel. However, travel time will remain a necessity to arrive at your work, so to what extent is this utility decrease present? Do AV users really show less aversion to longer travel times and can these be modelled with the use disutility function? They might not use their time productively but just enjoy the fact of not having to drive. Or they might even experience disadvantages when they 'have to' engage in activities, while the driving task was more or less considered relaxing. These aspects are important to regard when interpreting this modelling approach and its outcomes.

No ODD has been included since this study was only focused on fully AVs (level 5). However as mentioned, incorporating an ODD will probably have an effect on route choice. It might be that vehicles with an ODD will use longer routes with consecutive segments within that ODD. This may increase the total VKM, primarily on the main road network, but may reduce the intensified usage on the underlying road network. The increase in VKM on the main road network might result in more extreme effects regarding departure time choices.

The model used certain calibrated preferred arrival time profiles. These profiles strongly affect the deduced departure time profiles and with that the network travel times, flows and route choice. Using a different profile would have had a significant impact on this study's outcome.

7 Conclusion & Recommendations

In this study a macroscopic dynamic transportation model has been used to investigate network effects of activity based departure time choice with automated vehicles (AVs). Since AVs bring the ability to perform home or work activities during travel, this can change travellers' departure time preferences. These preferences have been modelled with an extended version of the most widely used $\alpha - \beta - \gamma$ model. Previous work has shown the effects of these preferences within a theoretical single link setting (bottleneck model) and showed that using the extended $\alpha - \beta - \gamma$ led to skewed congestion patterns. This study set out to investigate the size and direction of these effects within a network. Therefore a transportation model was used on the 'Haaglanden' road network, which ensured that multiple origins and destinations as well as route choice could be incorporated.

To look into the departure time choice related to different types of on-board activities, a differentiation was made between home/work activities and three AV types have been defined: Home, Universal and Work AVs. These AVs differ from each other in the way that they are each associated with a different mathematical formulation of their scheduling preferences based on utility functions. These utilities have been mathematically rewritten and arranged to enable integration in the departure time choice module within the transportation model. The three AV types and a reference situation, i.e. conventional vehicle, were tested on the road network of the 'Haaglanden' region. By means of a dynamic traffic assignment, each mode has been assigned to the network separately.

The model results showed that congestion (delays) increased when AVs were assigned to the network and that based on the type of AV, the departure time choice shifted either to the beginning (Home AV) or to the end (Work AV). Similar trends could be observed regarding travel times. Next to the increase in travel times (delays) with AVs, Home AVs increased it more to the beginning of the peak, Work AVs more to the end, whereas Universal AVs showed a combination of both. The biggest increase in travel times was observed with Universal AVs. Moreover, the total vehicle-kilometres (VKM) increased with the introduction of AVs compared to the reference situation. This overall increase could in particular be assigned to a more intensive use the underlying road network, meaning urban and provincial/distributor roads.

Though the direction of these effects could be identified, the size of some of them remained small and could in some cases even be considered insignificant. A sensitivity analysis was conducted to investigate the model's outcome to the input parameters and the influence of different penetration rates of AVs. The effect of penetration rates was analysed with Universal AVs compared to non-AV. Results showed that with increasing the share of AVs, non-AV users were 'forced' to shift their departures more to the beginning of the morning period. At the same time, their overall travel times decreased, which can be explained by the fact that they show a greater aversion to longer travel times than the share of AV users. The sensitivity of the model's outcome regarding the model parameters has been analysed with different ratios of $\alpha - \beta - \gamma$ parameters and efficiency factors. The first showed that the more important/strict arriving at the preferred arrival time is, meaning the significance of β and γ, the more the departure times shift to the preferred departure times but the more travel times increase. The second showed that with increased efficiency of on-board activities, making the efficiency factors more extreme, less aversion was assigned to travel time and thus travel times increased.

So what have we learned? It seems that not all effects which AVs are expected to bring, are as positive as some would think. This study pointed out that with introducing fully AVs within larger road networks while accounting for the performed on-board activity, congestion might increase. This is a result of the ability to spend trip time productively which results in less aversion to longer travel times. This may lead to an increase in congestion levels and VKM which is unfavourable with regard to emission levels. Furthermore a small but significant increase was observed on the usage underlying road network which is considered to be disadvantageous with regard to traffic safety. Considering emissions, the net effect of changes CO_2 emissions remains questionable. However, the increase in VKM on urban/provincial roads leads to a negative impact towards noise and air pollution (NO_x and *PM10*) in these areas.

On the other hand, one might argue that one of the positive aspects associated with AVs is a better road/vehicle safety. However, there is still a long way to go before all, or even a significant part, of the vehicles on the road will be (fully) AVs. And it is especially those mixed traffic situations, in which both non-AVs and AVs share the same road network, which might be the most hazardous. Another aspect to bear in mind is the trend towards more sustainability with modern (electrical) cars. This will reduce the negative impact of increased noise and air pollution.

Moreover, it was observed that with mixed traffic, non-AV users shifted their departure times more to the beginning of the morning period while AV users shifted the departures more to peak travel time moments. Since AV users have less aversion to longer travel times, they have the opportunity to arrive closer to their preferred arrival times. This implies that non-AV users will come out on the losing end when it comes to these mixed traffic situations.

So what can be done to improve this and what is in the best social interest for everyone? There are several options one could think of to level the aforementioned differences. One option could be to introduce designated routes for AVs. This way the longer travel times and routes are linked to the users that can better tolerate these. It must be noted that these routes should primarily use the main road network to be beneficial with respect to traffic safety. This is something that is actually already happening to some extent with the Operational Design Domain (ODD) of lower levels of AVs. A vehicle which is only able to be fully automated for a specific design domain may already choose routes which are constructed in such a way that it connects consecutive sections within its ODD. These are often the roads within the main road network, which would then be associated with a better traffic safety. In addition, the travel times at peak moments would increase less for non-AV users meaning they do not have to shift their departure times outside of these peak moments.

Another direction of alternatives one could think of is the implementation of pricing systems. This can either be done with respect to road types or time periods. The first one could be done with implementation of charges for driving (AVs) on the underlying road network. Regarding time periods, charges for engaging in a trip outside of peak hours could be implemented to counter the expected increase in travel times. This would especially target the AV users since they are assumed to be more flexible due to the ability to be productive on-board.

Lastly, more and more city centres are becoming pedestrian areas where no car traffic is allowed. Although these type of measures will decrease the VKM in urban areas, this implies traffic needs to disperse to the main road network, increasing congestion on motorways which probably makes the impact on departure time choice more extreme.

All in all, there are many options to think about but we can also ask ourselves to what extent today's solutions will solve future problems. We do not yet know to what extent traffic situations will return to 'normal' when the COVID-19 crisis lies behind us. Will people return to their schedules and commute to work 5 days a week, bringing congestion back to pre-COVID-19 levels? Or have the regulations associated with the crisis set in motion irreversible trends which lead to less traffic demand, therefore mitigating the congestion problem?

Even though we do not know exactly how these phenomena will effect our future way of transportation, it is important to investigate the direction and size of effects these technological developments will bring. It is never too early to start thinking about possible future effects with the aim to take effective measures in time.

Recommendations for further research
Building on the findings presented in this research, several aspects are identified which require further investigation.

First, the simulation model that has been used in this study, was unable to capture some critical elements associated with this research. This was partly due to computational time limitations but also some restricting features with the used modelling software. The critical elements we refer to are not incorporating blocking back and setting a maximum jam density. Since these have an impact on one of the key indicators of this research, namely the calculating travel times, it would be recommended to further investigate this aspect by means of more dynamically accurate modelling. Additionally, further research may increase the level of detail in time intervals. Whereas this study used 10 minute time periods, which influenced the departure time choice distributions, it is recommended to increase the number of intervals to investigate the departure times for instance per minute.

This research has used the extended $\alpha - \beta - \gamma$ model with a certain set of adopted model parameters to describe departure time preferences. Although, the values to adopt and the effect they had on the model outcomes has been investigated by means of a concise literature review and sensitivity analysis respectively, this is considered too limited. It is recommended that further research is conducted to determine more substantiated values. This refers to our valuation of (strict and flexible) arrival times and if these are perhaps getting less strict. Moreover, what on-board productivity levels can we assign to future AVs? Lastly, we discussed the significant effect of the used PAT profiles which is inherently related to the use of the $\alpha - \beta - \gamma$ model. Further research might also comprise the trend towards more flexible working times and/or increased working from home.

One interesting element to address here are the capacity implications. This research used the same road capacities for non-AVs and AVs. However, up to this point it remains questionable if introducing AVs will be beneficial towards this road capacity. Previous work presented in STAD showed that, once AVs will not have cooperative driving, this will lead to reduced capacities and therefore congestion will only increase. So, a highly recommended direction for further research is the investigation of network effects with more variability in road capacities associated with AVs.

Another aspect to further investigate, would be incorporating heterogeneity among travellers. What will it mean when not all commuting travellers will engage in home/work activities during travel? In addition, endogeneity should be looked into. What if travellers could assign themselves to use a certain type of AV, i.e. engage in a certain type of activity. This will probably flatten the congestion peak since travellers can choose which activity they will engage in and therefore their departure time preferences change.

This study assumed level 5 of automation. Currently lower levels are already being implemented on a wider scale. Therefore the inclusion of, for instance an ODD should be looked into. What will happen when lower levels will use consecutive roads and segments which lie within their ODD? This affects route choice which is an important aspect when assessing network effects with AVs. It is suggested to further study the impact when including characteristics of lower levels of automation.

Lastly, an important extension of this study would be to also differentiate in travel time valuation on the route choice level. Where this study used the same probabilities to choose a specific route for both AVs and non-AVs, it would be interesting to capture the effect of on-board VTT respecting route choice. It is suggested that further research will investigate the network effects regarding this element as well.

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Appendix A - Disutility derivations

This appendix presents the derivations to arrive at the disutility functions based on the $\alpha - \beta - \gamma$ model set-up. This is done for each situation and for each type of AV. For consistency reasons, this follows the notation and definitions similar to Pudāne (2019). The following situations have been identified:

1. Departure time (t) before and arrival time $(t + T(t))$ before preferred arrival time t^*
   $t \leq t^*, t + T(T) \leq t^*$
2. Departure time (t) before and arrival time $(t + T(t))$ after preferred arrival time t^*
   $t \leq t^*, t + T(T) > t^*$
3. Departure time (t) after and arrival time $(t + T(t))$ after preferred arrival time t^*
   $t > t^*, t + T(T) > t^*$

Next to these three situations, three AVs have been distinguished:

- **Home AVs**
  Independent of departure time t it is optimal to engage in home activities during the entire trip. If $k = 1$, this results in only taking into account the on-trip utilities associated with home activities.
- **Work AVs**
  Independent of departure time t it is optimal to engage in work activities during the entire trip. If $k = 0$, this results in only taking into account the on-trip utilities associated with home activities.
- **Universal AVs**
  It is optimal to switch activities during trip at t^*, following:
  $e_h h(x) > e_w w(x), x \leq t^*$
  $e_h h(x) < e_w w(x), x > t^*$
  In this case, the switching point k is similar to t^*, making this the upper bound of the second integral in equation 3 and the lower bound of the second integral in equation 4.

Equation 1 and 2 describe the utility functions associated with home and work activities respectively. The total utilities for home and work activities can then be calculated with integrals over time (equation 3 and 4). The total utility is a summation of those two (equation 5)

$$h[x] = \alpha \tag{1}$$

$$w[x] = \begin{cases} \alpha - \beta, & if\, x \leq t^* \\ \alpha + \gamma, & if\, x > t^* \end{cases} \tag{2}$$

$$H[t,k] = \int_0^t h[x]dx + e_h \int_t^{t+kT[t]} h[x]dx \tag{3}$$

$$W[t,k] = \int_{t+T[t]}^{\Omega} w[x]dx + e_w \int_{t+kT[t]}^{t+T[t]} w[x]dx \tag{4}$$

$$V[t,k] = H[t,k] + W[t,k] \tag{5}$$

$h[x]$ = Utility associated with home activities
$w[x]$ = Utility associated with work activities
t^* = Preferred arrival time
t = Departure time
$T(t)$ = Travel time, depending on t
k = Switching point k $[0, 1]$
e_h = Efficiency factor associated with home activities
e_w = Efficiency factor associated with work activities
$H[t, k]$ = Total home utility
$W[t, k]$ = Total work utility
$V[t, k]$ = Total utility

To calculate the total disutility, we need to subtract the derived utility $V[t, k]$ (5) from a hypothetical utility which would be the utility if there was zero travel time and the departure and arrival time were the same, i.e. $T[t] = 0$ and $t = t^*$. This hypothetical utility V_h can then be derived as follows:

$$\begin{aligned} V_h &= H[t,k] + W[t,k] \\ &= \int_0^{t^*} h[x]dx + \int_{t^*}^{\Omega} w[x]dx \\ &= \alpha t^* + (\alpha+\gamma)\Omega - (\alpha+\gamma)t^* \\ &= (\alpha+\gamma)\Omega - \gamma t^* \end{aligned} \tag{6}$$

For every derivation that follows, this hypothetical utility V_h remains the same. The total disutility is called $U[t, k]$ and can now be calculated as follows:

$$U[t,k] = V_h - V[t,k] \tag{7}$$

All derivations describe the white areas in Figure 1 to 9 encapsulated by the horizontal lines with height α and γ and the home and work utilities, depicted as the areas with vertical and horizontal lines respectively.To distinguish the different cases, AV types and travel time periods, the following notation is used: $U_{AVtype,x}[t, k]$ in which $AVtype$ can be h, u or w for home, universal and work AVs respectively. x can be 1 to 3 depending on the situation as described on the previous page. For instance $U_{h,1}[t, k]$ refers to the disutility of a Home AV regarding the situation with departure time before t^* and arrival time before t^*.

Home AV, situation 1: Departure time (t) and arrival time ($t + T(t)$) before preferred arrival time t^*. Since the Home AV is considered, k = 1. Figure 1 schematically shows what happens with the utilities during the time period $[0, \Omega]$.

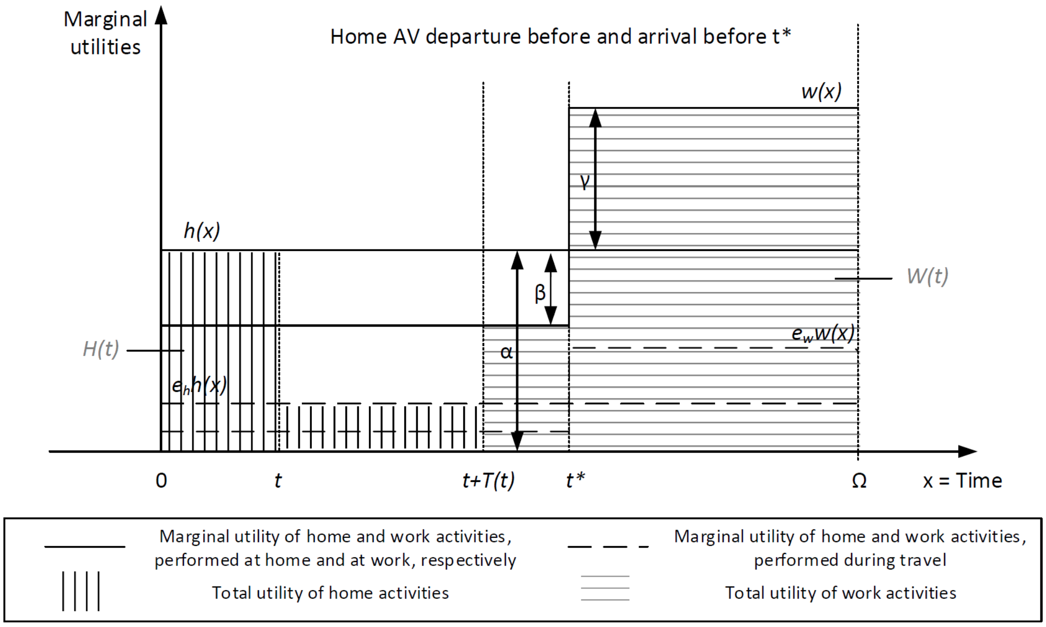

Figure 1: Scheduling preferences including utility from on-board activities in $\alpha - \beta - \gamma$ setting: Home AV, departure and arrival before t^*

$$
\begin{aligned}
H[t,k] &= \int_0^t h[x]dx + e_h \int_t^{t+T[t]} h[x]dx \\
&= \alpha t + e_h \alpha T(t) \\
W[t,k] &= \int_{t+T[t]}^{\Omega} w[x]dx + e_w \int_{t+T[t]}^{t+T[t]} w[x]dx \\
&= (\alpha+\gamma)(\Omega - t^*) + (\alpha - \beta)(t^* - (t + T(t))) \\
V[t,k] &= H[t,k] + W[t,k] \\
&= \alpha t + e_h \alpha T(t) + (\alpha+\gamma)(\Omega - t^*) + (\alpha - \beta)(t^* - (t + T(t))) \\
U_{u,1}[t,k] &= V_h - V[t,k] \\
&= \Big((\alpha+\gamma)\Omega - \gamma t^*\Big) - \Big(\alpha t + e_h \alpha T(t) + (\alpha+\gamma)(\Omega - t^*) + (\alpha - \beta)(t^* - (t + T(t)))\Big)
\end{aligned}
$$

Further rewriting results in the following final disutility function for the Universal AV in situation 1:

$$U_{u,1}[t,k] = \alpha(1 - e_h)T(t) + \beta(t^* - (t + T(t)) \tag{8}$$

Home AV, situation 2: Departure time (t) before and arrival time ($t + T(t)$) after preferred arrival time t^*. Since the Home AV is considered, k = 1. Figure 2 schematically shows what happens with the utilities during the time period $[0, \Omega]$.

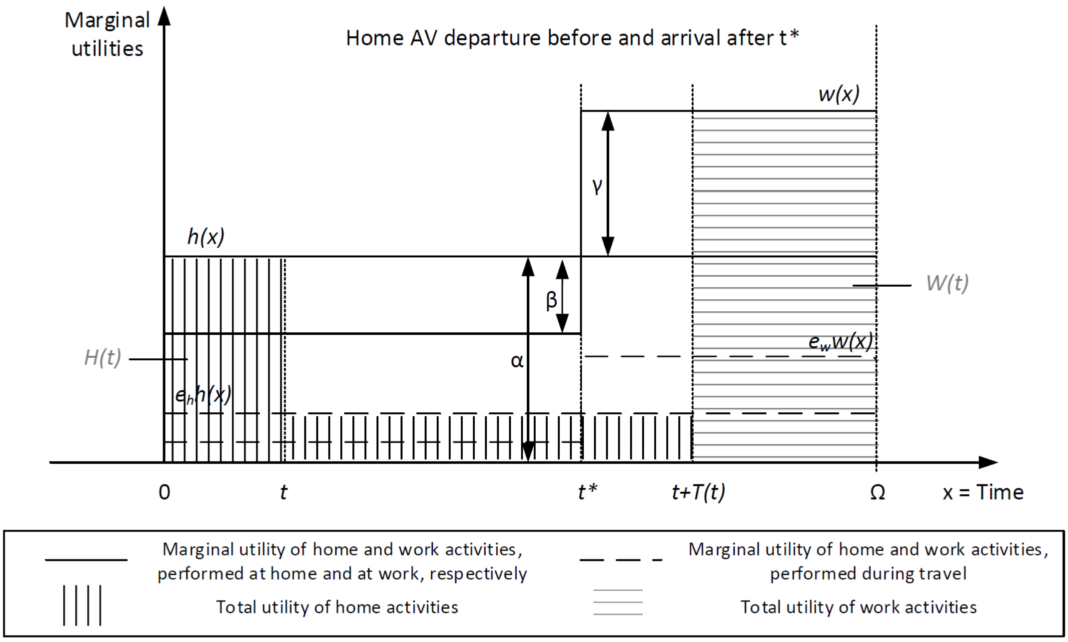

Figure 2: Scheduling preferences including utility from on-board activities in $\alpha - \beta - \gamma$ setting: Home AV, departure before and arrival after t^*

$$
\begin{aligned}
H[t,1] &= \int_0^t h[x]dx + e_h \int_t^{t+T[t]} h[x]dx \\
&= \alpha t + e_h \alpha T(t) \\
W[t,1] &= \int_{t+T[t]}^{\Omega} w[x]dx + e_w \int_{t+T[t]}^{t+T[t]} w[x]dx \\
&= (\alpha+\gamma)(\Omega - t + T(t)) \\
V[t,1] &= H[t,1] + W[t,1] \\
&= \alpha t + e_h \alpha T(t) + (\alpha+\gamma)(\Omega - t + T(t)) \\
U_{h,2}[t,1] &= V_h - V[t,1] \\
&= \Big((\alpha+\gamma)\Omega - \gamma t^*\Big) - \Big(\alpha t + e_h \alpha T(t) + (\alpha+\gamma)(\Omega - t + T(t))\Big)
\end{aligned}
$$

Further rewriting results in the following final disutility function for the Home AV in situation 2:

$$
U_{h,2}[t,k] = \alpha(1 - e_h)T(t) + \gamma(t + T(t) - t^*) \tag{9}
$$

Home AV, situation 3: Departure time (t) and arrival time $(t+T(t))$ after preferred arrival time t^*. Since the Home AV is considered, k = 1. Figure 3 schematically shows what happens with the utilities during the time period $[0, \Omega]$.

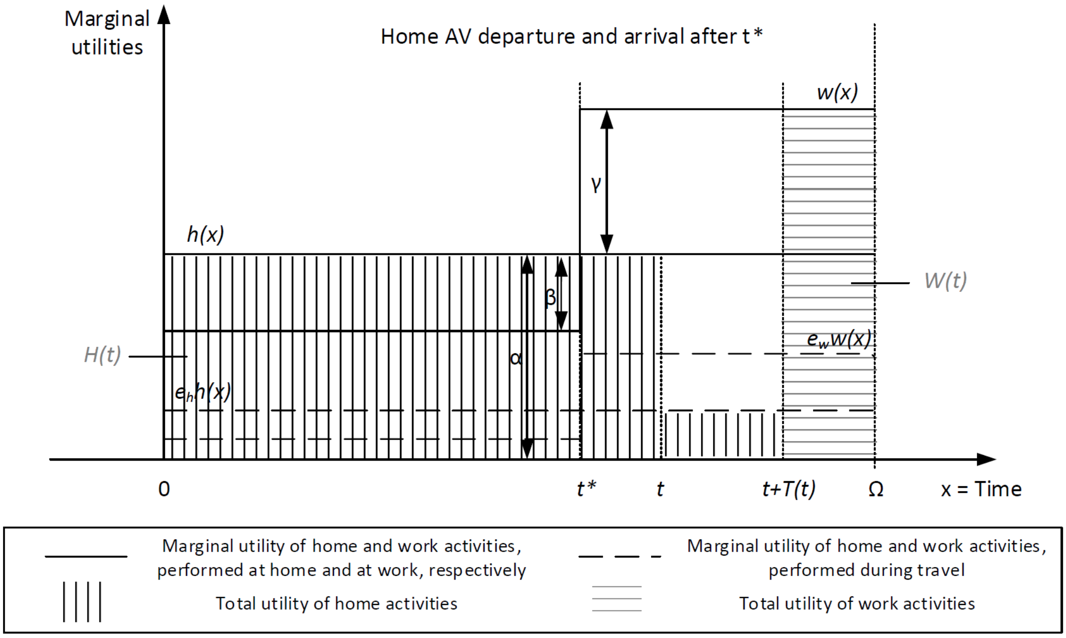

Figure 3: Scheduling preferences including utility from on-board activities in $\alpha-\beta-\gamma$ setting: Home AV, departure and arrival after t^*

$$
\begin{aligned}
H[t,1] &= \int_0^t h[x]dx + e_h \int_t^{t+T[t]} h[x]dx \\
&= \alpha t + e_h \alpha T(t) \\
W[t,1] &= \int_{t+T[t]}^{\Omega} w[x]dx + e_w \int_{t+T[t]}^{t+T[t]} w[x]dx \\
&= (\alpha+\gamma)(\Omega - t + T(t)) \\
V[t,1] &= H[t,1] + W[t,1] \\
&= \alpha t + e_h \alpha T(t) + (\alpha+\gamma)(\Omega - t + T(t)) \\
U_{h,3}[t,1] &= V_h - V[t,1] \\
&= \Big((\alpha+\gamma)\Omega - \gamma t^*\Big) - \Big(\alpha t + e_h \alpha T(t) + (\alpha+\gamma)(\Omega - t + T(t))\Big)
\end{aligned}
$$

Further rewriting results in the following final disutility function for the Home AV in situation 3:

$$U_{h,3}[t,k] = \alpha(1-e_h)T(t) + \gamma(t+T(t)-t^*) \tag{10}$$

It can be noted that this is the same result as Home AV situation 2. This corresponds to what can be observed figuratively as well. Once you arrive after the preferred arrival time using a Home AV, the on-board utility remains $e_h\alpha$, independent of the departure time. The individual will, based on travel times, choose the option with the lowest total disutility.

Universal AV, situation 1: Departure time (t) and arrival time $(t + T(t))$ before preferred arrival time t^*. Since the Universal AV is considered, the switching point of home/work activities is $t*$. Figure 4 schematically shows what happens with the utilities during the time period $[0, \Omega]$.

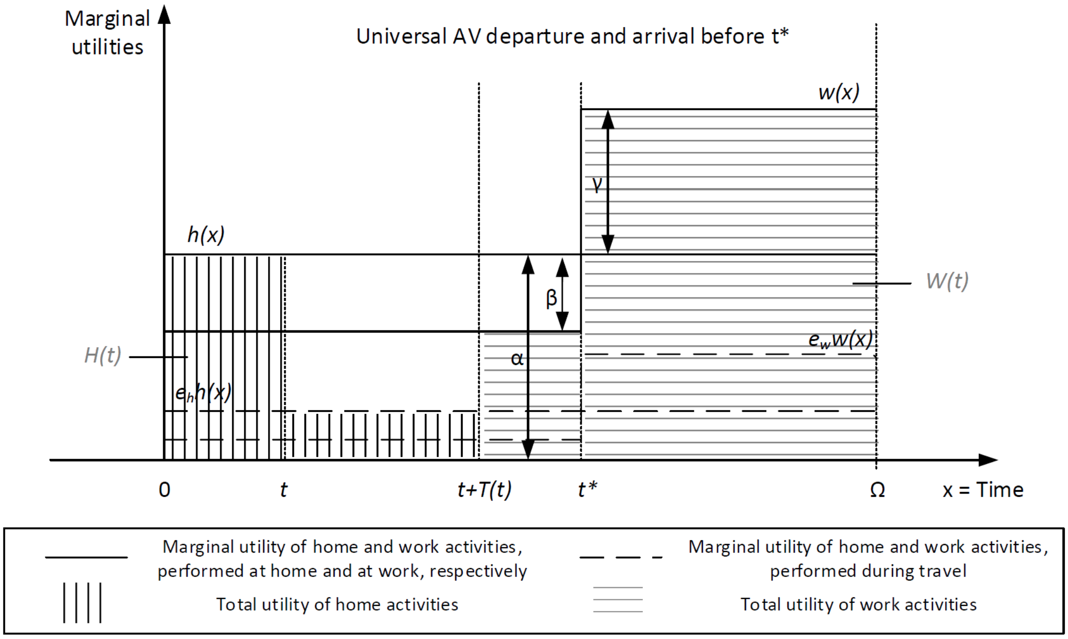

Figure 4: Scheduling preferences including utility from on-board activities in $\alpha - \beta - \gamma$ setting: Universal AV, departure and arrival before t^*

In this situation the individual arrives before t^*. Since a Universal AV is actually similar to Home AV for $x \leq t^*$, this situation is mathematically identical to the Home AV situation 1.

$$\begin{aligned}
H[t,k] &= \int_0^t h[x]dx + e_h \int_t^{t+T[t]} h[x]dx \\
&= \alpha t + e_h \alpha T(t) \\
W[t,k] &= \int_{t+T[t]}^{\Omega} w[x]dx + e_w \int_{t+T[t]}^{t+T[t]} w[x]dx \\
&= (\alpha+\gamma)(\Omega - t^*) + (\alpha - \beta)(t^* - (t + T(t))) \\
V[t,k] &= H[t,k] + W[t,k] \\
&= \alpha t + e_h \alpha T(t) + (\alpha+\gamma)(\Omega - t^*) + (\alpha - \beta)(t^* - (t + T(t))) \\
U_{u,1}[t,k] &= V_h - V[t,k] \\
&= \Big((\alpha+\gamma)\Omega - \gamma t^*\Big) - \Big(\alpha t + e_h \alpha T(t) + (\alpha+\gamma)(\Omega - t^*) + (\alpha - \beta)(t^* - (t + T(t)))\Big)
\end{aligned}$$

Further rewriting results in the following final disutility function for the Universal AV in situation 1:

$$U_{u,1}[t,k] = \alpha(1 - e_h)T(t) + \beta(t^* - (t + T(t)) \tag{11}$$

Universal AV, situation 2: Departure time (t) before and arrival time $(t + T(t))$ after preferred arrival time t^*. Since the Universal AV is considered, the switching point of home/work activities is $t*$. Figure 5 schematically shows what happens with the utilities during the time period $[0, \Omega]$.

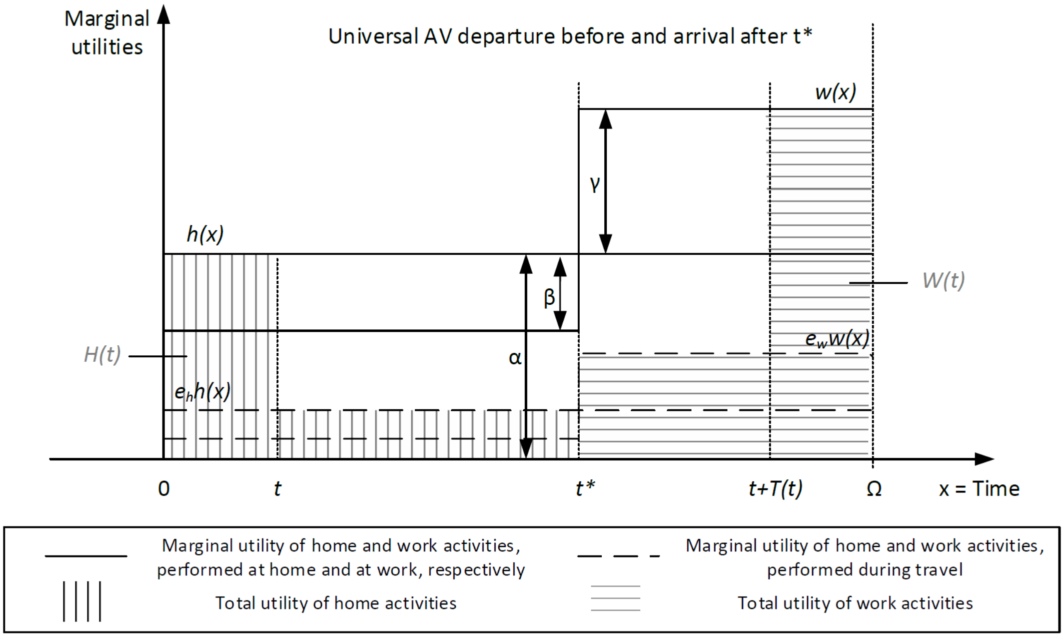

Figure 5: Scheduling preferences including utility from on-board activities in $\alpha - \beta - \gamma$ setting: Universal AV, departure before and arrival after t^*

$$
\begin{aligned}
H[t,k] &= \int_0^t h[x]dx + e_h \int_t^{t^*} h[x]dx \\
&= \alpha t + e_h \alpha (t^* - t) \\
W[t,k] &= \int_{t+T[t]}^{\Omega} w[x]dx + e_w \int_{t^*}^{t+T[t]} w[x]dx \\
&= (\alpha + \gamma)(\Omega - (t + T(t))) + e_w(\alpha + \gamma)(t + T(t) - t^*) \\
V[t,k] &= H[t,k] + W[t,k] \\
&= \alpha t + e_h \alpha (t^* - t) + (\alpha + \gamma)(\Omega - (t + T(t))) + e_w(\alpha + \gamma)((t + T(t)) - t^*) \\
U_{u,2}[t,k] &= V_h - V[t,k] \\
&= \Big((\alpha + \gamma)\Omega - \gamma t^*\Big) - \Big(\alpha t + e_h \alpha (t^* - t) + (\alpha + \gamma)(\Omega - (t + T(t))) + e_w(\alpha + \gamma)((t + T(t)) - t^*)\Big)
\end{aligned}
$$

Further rewriting results in the following final disutility function for the Universal AV in situation 2:

$$U_{u,2}[t,k] = \alpha T(t) + \gamma((t + T(t)) - t^*) - e_h \alpha (t^* - t) - e_w(\alpha + \gamma)((t + T(t)) - t^*) \quad (12)$$

Universal AV, situation 3: Departure time (t) and arrival time ($t + T(t)$) after preferred arrival time t^*. Since the Universal AV is considered, the switching point of home/work activities is t^*. For this case, this means that only work activities are performed since $t > t^*$, so $k = 0$. This is similar to a Work AV (situation 3). Figure 6 schematically shows what happens with the utilities during the time period $[0, \Omega]$.

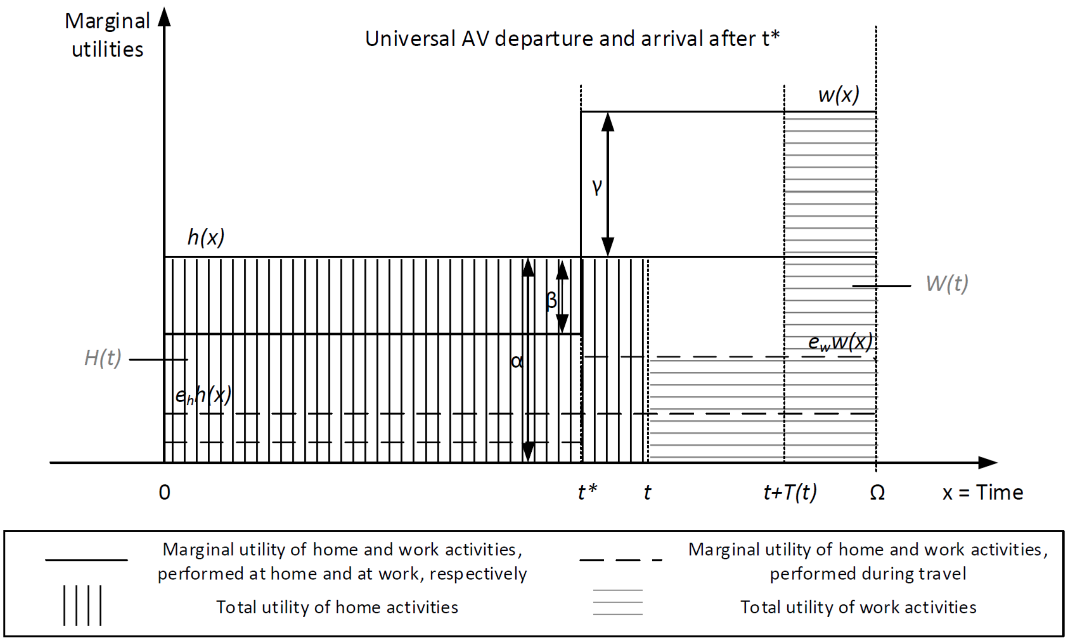

Figure 6: Scheduling preferences including utility from on-board activities in $\alpha - \beta - \gamma$ setting: Universal AV, departure and arrival after t^*

$$
\begin{aligned}
H[t,0] &= \int_0^t h[x]dx + e_h \int_t^t h[x]dx \\
&= \alpha t \\
W[t,0] &= \int_{t+T[t]}^{\Omega} w[x]dx + e_w \int_t^{t+T[t]} w[x]dx \\
&= (\alpha+\gamma)\Omega - (\alpha+\gamma)(t+T(t)) + e_w(\alpha+\gamma)T(t) \\
V[t,0] &= H[t,k] + W[t,k] \\
&= \alpha t + (\alpha+\gamma)\Omega - (\alpha+\gamma)(t+T(t)) + e_w(\alpha+\gamma)T(t) \\
U_{u,3}[t,0] &= V_h - V[t,k] \\
&= \Big((\alpha+\gamma)\Omega - \gamma t^*\Big) - \Big(\alpha t + (\alpha+\gamma)\Omega - (\alpha+\gamma)(t+T(t)) + e_w(\alpha+\gamma)T(t)\Big) \\
&= -\gamma t^* - \alpha t + \alpha(t+T(t)) + \gamma(t+T(t)) - e_w(\alpha+\gamma)T(t)
\end{aligned}
$$

Further rewriting results in the following final disutility function for the Work AV in situation 3:

$$
U_{u,3}[t,k] = \alpha T(t) + \gamma((t+T(t)) - t^*) - e_w(\alpha+\gamma)T(t) \tag{13}
$$

Work AV, situation 1: Departure time (t) and arrival time ($t + T(t)$) before preferred arrival time t^*. Since the Work AV is considered, k = 0. Figure 7 schematically shows what happens with the utilities during the time period $[0, \Omega]$.

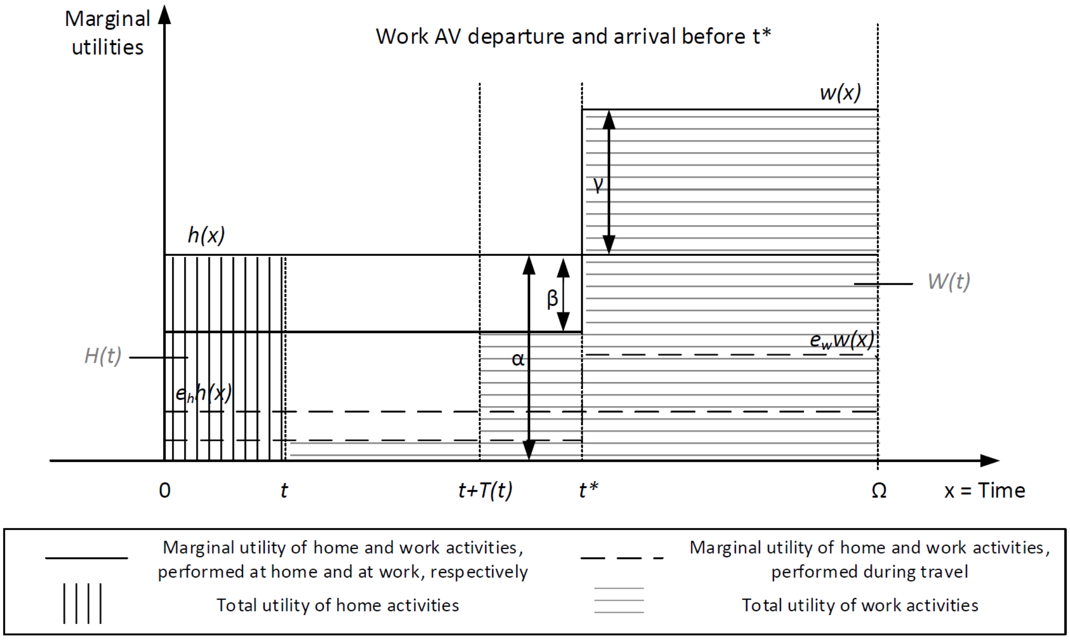

Figure 7: Scheduling preferences including utility from on-board activities in $\alpha - \beta - \gamma$ setting: Work AV, departure and arrival before t^*

$$
\begin{aligned}
H[t,0] &= \int_0^t h[x]dx + e_h \int_t^t h[x]dx \\
&= \alpha t \\
W[t,0] &= \int_{t+T[t]}^{\Omega} w[x]dx + e_w \int_t^{t+T[t]} w[x]dx \\
&= (\alpha - \beta)(t^* - (t + T(t))) + (\alpha + \gamma)\Omega - \alpha t^* - \gamma t^* + e_w(\alpha - \beta)T(t) \\
V[t,0] &= H[t,k] + W[t,k] \\
&= \alpha t + (\alpha - \beta)(t^* - (t + T(t))) + (\alpha + \gamma)\Omega - \alpha t^* - \gamma t^* + e_w(\alpha - \beta)T(t) \\
U_{w,1}[t,0] &= V_h - V[t,k] \\
&= \Big((\alpha + \gamma)\Omega - \gamma t^*\Big) - \Big(\alpha t + (\alpha - \beta)(t^* - (t + T(t))) + (\alpha + \gamma)\Omega - \alpha t^* - \gamma t^* + e_w(\alpha - \beta)T(t)\Big)
\end{aligned}
$$

Further rewriting results in the following final disutility function for the Work AV in situation 1:

$$U_{w,1}[t,k] = \alpha(t^* - t) - e_w(\alpha - \beta)T(t) - (\alpha - \beta)(t^* - (t + T(t))) \tag{14}$$

Work AV, situation 2: Departure time (t) before and arrival time ($t+T(t)$) after preferred arrival time t^*. Since the Work AV is considered, k = 0. Figure 8 schematically shows what happens with the utilities during the time period $[0, \Omega]$.

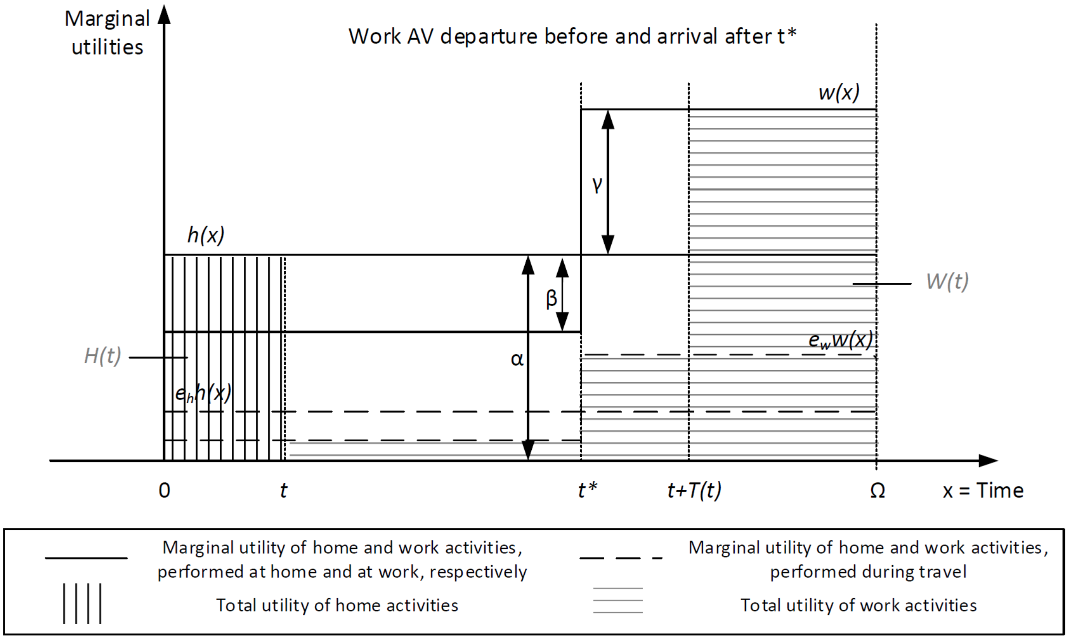

Figure 8: Scheduling preferences including utility from on-board activities in $\alpha - \beta - \gamma$ setting: Work AV, departure before and arrival after t^*

$$
\begin{aligned}
H[t,0] &= \int_0^t h[x]dx + e_h \int_t^t h[x]dx \\
&= \alpha t \\
W[t,0] &= \int_{t+T[t]}^{\Omega} w[x]dx + e_w \int_t^{t+T[t]} w[x]dx \\
&= (\alpha+\gamma)\Omega - (\alpha+\gamma)(t+T(t)) + e_w(\alpha+\gamma)((t+T(t)) - t^*) + e_w(\alpha-\beta)(t^*-t) \\
V[t,0] &= H[t,k] + W[t,k] \\
&= \alpha t + (\alpha+\gamma)\Omega - (\alpha+\gamma)(t+T(t)) + e_w(\alpha+\gamma)((t+T(t)) - t^*) + e_w(\alpha-\beta)(t^*-t) \\
U_{w,2}[t,0] &= V_h - V[t,k] \\
&= \Big((\alpha+\gamma)\Omega - \gamma t^*\Big) - \Big(\alpha t + (\alpha+\gamma)\Omega - (\alpha+\gamma)(t+T(t)) + e_w(\alpha+\gamma)((t+T(t)) - t^*) \\
&\quad + e_w(\alpha-\beta)(t^*-t)\Big) \\
&= \gamma(t+T(t)) - \gamma t^* + \alpha(t+T(t)) - \alpha t - e_w(\alpha+\gamma)((t+T(T)) - t^*) - e_w(\alpha-\beta)(t^*-t)
\end{aligned}
$$

Further rewriting results in the following final disutility function for the Work AV in situation 2:

$$U_{w,2}[t,k] = \alpha T(t) + \gamma((t+T(t)) - t^*) - e_w(\alpha-\beta)(t^*-t) - e_w(\alpha+\gamma)((t+T(t)) - t^*) \qquad (15)$$

Work AV, situation 3: Departure time (t) and arrival time ($t + T(t)$) after preferred arrival time t^*. Since the Work AV is considered, k = 0. Figure 9 schematically shows what happens with the utilities during the time period $[0, \Omega]$.

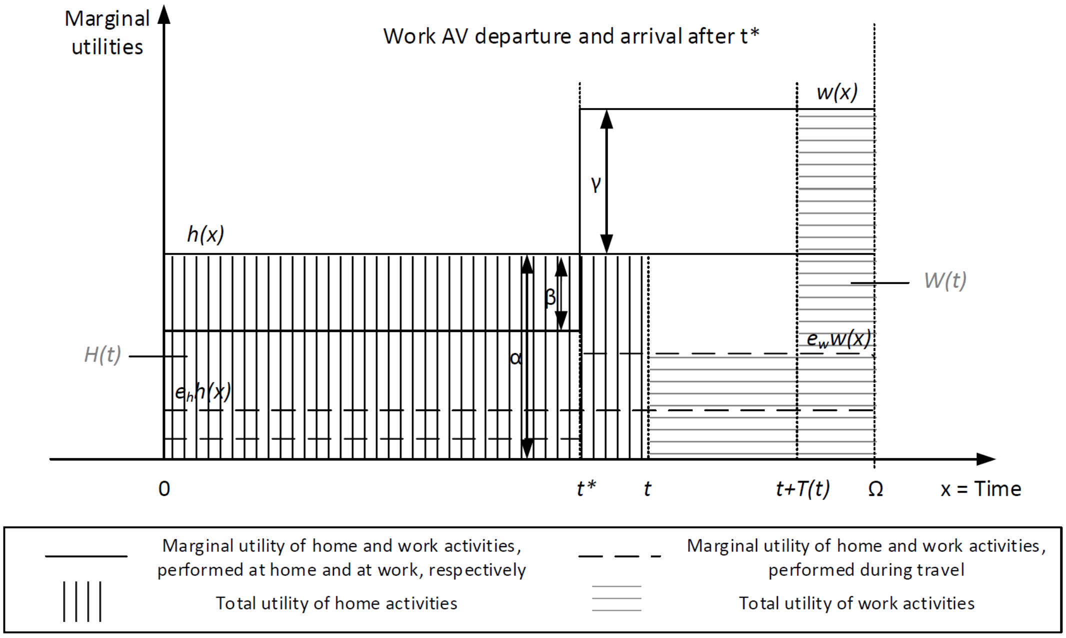

Figure 9: Scheduling preferences including utility from on-board activities in $\alpha - \beta - \gamma$ setting: Work AV, departure and arrival after t^*

$$
\begin{aligned}
H[t,0] &= \int_0^t h[x]dx + e_h \int_t^t h[x]dx \\
&= \alpha t \\
W[t,0] &= \int_{t+T[t]}^{\Omega} w[x]dx + e_w \int_t^{t+T[t]} w[x]dx \\
&= (\alpha+\gamma)\Omega - (\alpha+\gamma)(t+T(t)) + e_w(\alpha+\gamma)T(t) \\
V[t,0] &= H[t,k] + W[t,k] \\
&= \alpha t + (\alpha+\gamma)\Omega - (\alpha+\gamma)(t+T(t)) + e_w(\alpha+\gamma)T(t) \\
U_{w,3}[t,0] &= V_h - V[t,k] \\
&= \Big((\alpha+\gamma)\Omega - \gamma t^*\Big) - \Big(\alpha t + (\alpha+\gamma)\Omega - (\alpha+\gamma)(t+T(t)) + e_w(\alpha+\gamma)T(t)\Big) \\
&= (\alpha+\gamma)\Omega - \gamma t^* - \alpha t - (\alpha+\gamma)\Omega + (\alpha+\gamma)(t+T(t)) - e_w(\alpha+\gamma)T(t) \\
&= \gamma(t+T(t)) - \gamma t^* + \alpha(t+T(t)) - \alpha t - e_w(\alpha+\gamma)T(t)
\end{aligned}
$$

Further rewriting results in the following final disutility function for the Work AV in situation 3:

$$
U_{w,3}[t,k] = \alpha T(t) + \gamma((t+T(t)) - t^*) - e_w(\alpha+\gamma)T(t) \tag{16}
$$

It can be noted that this is the same result as Universal AV situation 3. This corresponds to what can be observed figuratively as well. Arriving after the preferred arrival time using a Work AV, is similar to using a Universal AV for this same arrival pattern. I.e. the on-board utility remains $e_w(\alpha+\gamma)$ for both types of AVs.

Appendix B - Programming code

This appendix provides screenshots with the programming code of several modules from the modelling framework. The code has been written the general-purpose programming language Ruby and is shown in the text editor SciTE. Figure 10 shows the code for creating demand per user class. Figure 11 shows the code for the implemented $\alpha - \beta - \gamma$ preferences in the departure time choice module. Figure 12 shows the code to arrive at probabilities from the previously calculated utilities within the departure time choice script.

```
def createparticipants_aby()
#Link network
network = OtNetwork.new
network.objectType = CENTROIDS
#Define total demand matrix and create empty duplicates
mattot = $mc[1,1,1,1]
mathav = mattot.dup
matuav = mattot.dup
matwav = mattot.dup
matnav = mattot.dup
mathav.multiply!(0)
matuav.multiply!(0)
matwav.multiply!(0)

#Define network selection
allzones1 = network.selection('Allzones')
allzones2 = network.selection('Allzones')

writeln "creating participants"

#Fill empty matrices with associated demand per user class
allzones1.each do |az1|
allzones2.each do |az2|
        mathav[az1,az2] = $parthome*mattot[az1,az2]
        matuav[az1,az2] = $partuniv*mattot[az1,az2]
        matwav[az1,az2] = $partwork*mattot[az1,az2]
        matnav[az1,az2] = (1 - ($parthome + $partuniv + $partwork))*mattot[az1,az2]
    end
end
#Assign matrix cube to new demand per user class
$mc[1,2,1,1] = matnav
$mc[1,3,1,1] = mathav
$mc[1,4,1,1] = matuav
$mc[1,5,1,1] = matwav
end
```

Figure 10: Programming code for creating demand per user class

```
#   i = preferred departure time (time block)
#   j = All other choice options to depart in (time block)
#   i + ttff = preferred arrival time (time block)
#   j + tt = actual arrival time (time block)

# ######################################################
writeln "CALCULATE TOTAL DISUTILITY"
# ######################################################
utility = Array.new
minutility = OtMatrix.new($nrofzones)
utilityS = Array.new
for i in 1..$nrperiods do
  utility[i] = Array.new
  utilityS[i] = Array.new
  for j in 1..$nrperiods do
    tt = $sc[$dynod[0],$m,$periods[j-1],2,1,1]
    ttff = $sc[$dynod[0],$m,$periods[i-1],1,1,1]
    tt.divide!($matdur)
        tt.ceil!
  utility[i][j] = OtMatrix.new($nrofzones)
  utilityS[i][j] = OtMatrix.new($nrofzones)
    for o in 1..$nrofzones do
      for d in 1..$nrofzones do
        if $totaldemand[o,d] != 0
  # ---------------- MODE 2: NON AV ------------------
          if $m == 2
            if j < (i + ttff[o,d]) && (j + tt[o,d]) < (i + ttff[o,d])
              utility[i][j][o,d] = -(tt[o,d]*$alpha + ((i + ttff[o,d])-(j + tt[o,d]))*$beta)
            else
              utility[i][j][o,d] = -(tt[o,d]*$alpha + ((j + tt[o,d])-(i + ttff[o,d]))*$gamma)
            end
          end
# -------------- MODE 3: HOME AV ------------------
          if $m == 3
            if (j) < (i + ttff[o,d]) && (j + tt[o,d]) < (i + ttff[o,d])
              utility[i][j][o,d] = -(tt[o,d]*$alpha*(1.0-$effh) + ((i + ttff[o,d])-(j + tt[o,d]))*$beta)

            else
              utility[i][j][o,d] = -(tt[o,d]*$alpha*(1.0-$effh) + ((j + tt[o,d])-(i + ttff[o,d]))*$gamma)
            end
          end

# -------------- MODE 4: UNIVERSAL AV --------------
          if $m == 4
            if j < (i + ttff[o,d]) && (j + tt[o,d]) < (i + ttff[o,d])
              utility[i][j][o,d] = -(tt[o,d]*$alpha*(1.0-$effh) + ((i + ttff[o,d])-(j + tt[o,d]))*$beta)

            elsif j < (i + ttff[o,d]) && (j + tt[o,d]) > (i + ttff[o,d])
              utility[i][j][o,d] = -(tt[o,d]*$alpha + ((j + tt[o,d])-(i + ttff[o,d]))*$gamma
              - ((i + ttff[o,d]) - j)*$effh*$alpha - ((j + tt[o,d])-(i + ttff[o,d]))*$effw*($alpha+$gamma))

            else
              utility[i][j][o,d] = -(tt[o,d]*$alpha + ((j + tt[o,d])-(i + ttff[o,d]))*$gamma - tt[o,d]*$effw*($alpha+$gamma))
            end
          end

# -------------- MODE 5: WORK AV --------------
          if $m == 5
            if j < (i + ttff[o,d]) && (j + tt[o,d]) < (i + ttff[o,d])
              utility[i][j][o,d] = -(((i + ttff[o,d])-j)*$alpha - tt[o,d]*$effw*($alpha-$beta)
              - ((i + ttff[o,d])-(j + tt[o,d]))*($alpha-$beta))

            elsif j < (i + ttff[o,d]) && (j + tt[o,d]) > (i + ttff[o,d])
              utility[i][j][o,d] = -(tt[o,d]*$alpha + ((j + tt[o,d])-(i + ttff[o,d]))*$gamma
              - ((i + ttff[o,d]) - j)*$effw*($alpha-$beta) - ((j + tt[o,d])-(i + ttff[o,d]))*$effw*($alpha+$gamma))

            else
              utility[i][j][o,d] = -(tt[o,d]*$alpha + ((j + tt[o,d])-(i + ttff[o,d]))*$gamma - tt[o,d]*$effw*($alpha+$gamma))
            end
          end
        end
      end
    end
  end
end
```

Figure 11: Programming code for utility calculations for each mode

```
# ########################################################
writeln "APPLY PROBABILITIES AND SAVE OUTPUT"
# ########################################################

# Get preferred departure time OD-matrices
prefarray = Array.new
for i in 1..$nrperiods do
  prefarray[i] = Array.new
  for j in 1..$nrperiods do
    prefarray[i][j] = $mc[$dynod[0],$m,$periods[i-1],1]
    prefarray[i][j].multiply!(utility[i][j])  # Calculate new departure time OD-matrices
  end
end

# Aggregate new departure time OD-matrices
newdemand = Array.new
for j in 1..$nrperiods do
  newdemand[j] = OtMatrix.new($nrofzones)
  for i in 1..$nrperiods do
    newdemand[j].add!(prefarray[i][j])
  end
end

# ########################################################
writeln "Write new departure matrices"
# ########################################################
totnew = OtMatrix.new($nrofzones)
for i in 1..$nrperiods do
  if $iter == 1
     matold = $mc[$dynod[0],$m,$periods[i-1],1]
  else
     matold = $mc[$dynod[0],$m,$periods[i-1],2]
     matold.multiply!($iter)
        end
  newdemand[i].add!(matold)
  matold.free
  newdemand[i].divide!($iter+1)
  newdemand[i].replaceLt!(0,0)
        $mc[$dynod[0],$m,$periods[i-1],2] = newdemand[i]
  totnew.add!(newdemand[i])
end
$mc[$dynod[0],$m,1,2]=totnew
```

Figure 12: Programming code for creating demand per user class