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Modelling Urban Driving and Stopping Behavior for Automated Vehicles

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Semester Project

June 2017

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September 2017

Abstract

The implementation of automated vehicle technology in urban environment is inevitable. The report is a contribution to the quantification of the impacts of this implementation. The research described in this report uses VISSIM to (1) model driving behavior of automated vehicles within an urban network, (2) model parking behavior of automated vehicles for different parking configurations in an abstract model, and (3) apply the modelled behavior to a case study in Manhattan, New York. After extracting results of the traffic flow of networks with different parking configurations, the results are compared directly and using a cost-benefit analysis. For example, the travel time is found to increase by up to 15% because of vehicles stopping curbside. If drop-off infrastructure were to be provided, this value is found to be only between 0-5%. The net value of providing this new infrastructure is found to be 1'043 USD per hour for a scenario of a demand being 100% of the capacity of a 2-lane road in a fully automated fleet. Even though the research is of proof-of-concept value, it shows that transport policy-makers, urban planners and infrastructure managers are challenged with a transformation in vehicle stopping behavior that must be addressed.

Keywords

Automated vehicles; parking; urban; microscopic; drop-off; cost-benefit analysis;

Preferred citation style

Elvarsson, A. B. (2017) Modelling Urban Driving and Stopping Behavior for Automated Vehicles, *Semester Project*, IVT, ETH Zürich, Zürich.

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1 Introduction

The rise of automated vehicles has spurred large interest among both the public and the scientific community. A substantial change in travel behavior is to be expected. Fully automated vehicles are expected to reduce road accidents, environmental impacts and cost of travel as well as increase comfort and mobility of immobile members of the society (Fagnant and Kockelman, 2015).

There is a lot of speculation regarding how automated vehicles (AVs) will change travel behavior, and some consider its impact to be even larger than when horse carriages were replaced by the first automobiles (Johnson et al., 2015). This impact on travel behavior will influence the driving behavior of vehicles and the infrastructure needs, particularly in urban environments. The speculation is universal. In Iceland, programs to improve public transport networks are being questioned because of the potential benefits of AVs and their possible ability to replace public transport (Ingvarsdóttir, 2017). In Florida, there have already been set up guidelines for how AVs be best implemented with respect to infrastructure and land use (Chapin, 2016).

The benefits of implementing AVs have been discussed, but modelled only to a limited extent. To envision these benefits, the modelling of an urban network with behavioral parameters can be used to help predict the behavior of the traffic flow. Previous research has considered networks on a mesoscopic level (Ambühl et al., 2016) and in a highway environment (Hartmann et al., 2017). Discussions on the impact on urban space are also taking place (Bätzner, 2017), but quantifying the impact of the AV penetration rate in an urban environment has not been done yet, perhaps because of its complex nature, and the various input parameters on which a model is dependent. It is for example still a matter of uncertainty whether every person will own their own AV, or if this will be provided by transportation network companies (TNCs) such as Uber and Lyft. To lead the trend, the municipality Innisfil in Canada has already replaced its public transport with subsidized Uber-trips (BBC.co.uk, 2017).

Other municipalities are troubled by the introduction of TNCs: San Francisco and New York are considering reducing their availability (SFMTA, 2016; Schaller, 2017). Curbside halting has become a problem causing increased congestion in the city of New York (Schaller, 2017). However, offering shared automated vehicle (SAV) services may reduce the vehicle fleet by up to 90% according to Bösch et al. (2016). As these SAV services would be run by TNCs, it is of interest to see if the problem of curbside halting can be addressed differently than reducing TNC availability, or worse, exiling them from cities.

This work thus aims to,

1. model driving behavior of automated vehicles within an urban network,
2. model parking behavior of automated vehicles for different parking configurations, and
3. apply the modelled behavior to a case study in Manhattan, New York.

The paper is structured with a literature review in chapter 2, setting up an abstract model in chapter 3, reporting results on the abstract model and a case study in chapter 4 and discussing them in chapter 5, followed by conclusions in chapter 6.

2 Literature review

With the rise of automated vehicles, a substantial change in travel behavior is to be expected. Fully automated vehicles are expected to reduce road accidents, environmental impacts and cost of travel as well as increase comfort and mobility of immobile members of the society (Fagnant and Kockelman, 2015).

Yet, it is unclear, in which form automated vehicles will become a reality: Will every household own an automated vehicle, or even two or three? Or will the market provide shared automated vehicle (SAV) services which handle mobility within urban environments? In the latter case, current forms of Transportation Network Companies (TNC), which are by some researchers called ride-sourcing services, may already give an idea of the usage patterns. Thus, the impacts on the transport system of future shared automated vehicle (SAV) services can be inferred. The municipality of Innisfil, Canada, is an early example of this trend as they have hired Uber, a TNC, to replace public transport within the municipality (BBC.co.uk, 2017). TNC services are more tailored to the user than public transportation, which requires heavy investment and infrastructure to operate. SAV services are being discussed as viable, and realistic implementations of automated vehicles (Fagnant and Kockelman, 2016; Hanna et al., 2016; Zachariah et al., 2014; Zhang et al., 2015). In the end, these services will stand and fall with their ability to offer competitive prices.

Bösch et al. (2017) have thoroughly calculated the costs of such shared AV services and compared them with other services such as public transport and privately-owned vehicles. According to their results, the most expensive option, the privately-owned AV, becomes the cheapest option once a person has purchased the car and considers those costs as sunk costs. Elvarsson and Fasching (2017) have performed a stated-choice experiment on the willingness of people to pay for SAV services. Becker (2016) discusses the impacts of vehicle automation on public transport, namely that buses and other public transport units may decrease in size, and their frequency increase. This is supported by the findings of Manser (2017).

Currently, policy makers around the world are hesitant to support TNCs claim to enter the market unhindered, as they often operate within loop-holes of currently over-regulated markets that have yet not been challenged by up-and-coming sharing economy initiatives. The TNC drivers are often not registered taxi drivers and some are consequently not adequately insured (Khosla, 2015; Fingas, 2015). Lohmann and Müller-Chen (2017) expect that in a world of AVs, Swiss law will not burden the TNCs or their passengers with insurance, but rather the AV producer. With many uncertainties, the largest hindrance seems to be the political willingness to pave the way for automated vehicle services. If the availability of SAV services, provided by TNCs, will be hindered, it may lead to a higher car ownership rate than otherwise. Khosla (2015) listed in a news article a non-exhausted list of locations where Uber was prohibited by law. Bösch et al. (2016) have calculated that the fleet-size may decrease by up to 90% given the availability of SAV services.

TNCs such as Uber and Lyft currently operate using vehicles owned or leased by the drivers. When drivers become redundant, TNCs may invest in their own fleet and operate it using similar strategies as low-cost airline carriers, where passenger turnover times are minimised, size of the plane fit to the demand, and an overall minimisation of operational costs and maximisation of revenue (Vidovic et al., 2013; Dennis, 2012). Furthermore, a dynamic pricing scheme is to be expected. This development will however be determined by the automotive producers' willingness to produce vehicles fitting to new business models. Consequently, Schiesser (2014) discusses a potential identity crisis within the automotive industry with the introduction of automated vehicles. But with new mobility trends, automotive vehicle producers will start focusing their products business-to-business instead of business-to-consumer. Private vehicle ownership would thus drop significantly, if, and only if, it is seen more attractive to rather use the SAV services (Bösch et al., 2017; Schoettle and Sivak, 2014). Those passengers, who see value in a privately-owned AV will purchase one, two or even three for their household, to make sure that all members' trips can be covered by the household fleet. This may increase total vehicle-kilometers travelled (VKT), as well as increasing the peak-hour demand. A discussion of different scenarios can also be found in Meyer et al. (2017).

At the same time as TNCs have become a viable alternative to the seldom used private car (SFMTA, 2016), TNCs have been pinpointed as the cause of increased congestion in cities such as New York and San Francisco. The San Francisco Municipal Transportation Agency, abbreviated SFMTA, reports that the 1‘800 registered taxis in the city have been outnumbered by 45‘000 registered Uber and Lyft vehicles (SFMTA, 2016). These vehicles park along the curbside when picking up and dropping off passengers, despite the municipality‘s attempts to put a stop to it (SFMTA, 2016; Schaller, 2017).

A topic of further speculation is the change in demand due to the transition to automated vehicles. Firstly, Harper et al. (2016) put together a review of different estimates of changes in vehicle miles travelled, themselves estimating a 14% increase due to new demand from ‘underserved populations’. Secondly, there is discussion of a decrease in the value of travel time savings (VTTS). This is defined as the willingness to diminish travel time, split into the intrinsic value of travel, and the value of doing something else (Jara-Diaz et al., 2008). As drivers are now passengers, there is time which is freed up that can be utilised in other ways than paying attention to the road (Becker et al., 2016). This is disputed by a study by Schoettle and Sivak (2014) showing survey results that people will choose not to be productive, but rather watch the road, or other leisure activities. According to the US Department of Transportation (USDOT), this value is currently set at 12.80 USD per hour for a weighted average over all trip purposes and all surface modes, except for high speed rail (USDOT, 2014). Thirdly, Meyer et al. (2017) also discuss the effects of induced demand that is to be expected. Lastly, the vehicle demand may be affected because of the increased use of carpooling SAV services (Elvarsson and Fasching, 2017). The demand will certainly be affected by the implementation of automated vehicles, but how these changes will add up and affect the overall VKT is yet unanswered.

The impact of automated vehicles on road capacity has also been discussed. On this matter, a mesoscopic simulation has been used to show that with headway reduced from 2.0 to 0.5 seconds and standstill distance from 1.2 m to 0.5 m, a 11-12% decrease in road space needed per vehicle can be achieved (Ambühl et al., 2016). Headway is currently modelled using the Wiedemann car following model (1974) which has been used for microscopic simulations, but may become obsolete once human reactions are removed from in-traffic decision-making. When AVs can communicate between themselves with short enough latency time, one might also see that traffic signals become redundant for car traffic (Hult et al., 2016). AVs will be able to synchronise their behavior, so a flatter speed distribution will be observed (PTV Group, 2017). At the same time, Le Vine et al. (2015) discuss the decrease of desired acceleration to the rates of public transport of 1.34 m^2/s. This development is due drivers becoming passengers and consequently not feeling comfortable with as steep acceleration rates as if they would be at the steering wheel themselves. As a result, these rates should drop from the current desired acceleration rates' upper bound of 3.5 m^2/s (Le Vine et al., 2015).

Whether these rates will drop as severely will be a matter of technological development by automobile manufacturers to create a vehicle, which acceleration rates will not affect the travel time of passengers. In the field of passenger rail transport, engineers have implemented tilting technologies, to achieve high speeds in curves without reducing passenger comfort leading to an achievement of travel time savings of 8 to 12% (Weidmann, 2016). Audi and Mercedes have already started using this technology in their vehicles which could dampen the reduction of the actual desired acceleration rate (Grünweg, 2011; Grünweg 2014).

The capacity of an urban road segment is interdependent on the flow within the segment, the composition of the traffic as well as the intersection flows on either end of the segment. The number of pedestrians has an impact, as well as the lane width and distance between crossings. The capacity of a road in an urban setting has been assessed by the Irish National Transport Administration (2017) as between 650 and 850 passenger car units per hour per lane on a busy urban road. What may increase this number with the transition to AVs is the previously mentioned reduced road space needed per vehicle (Ambühl et al., 2016), the effective use of signal-less intersections (Hult et al., 2016), as well as a size reduction of vehicles (Chapin, 2016).

Reduced capacity leads to a reduced traffic flow ceteris paribus, which leads to added costs in increased time spent reaching one's destination as well as increased fuel costs and emission costs. Fuel consumption with a microscopic simulation has been modelled by Kwak et al. (2012) and the social costs of emission are calculated by Hill et al. (2009) as 0.37 USD per gallon. Recent fuel prices as of May 22, 2017 are 2.399 USD per gallon (Energy Information Administration, 2017).

To avoid on-road parking, drop-off zones are used in Hong Kong and Singapore. These configurations sparked the idea of researching their effect further, specifically in the hypothetical situation of a transportation network based on SAV services. In Europe, these configurations are mostly used for bus stops.

Figure 1: An example of a drop-off zone in a sub-urban area in Singapore

Source: Arnd Bätzner, private collection

Figure 2: A drop-off zone for taxis in Hong Kong

Source: Arnd Bätzner, private collection

For the purposes of modelling curbside halting, one must also consider for how long the vehicles are expected to park. Considerable research has been performed on the boarding and alighting of public transport services for trains (Daamen et al., 2008; Lehnhoff and Janssen, 2003) and buses (Guenthner and Sinha, 1983; Sun et al., 2014; Bian et al., 2015), but literature on drop-off times of taxis or private vehicle drop-off is scarce.

3 Setup of model and cost-benefit analysis

To simulate traffic behavior within an urban environment, the microscopic simulation software VISSIM, developed by PTV Group was used (PTV Group, 2016). A microscopic traffic model is a temporal and spatial representation of real-life traffic behavior based on psycho-physical behavior parameters, where the location of all modelled elements can be identified with a high temporal and spatial resolution (Vortisch, 1988).

VISSIM is built for simulating conventional traffic. As intercommunicating, fully informed, self-learning automated vehicles will follow each other differently than human drivers, this will lead to difficulties in programming the car-following behavior of automated vehicles in VISSIM. The limitations of the models are addressed in each of the following sections.

3.1 Driving behavior

VISSIM applies the Wiedemann car-following model for every link, not every vehicle (PTV Group, 2016). This means that every vehicle, be it a passenger car, truck, bus or an automated vehicle shows the same car-following behavior. Therefore, to model the different behavior of automated vehicles for different penetration rates, the traffic behavior parameters have been set for penetration rates of 0% and 100% and then arbitrarily approximated between the levels as shown in Table 1. Aggregating behavior in this way is a clear limitation, because AVs will behave very differently to conventional vehicles in the transition phases of AV penetration rates from 20%-80%. AV penetration rate is the share of AVs of total fleet size.

The Wiedemann car-following model sets a desired following distance according to previously set behavior parameters that try to simulate the attentiveness and the aggressiveness of the driving behavior. The distance is a function of a fixed standstill distance, and a varying safety distance, which is a function of vehicle speed (Wiedemann, 1974).

The desired following distance is calculated as:

$$d = ax + bx$$

where ax is the standstill distance and bx is safety distance calculated as:

$$bx = (bx_{add} + bx_{mult} \cdot z) \cdot \sqrt{v}$$

in which v is the vehicle speed in m/s and z is a normally distributed variable with a mean of 0.5 and standard deviation of 0.15 (Wiedemann, 1974).

Table 1: Input parameters for different AV penetration rates

Parameter		0%	20%	40%	60%	80%	100%
Vehicle acceleration							
- Mean at v=0 m/s	[m/s^2]	3.0[1]	2.8	2.5	2.2	1.7	1.3[2]
Vehicle deceleration							
- Mean at v=0 m/s	[m/s^2]	2.7[1]	2.4	1.8	1.7	1.5	1.2[2]
Desired speed distribution							
- Minimum	[km/h]	48[1]	48	49	49	49	50[4]
- Maximum	[km/h]	58[1]	57	57	57	55	54[4]
Standstill distance	[m]	2.0[1]	1.8	1.6	1.4	1.2	1.0[5]
Safety distance							
- Additive part	[-]	3.0	2.6	2.2	1.8	1.65	1.5[3]
- Multiplicative part	[-]	4.0	3.6	3.2	2.8	2.65	2.5[3]

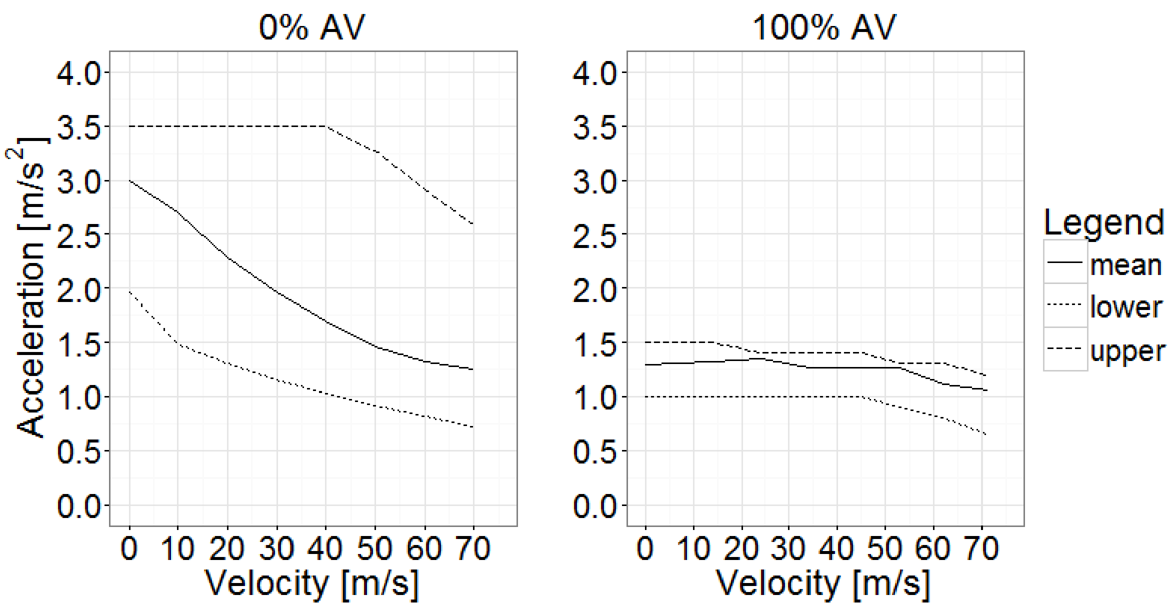
[1] (PTV Group, 2016)
[2] (Le Vine et al, 2015)
[3] (CDM Smith, 2014)
[4] Flatter speed distribution based on (PTV Group, 2017)
[5] Minimum value as per (PTV Group, 2016)

For an AV penetration rate of 0%, we use the default values of the VISSIM model, except for the safety distance additive and multiplicative bx-parameters. The default values are 2.0 for the additive parameter and 3.0 for the multiplicative parameter, but they are set to 3.0 and 4.0 respectively to account for the slower speeds within the urban environment (PTV Group, 2016). For automated vehicles, the parameters were set to those of an aggressive driver, namely 1.5 for the additive parameter and 2.5 for the multiplicative (CDM Smith, 2014) due to the lack of any better estimates. It is thus assumed that automated vehicles will follow more closely than conventional cars.

Standstill distance is the distance between the rear-bumper and the front-bumper of two vehicles standing still in traffic. It is set on 2.0 m as per default, and has tolerance of 1 m, according to the VISSIM manual (PTV Group, 2016). To avoid negative values, we set the standstill distance for 100% penetration rate to 1.0 m.

The mean of the automated vehicle acceleration distribution is set at that of a bus acceleration distribution, 1.3 m^2/s, as per Le Vine et al. (2016). The distribution is interpolated between this value and the default as per Table 1, graphically presented in Figure **3**.

Figure 3: Desired acceleration distribution and boundaries for penetration rates 0% and 100%

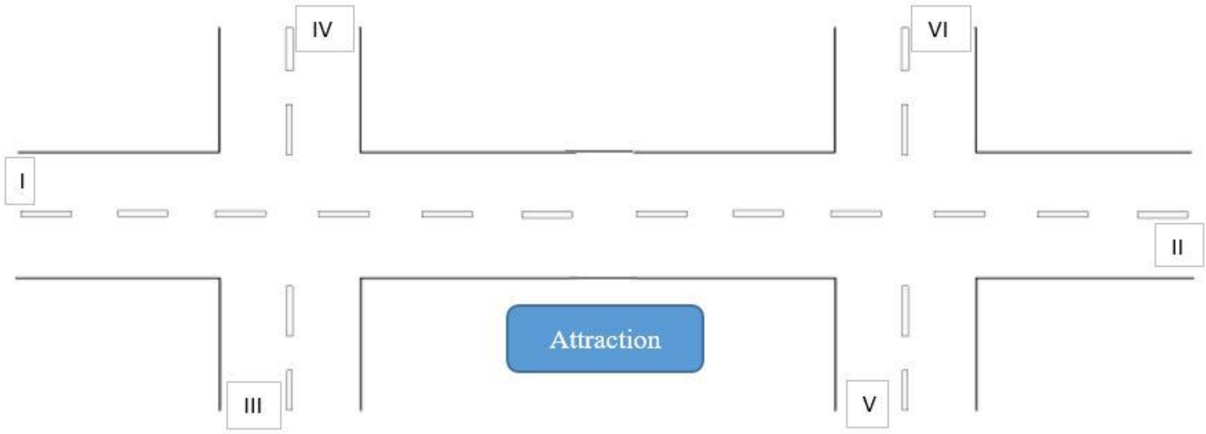


Desired deceleration is fixed at 1.2 m^2/s for automated vehicles and 2.7 m^2/s for conventional vehicles as per default. Desired speed distribution is a uniform distribution expected to have a smaller range with an increased automated vehicle penetration rate (PTV Group, 2016). It is therefore set at a range of 50-54 km/h instead of the default 48-58 km/h. This attribute, as well as the other above-mentioned attributes, are aggregated over all vehicles travelling on the modelled link. This means that although AVs will behave differently than the conventional vehicles in the system, the model expects them to behave in the same way because they travel on the same link.

3.2 Network

The network is based on a main arterial road and two roads running perpendicular to it. In the segment between the two intersections, an attraction is placed such that vehicles decide to stop there, simulating an action of dropping a person off. To better observe the effect of different ways of stopping by the attraction and minimise the congestion effect from the demand, a left-turn pocket was placed for the main road at both intersections.

Figure 4: Schematic layout of the model and intersections



A capacity of 850 passenger cars per hour per lane ($pc/(h \cdot \ln)$) was used for this urban environment (National Transport Authority, 2017). This gives main road capacities of 1700 $pc/(h \cdot \ln)$ for a 2-lane model and 2550 $pc/(h \cdot \ln)$ for a 3-lane model. Although capacities do not increase perfectly linearly with number of lanes, we assume this arbitrarily. All lanes are 3.5 m wide so that the lateral distance would not influence the capacity. Lane changes are allowed within links.

3.3 Demand

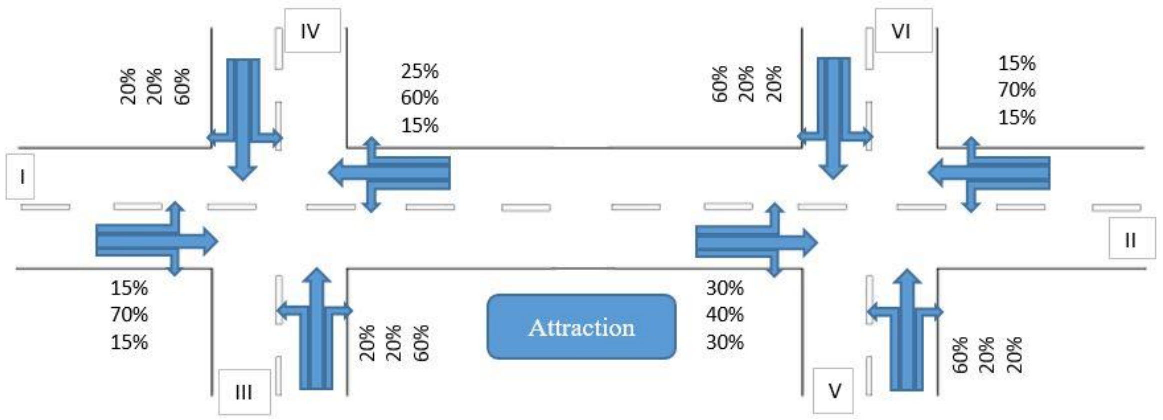
The demand of the traffic driving from left to right across the model in front of the attraction is varied. The variation levels were 60%, 80% and 100% of the total capacity calculated above, resulting in the demand per variation on the main road as shown in Table **2**.

Table 2: Main road demand levels

Capacity level	2 Lane	3 Lane
60%	1020	1530
80%	1360	2040
100%	1700	2550

The demand was converted into vehicle inputs and applied to the network using vehicle static routes. The share per route was calculated multiplying the share choosing each route using the turn volumes as shown in Figure 5. U-turns were not modelled to prevent this leading to a reduction in the traffic flow.

Figure 5: Turn volumes



It was assumed that those vehicles reaching the attraction from roads I, IV and III would have a 20% probability of parking. This is equivalent to 340 vehicles for 2 lane system and 510 vehicles for 3-lane model that stop over the time-span of an hour, when demand is 100% of capacity. If we assume an office block of 2000 work places, we see these vehicles serving 17-26% of the employees. Since employees may use other modes, and their arrival be distributed over more than one hour, 20% stopping demand of the traffic demand is considered reasonable, but must be considered when modelled for every case differently.

3.4 Stopping

To simulate the drop-off behavior, 12 parking spaces were placed within the network. Given an average 30 second parking duration, 12 parking spaces, in which vehicles stop and drop off, should be able to service 1440 vehicles per hour. This is a simple calculation of $\frac{12PP}{0.5\min}\cdot\frac{60\min}{1hr}$. This capacity is however also limited to surrounding traffic as well as overtaking behavior, but the capacity copes with the parking demand in any case. Given a parking demand of 510 for the 100% demand scenario of the 3-lane model the parking facilities are occupied 35% of the time. Although the utilisation rate would preferably be higher for the operator of the infrastructure, it is left beyond the scope of this work to fit the parking supply to the parking demand.

These parking spaces were either (i) placed sporadically around the curbside of the attraction, (ii) concentrated at the curbside the middle of the main road, or (iii) placed in a bus-pocket at the middle of the main road. A fourth scenario had no parking performed at all.

More configurations, such as a drive-in option that is commonly seen in front of hotels was also considered. Preliminary results were like those of the bus-pocket, while simultaneously being more space-consuming. Other designs such as fishbone designs were also considered. These designs were not further analysed within this report, but should be researched further.

3.4.1 Stopping duration

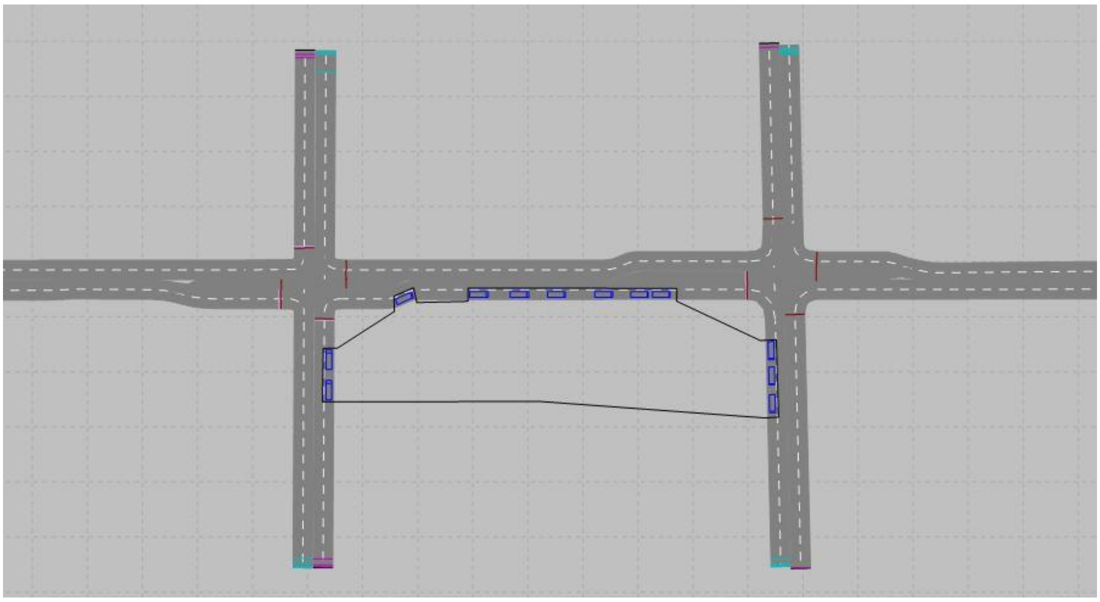
Literature on the parking duration of taxis or private vehicles in drop-off zones is scarce. Based on vehicle counts and time measurements of private vehicles, taxis and TNCs performed in Basel and Zurich airports, the author found this time to be Poisson distributed. The time measured from the door opening, until the passenger left had a mean of 37 seconds from a sample of 35 stopping vehicles. This count is explained in further detail in Appendix A. The fastest drop-off, measured from the car arriving until the car left, took 18 seconds and the passenger only took 3 seconds to get out and leave the parking area. Within the data set, there were passengers who had trouble with payment of the Taxi or took time to say goodbye to a loved one leading to an increased parking time. It was also observed that additional parking time was a result of the driver stepping out of the vehicle, for example to help with baggage. Although payment will be automatic for SAVs, and there will be no driver to leave the car, the passengers may still take extra time to take out baggage, and should be provided with an incentive to leave rapidly, so that passenger turnover is maximised. These ideas of curbside parking rates have for example been discussed by Shoup (2005).

It is assumed that the drop-off time will drop to a mean of 30 seconds as passengers get increasingly used to an efficient drop-off routine, and the willingness to avoid potential parking fees that would potentially be applied to urban drop-off zones, like those discussed by Shoup (2005). In VISSIM, this time distribution is bounded between 0 and 140 seconds with a mean of 30 and standard deviation of 10.

3.4.2 Parking configuration

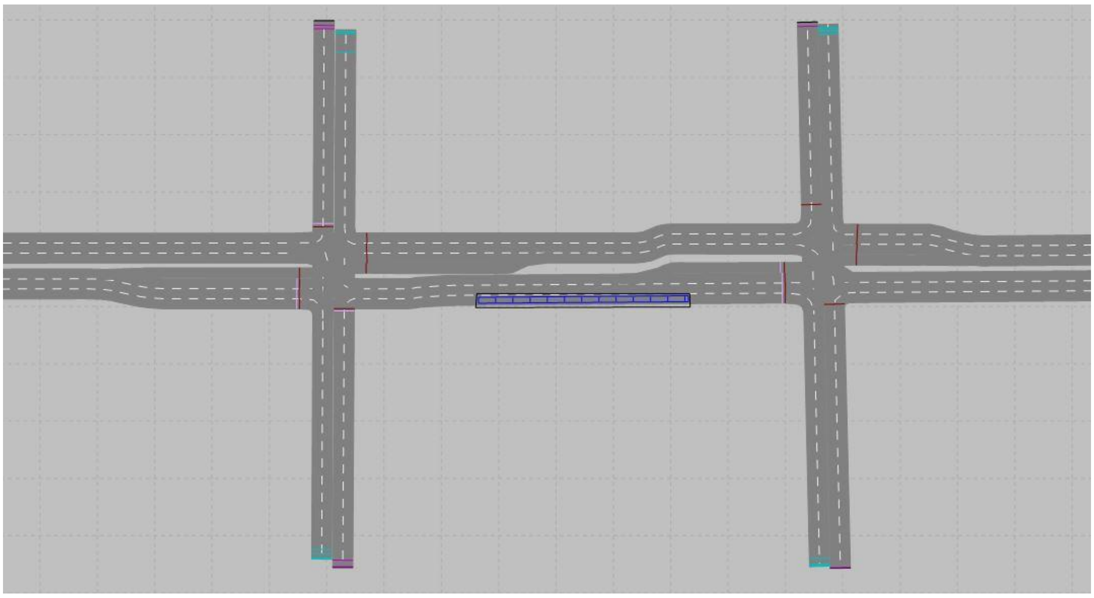
Parking configuration is varied to test for the effect of parking behavior on traffic flow. To simulate sporadic curbside halting, two parking spaces were located on road III, seven on the main road and three on road V. The spaces were distributed along the road, but at a distance from the intersection, as to show that the spaces were not concentrated on one drop-off zone. For this configuration was the only one with parking in the side streets, the parking routes were different from the other scenarios. The parking route for vehicles originating on road III was split so that vehicles would decide to park in the two spaces on road III with 10% probability, and park in the others with 10% probability, resulting in a total of 20% of the demand originating on road III, and turn right on to the main road, will park. Vehicles from road I and IV parked in the ten parking lots on the main road and road V with 20% probability. The set up of the parking lots is shown in Figure **6**.

Figure 6: Sporadically located parking spaces for a 2-lane model. VISSIM screenshot.



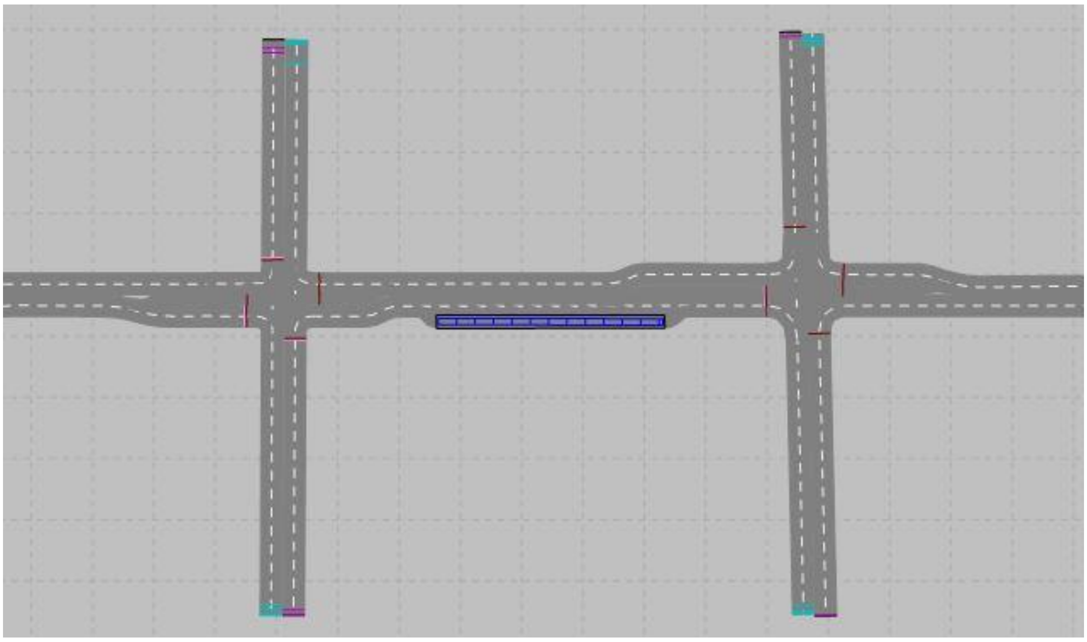
Another variation was a concentrated drop-off zone with twelve parking spaces placed curbside in front of the attraction. This is modelled as shown in Figure **7**.

Figure 7: Curbside drop-off zone for a 3-lane model. VISSIM screenshot.



Thirdly, the possibility of parking infrastructure is considered. Removing the parking from the road and providing a drop-off zone in a bus-stop lay-over option shown in Figure **8**.

Figure 8: Bus-stop lay-over alongside road for a 2-lane model. Screenshot from VISSIM.



The fourth variation was that no parking occurred at all.

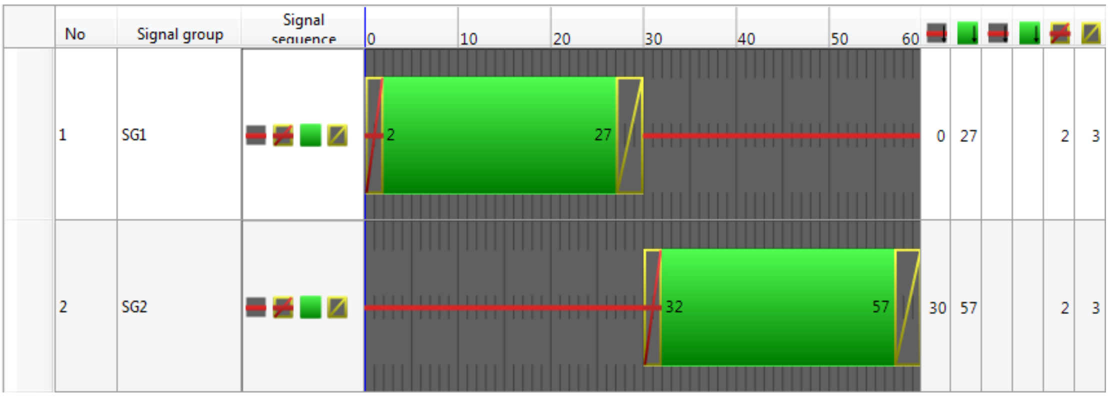
3.5 Lanes and signal control

As vehicles become increasingly automated and can communicate amongst themselves, possibilities of signal-less intersections arise. These have not been modelled within the scope of this paper as this is not yet an option provided by the VISSIM software.

The network was tested with the main road being both a 2-lane and 3-lane road. This had the effect that the signal control developed for the two-lane model did not match the needs of the 3-lane model, particularly for the left-turning lane.

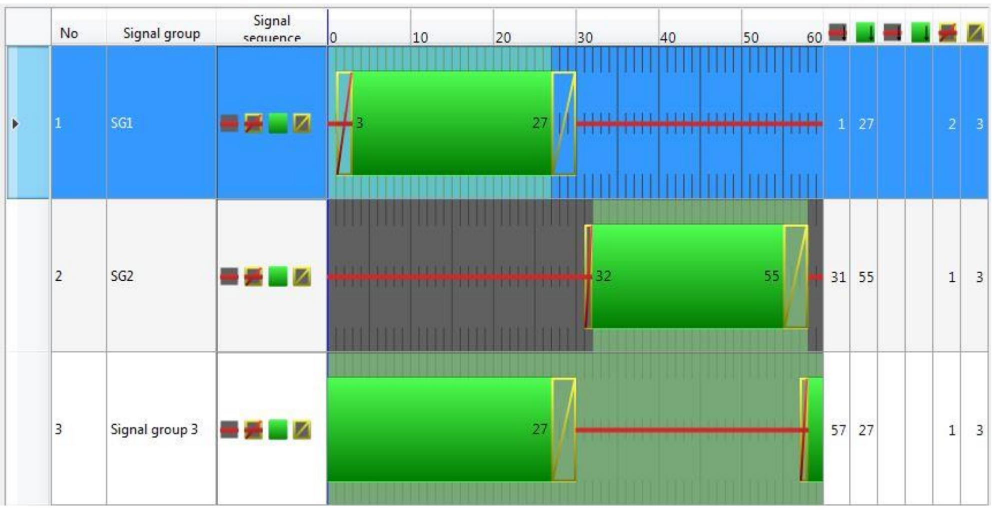
For the two-lane model, a simple signal controller system was set up with inter-green times of 5 seconds, chosen as a suggested default value, and a signal head placed on each lane. The signal program can be viewed in the following Figure **9**.

Figure 9: Signal program for 2-lane model



For the three-lane model, before the main road traffic going straight and turning right had green, five seconds were allowed for the left-turn green without other disturbances. For this, we create the third signal group. The results are that the two-lane and three-lane models are not easily comparable because capacity gains achieved in the three-lane model may be due to the suitability of the signal programme. It should also be mentioned that these programmes were selected arbitrarily and are potentially sub-optimal. To control for this variable, the three-lane model signal control can be applied to the two-lane model, despite this not being necessary for the required flow levels.

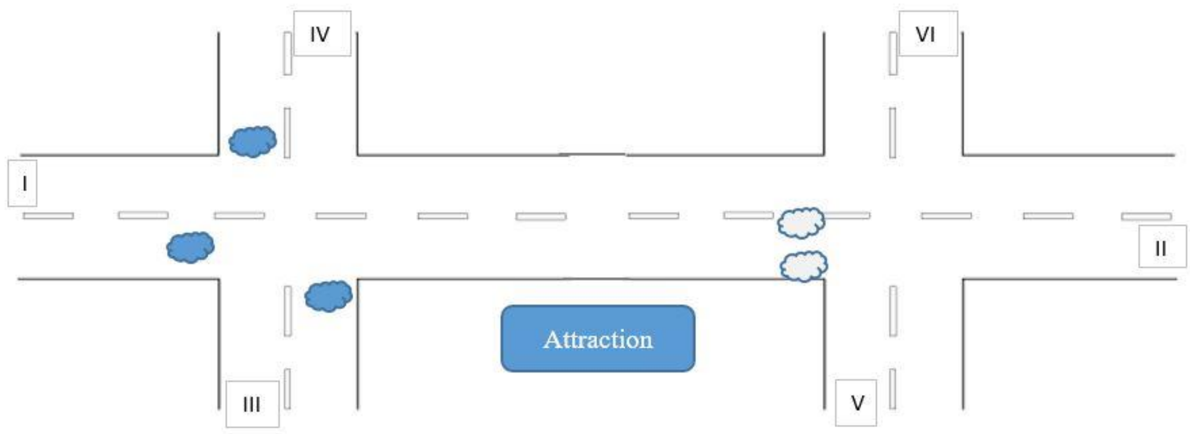
Figure 10: Signal program for 3-lane model



Queue counters were placed at links with signal heads. At the left intersection, it was for all directions towards the main road. This means that for road I, only the straight-heading lane was measured, as the left-turning lane was irrelevant. At the right intersection, a queue counter was placed across the whole intersection.

The queue counters were placed as an attempt to catch the queueing effect caused by the different parking behaviors modelled. These will then be compared between different parking variations. The counters are grouped for each intersection.

Figure 11: Location of queue counters



3.6 Simulation parameters

Ten simulation runs were performed to take an average of the results. The simulations ran for 3600 seconds, an hour, with 10 time steps per second. A random seed of 42 was used, with an increment of 1.

3.7 Other parameters

The research is performed under lab conditions and with controlled variables, and we are thus able to draw conclusions based on these assumptions. There are several parameters, which in real-life would affect the results of this study and have not been included in this report, but should however be addressed.

This model focuses on the transformation from conventional vehicles to automated vehicles and, thus, does not include heavy vehicles. The model also does not include further differences in traffic composition such as cyclists and is undisturbed by pedestrians despite simulating urban environments. The absence of public transport has a significant impact as they are provided signal priority in many cities. This will however be less of a problem in a fully automated scenario, where public transport units and vehicles can communicate between themselves. For a discussion on the interaction between AVs and public transport and pedestrians, please see Trachsel (2017). This simple model only simulates the stopping around one location, say a building. In a real-life urban network, the cars will stop even more sporadically, with more than just one attraction point and will thus cause more diverse behavior. This is partially provided by the case study, discussed in chapter 4.2.

3.8 Summary of parameters

The parameters discussed in the chapter are summarised in the following Table 3.

Table 3: Model parameters summarised

Lane number	Parking configuration	AV penetration rate	Demand
2 lanes	Sporadic curbside parking	0%	60% of capacity
3 lanes	Curbside drop-off zone	20%	80% of capacity
	Bus-stop lay-over	40%	100% of capacity
	No parking	60%	
		80%	
		100%	

When modelling the driving behavior, we assume no parking to take place. When modelling effects of parking configurations, the scenarios are compared to when no parking takes place.

The 144 different scenarios are created in separate models and their results are analysed separately. Average delay, average stops per vehicle, average vehicle speed and total travel time over the ten simulations have been considered and their results reported. Maximum queue length and average queue stops were considered to interpret the results.

3.9 Setup of cost-benefit analysis

The different parking configurations considered are evaluated based on the cost of travel time savings, cost of increased fuel consumption and the social cost of emissions. A value of travel time savings of 12.80 USD per hour was used (USDOT, 2014), as well as fuel prices from the Energy Information Administration (2017) and the fuel consumption model from Kwak et al. (2012).

The only parking configuration causing added infrastructure and land use is the bus-pocket drop-off zone configuration. The cost of the infrastructure required for a bus drop-off parking configuration is mainly based on the land costs, but also on the construction costs of the infrastructure. According to AASHTO, parking width is set to a minimum of 2.1 m in urban environments, but recommend a design value of 2.4 m, for a 6.0 m long lot (AASHTO, 2001). Additionally, 2.4 m are added on either side of the lot for the transition curb between the drop-off zone and the street curb. The spaces may have to be designed wider if buses are also to be accounted for, but this is left beyond the scope of this report. For one drop-off zone of 12 parking spaces, this makes 184 m^2. Assuming buildable land prices from Manhattan at 6220 USD/m^2 (Hughes, 2015), and construction costs of a maximum of 30,000 USD per location (Arlington, n.d.), a value of the infrastructure would be 1’176’470 USD. If the value is then calculated per hour over 10 years, which we set as the discounting period, the cost of the infrastructure is 13 USD per hour.

$$C_{i,I} = \frac{A_I \cdot c_{land} + c_I}{10 yr \cdot (365 \cdot 24 hr / yr)}$$

We set up the costs for the cost-benefit analysis for each scenario i, where D stands for delay, F for fuel, E for emissions and I for infrastructure-related.

$$\begin{aligned} &C_i = C_{i,D} + C_{i,F} + C_{i,E} + C_{i,I} \\ &\rightarrow C_{i,D} = D_i \cdot VTTS \cdot vehicles \\ &\rightarrow C_{i,F} = c_{fuel} \cdot f \\ &\rightarrow C_{i,E} = c_{emissions} \cdot f \end{aligned}$$

The delay costs are calculated for the total number of vehicles in the network, the fuel costs using the unit costs of a gallon of fuel and the fuel consumption, f, calculated using the model from Kwak et al. (2012). The unit cost of emissions is assumed from Hill et al. (2008). c_I stands for the cost of infrastructure, which is 30,000 USD (Arlington, n.d.) and is added to the multiplied area of the parking infrastructure multiplied by the unit cost of land. The lost revenue from the removed parking spaces, to make space for the sporadic parking configuration with curbside parking spaces is not included in the analysis, although mentioned for completeness. Similarly, the value of the buildable land which is currently under use for parking spaces is not included in the analysis. These values, and more, should be included when performing a thorough cost-benefit analysis for specific segments.

The benefits of the income of a potential parking fee is included in the analysis. The author does not express an opinion in what form this should be charged, but assumes here that an average parking fee of 0.5 USD per vehicle stopped is imposed.

$$B_i = B_{i,P}$$

The Net Value for each case is calculated as a reference to the sporadic parking configuration, obviously leading to the net value of the sporadic parking reference case to be 0. We ignore discount rates.

$$NV_i = B_i - C_i$$

We can consider the net value to be the savings of performing the shift to another parking configuration instead of sporadic parking. Calculating the ratio between the Net Value of a parking configuration over its costs, C_i, gives us a benefit-cost ratio, where a value of larger than 0 is economically justifiable, and under 0 not justifiable.

$$(B / C)_i = \frac{NV_i}{C_i}$$

Calculating the benefit-cost ratio for concentrated curbside parking and the bus drop-off configuration, we then calculate the marginal savings made if the bus-drop off option is chosen over the concentrated parking configuration.

$$MS = \frac{\Delta NV}{\Delta C} = \frac{NV_{drop-off} - NV_{concentrated}}{C_{drop-off}}$$

Here a negative value would mean that the concentrated curbside parking should be preferred.

It is to be iterated that this setup is not according to any of the numerous cost-benefit analysis standards. Consequently, the values produced for the scenarios can only be compared across the scenarios, and not with other projects.

4 Results

Firstly, AV behavior has been modelled in a network simulating an urban environment. Results are presented for different demand levels over different AV penetration rate levels. Then, based on the modelled behavior, the problem of curbside halting is addressed and various ways to set up parking facilities within urban environments are modelled and their impact evaluated.

A brief cost-benefit analysis is performed accounting for the cost of delay, the cost of fuel consumption, societal cost of emissions and the cost of new parking infrastructures and their respective added land use. Furthermore, the benefits of a new parking fee scheme are considered and discussed. The cost-benefit analysis is performed to get an idea of the monetized effect of new parking infrastructure.

In chapter 4.2, a case study from Manhattan, New York is considered, where the tools developed in the abstract model are applied to a real-life case.

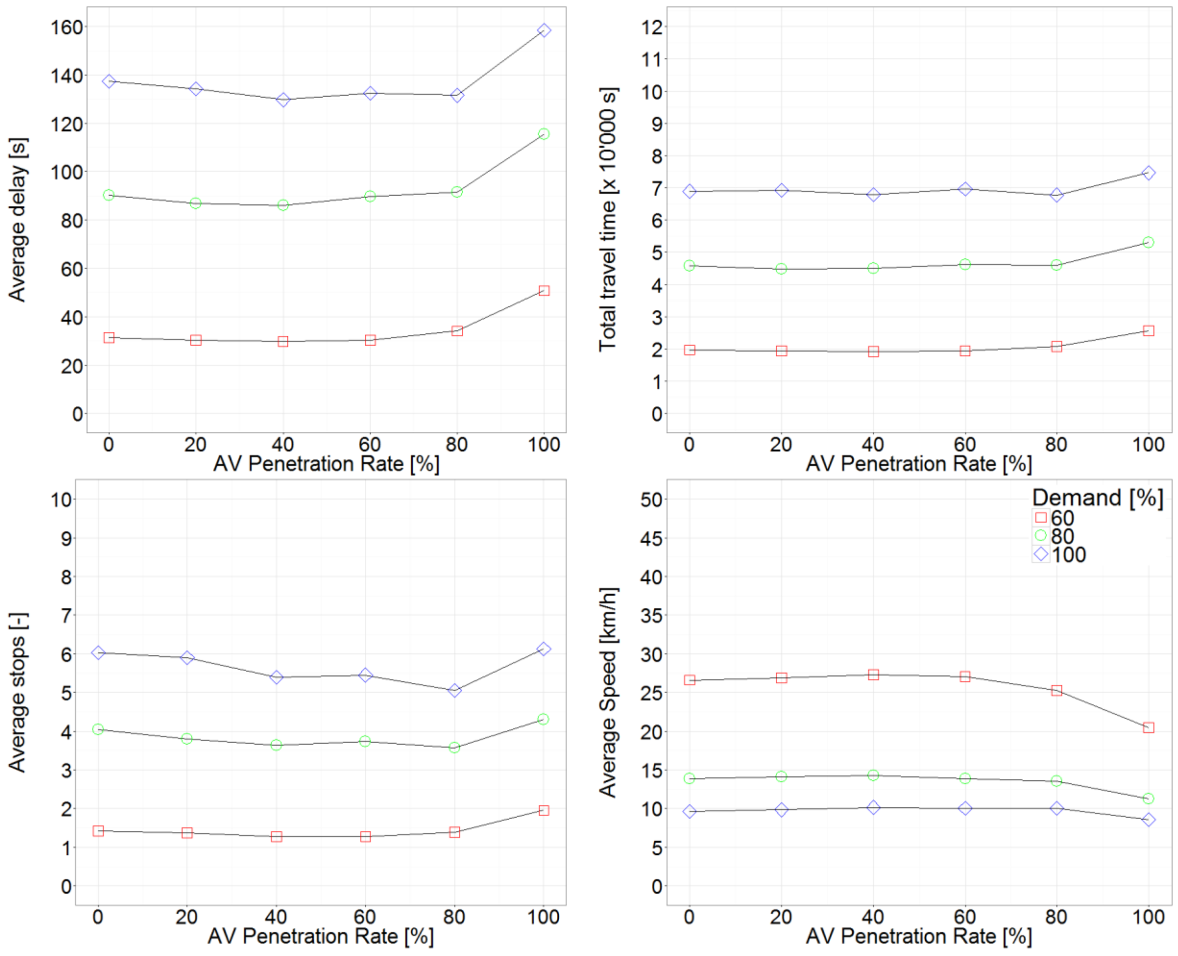
4.1 Abstract model

4.1.1 Network performance with increasing AV penetration rate

Yang et al. (2016), Fagnant and Kockelman (2015) and Ambühl et al. (2016) are among those who have discussed improved network performances with increased AV penetration rates. Before the simulations were executed, it was hypothesised that the same would occur for this model. A more homogeneously behaving vehicle fleet, with flatter speed distributions and narrower following driving behavior was hypothesised to create a smoother flow, and consequently lead to decreased delay and increasing average speed. However, in the transition phase from 20% AV penetration rate to 80%, it can be expected that the effect of the heterogeneous vehicles should result in reduced network performance. This is for example the result of the analysis of Hartmann et al. (2017). As all vehicles are aggregated in this model, these effects will not be observed.

To test these hypotheses the model described in the previous chapter has been observed without parking taking place, and the results evaluated.

Figure 12: Network performance results for 2-lane model when no parking takes place

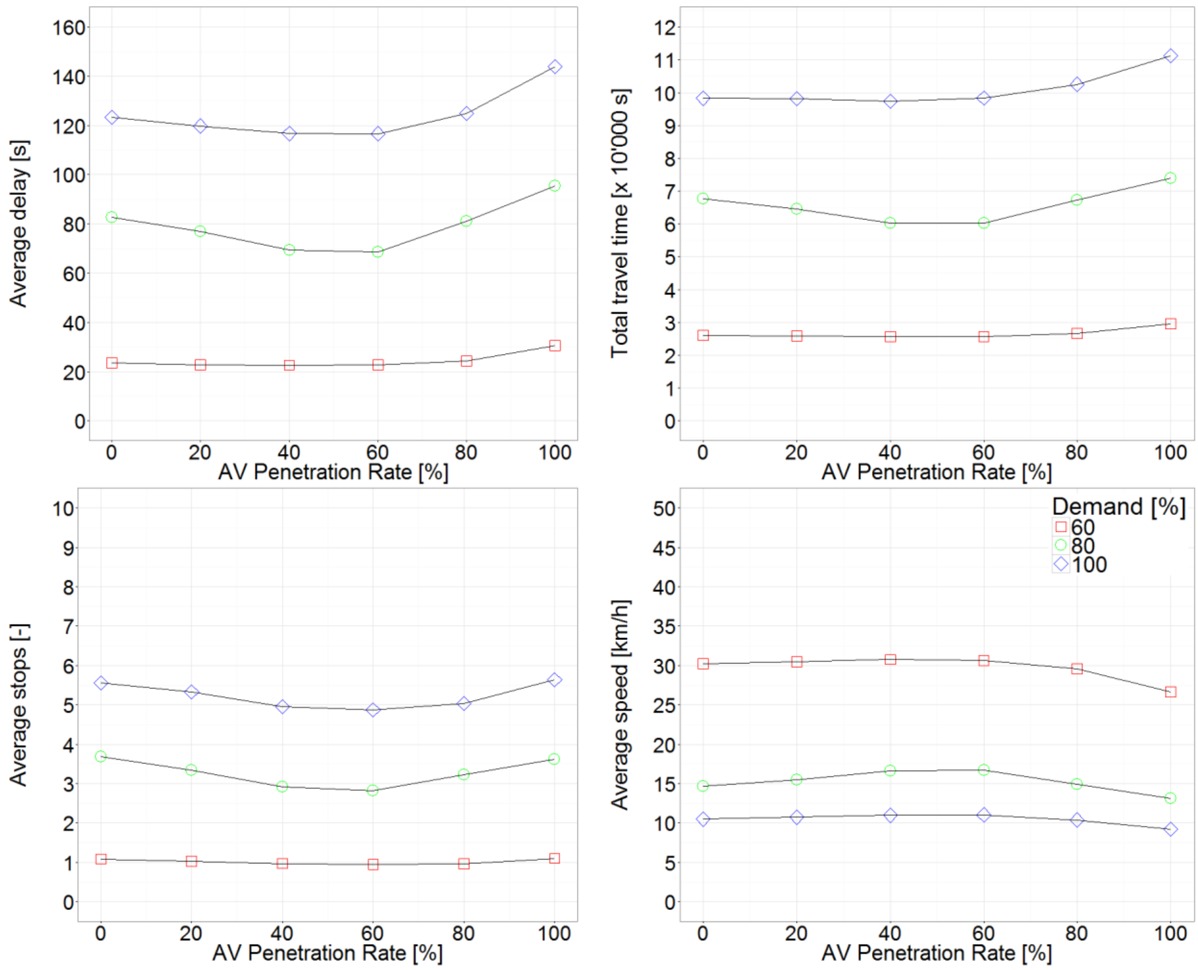


The average delay is defined as “the delay of a vehicle in leaving a travel time measurement is obtained by subtracting the theoretical travel time from the actual travel time” (PTV Group, 2016). A reduction in the delay can be observed from 0 to 40% AV penetration rate. After this point, the delay increases, especially for the case of 100% AV penetration rate. We see the same trend for the total travel time, as well as for the average speed, which reduces after the AV penetration rate exceeds 40%.

Average stops are counted as the total amount of full stops made by all vehicles divided by the number of vehicles within the network (PTV Group, 2016).

As an example for the results being consistent for the three-lane model, the results have been presented in Figure 13.

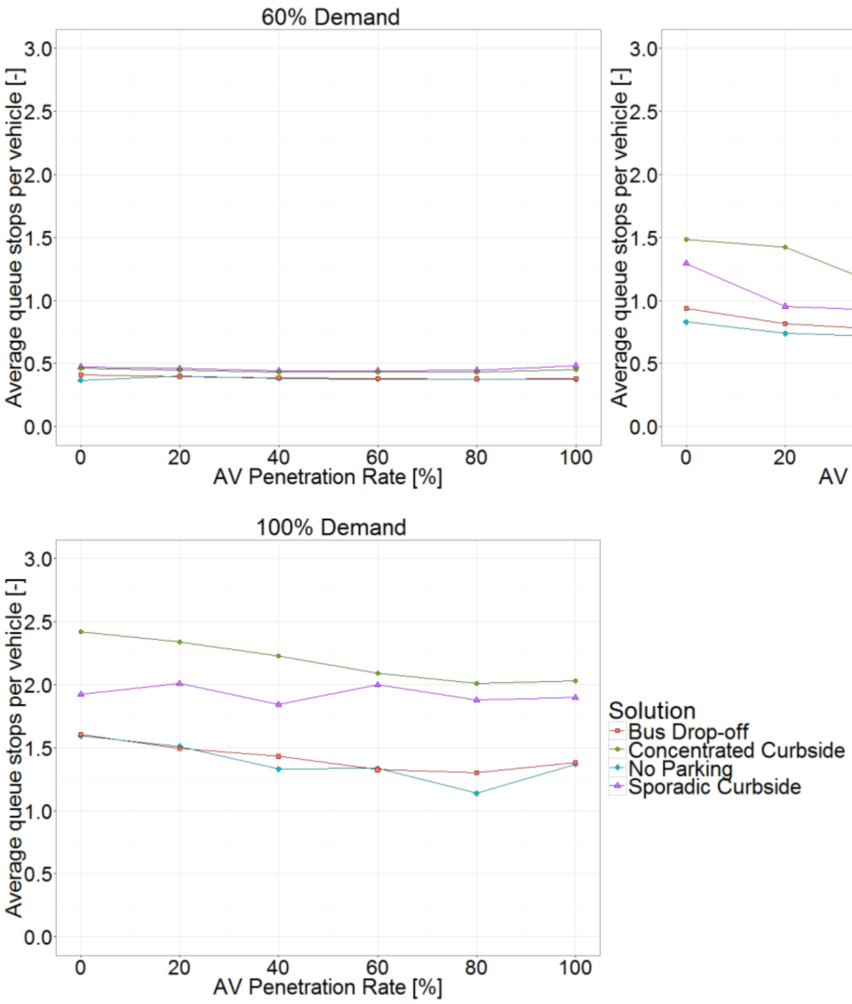
Figure 13: Network performance results for 3-lane model when no parking takes place



Observing the simulation more closely, the saturation rate of the main road increased and spillback from the segment where the parking took place onto the western intersection seemed imminent as AV penetration rate increased. At 60% AV penetration rate onwards, this queue decreased and the traffic began stacking up on the originating roads I, III and IV. It can be observed that the queues on the main road decreased. The desired acceleration curve seemed to have the effect that intersection capacity is reduced, as predicted by Le Vine et al. (2015).

The results from the queue counters show a different result. The queue counters count a certain pre-set distance back from where they are placed for those vehicles moving at a speed of 5-10 km/h, for a certain maximum headway. From the maximum queue lengths of the network, one may generally see a decreasing trend over an increase in the AV penetration rate as shown in Figure **14** and Figure 15.

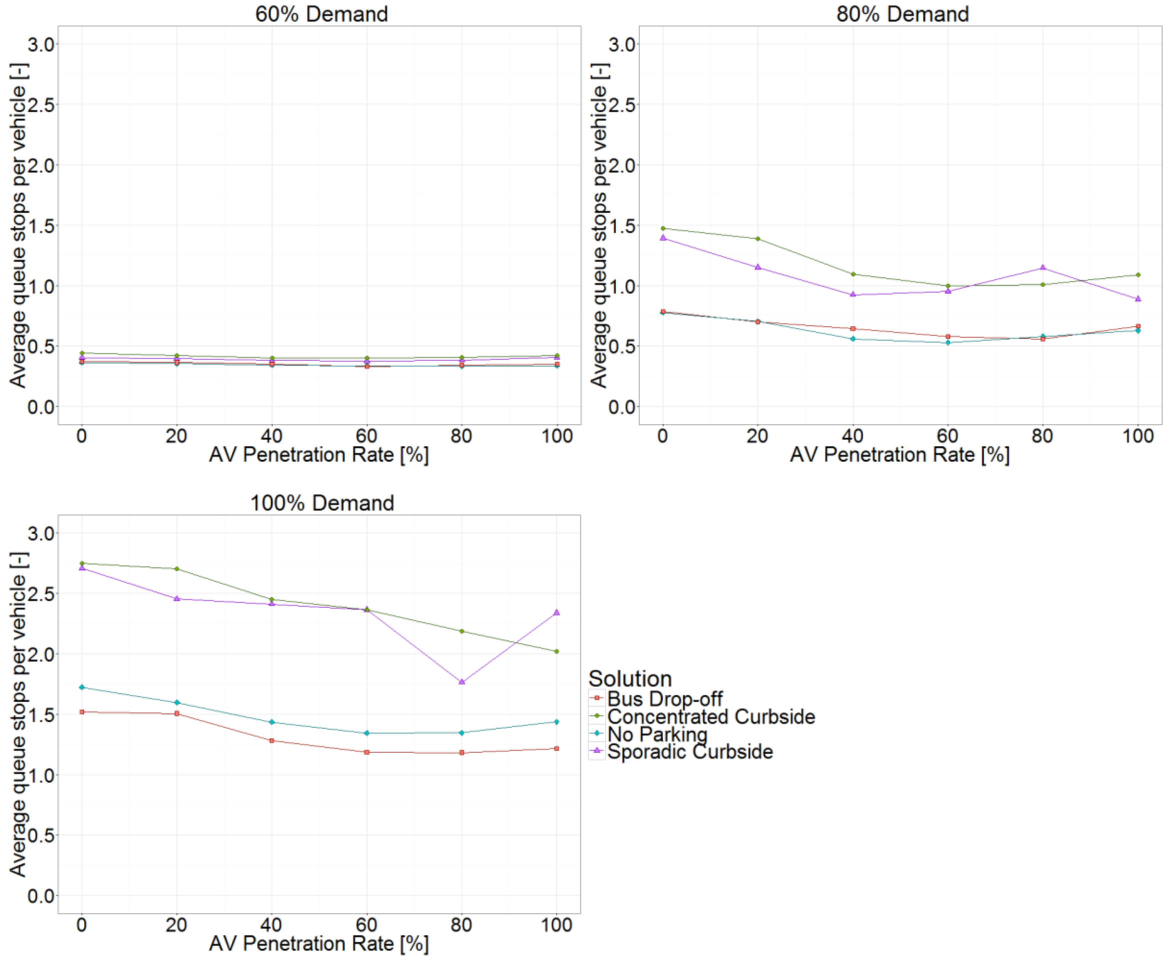
Figure 14: Average queue length results of queue counters for 2-lane model



The results are stagnant, but trending downwards indicating that queues are decreasing. This can however also be explained by the reduced deceleration rate of the vehicles with increasing AV penetration rate. The cars are thus less likely to come to a full stop within the queue.

All in all, the model does not behave as one would have expected. The network performance increases in the transition phases and then decreases as it approaches 100% AV penetration rate. This can be lead to the setup parameters of the model.

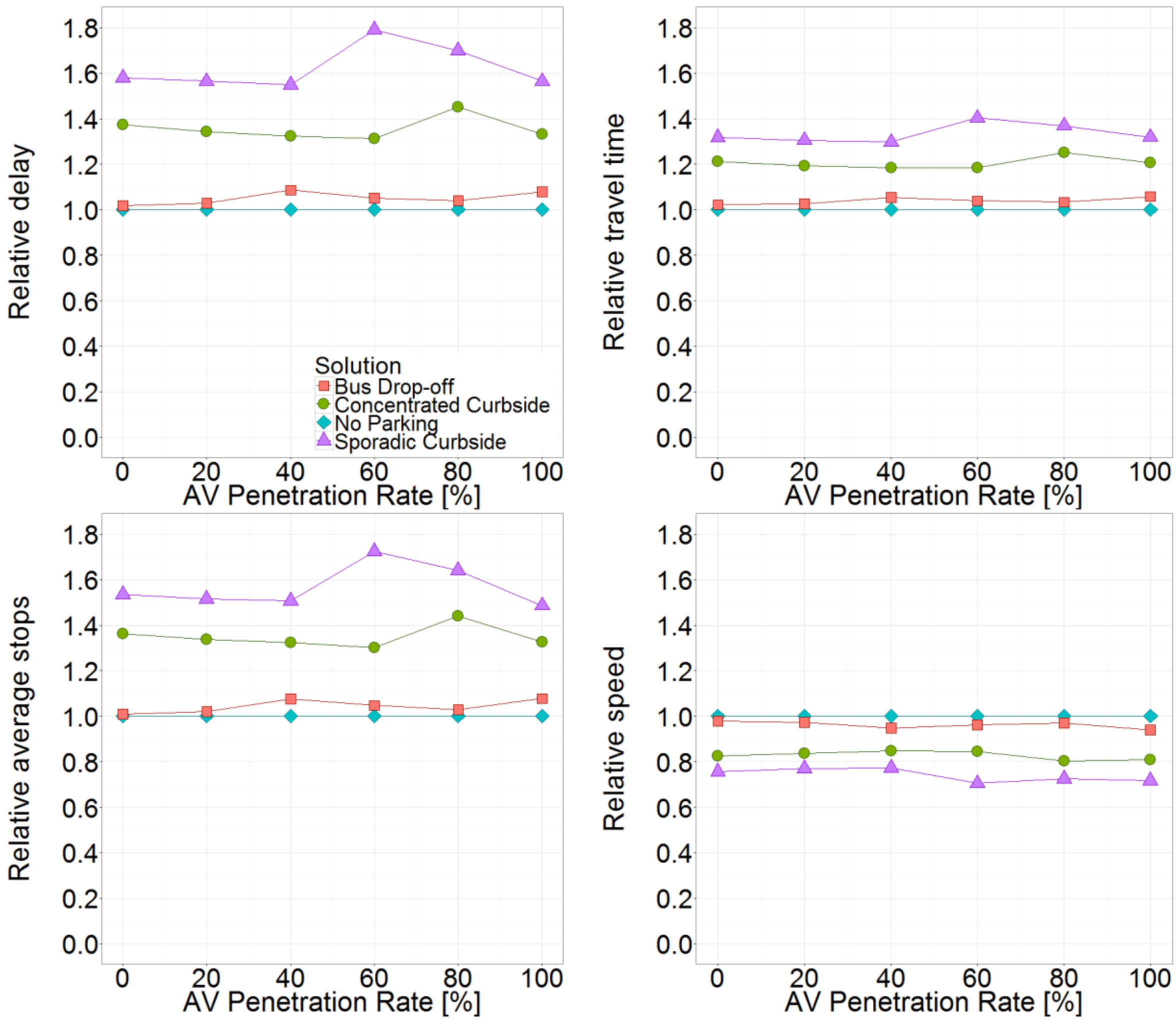
Figure 15: Average queue length results of queue counters for 2-lane model



4.1.2 Parking configuration

Secondly, we observe the impact that the parking configuration has on traffic flow. Currently, San Francisco and New York reportedly deal with the situation, where vehicles are parking sporadically around an attraction, and halting curbside without respecting curbside halting regulations. Let us consider how different parking configurations' performances are in comparison to the situation if no parking takes place.

Figure 16: Relative results to those of 'no parking' for 2 lane model at 60% demand



It can be observed that allowing vehicles to park sporadically around an attraction for the case of 60% demand results in the most delay in the network. For 80% and 100% demand, it proves to be worse to concentrate the parking in one drop-off zone. These results are consistent with the results of total travel time, which show that travel time is increased by concentrating the drop-off zone. This is also consistent for two and three-lane models. It was observed in the simulations that a queue began forming behind the concentrated drop-off zone.

For the graph of the average delay in Figure **16**, a sudden increase in the difference between the delay measured between the scenarios of sporadic curbside parking configuration and no parking is identifiable at AV Penetration level of 60%. To explain this, it can be observed that the absolute value of the delay in Figure **12** does not begin to increase until at AV penetration level of 80% for the 60%-demand level. These absolute value increases begin at the 40% AV rate for the sporadic parking configurations at 60% and 100% demand and at 60% AV rate for the 80% demand level (See Appendix B).

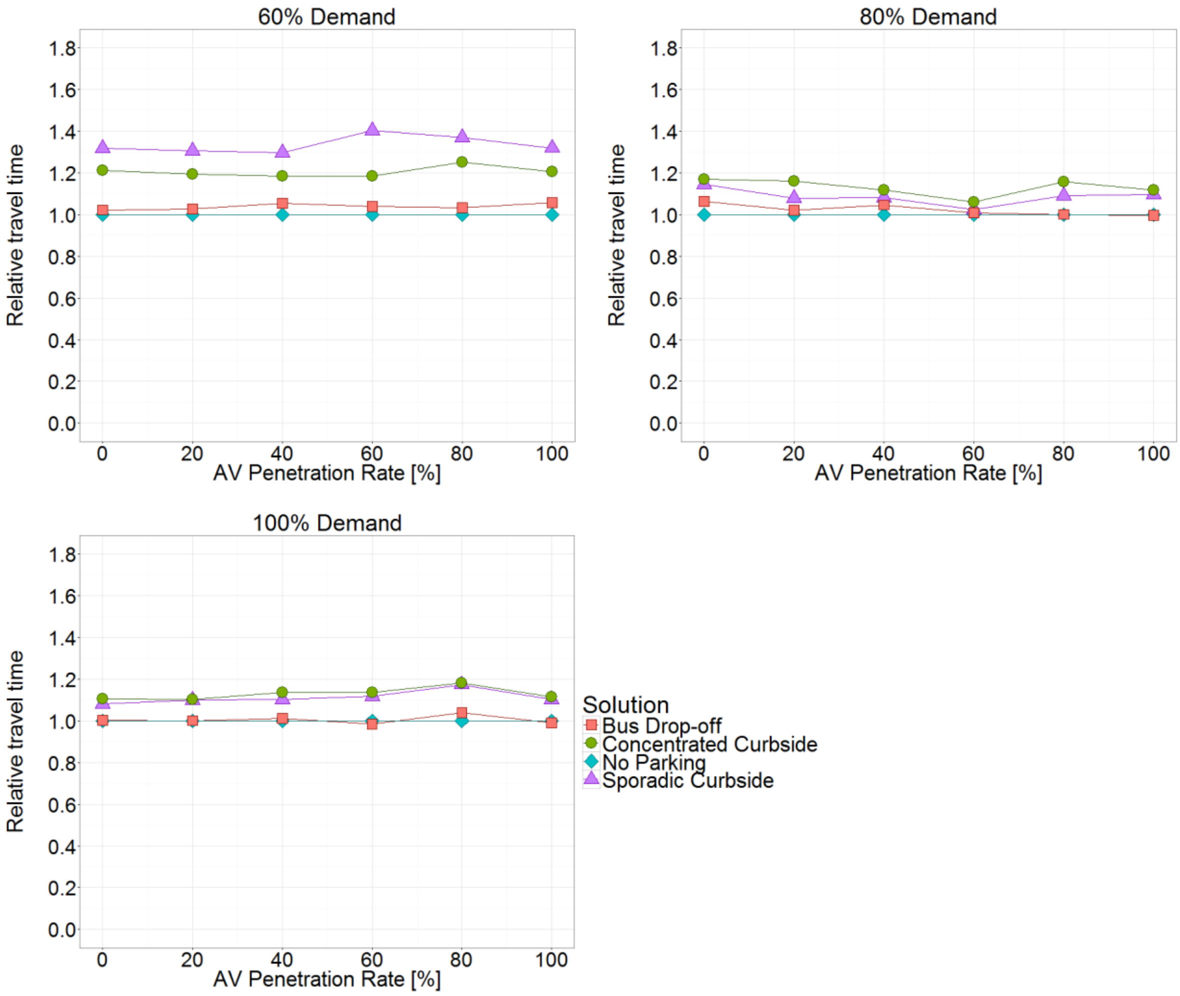
The results seem to cluster together in two groups: On the one hand, the results of the concentrated curbside and those of the sporadic curbside parking seem to give similar results. The bus drop-off configuration seems to remove the effect of the parking as their results consistently are close to 1 when compared to the ‘No Parking’ option.

The average speed of a link with a bus drop-off zone, and thus the flow over all AV penetration rates, give similar results to that of no parking. These results are consistent for the 2-, and 3-lane model. The graph of stops made within the network provides evidence to support this result.

From the figure, the travel time in the system is increased by 30-40% if vehicles are left to park sporadically over the network. This difference reduces to 0-10% if a bus drop-off zone is used for drop-off purposes. The travel time difference decreases with increasing AV penetration rate.

These results are consistent for 80% and 100% demand levels, although they are differently scaled as seen in Figure **17**. The bus drop-off configuration consistently results in the optimal in the optimal network performance. For the 80% demand level, the travel time in the system is increased by only 10-15% if vehicles are left to stop sporadically, whereas the difference is 0-5% for the bus-drop off zone.

Figure 17: Relative travel time to those of ‘no parking’ for 2 lane model



4.1.3 Cost-Benefit Analysis

As the results from the above section show an improved network performance for the bus drop-off solution, it is beneficial to conduct a brief cost-benefit analysis to understand if an investment into the parking facilities would be socially beneficial.

The cost of travel time increase is the largest contributor to the total cost ranging from 71-84%, followed by the increased fuel costs of 14-24%, the societal emission costs of 2-4% and infrastructure costs of 0-3%. Table **4** and Table **5** are analyses of the Cost-benefit analyses for 2- and 3-lane models shown in Table 6 and Table 7, respectively. Generally, with increasing AV penetration rate, one can observe increasing marginal savings.

Table 4: Benefit-Cost Ratios and Marginal Cost for 2-lane model

		Parking configuration				
		Concentrated		*Bus drop-off*		
AV %	Demand	B-C Ratio	B-C Ratio without fee	B-C Ratio	B-C Ratio without fee	Marginal Savings of Bus drop-off
0%	60%	0.30	0.13	0.65	0.44	9.6 %
	80%	0.05	-0.03	0.17	0.09	13.5 %
	100%	0.04	-0.02	0.16	0.09	20.8 %
20%	60%	0.33	0.15	0.63	0.41	7.9 %
	80%	-0.01	-0.09	0.15	0.06	17.0 %
	100%	0.06	0.00	0.18	0.11	21.0 %
40%	60%	0.33	0.15	0.55	0.33	5.7 %
	80%	0.04	-0.04	0.12	0.03	8.2 %
	100%	0.03	-0.04	0.17	0.10	25.6 %
60%	60%	0.50	0.31	0.77	0.56	6.5 %
	80%	0.05	-0.04	0.10	0.01	5.2 %
	100%	0.04	-0.02	0.23	0.16	32.0 %
80%	60%	0.30	0.15	0.70	0.51	12.2 %
	80%	0.01	-0.06	0.19	0.10	19.2 %
	100%	0.05	-0.01	0.22	0.15	30.1 %
100%	60%	0.25	0.14	0.47	0.34	10.0 %
	80%	0.05	-0.01	0.19	0.12	17.3 %
	100%	0.04	-0.01	0.20	0.13	28.2 %

Table 5: Benefit-Cost Ratios and Marginal Cost for 3-lane model

		Parking configuration				
		Concentrated		*Bus drop-off*		
AV %	Demand	B-C Ratio	B-C Ratio without fee	B-C Ratio	B-C Ratio without fee	Marginal Savings of Bus drop-off
0%	60%	0.18	-0.05	0.36	0.09	6.4 %
	80%	0.11	0.03	0.23	0.14	17.9 %
	100%	0.08	0.01	0.27	0.19	41.8 %
20%	60%	0.18	-0.06	0.35	0.07	5.8 %
	80%	0.10	0.01	0.26	0.16	22.6 %
	100%	0.05	-0.02	0.25	0.17	45.0 %
40%	60%	0.19	-0.06	0.37	0.09	6.2 %
	80%	0.10	0.01	0.24	0.14	18.9 %
	100%	0.08	0.02	0.33	0.25	53.5 %
60%	60%	0.20	-0.05	0.37	0.09	5.7 %
	80%	0.15	0.05	0.25	0.14	13.0 %
	100%	0.08	0.01	0.32	0.25	55.0 %
80%	60%	0.19	-0.04	0.36	0.10	6.3 %
	80%	0.20	0.11	0.29	0.20	12.2 %
	100%	0.08	0.02	0.30	0.23	51.1 %
100%	60%	0.15	-0.02	0.25	0.06	5.0 %
	80%	0.12	0.04	0.15	0.07	5.2 %
	100%	0.10	0.04	0.28	0.21	47.0 %

The impact of accounting for a drop-off fee of an average of 0.5 USD per parked vehicle is considered. This fee is arbitrarily set, and may also vary within a dynamic pricing scheme. The savings made from a concentrated curbside stopping configuration only become positive once this fee is implemented. With a parking fee, the benefit-cost ratio ranges between 0.05 and 0.20, which is in the same range as the bus drop-off scenario without the parking fee, 0.06-0.23. With the parking fee, the drop-off scenario’s benefit-cost ratio ranges between 0.15 and 0.37. The marginal savings show the relative advantage of investing in a bus drop-off infrastructure over a concentrated curbside configuration, in terms of the net value which is extracted from either option in relation to cost of setting up the bus-stop infrastructure. The marginal savings range from 5 to 55% across the different scenarios.

Table 6: Cost Benefit Analysis for 2 Lane Model

Parameters		Parking Configurations						
		Sporadic	*Concentrated*			*Bus drop-off*		
AV Penetration	Demand	Costs	Costs	Benefits	Net Value	Costs	Benefits	Net Value
0%	60%	688	608	255	182	479	102	311
	80%	1’719	1’764	340	90	1’583	136	272
	100%	2’622	2’688	425	104	2’409	170	383
20%	60%	662	576	255	188	470	102	294
	80%	1’544	1’689	340	-10	1’461	136	218
	100%	2’673	2’683	425	161	2’401	170	442
40%	60%	644	559	255	187	483	102	263
	80%	1’557	1’624	340	69	1’514	136	179
	100%	2’615	2’714	425	71	2’370	170	415
60%	60%	739	562	255	279	475	102	366
	80%	1’503	1’562	340	77	1’491	136	147
	100%	2’737	2’787	425	119	2’358	170	549
80%	60%	784	684	255	202	520	102	366
	80%	1’618	1’730	340	24	1’471	136	283
	100%	2’801	2’833	425	138	2’429	170	543
100%	60%	1’020	897	255	226	762	102	361
	80%	1’963	1’991	340	107	1’759	136	340
	100%	2’949	2’984	425	134	2’606	170	512

Note: Costs are calculated based on US DOT estimates of VTTS (2014), social costs due to emissions based on Hill et al. (2009), fuel consumption from model of Kwak et al. (2012) and cost of fuel from the US Energy Information Administration (2017).
Benefits are based on Parking fees, based on assumptions. All values are in USD/hr.

Table 7: Cost Benefit Analysis for 3 Lane Model

Parameters		Parking Configurations						
		Sporadic	*Concentrated*			*Bus drop-off*		
AV Penetration	Demand	Costs	Costs	Benefits	Net Value	Costs	Benefits	Net Value
0%	60%	619	654	153	118	568	153	204
	80%	2482	2419	204	267	2178	204	508
	100%	3784	3746	255	293	3184	255	854
20%	60%	594	633	153	114	555	153	193
	80%	2343	2322	204	225	2019	204	528
	100%	3764	3830	255	189	3225	255	794
40%	60%	591	626	153	118	543	153	201
	80%	2222	2210	204	216	1956	204	470
	100%	3945	3881	255	320	3162	255	1039
60%	60%	598	626	153	124	550	153	201
	80%	2189	2088	204	305	1914	204	479
	100%	4020	3966	255	308	3228	255	1046
80%	60%	638	665	153	126	580	153	211
	80%	2585	2324	204	465	2161	204	628
	100%	4151	4065	255	341	3379	255	1027
100%	60%	866	885	153	134	817	153	202
	80%	2772	2664	204	312	2594	204	382
	100%	4467	4310	255	412	3679	255	1043

Note: Costs are calculated based on US DOT estimates of VTTS (2014), social costs due to emissions based on Hill et al. (2009), fuel consumption from model of Kwak et al. (2012) and cost of fuel from the US Energy Information Administration (2017).
Benefits are based on Parking fees, based on assumptions. All values are in USD/hr.

4.2 Case study

A segment of 2^{nd} Avenue on Manhattan, New York between 42^{nd} and 43^{rd} Street was chosen as a case study for the model. The segment is a 5-lane road, one of which is shared with bicyclists. An additional lane is on the right-hand side for buses only. Although this lane is also used for parking, it is not counted towards the lane number for this model. The left-turn onto 42^{nd} Street is added however.

Figure 18: Screenshot from Google Street View, driving south down 2^{nd} Avenue

Source: Google

Traffic travels southbound along 2^{nd} Avenue, and westbound along 43^{rd} Street, but both west- and eastbound on 42^{nd} Street. The traffic on 43^{rd} street travels on one lane, but 42^{nd} Street has 3 lanes dedicated to traffic in both directions.

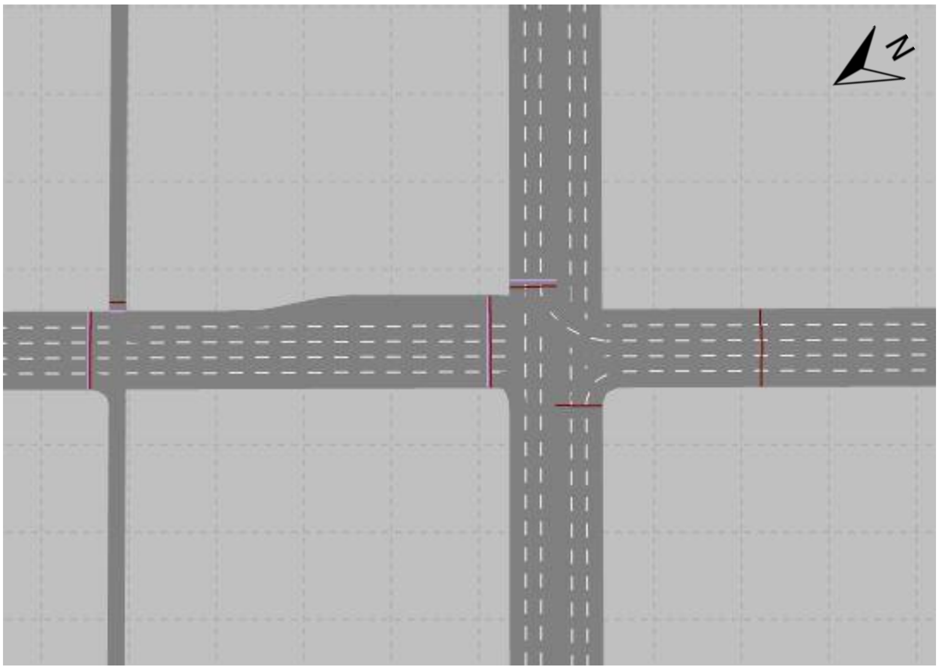
We repeat the key paramerers of the model shown in Table 1:

Table 1: Input parameters for different AV penetration rates

Parameter		0%	20%	40%	60%	80%	100%
Vehicle acceleration							
- Mean at v=0 m/s	[m/s^2]	3.0[1]	2.8	2.5	2.2	1.7	1.3[2]
Vehicle deceleration							
- Mean at v=0 m/s	[m/s^2]	2.7[1]	2.4	1.8	1.7	1.5	1.2[2]
Desired speed distribution							
- Minimum	[km/h]	48[1]	48	49	49	49	50[4]
- Maximum	[km/h]	58[1]	57	57	57	55	54[4]
Standstill distance	[m]	2.0[1]	1.8	1.6	1.4	1.2	1.0[5]
Safety distance							
- Additive part	[-]	3.0	2.6	2.2	1.8	1.65	1.5[3]
- Multiplicative part	[-]	4.0	3.6	3.2	2.8	2.65	2.5[3]

[1] (PTV Group, 2016)
[2] (Le Vine et al, 2015)
[3] (CDM Smith, 2014)
[4] Flatter speed distribution based on (PTV Group, 2017)
[5] Minimum value as per (PTV Group, 2016)

Figure 19: Set up of the model. VISSIM screenshot.

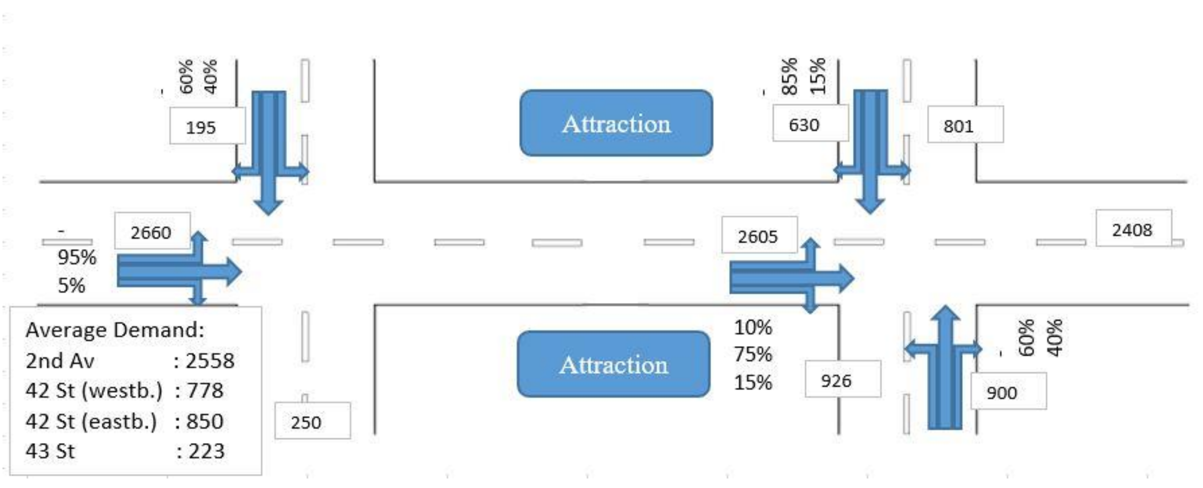


Having set up the model in the same way as described for the abstract model in Chapter 3, the demand was altered to fit traffic counts provided by the New York Department of Transport. The peak hour counts are given as averages over a section of blocks shown in the following table (NYDOT, 2009; NYDOT, 2011; NYDOT, 2014). The average peak hour demand measured in New York is reported in Table **8**. The demand per link segment and the link's average demand implemented in the model is reported in Figure **20**.

Table 8: Average peak hour demand rates and year of measurement

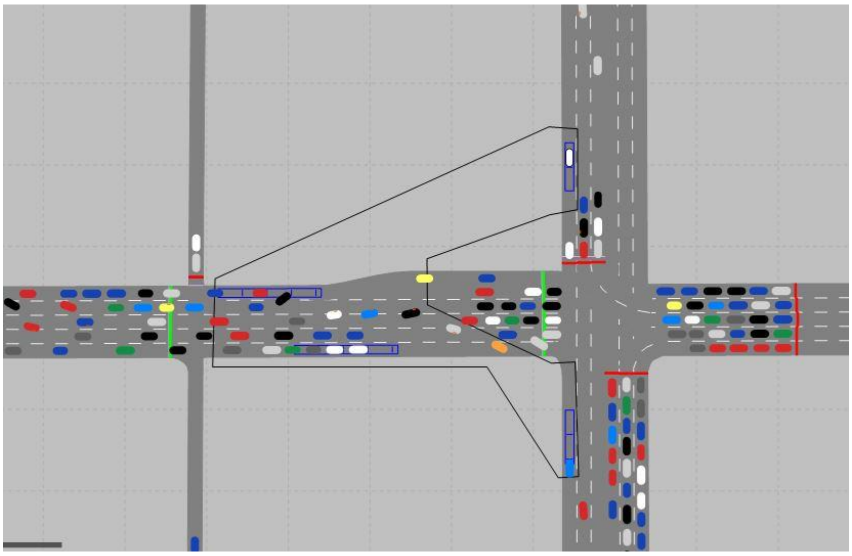
Road section	Peak hour	Section	Year
2nd Avenue	2597	From 59th Street to 42nd Street	2014
42nd Street westb.	752	From 5th Avenue to Franklin D Roosevelt Drive	2011
42nd Street eastb.	842	From 5th Avenue to Franklin D Roosevelt Drive	2011
43rd Street	220	From 5th Avenue to 1st Avenue	2009

Figure 20: Turn volumes and average demand over segments



To emulate spillback effects of a saturated network, another signal head was located on 2nd Avenue after crossing the intersection of 42nd Street. A screenshot from VISSIM gives an idea of its effect in Figure **21**.

Figure 21: Spillback effects in Case Study. VISSIM screenshot.



The signal programme was also set differently from that of the abstract model, with longer green-times for 2nd Avenue.

The three scenarios were set up for the case study: sporadic parking as in Figure **22**, concentrated curbside parking in Figure **23** and the bus drop-off zone in Figure **24**.

Figure 22: Sporadic parking set up. VISSIM screenshot.

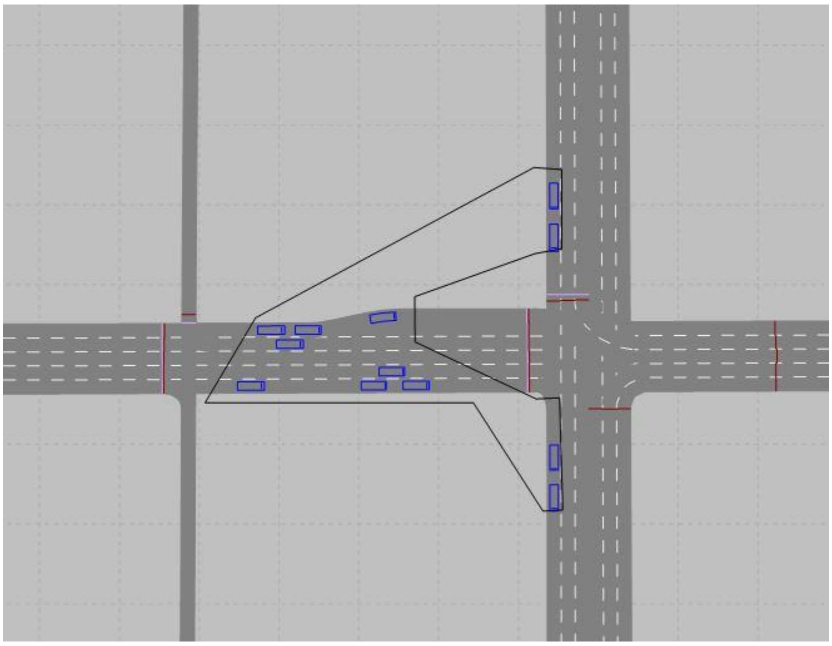
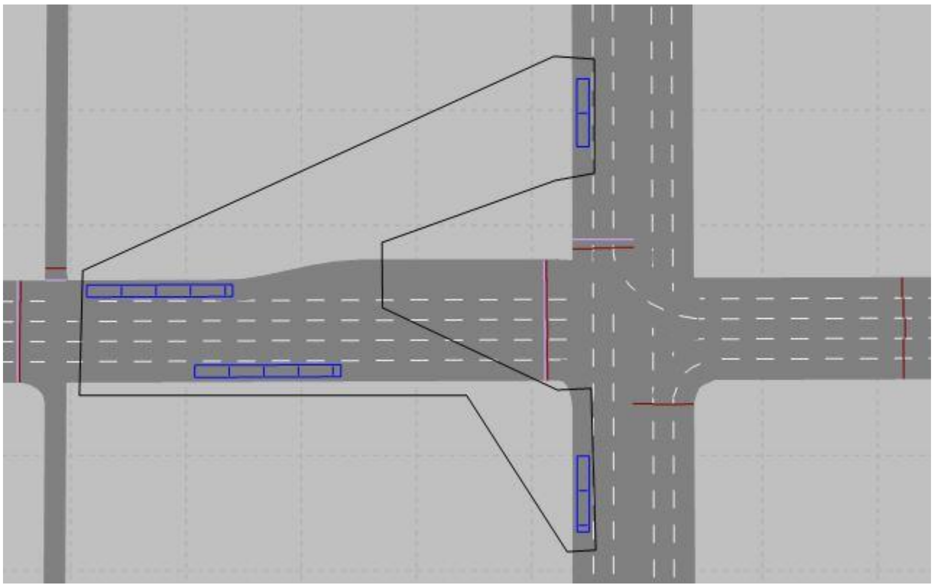
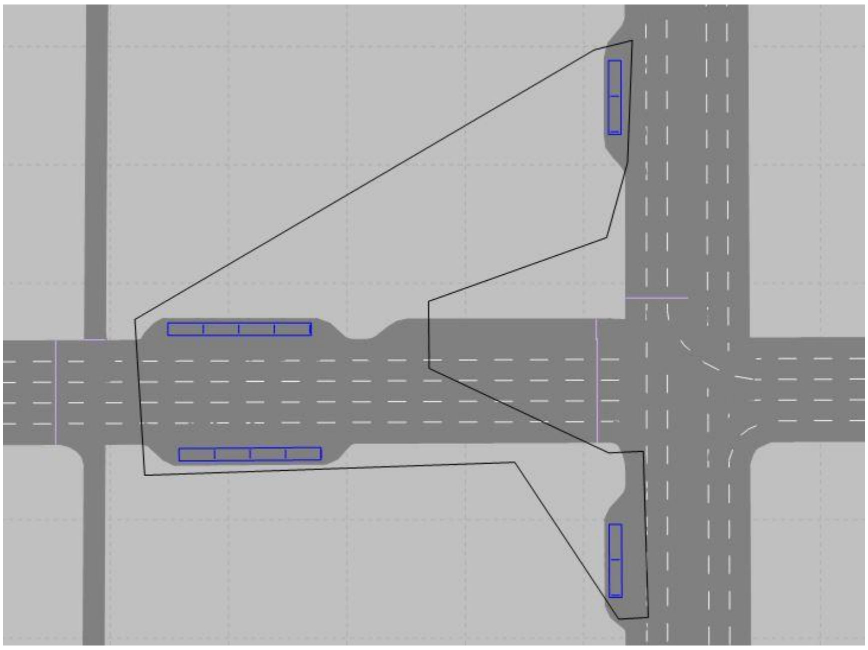


Figure 23: Set up of concentrated curbside parking scenario. VISSIM screenshot.



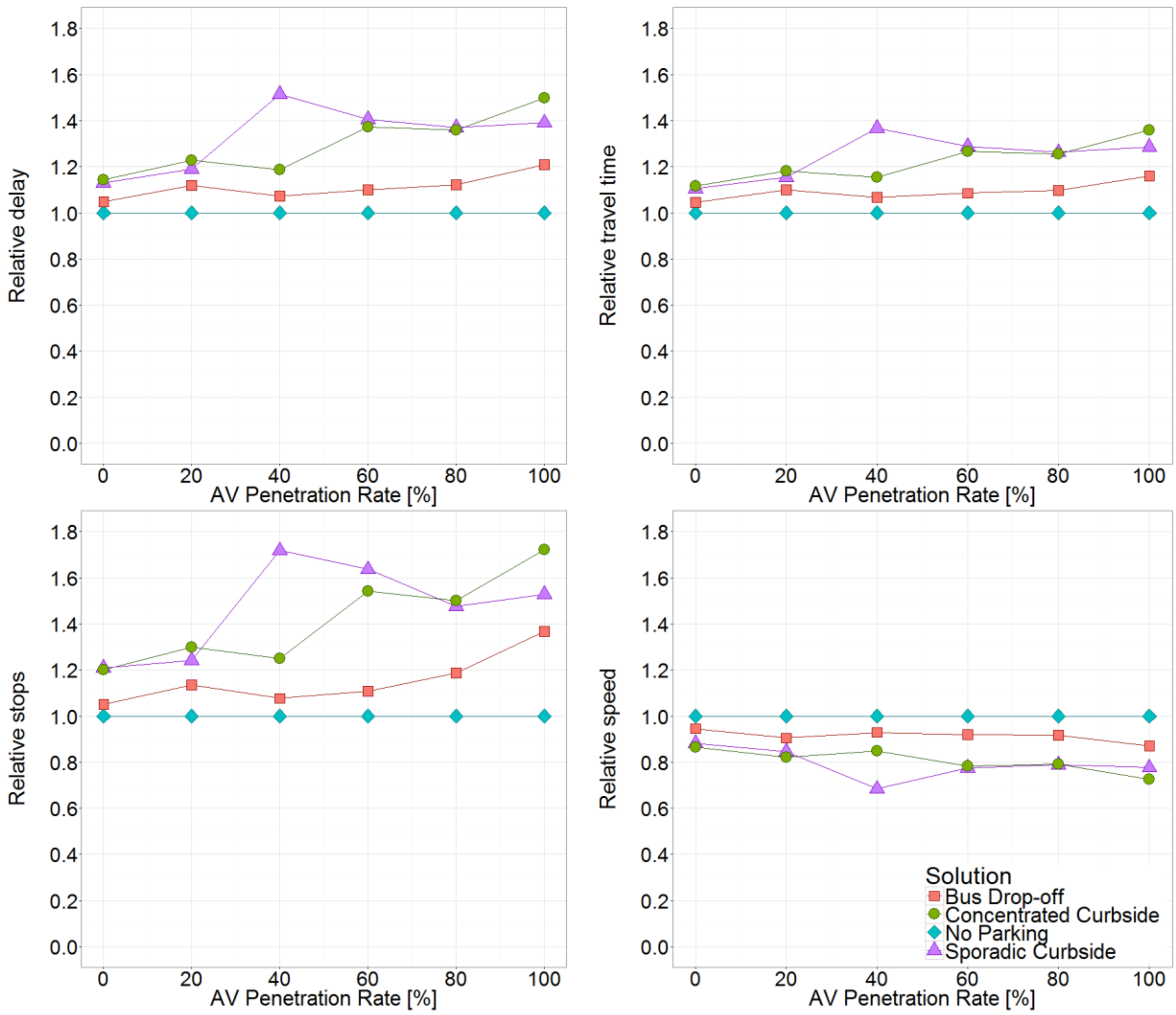
The drop-off zones have been defined on either side of the road, as to simulate real-life. A passenger would not, under normal circumstances, expect to be dropped off across the street from his final destination. The parking space utilisation rate is about 47% using a 20% probability of parking.

Figure 24: Set up of drop-off zone scenario. VISSIM screenshot.



The case study is run for AV penetration rates of 0-100 with constant demand, but alternating scenarios. For this specific situation, the following results are recorded:

Figure 25: Relative results to those of ‘no parking’ for 2nd Avanue



Besides the outlier for Sporadic Curbside at 40% AV penetration rate, there is a consistent trend of the bus drop-off zone providing the best performance of the three parking configurations, and the curbside halting configurations behaving similarly. This is consistent with the results of the abstract model.

A cost-benefit analysis is performed, using a value of travel time savings of 24.10 USD per hour, which is the value of travel time savings for business travel, which is fitting for Manhattan (USDOT, 2014). Otherwise the model is set up identically as for the abstract model. The cost of buildable land 6220 USD/m^2 is used (Hughes, 2015).

The models all include 12 parking spaces. It has not been assessed whether this is sufficient to meet the demand of the neighboring attractions, but is not considered important for this analysis as results are only compared between themselves.

Table 9: Cost benefit analysis for case study around 2nd Avenue

	Parking Configurations						
	Sporadic	*Concentrated*			*Bus drop-off*		
AV %	Costs	Costs	Benefits	Net Value	Costs	Benefits	Net Value
0%	2’335	4’470	260	203	4’131	260	543
20%	4’414	3’746	260	142	3’434	260	454
40%	3’629	3’339	260	1’105	3’037	260	1’407
60%	4’184	2’790	260	328	2’262	260	856
80%	2’858	2’695	260	278	2’249	260	724
100%	2’713	3’470	260	13	2’832	260	652

Note: Costs are calculated based on US DOT estimates of VTTS (2014), social costs due to emissions based on Hill et al. (2009), fuel consumption from model of Kwak et al. (2012) and cost of fuel from the US Energy Information Administration (2017).
Benefits are based on Parking fees, based on assumptions. All values are in USD/hr.

Table 10: Benefit-Cost Ratios and Marginal Cost for Case Study

	Parking configuration				
	Concentrated		*Bus drop-off*		
AV %	B-C Ratio	B-C Ratio without fee	B-C Ratio	B-C Ratio without fee	Marginal Cost of Bus drop-off
0%	0.05	-0.01	0.13	0.07	21.4 %
20%	0.04	-0.03	0.13	0.06	19.6 %
40%	0.33	0.25	0.46	0.38	19.0 %
60%	0.12	0.02	0.38	0.26	33.2 %
80%	0.10	0.01	0.32	0.21	28.1 %
100%	0.00	-0.07	0.23	0.14	40.2 %

The results of the cost-benefit analysis are similar to those of the abstract models, and show an increasing trend of the marginal savings with increasing AV penetration rate. The net value of the bus-drop off reaches its maximum at 40% AV penetration rate, which was the point that the model showed anomalous behavior as discussed in the previous section. The marginal savings normalises this anomaly, however.

5 Discussion

General discussion on automated vehicles is yet not so focused. There are still many unanswered questions in how these will develop. Elvarsson and Fasching (2017) recorded that 59.6% of survey respondents believe that AV systems reduce accidents. These attitudes are recorded even though 93.5% of accidents can be lead back to human error (Winkle, 2015). This shows that the respondents of the survey are still sceptical of the potential benefits of AV. Many believe that the technology allowing AVs to communicate each other's speed between themselves allows traffic flow to be optimised, as well as making intersections redundant. Yang et al. (2016) are among those who discuss the benefit of incorporating trajectory design for connected automated vehicles. This model controlled the signal controllers as unchanged with increasing AV penetration rate.

The importance of changing signal head technology can be assessed as high based on the model. Observing a decrease in the performance of the network with increasing AV penetration rate hints at the impact that the acceleration rate of the vehicle has on the system, and is simultaneously opposing the general expectation that AVs make traffic flow more efficiently. It is therefore important to reduce the number of full stops of the vehicles within the network to avoid a reduction in efficiency. This can be achieved by an increasing amount of inter-vehicular communication, and signal-less intersections, but these are dependent on the improvement of AV latency times (Hult et al., 2016; Zhou et al.,2012).

We might however also see different results for the higher AV penetration rates if the modelled vehicles would accelerate simultaneously, and not consequently, as conventional vehicles do. Neither this, nor the effect of vehicle platooning, were implemented in the model. This would reduce the road space needed per vehicle, and possibly increase the capacity of the road, further than the model can. An unknown factor also not modelled was how the size of the vehicles will change.

The above-mentioned parameters all show that the empirical Wiedemann car-following model is perhaps not valid for automated vehicles. Further research based on tests performed by Google, and other automated vehicle producers would be very interesting to find a new car-following model which would be valid for self-learning interconnected automated vehicles. Likewise, data based on passenger comfort for different acceleration rates would be very helpful to validate the assumption of the acceleration distribution. This must be tested for vehicles with and without tilting technology.

Analysing the effects of the different parking configurations, the bus drop-off configuration proves consistently to be the most effective solution to improve the network performance.

The results of the abstract model are based on a hypothetical situation considering drop-off in front of one attraction, but urban environments are of course more dynamic than this. The urban environment is further simplified in the model, not including pedestrians, bicyclists, heavy vehicles or public transport. This simplification of real-life into the abstract model shows that the results should only be compared between themselves, and not be taken as universally true absolute values.

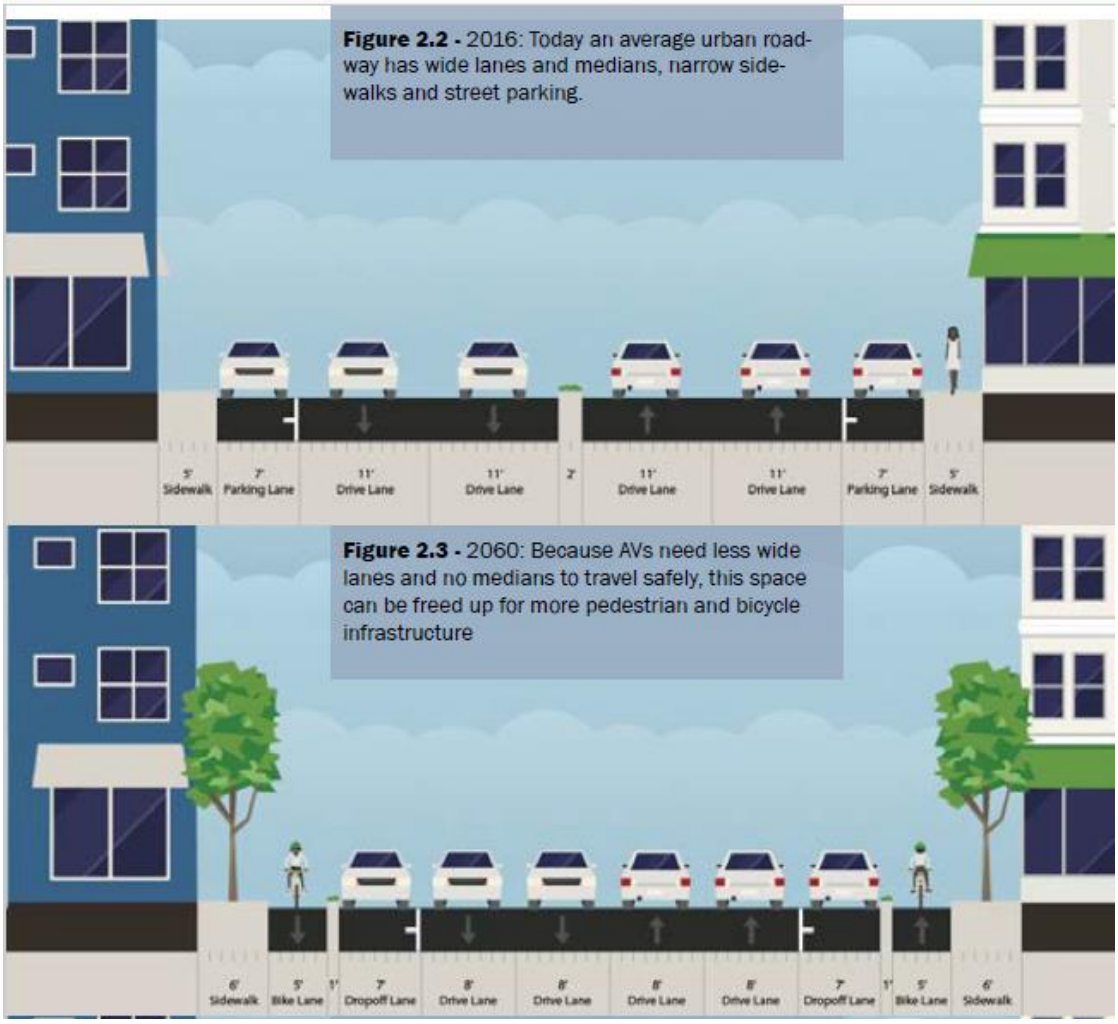
Assuming that vehicles park sporadically around the street today as defined by the model, the cost-benefit analysis performed shows that for the 3-lane abstract model, the net value of implementing bus drop-off zones range between 201 and 1’043 USD/hr for different scenarios of AV penetration and demand. The bus drop-off variation showed a benefit-cost ratio of 0.15-0.37 with a parking fee, and 0.06-0.25 without a parking fee. This means that if an average parking of 0.5 USD will be charged, the net value of transforming the infrastructure is 15% of the costs incurred by the traffic. For some scenarios of the concentrated curbside halting configuration without a parking fee, the benefit-cost ratio showed a negative value, implying the option to be economically unjustifiable.

These savings, for a fixed demand, in the case of 2nd Avenue between 42nd and 43rd Street, were calculated to range between 454 and 1’407 USD/hr for different AV penetration rates. According to this analysis, even a city with as high land prices as Manhattan is subject to the discussion of placing land under additional roadside infrastructure for an efficient drop-off routine. These results are based on assumptions, and should only be considered as a proof-of-concept value. The effect of change in demand has not been included in this analysis and should be considered when modelling more specifically. It does not consider differing effect of demand in any way.

Currently, authorities are faced by the challenge of TNCs increasing VKT and congestion within cities and some are calling for more stringent regulation on these initiatives. The next steps taken by policy-makers can be decisive in affecting future mobility choices. For example, restricting the availability of TNCs may encourage passengers to purchase their own automated vehicle. Alternatively, policy-maker can pave the way for the transformation from parking to drop-offs.

An important consideration is who the owner of such drop-off infrastructure ought to be. In most municipalities, it is the municipality who owns the road space. It therefore seems logical that the municipality invests in these drop-off zones alongside the reduction in lane width that will be possible with the implementation of AVs (Chapin, 2016). The possibility of public-private partnerships should however not be excluded, but this option needs to be researched further. Furthermore, some private grounds, such as those of hotels, may have their own onsite drop-off facilities. These sorts of drive-in configurations are land-intensive and would probably not be suitable solutions for Manhattan, New York.

Figure 26: Redistribution of road space with the coming of automated vehicles.



Source: Chapin (2016)

First tests of the abstract model eliminated a land-intensive drive-in parking configuration and this was not modelled further. This parking variation as well as any other may provide interesting results, and should be researched further to find an optimal design of future parking configurations.

Some scenarios seem to show anomalies and large differences between similar values. Examples of these are for Sporadic Parking at 40% AV Penetration rate in Figure **25** and at 60% in Figure **16** and are explained by a sudden difference in the absolute values. In future modelling, more than 10 simulation runs should be run so that averages can be found over a larger sample of runs.

6 Conclusion

In this work, the driving and parking behavior of automated vehicles has been modelled within the boundaries set by VISSIM. The software is designed to model psycho-physical parameters in human behavior in conventional vehicles. Modelling automated vehicles in VISSIM is still a recent practice, and not fully supported by the software. Future research should attempt to address this.

The effective implementation of automated vehicles will be dependent on many variables, including the ability to establish signal-less intersections, reliable inter-vehicular communications, and their interactions with pedestrians. None of these variables have been modelled within the scope of this work as they are not (yet) supported by VISSIM.

Further research is also required for the car-following models of automated vehicles to model their driving behavior. Their size distribution will also have an impact on the road space required per vehicle. The acceleration distribution suggested by Le Vine et al. (2015) needs to be experimented further and validated with and without technology, such as tilting technology, to increase the value of acceleration where the comfort threshold lies.

It is worth mentioning that the assumptions made by the author for modelling purposes should not be interpreted to be more probable, or preferred, outcomes. The author discusses the complexity of predicting possible outcomes and input parameters into the model, and attempts to address these and assume values which can be reasoned.

This work shows that there are better configurations than allowing vehicles to park sporadically within the road space. The possibilities of parking configurations have not been exhausted in this work, and they should be considered to find effective solutions which positively impact the traffic flow.

Based on the model, policy-makers can have significant cost-reducing impacts through effective transport planning. The case study in New York showed potential savings for society of up to 1’407 USD/hr in comparison to the reference state of sporadic curbside halting. Although this calculation is based on numerous assumptions, it shows that savings of this order of magnitude should not be ignored.

7 Thanks

Many thanks go out to the very helpful Henrik Becker and Arnd Bätzner who supervised my work and guided me towards my goal. Thanks to Professor Kay Axhausen for his invaluable feedback. Furthermore, Qiao Ge was very helpful in discussing modelling possibilities in

VISSIM. Finally, thank you to Dominic Trachsel, with whom I had plenty of discussion and spent time with at the Zurich airport to collect data on taxi drop-offs.

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A Parking duration

As literature on the drop-off times of taxis and private vehicles is scarce, Arnor Elvarsson and Dominic Trachsel found motivation to time these in typical drop-off zones. Over a total of 2.5 hours, 35 vehicles were recorded.

The time variables of the experiment were taken from the experiment of Daamen et al. (2008) and adapted to the service of taxis and private individual vehicles. Daamen et al. conducted a closed laboratory experiment on the boarding and alighting of railway wagons with a range of variables that they controlled for, and experimented their effect on boarding and alighting behavior.

In this experiment, the time was measured in intervals from the car coming to a full stop and until

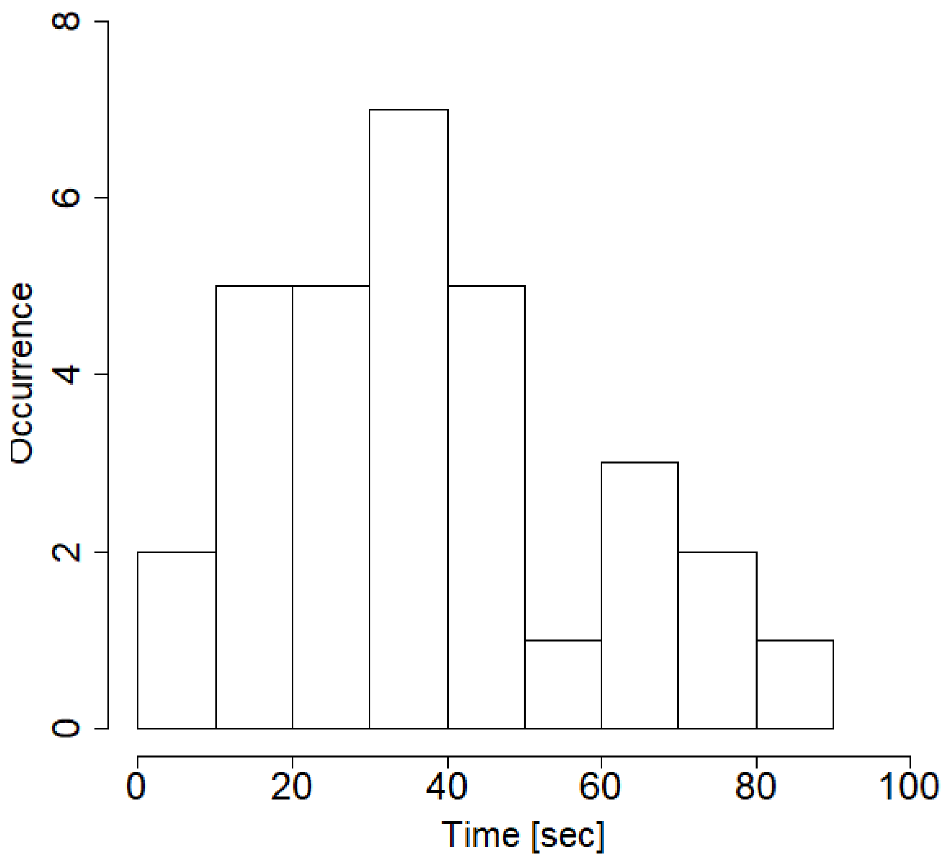
1. the first door opened
2. the last passenger exited
3. the baggage was all removed
4. all passengers had left the vicinity of the vehicle
5. the vehicle left

Further information on the measured vehicle was also collected, i.e. whether the vehicle had an Uber registration on the windshield, whether the driver exited to help with baggage, and how many passengers were in the vehicle. The fastest drop-off, measured from the car arriving until the car left, took 18 seconds and the passenger only took 3 seconds to get out and leave the parking area. Within the data set, there were passengers who had trouble with payment of the Taxi or took time to say goodbye to a loved one leading to an increased parking time. It was also observed that additional parking time was a result of the driver stepping out of the vehicle, for example to help with baggage.

In analysing the data, the time between the car coming to a full stop and the first door opening was therefore removed from the analysis, as well as the last time interval, between the last passenger leaving until the vehicle left. In the first time interval, the data set was varied as some passengers spent time inside the vehicle to pay for the taxi, discuss with the driver or even say goodbye. Saying goodbye was however mostly used in the time between the baggage being removed and all passengers leaving the vehicle's vicinity. In some occasions, taxi drivers took time after the passenger had left to wait for the next pick-up location.

Using the time between the first door opening and the vehicle leaving a Poisson distribution of the drop-off times could be identified. After removing four outliers, a mean of 37.7 seconds was found and the following probability distribution function plotted:

Figure 27: Poisson-distributed probability density function of taxi drop-off times



As mentioned, there was still time between the baggage being removed and the passengers leaving the vicinity where the leaving passengers discussed with the driver, or spent time saying goodbye to the person. There is therefore potential in further time reductions.

For the purpose of this paper, it is found reasonable to estimate a mean of 30 seconds for the stopping time. If passengers have an incentive to minimise the time they spend on the drop-off routine, they will do so. Also out of social pressure if they are carpooling the vehicle with others that have a different final destination. Passengers will furthermore have an easier payment option as it will become automatic, but the possibility of high drop-off times is still there if baggage must be removed from the vehicle.

Finally, the sample only includes 35 vehicles, and 31 vehicles after anomalies were excluded. This sample must be increased in order to get any sort of statistical significance of the collected data, which was not even tested for due to the small sample size.

Table 11: Raw data from drop-off time survey

Door opens	Last passenger	Baggage out	Passenger left	Vehicle left
[s]	[s]	[s]	[s]	[s]
8	23		60	78
37	39		65	75
26	31	54	59	67
170	173	183	186	200
10	12	30	32	44
16	30	52	58	72
6		20	23	32
70	80	77	85	118
3	5	22	34	64
13	30	52	61	126
3	11	24	41	60
7	9	38	44	51
3	4	5	6	18
3	9	14	16	24
3	11	20	37	54
2	9	20	43	63
17	41	44	58	82
15	29	49	121	139
20	58	56	64	77
7	24	52	85	90
11	20	33	38	43
12	17	29	140	140
4	13	68	78	88
20	45	60	90	95
3	20	105	120	120
4	30	50	68	65
3	12	12	12	25
2	9	20	27	38
1	20	31	38	38
3	23	23	39	38
1	25	43	65	86
9	14	29	92	107
3	33	110	120	160
1	10	16	20	23
1	8	19	31	55

B Results

B.1 No parking

B.1.1 2 lane model

Figure 28: Average delay for 2 lane model

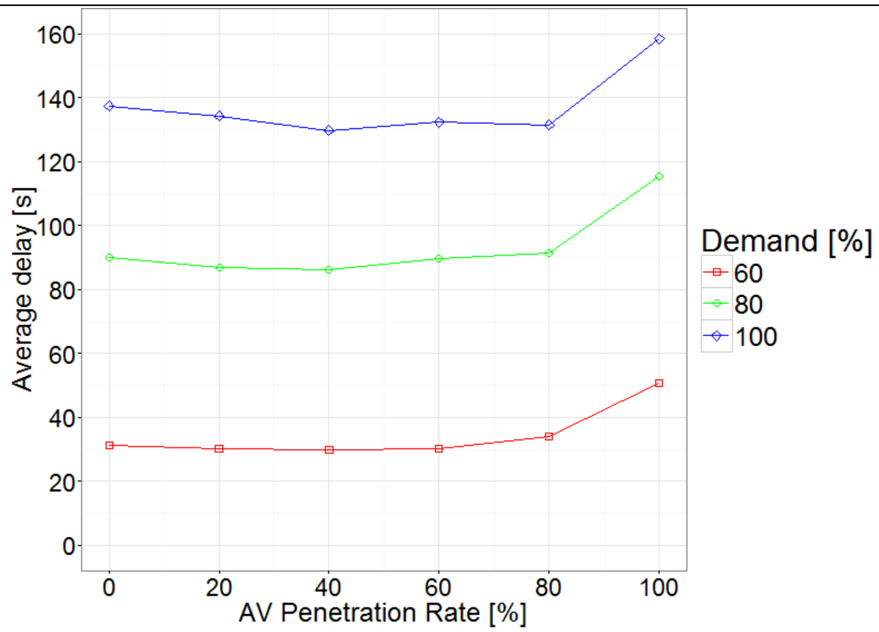


Figure 29: Average stops for 2 lane model

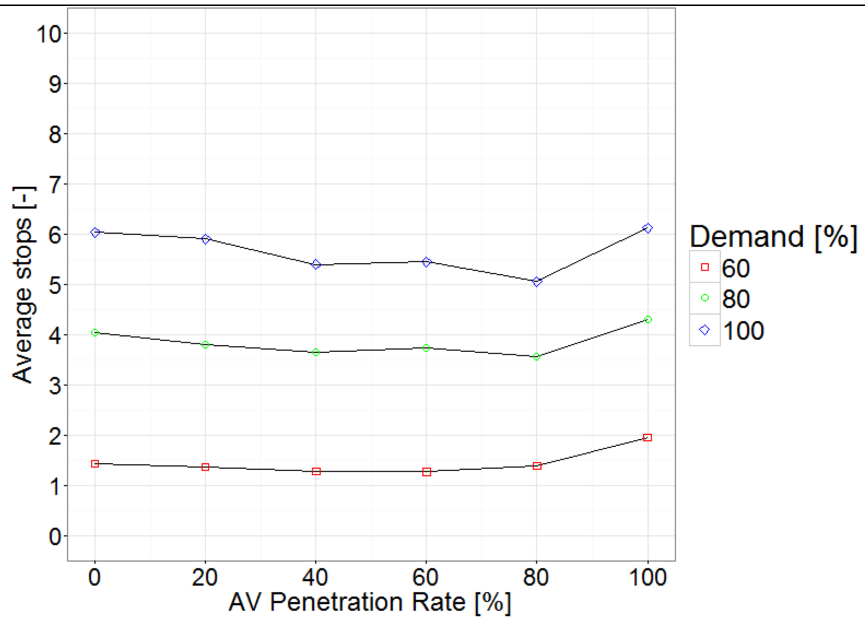


Figure 30: Total travel time for 2 lane model

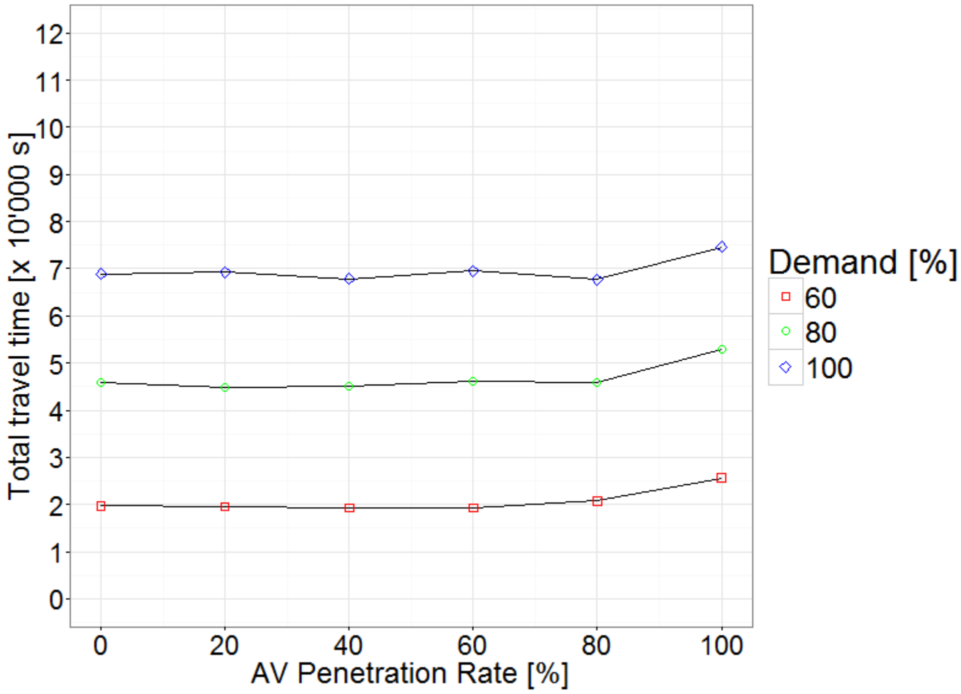
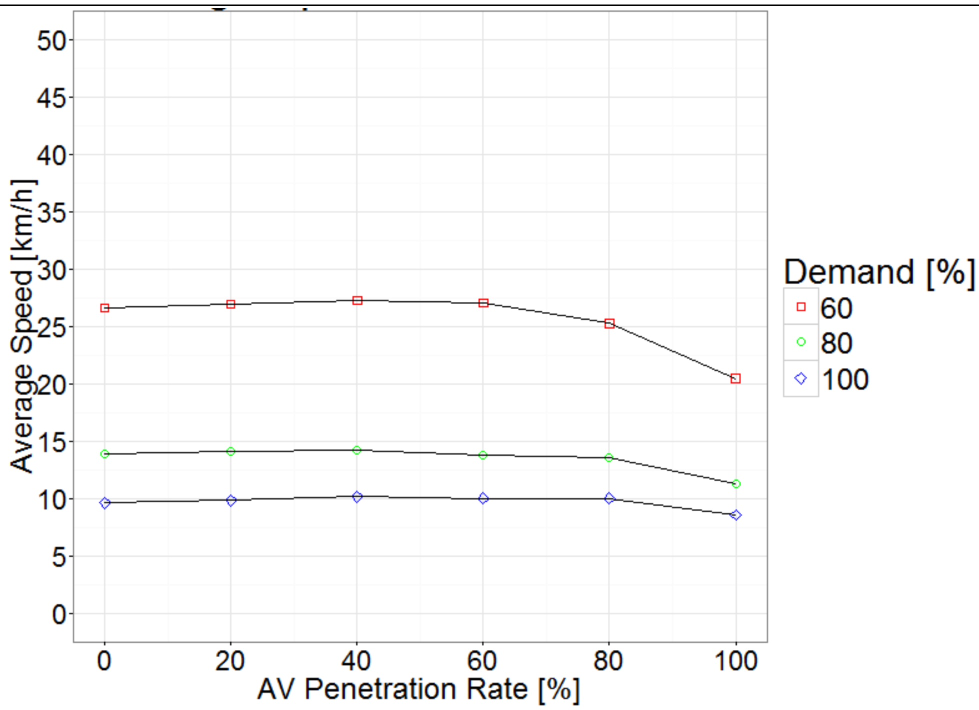


Figure 31: Average speed for 2 lane model



B.1.2 3 lane model

Figure 32: Average delay for 3 lane model

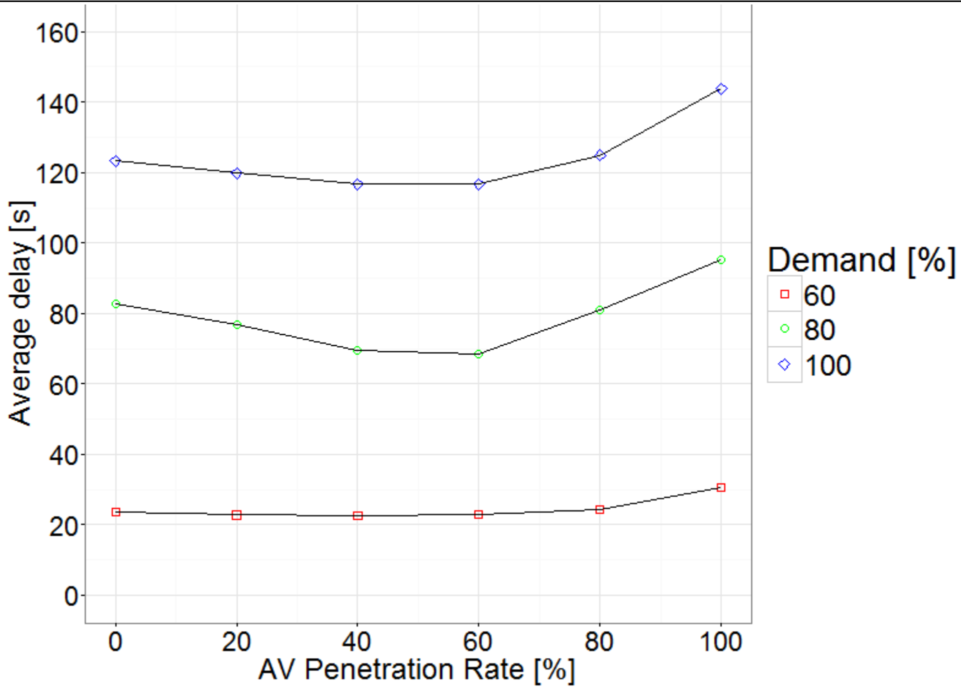


Figure 33: Average stops for 3 lane model

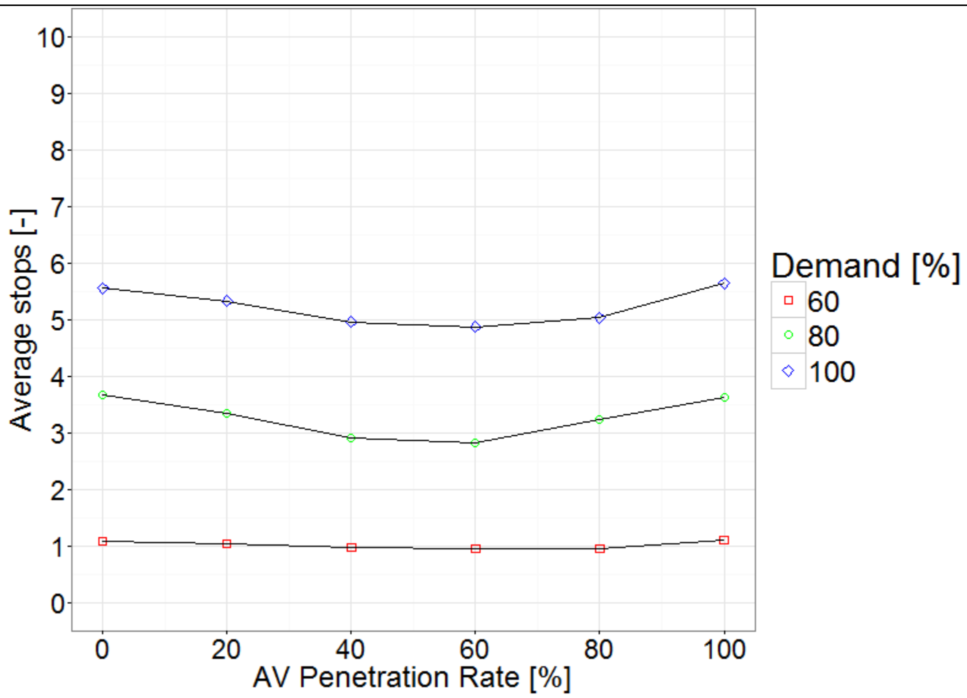


Figure 34: Total travel time for 3 lane model

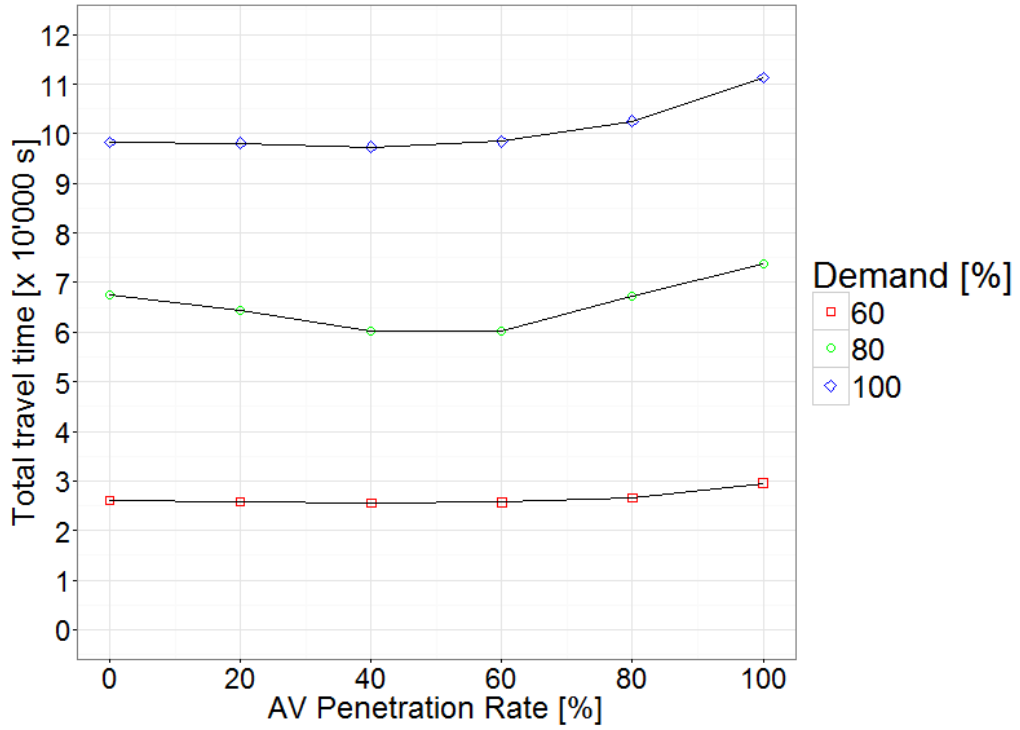


Figure 35: Average speed for 3 lane model