

Management of Freeway On-Ramps using Connected and Automated Vehicles

Joel Schaniel

Seminar Project

July 2021

Management of Freeway On-Ramps using Connected and Automated Vehicles

Joel Schaniel
IVT
ETH Zürich
CH-8093 Zurich
joelsc@student.ethz.ch

July 2021

Abstract

The development of Connected and Automated Vehicles (CAV) has gained momentum in the last couple of years. Besides benefits to convenience, the technology also has the potential to improve traffic flow. A literature review revealed a research gap when it comes to optimization approaches for multi-lane freeway traffic. On-ramps and bottlenecks are major drivers of congestion in freeway systems and should therefore be the focus of optimization efforts. This work suggests a heuristic optimization approach for a freeway on-ramp section. The algorithm applies a cooperative merging strategy, which is then tested through micro simulation in Aimsun Next. Furthermore, the impact of homogeneous driving behavior in combination with cooperative strategy is evaluated. The findings show a marked improvement of the traffic system. The average delay time decreased by up to 46% after introduction of the strategy. Similarly, favorable developments were observed for all other key variables such as harmonic speed, flow, and density. Homogeneous driving behavior amplified the positive effect of the cooperative strategy. To assess the full potential of the algorithm, further simulations are necessary.

Contents

List of Tables	1
List of Figures	2
1 Introduction	3
2 Methods and Simulation Design	7
2.1 Methodology	7
2.1.1 Cooperative Strategy	7
2.1.2 Homogeneity	10
2.2 Simulation Design	10
2.2.1 Toy Network	10
2.2.2 Traffic Demand	11
2.2.3 Simulation Parameters	11
2.2.4 Simulation Runs	12
3 Results and Discussion	14
3.1 Cooperative Strategy	14
3.2 Homogeneity	15
3.3 Scenario Comparison	16
3.4 Comparison with Literature	20
4 Conclusion	22
5 References	23
A Simulation Parameters	25

List of Tables

1 Origin-Destination-matrix over the simulation duration of 2 h	11
2 Comparison of all behavioral parameters that were changed in order to create a vehicle class with more homogeneous driving behavior	12
3 Default parameters of Aimsun Next simulations	25

List of Figures

1	Conceptual representation of the on-ramp section	7
2	Conceptual case differentiation	8
3	Toy network	11
4	Share of vehicles with homogeneous driving behavior	13
5	Comparison of delay time between different penetration rates of vehicles following the cooperative strategy	15
6	Comparison of all scenarios with 100% cooperative driving behavior and different penetration rates of homogeneity.	16
7	Scenario overview: Comparison of delay time in s/km over all calculated scenarios and the whole network	17
8	Scenario overview: Comparison of flow in veh/h over all calculated scenarios and the whole network	18
9	Scenario overview: Comparison of the harmonic speed in km/h over all calculated scenarios and the whole network	19
10	Scenario overview: Comparison of the density in the network in veh/km over all calculated scenarios	19
11	Scenario overview: Comparison of the number of lane changes in all calculated scenarios and over the whole network	20

1 Introduction

The advancement of technology is making our daily life more efficient and more convenient. In terms of transportation, this is reflected in the development of autonomous vehicles. New assistance systems can take over more and more task of the driver and a complete automatisisation is foreseeable in the near future. Automated Vehicles (AV) are beneficial to society in many aspects, such as reduced fuel consumption and CO₂ emission or increased road safety and comfort. Additionally, AVs allow for new user groups to be included. For example, it is possible for children, elderly or disabled people to travel independently without a driving license. Therefore, the development of autonomous vehicles is projected to advance quickly. However, all the advantages mentioned also lead to the fact that motorized individual transport becomes more attractive. Hence, it can be assumed that demand in mobility will increase (Axhausen, 2018b). Since AVs primarily generate individual benefits for their users and interact similarly with surrounding vehicles as conventional cars, the increase in demand might lead to an increase in congestion. A way to mitigate the effects of additional traffic is the introduction of Connected and Automated Vehicles (CAV). CAVs can communicate with other CAVs (vehicle-to-vehicle, V2V) or the surrounding infrastructure (vehicle-to-infrastructure, V2I). The two communication types are referred to as V2X for the purposes of this paper. V2X further improves road safety and allows the vehicles to adapt on changing circumstances before their own sensors detect the incident. Moreover, CAVs allow for Cooperative Adaptive Cruise Control (CACC). Thereby, route choice, speed and driving behavior is chosen depending on the current traffic situation to smoothen the overall traffic flow. The individual vehicles hereby subordinate themselves to the generality and thus enable the system state to shift from user equilibrium to system optimum. This means, that the system can always work on highest capacity, providing the best service possible for society. This should normally also lead to advantages for an individual CAV compared to the non-cooperative case (Axhausen, 2018a).

Due to the steady growth in population and mobility, the swiss freeway system is under increasing pressure. Especially near urban centers, congestion is common during peak hours. Frequent roots of congestion are network bottle necks or on-ramps. However, road expansions are often not feasible for political, spatial, financial, and environmental reasons. Traffic management approaches gained momentum in the last decades, as a possibility to improve traffic flow without building additional capacities. Good examples for that are the canton of Aargau, where traffic management concepts for all regional centers are in progress (Canton of Aargau, 2021) or the swiss federal office for roads (ASTRA), which implements several traffic management techniques on the national freeway system.

One of them is the installation of ramp metering around the city of Zürich (ASTRA, 2015). The positive effect on the traffic flow is proven for example in Cassidy and Rudjanakanoknad (2005). By considering the new technological advancements described above, ramp metering can be further improved. CAVs, supported by a smart infrastructure, can make ramp metering more dynamic and ease the pressure on the network without further infrastructure enlargements. The scope of CAV's potential has not yet been fully grasped. Hence, this work studies the effect of CAVs and CACC on the traffic flow on freeways and on-ramp sections.

Proceeding In a first step, the rest of this section summarizes different coordination approaches from literature. Then, in section 2 the test network and the suggested methodology are presented. Afterwards, Section 3 shows the simulation results and discusses them in detail. Finally, a brief summary and ideas for further research follow.

Literature Review The influences of AVs on traffic flow are already well documented (Axhausen, 2018b). Davis (2007) demonstrated through simulation that Adaptive Cruise Control, as used in AVs is able to stabilize the traffic flow and reduce congestion due to disturbances. However, it does not reduce congestion due to on-ramps or bottlenecks. This sources of congestion can be tackled by introducing CACC. The benefits of CACC and CAVs have also become the focus of researchers in recent years. A good overview of previous approaches to optimize road systems by using CAVs is given in Rios-Torres and Malikopoulos (2017). In their review paper, they list different approaches to coordinating CAVs in intersections and merging areas. First of all, they distinguish between centralized and decentralized approaches. In centralized approaches, a controller, for example provided by the road operator, manages a whole section. It communicates with all vehicles in range and has therefore full information about the current situation. Decentralized approaches, on the other hand, operate without a higher-level coordinating authority. In these systems, all vehicles communicate with the surrounding vehicles and exchange information directly. While centralized approaches have the advantage of being able to save a lot of computing power and tend to deliver better results, decentralized approaches have the advantage that no additional infrastructure needs to be built and information can be passed on even over long distances. Rios-Torres and Malikopoulos (2017) present for both approaches a number of different implementation methods tested by other scientist. Heuristic methods and optimization approaches exist for both centralized and decentralized approaches. Thereby, a trade-off between computation time and optimality is always necessary. However, their study does not compare results in terms of travel time savings, allowing no conclusions to

be drawn about which strategy is the most promising.

Letter and Elefteriadou (2017) demonstrated for an on-ramp section on a single-lane highway, that an optimization software can reach the maximal possible capacity (depending on the minimum safety time gap). Their approach bases on V2I communication within a communication range of 150 m. While they managed to reach an optimal solution for any demand split, the applicability on more complex networks, such as a freeway with two lanes is unclear due to the exponential increase of computational time with rising complexity. Wang *et al.* (2018) show that even the early establishment of a fixed sequence according to the first-in-first-out principle can improve traffic flow. An early adaption of speed and position can improve travel time by 5.3% for low demands and 10.5% in high demand cases. A more advanced strategy of Omidvar *et al.* (2020) shows, that even a CAV penetration rate of around 25% achieves first improvements in the traffic flow. With higher penetration rates results improve further. In contrast, Zhou *et al.* (2017) demonstrate, that a share of 5% AV is already able, to relief the system from oscillating behavior. However, they also conclude, that a share of 25% is necessary for reliable results. Their work bases on the Intelligent Driver Model developed by Treiber *et al.* (2008). Zhou *et al.* (2017) add a cooperative component to the model, making it applicable to CAVs as well. One of the major advancements of the so called "Cooperative Intelligent Driver Model" is the implementation of adding Lane-Changing Impact rules to the model, allowing to model multi-lane freeway sections. Despite this addition, they consider no lane changes in the merging section. Thereby, they simplify their approach to a similar situation as a single-lane freeway, not using most of the potential of the additional lane.

All publications mentioned so far deal with a single freeway lane. Hence, an important factor is missing for a realistic reflection of typical European freeway sections. The optimization of freeways with multiple lanes has only recently come into the focus of researchers.

Pan *et al.* (2021) approach the optimization of multi-lane freeway traffic with a reinforcement learning technique. After implementing multiple control strategies such as ramp metering, lane-changing control or speed control, the algorithm finds an optimal combination of strategies to minimize travel time costs for different penetration rate of CAVs. Their model bases on a Cell Transmission Model (Daganzo, 1994), working therefore with discrete position steps. While they introduce conventional human-driven cars with lagging response, CAVs are modelled to react instantaneous. Moreover, all rules are defined as binding for CAVs and as recommendations for conventional cars. This means that all CAVs but only few conventional vehicles follow the strategies. The

results indicate that the integrated control strategy can reduce overall travel time costs by reducing lane change maneuvers and vehicle queuing at the bottleneck while smoothing traffic flow and suppressing the negative effects of the shock wave. The study shows that the positive effect of ramp metering is no longer significant if the penetration rate of CAVs is high.

Ding *et al.* (2021) apply a heuristic approach to optimize multi-lane freeway merging for CAVs. They investigate a section of a two-lane freeway with an on-ramp. In this scenario, they compare a non-cooperative driving behavior with a cooperative behavior. For the cooperative behavior, a lane-changing model is in place. It determines which mainline vehicles should change from the outer to the inner lane depending on the on-ramp traffic demand. In a second step, a linear program defines the order of merging in a given time frame. Thereby, the condition for safe time gaps between following vehicles must be fulfilled. Ding and colleagues (2021) defined a strict setting for CAVs. All vehicles behave homogeneous, lane-changes within the merging area are not allowed, and trucks or other vehicle types are not considered. The results show that the delay time can be reduced by introducing CAVs.

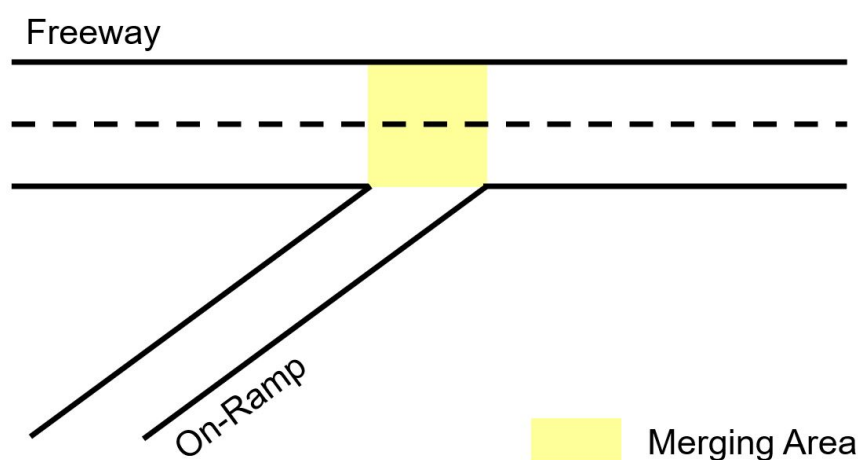
2 Methods and Simulation Design

2.1 Methodology

2.1.1 Cooperative Strategy

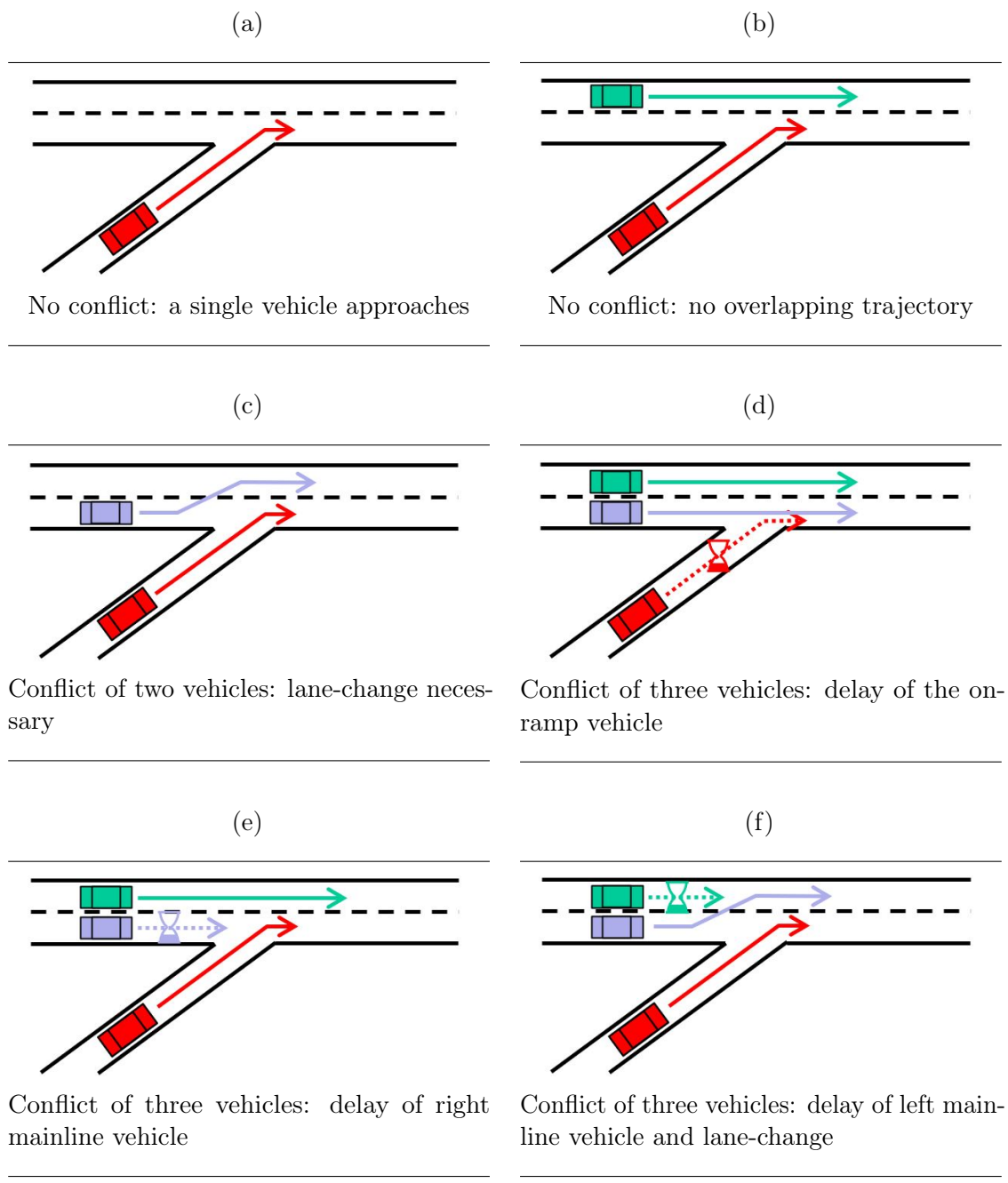
The approach was created after a proper literature review. Since most of the studies concentrate on optimization of freeway merging with only one mainline lane, a new methodology for multiple mainline lanes was created. Compared to a case with only one freeway line, every additional lane adds new possibilities to arrange the incoming traffic and to optimize the flow. However, the heuristic concept shares many ideas with the publications of Zhou *et al.* (2017) and Ding *et al.* (2021). Looking at a conceptual on-ramp, as shown in Fig. 1, only a limited number of cases can occur.

Figure 1: Conceptual representation of the on-ramp section



All possible cases are shown in Fig. 2. The simplest case is one or zero vehicles approaching the merging area. In this case, no conflict occurs. The same applies when two vehicles approach the merging area whose trajectories do not intersect. These cases are shown in Figure 2(a) and 2(b). The next best case is when two vehicles with overlapping trajectories approach the merging area simultaneously. This case can be resolved by the vehicle on the freeway changing lanes (Fig. 2(c)). Then, there is the case of a conflict with three vehicles involved. To solve this issue one of the three vehicles must be decelerated to delay its arrival time at the merging point. These possibilities are pictured in Fig. 2(d) to 2(f)).

Figure 2: Conceptual case differentiation



To optimize the overall system, the vehicle whose delay causes the smallest disruption in the network should be slowed down. An algorithm was created to differentiate between all mentioned cases and perform the necessary interventions. The algorithm consists of different functions which are described in the following list:

- The delay time in seconds per kilometer within the merging area is measured constantly for every lane. If the delay time on the left mainline lane is bigger than on

the right mainline lane, vehicles on the right lane get detected around 130 m before the merging area and instructed to change to the left lane if possible. Trucks remain on the right lane. However, this lane change rule is only applied if a minimum loss time of 10 s/km occurs and the loss time on the left lane is not greater than 40 s/km. These additional rules can be used to ensure that unnecessary lane changes are avoided in free flow or congested conditions.

- Around 100 m before the merging point, all vehicles are detected. The section between detection and the merging point is defined as pre-merge area. All vehicles within the pre-merge area are gathered in a list. The arrival time at the merging point is estimated for every vehicle in the list, based on its current speed and distance to the merging point. The list is sorted by the estimated arrival time.
- The arrival times of all vehicles in the pre-merge area are compared and a case differentiation (see Fig. 2) is performed. To do so, a for-loop iterates through all vehicles in the list.
- A conflict exists if the projected arrival time of two vehicles with overlapping trajectories differs by less than 0.9 s. This interval is called the desired time gap (dtg) and is defined on the basis of empirical observations. It also coincides with the findings of Zhou *et al.* (2017).
- If conflicts between more than two vehicles appear, an additional for-loop is triggered. It iterates through all remaining vehicles in the pre-merge area, starting with the conflicting vehicles until the end of the list. Thereby, the vehicles are sorted by lane. For the first vehicle in each lane, it is calculated how much the vehicle must be delayed to enter the merging area without a conflict. For all other vehicles behind, the time gap tg_i between the vehicle i and its predecessor ($i - 1$) is calculated. A buffer time bt_i is defined as $tg_i - dtg$. Then the delay time dt_i for every vehicle is calculated by subtracting bt_i from dt_{i-1} . Lastly, the overall delay time per lane is then summed up over all vehicles within a lane: $\sum_{i=0}^n dt_i$.
- After the delay time has been determined for all three lanes, the first vehicle in the lane with the least delay time is instructed to delay its arrival time at the merging point. More precisely, the vehicle is instructed to reduce its speed by its normal deceleration rate (around 4 m/s²). The successors adapt their speed then automatically to keep the desired time gap.
- In the next time step, the arrival time of all vehicles at the merging point are estimated based on the adjusted speeds, if the conflict still exists, the same algorithm applies again. Since the lane with the least delay time will have even lower delay times (due to the decrease in speed), it is most likely, that the same vehicle has to decelerate further.

2.1.2 Homogeneity

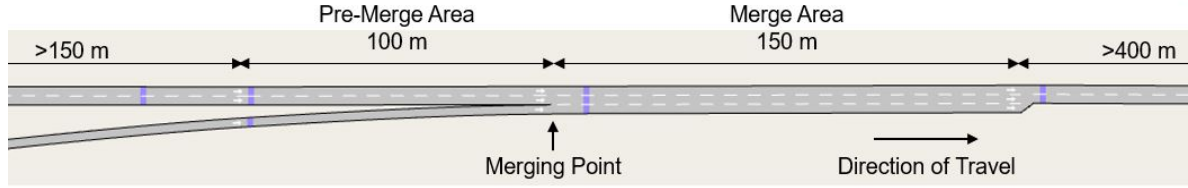
A second hypothesis is that homogeneity in driving behavior could have a positive impact on the traffic flow. If all vehicles drive with homogeneous and constant speed, overtaking is unnecessary and traffic flow is smoother. To test this hypothesis, new vehicle classes of homogeneous AVs and homogeneous AV-Trucks were created. These classes have different behavioral parameters implemented. An overview over all changed parameters follows in Section 2.2.3 and shows the difference between the conventional AVs and the homogeneous AVs.

2.2 Simulation Design

2.2.1 Toy Network

The approach was tested with the traffic simulation software Aimsun Next 20.0.2. The network consists of a two-lane freeway and an on-ramp with one lane. This represents a typical freeway merging area in Switzerland. The network is pictured in Fig. 3. Overall a network length of around 1150 m is simulated. It is composed of a section of freeway of approximately 900 m and an on-ramp section of around 250 m. On the freeway, a 250 m long section is simulated before the merging point. At the merging point, the 150 m long merging area begins. In this area the freeway has three lanes, whereby the right lane can only be used by on-ramp vehicles entering the freeway. Changing lanes to the right lane is prohibited. After the merging area, there is a 500 m long two-lane section of freeway up to the network exit. However, most important section of the network is the pre-merge area, which starts 100 m before the merging point and ends at the merging point. Large parts of the optimization algorithm are applied to this section (Section 2.1.1). The geometry of the simulated section was chosen to be as realistic as possible. The speed limit on all sections is 120 km/h. During implementation, care was taken to avoid disturbing influences on the speed traveled, for example due to tight curve radii.

Figure 3: Toy network



2.2.2 Traffic Demand

The traffic demand is divided in only two origin-destination-relations. The distribution is shown in Table 1. The demand consists of two vehicle types: 80% cars and 20% trucks.

Table 1: Origin-Destination-matrix over the simulation duration of 2 h

O \ D	Freeway
Freeway	5000
On-Ramp	2000

2.2.3 Simulation Parameters

Aimsun Next is a meso-micro hybrid simulation software, working as a Discrete Time Simulation (DTS). Hence, the simulation is updated after every predefined timestep. All vehicle classes use the default Adaptive Cruise Control (ACC) car-following model provided by Aimsun Next (Aimsun, 2021). For lane changing, the default model from Aimsun was used too, which is based on the Gipps model (Aimsun, 2021; Gipps, 1986). An overview over the model parameters is given in Table 3 in Appendix A. The implementation of the cooperative strategy is done via the API interface of Aimsun and is written in C++ on VisualStudio 2013/2019. The code overwrites parts of the default models for all vehicles that support the strategy through V2X deployment.

However, to investigate the influence of homogeneity, vehicle classes with adjusted parameters were created. A list of differences is shown in Table 2. Most of these adjustments relate to the deviation. By reducing the deviation, a more uniform response of the vehicles can be achieved. In addition, extreme values become very rare. The only parameter where not only the deviation is adjusted is the Maximum Desired Speed. Here, the maximum

Table 2: Comparison of all behavioral parameters that were changed in order to create a vehicle class with more homogeneous driving behavior

Parameter		Unit	AV Cars		AV Trucks	
			normal	homog.	normal	homog.
<i>Max. Desired Speed</i>	<i>Mean</i>	[km/h]	110	100	85	85
<i>Max. Desired Speed</i>	<i>Dev.</i>	[km/h]	10	2	10	2
<i>Speed Limit Acceptance</i>	<i>Dev.</i>	[-]	0.1	0.02	0.1	0.02
<i>Max. Acceleration</i>	<i>Dev.</i>	[m/s ²]	0.2	0.1	0.5	0.25
<i>Normal Deceleration</i>	<i>Dev.</i>	[m/s ²]	0.25	0.1	1	0.4
<i>Max. Deceleration</i>	<i>Dev.</i>	[m/s ²]	0.5	0.1	0.5	0.1
<i>Desired Time Gap</i>	<i>Dev.</i>	[s]	0.4	0.1	0.4	0.1

speed of cars is adjusted to that of trucks in order to reduce the conflicts between the two vehicle classes.

2.2.4 Simulation Runs

A total of 155 replications of the simulation are performed. These are distributed over 31 scenarios, each of which is simulated with five random seeds. The scenarios differ in their composition between the vehicle classes. Firstly, the influence of the cooperative strategy is measured by six different penetration rates of vehicles supporting V2X (and thereby the strategy). In the worst scenario, no vehicle drives with the cooperative strategy (0%). Other scenarios have penetration rates of 20%, 40%, 60%, 80% and 100%. Secondly, the influence of homogeneity is also measured by six different penetration rates (0%, 20%, 40%, 60%, 80%, 100%). Since V2X is defined as a basic requirement for homogeneous driving behavior, the share of vehicles with homogeneous driving parameters always refer to the AVs with V2X. What this means is shown in Fig. 4. To evaluate all combinations, 36 scenarios are necessary but since the number of vehicles with homogeneous vehicles stays 0 for all cases where no vehicles follows the cooperative strategy, only 31 scenarios must be considered.

Figure 4: Share of vehicles with homogeneous driving behavior among all vehicles in every scenario.

Reading example: In the scenario, where 60% of all vehicles are equipped with V2X and the penetration rate of homogeneous vehicles among those is also 60%, $0.6 \cdot 0.6 = 36\%$ of all vehicles have a homogeneous driving behavior.

		Share of vehicles following the cooperative strategy					
		0%	20%	40%	60%	80%	100%
Share of homogeneity among vehicles following the cooperative strategy	Share of homogeneity among all vehicles	0%	20%	40%	60%	80%	100%
	0%	0%	0%	0%	0%	0%	0%
	20%	0%	4%	8%	12%	16%	20%
	40%	0%	8%	16%	24%	32%	40%
	60%	0%	12%	24%	36%	48%	60%
	80%	0%	16%	32%	48%	64%	80%
	100%	0%	20%	40%	60%	80%	100%

3 Results and Discussion

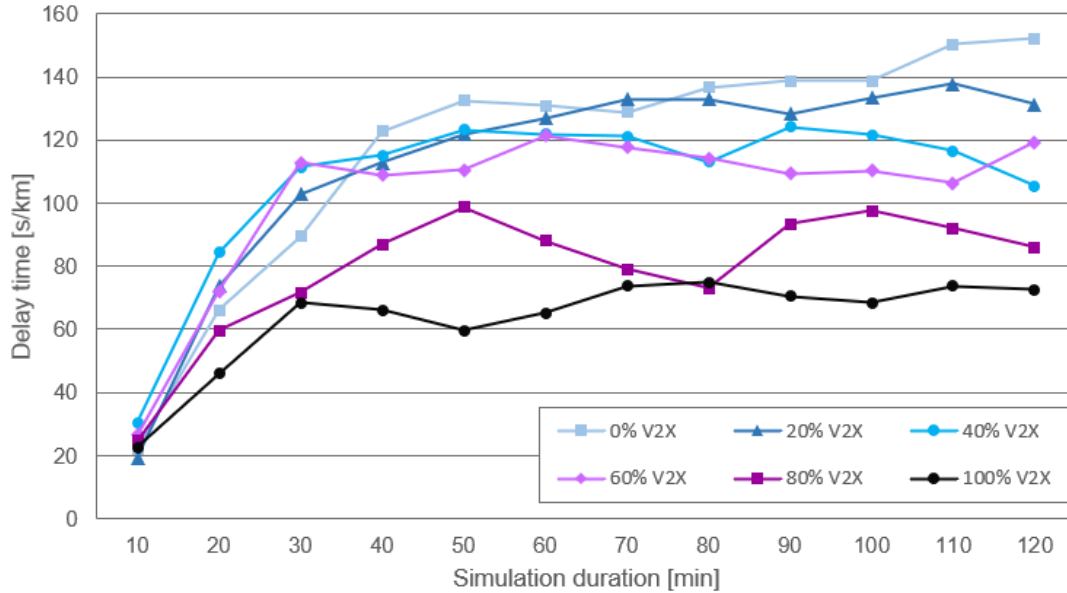
3.1 Cooperative Strategy

First of all, Fig. 5 compares all scenarios, where no vehicles with homogeneous driving behavior are present. Therefore, homogeneity has no impact on these results. It illustrates the development of delay times in the whole network over the course of the simulation. The values are aggregated over intervals of 10 min each. It is clearly visible, that the network needs about 30 min to fill and to reach a stable condition. As mentioned in Section 2.1.2, the share of V2X corresponds to the share of vehicles following the cooperative strategy.

The graph clearly shows that the cooperative strategy is capable of reducing the delay time. The larger the proportion of vehicles with V2X, the lower the delay time per kilometer. However, the figure also shows that the delay time is not inversely proportional to the penetration rate. The time gain is relatively small up to a penetration rate of 60% V2X vehicles, after which there is a clear drop in delay time. Over the entire simulation period, the delay time decreases on average from 117 s without V2X vehicles to 64 s with 100% V2X vehicles. This corresponds with a reduction of 46%.

Some time series show significant variation over the simulation period (e.g. 80% V2X). This could be related to the fact that each time series is based on only five replications. It is suspected that an increase in the number of simulation runs would produce more consistent time series.

Figure 5: Comparison of delay time between different penetration rates of vehicles following the cooperative strategy over the whole simulation period. All scenarios with 0% homogeneous driving behavior.

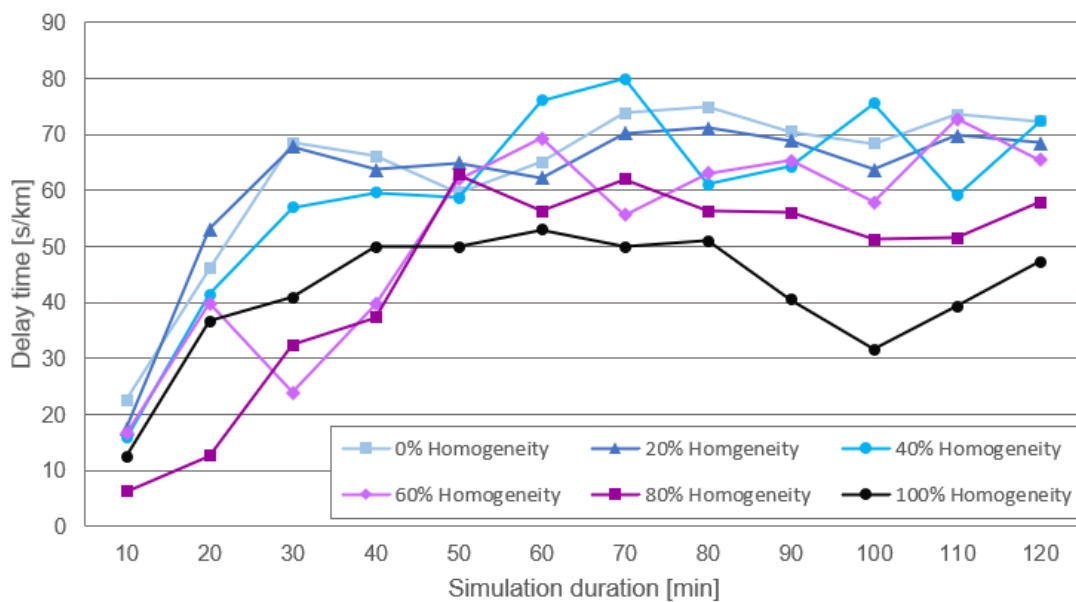


3.2 Homogeneity

Fig. 6 compares scenarios with different penetration rates of homogeneous driving behavior over the course of the whole simulation. In the compared scenarios, all vehicles follow the cooperative strategy (100% V2X). As before, a warm-up period of around 30 min is needed, to fill the network. Afterwards, the delay time reaches a certain level, but fluctuations are rather big. The main reason for this is that only five replications per scenario were simulated. Further, this might reflect a behavior that was observed during the visual analysis of the micro simulation. Thereby, wave patterns were observed in these scenarios, meaning that congestion occurred regularly but the cooperative strategy and the homogeneous driving behavior helped to reduce congestion after a while. Even though the delay time is volatile, a clear trend can be seen. The worst of these scenario where 0% of all vehicles have homogeneous behavioral parameters implemented has an average delay time of 64 s. On the other hand, the best scenario with 100% homogeneity reaches an average delay time of 42.0 s. This is a difference of 34%. Hence, homogeneity can help reduce the overall delay time and make the traffic flow more fluent. By analyzing Fig. 6 it is remarkable, that homogeneity seems to have only a little advantage unless

a majority of the vehicles drives with homogeneous behavioral parameters. This might have two reasons. Firstly, with a low penetration rate, homogeneity parameters have no impact since homogeneous driving is not achieved. Secondly, in order to make the traffic flow smoother, the homogeneous driving parameters slow down vehicles (e.g. due to the lower Maximum Desired Speed). Therefore, with low penetration rates the driven speed on the freeway may decrease without creating substantial benefits from the homogeneous driving.

Figure 6: Comparison of all scenarios with 100% cooperative driving behavior and different penetration rates of homogeneity.



3.3 Scenario Comparison

In this chapter, several key figures for assessing the success of the implemented strategies are shown for all scenarios. In the following tables, average values over the whole simulation period and over all replications (five each) are presented. In Fig. 7 the average delay time in s/km is shown for all scenarios. The delay time in the base scenario with no vehicles following the cooperative strategy is with 117.1 s/km the worst of all scenarios. With an increased share of vehicles following the cooperative strategy and a higher share of homogeneous behavior among the vehicles the delay time drops drastically. In the best scenario with 100% homogeneously, cooperatively driving vehicles an average delay time of 42 s/km is reached. This corresponds to a decrease of more than 64%. Comparing the

impact of the cooperative strategy and the homogeneity adaptations, it can be stated that the cooperative strategy has a bigger impact than homogeneity. Nevertheless, homogeneity improves the system by a lot and has a huge potential. In AVs, homogeneous driving behavior is very simple to achieve since it can be implemented by a software update. However, standard values must be defined by authorities or the car manufacturing industry. The tableau shows some inconsistencies, for example in the second column where 20% of the vehicles follow the cooperative strategy. This might be due to the already mentioned low number of replications per scenario. Furthermore, the absolute number of cars with homogeneous driving behavior changes in this column only by 4% from one scenario to the next (see Fig. 4 in Section 2.1.2).

Figure 7: Scenario overview: Comparison of delay time in s/km over all calculated scenarios and the whole network

Delay Time [s/km]		Share of vehicles following the cooperative strategy					
		0%	20%	40%	60%	80%	100%
Share of homogeneity among vehicles following the cooperative strategy	0%	117.1	112.9	107.4	102.4	79.1	63.6
	20%	-	109.8	104.6	95.3	80.7	62.0
	40%	-	102.1	101.9	86.9	79.2	60.2
	60%	-	106.2	99.8	89.4	64.9	52.9
	80%	-	110.7	90.5	80.0	66.7	45.3
	100%	-	106.2	96.6	73.1	64.3	42.0

Fig. 8 compares the flow in all scenarios. This shows a similar picture as before. The flow increases by 12% from the base scenario without cooperative strategy to the best case with 100% V2X and full homogeneity. With a flow of 3414 vehicles in the best case, practically the entire demand can be served. However, a higher demand must be chosen to define, if the maximal theoretical capacity of a two-lane highway can be reached.

Similar results are seen for harmonic speed (Fig. 9) and density (Fig. 10). The harmonic speed increases from 23.7 km/h to 45.4 km/h. This is an improvement of more than 91%.

The density thereby decreases by around 42% from 50.3 to 29.3 vehicles per kilometer.

By looking at the colour patterns of the scenario comparison, the same behavior is visible for all key figures (see Fig. 7 - 10). This is an expected behavior, since all shown key figures are clearly interdependent.

Figure 8: Scenario overview: Comparison of flow in veh/h over all calculated scenarios and the whole network

Flow [veh/h]		Share of vehicles following the cooperative strategy					
		0%	20%	40%	60%	80%	100%
Share of homogeneity among vehicles following the cooperative strategy	0%	3042	3048	3062	3073	3197	3227
	20%	-	3080	3082	3114	3211	3253
	40%	-	3094	3116	3158	3241	3326
	60%	-	3079	3137	3191	3309	3339
	80%	-	3083	3153	3247	3309	3392
	100%	-	3109	3173	3258	3373	3414

Another interesting values is the number of lane changes per kilometer. This is an important characteristic since lane changes can cause disturbances in the traffic flow. This is especially critical if the network operates under big loads. Fig. 11 compares the number of lane changes in all scenarios. On the one hand, cooperative strategy can significantly reduce the number of lane changes. The number drops from over 3000 to around 2200 lane changes, corresponding to a decrease of ca. 26%. This is remarkable since the implemented algorithm itself triggers additional lane changes. However, this can evidently be compensated by the ordering of the vehicles. On the other hand, the number of lane changes increases with increasing level of homogeneity. This is counter intuitive, because an increased amount of drivers with homogeneous behavior is expected to reduce the need for overtaking. A possible explanation could be, that scenarios with

Figure 9: Scenario overview: Comparison of the harmonic speed in km/h over all calculated scenarios and the whole network

Harmonic Speed [km/h]		Share of vehicles following the cooperative strategy					
		0%	20%	40%	60%	80%	100%
Share of homogeneity among vehicles following the cooperative strategy	0%	23.7	24.4	25.3	26.2	31.5	36.5
	20%	-	24.8	25.8	27.6	31.0	37.0
	40%	-	26.2	26.2	29.4	31.3	37.5
	60%	-	25.5	26.6	28.8	35.6	40.4
	80%	-	24.7	28.5	31.0	34.9	43.8
	100%	-	25.4	27.2	32.9	35.6	45.4

Figure 10: Scenario overview: Comparison of the density in the network in veh/km over all calculated scenarios

Density [veh/km]		Share of vehicles following the cooperative strategy					
		0%	20%	40%	60%	80%	100%
Share of homogeneity among vehicles following the cooperative strategy	0%	50.3	48.9	47.2	45.8	39.5	34.3
	20%	-	48.5	46.7	44.1	40.4	34.2
	40%	-	46.1	46.3	41.9	40.4	34.5
	60%	-	47.3	46.0	43.3	36.3	32.2
	80%	-	48.9	43.2	40.9	37.1	30.2
	100%	-	47.9	45.5	38.7	36.9	29.3

less homogeneity suffer from heavier congestion. In this case, lane changes are suppressed by the algorithm (see Section 2.1.1).

Figure 11: Scenario overview: Comparison of the number of lane changes in all calculated scenarios and over the whole network

Number of lane changes [# / km]		Share of vehicles following the cooperative strategy					
		0%	20%	40%	60%	80%	100%
Share of homogeneity among vehicles following the cooperative strategy	0%	3029	2962	2832	2700	2455	2152
	20%	-	2984	2841	2709	2516	2162
	40%	-	2993	2895	2734	2593	2278
	60%	-	3029	2871	2756	2594	2265
	80%	-	3023	2897	2823	2579	2236
	100%	-	3020	2907	2802	2628	2281

3.4 Comparison with Literature

Comparing the findings with literature is difficult for several reasons. So far, most researchers have focused on single-lane freeways, which have other optimization characteristics. Secondly, different software and a variety car-following models are used for simulation. In addition to that, different demand cases and vehicle types as well as country-specific differences such as speed limits complicate the comparison.

Nonetheless, the results of Ding *et al.* (2021) are most suited for a comparison. In their simulation, they work with a similar network and use the same logic for their optimization algorithm. The approach is based on a stronger mathematical foundation. This is only possible due the uniform driving behavior and traveling speeds implemented for all vehicles. Especially the disturbing influence of trucks is thereby not considered. In contrast to the work of Ding *et al.* (2021), where all vehicle trajectories in the whole merging section

are controlled externally, the presented approach in this work only controls specific parts of the vehicle behavior. Therefore, it is not possible to compute exact arrival times at the merging point beforehand, meaning optimality cannot be reached with this approach. Additionally, the study of Ding *et al.* (2021) uses a non-cooperative control as base scenario, in which all lane-changing is prevented. This is not the case for the presented work, where the cooperative strategy is compared to conventional AVs. However, the results from Ding *et al.* (2021) are consistent with the here presented values. In a comparable demand case they reach a reduction of 38% of delay time (compared to 46% found in this study). Also in terms of flow a similar finding was achieved with both approaches.

4 Conclusion

The simulation clearly shows the benefit of a Cooperative Adaptive Cruise Control scheme. The heuristic approach is able to alleviate congestion effectively. To work properly, a certain penetration rate of CAVs is necessary. But in contrast to other publications it is proven, that the strategy also works with vehicles of different states of automatisisation. Furthermore, it is shown, that norms for homogeneous driving behavior for CAVs should be defined. The homogeneous behavior of all vehicles on the road has a positive effect on the traffic flow. With a high penetration rate of CAVs, the capacity of roads can be slightly increased as smaller distances between CAVs can be assumed. On the other hand, the safety gaps between vehicles remain capacity-determining and set boundaries to further capacity gains.

Limitations of the approach can be found in the model integration. The microscopic simulation software of Aimsun Next acts as a black box. Therefore, it is impossible to check if the default models of Aimsun oppose a part of the implemented algorithm. It is also not possible to change the underlying behavioral models over the API interface.

Further research is necessary to evaluate the full potential of the algorithm. For example, different demand cases must be considered. Especially tests with higher loads are necessary to test how close the code comes to optimality. Further research is also necessary to assess which homogeneity constraints are important and what impact small deviations have. In general, there is still great potential for research to exploit the benefits that CAVs bring to multi-lane freeway systems.

5 References

- Aimsun (2021) *Aimsun Next 20 User's Manual*, Aimsun SLU.
- ASTRA (2015) Verkehrsmanagement Schweiz (VM-CH), sep 2015, <https://www.astra.admin.ch/astra/de/home/themen/nationalstrassen/verkehrsmanagement.html>.
- Axhausen, K. W. (2018a) Verkehr I - Gleichgewichte in Netzen (lecture slides), mar 2018.
- Axhausen, K. W. (2018b) Verkehr I - Verkehrserzeugung und -verteilung (lecture slides), apr 2018.
- Canton of Aargau (2021) Verkehrsmanagement - Kanton Aargau, https://www.ag.ch/de/bvu/mobilitaet_verkehr/mobilitaet/verkehrsmanagement/verkehrsmanagement_1.jsp.
- Cassidy, M. J. and J. Rudjanakanoknad (2005) Increasing the capacity of an isolated merge by metering its on-ramp, *Transportation Research Part B: Methodological*, **39** (10) 896–913, dec 2005, ISSN 0191-2615.
- Daganzo, C. F. (1994) The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory, *Transportation Research Part B*, **28** (4) 269–287.
- Davis, L. C. (2007) Effect of adaptive cruise control systems on mixed traffic flow near an on-ramp, *Physica A: Statistical Mechanics and its Applications*, **379** (1) 274–290, jun 2007, ISSN 0378-4371.
- Ding, H., Y. Di, X. Zheng, H. Bai and W. Zhang (2021) Automated cooperative control of multilane freeway merging areas in connected and autonomous vehicle environments, *Transportmetrica B: Transport Dynamics*, **9**, 437–455, jan 2021, ISSN 2168-0566.
- Gipps, P. (1986) A Model for the Structure of Lane-Changing Decisions, *Transportation Research Part B-Methodological*, **20** (5) 403–414, oct 1986, ISSN 0191-2615.
- Letter, C. and L. Elefteriadou (2017) Efficient control of fully automated connected vehicles at freeway merge segments, *Transportation Research Part C: Emerging Technologies*, **80**, 190–205, jul 2017, ISSN 0968-090X.
- Omidvar, A., L. Elefteriadou, M. Pourmehrab and C. Letter (2020) Optimizing free-

way merge operations under conventional and automated vehicle traffic, *Journal of Transportation Engineering, Part A: Systems*, **146** (7), jul 2020.

Pan, T., R. Guo, W. H. K. Lam, R. Zhong, W. Wang and B. He (2021) Integrated optimal control strategies for freeway traffic mixed with connected automated vehicles: A model-based reinforcement learning approach, *Transportation Research Part C: Emerging Technologies*, **123**, 102987, feb 2021, ISSN 0968-090X.

Rios-Torres, J. and A. A. Malikopoulos (2017) A Survey on the Coordination of Connected and Automated Vehicles at Intersections and Merging at Highway On-Ramps, *IEEE Transactions on Intelligent Transportation Systems*, **18** (5) 1066–1077, may 2017, ISSN 1558-0016.

Treiber, M., A. Hennecke and D. Helbing (2008) Congested traffic states in empirical observations and microscopic simulations, *Institute of Theoretical Physics, University of Stuttgart*.

Wang, Z., G. Wu and M. Barth (2018) Distributed Consensus-Based Cooperative Highway On-Ramp Merging Using V2X Communications, paper presented at the *SAE International Conference*, University of California, Riverside, apr 2018.

Zhou, M., X. Qu and S. Jin (2017) On the Impact of Cooperative Autonomous Vehicles in Improving Freeway Merging: A Modified Intelligent Driver Model-Based Approach, *IEEE Transactions on Intelligent Transportation Systems*, **18** (6) 1422–1428, jun 2017, ISSN 1558-0016.

A Simulation Parameters

Table 3: Default parameters of Aimsun Next simulations

Default Vehicle Parameters					
Parameter	Unit	AV Cars		AV Trucks	
		Mean	Deviation	Mean	Deviation
<i>Max. Desired Speed</i>	[km/h]	110	10	85	10
<i>Speed Limit Acceptance</i>	[-]	1.1	0.1	1.05	0.1
<i>Maximum Yield Time</i>	[s]	10	2.5	35	10
<i>Reaction Time</i>	[s]	0.8		0.8	
<i>Reaction Time at Stop</i>	[s]	1.2		1.3	
<i>Max. Acceleration</i>	[m/s ²]	3	0.2	1	0.5
<i>Normal Deceleration</i>	[m/s ²]	4	0.25	3.5	1
<i>Max. Deceleration</i>	[m/s ²]	6	0.5	5	0.5
<i>ACC - Desired Time Gap</i>	[s]	1.2	0.4	1.2	0.4
<i>ACC - Speed Gain Free Flow</i>	[1/s]	0.4		0.4	
<i>ACC - Speed Gain Following</i>	[1/s]	0.07		0.07	
<i>ACC - Distance Gain</i>	[1/s ²]	0.23		0.23	
Scenario Parameters					
<i>Length of Statistical Interval</i>	[s]	60			
<i>Number of Replications</i>	[-]	5			
<i>Time Step Length</i>	[s]	0.5			