Transportation and spatial impact of automated driving in urban areas

An application to the Greater Copenhagen Area

M.F. Legêne



Transportation and spatial impact of automated driving in urban areas

An application to the Greater Copenhagen Area

by

Martijn Frederik Legêne

to obtain the degree of Master of Science at the Delft University of Technology, to be defended publicly on June 27, 2018 at 3:00 PM.

4151844	
August 21, 2017 – June 27, 20	018
Prof. dr. ir. B. van Arem,	TU Delft, CEG, chair
Dr. ir. G. H. A. Correia,	TU Delft, CEG
Ir. W. L. Auping,	TU Delft, TPM
Ing. P. van Koningsbruggen,	Technolution B.V.
Drs. H.E. Mein,	Technolution B.V.
	August 21, 2017 – June 27, 20 Prof. dr. ir. B. van Arem, Dr. ir. G. H. A. Correia, Ir. W. L. Auping, Ing. P. van Koningsbruggen,

An electronic version of this thesis is available at http://repository.tudelft.nl/ Mail: martijnlegene@gmail.com







Preface

This report is the result of my graduation as a completion of the master Transportation, Infrastructure, and Logistics at the Delft University of Technology. This work combines System Dynamics, Exploratory Modeling, and Geographic Information Systems into a user-friendly method to assess the transportation and spatial impact of automated vehicles in urban areas.

It was a challenging research especially regarding data preparations. During the thesis I had to learn how to do data analysis using the Python programming language. Much transportation data proved to be insufficiently detailed, so input data needed to be converted in order to prepare it for inclusion in this research. I want to thank my friends, especially Tim Romijn, and colleagues at Technolution for helping me with all Python-related issues.

Regarding the graduation committee, I first want to thank dr. ir. Gonçalo Correia for his supervision. His knowledge and our discussions helped this thesis directing towards a clear goal. He helped me staying motivated in this new type of research and to keep the amount of work achievable.

Next, I want to thank ir. Willem Auping for guiding me regarding the research method. His supervision brought the quality of this research to an entire new level, something that could not have been done without him.

I want to thank the chairman, prof. dr. ir. Bart van Arem for his feedback and his enthusiasm and knowledge regarding automated vehicles. Our first meeting resulted in great enthusiasm to set up a nice completion of my studies.

I want to thank Technolution for making it possible to present my work in Copenhagen and to carry out this research in a great environment. I learned a lot and I am very proud completing this research as a graduate intern at Technolution. I want to thank Drs. Edwin Mein for being available from the smallest question to biggest data- or modeling-related issues and Ing. Paul van Koningsbruggen for his feedback based on immense enthusiasm and experience in this field of study. I experienced both Paul and Edwin as passionate professionals. Their knowledge and contacts lowered the burden of graduating and our discussions helped this research to become an addition both scientifically and socially.

Lastly, I want to thank all my friends, family, and girlfriend who supported me in ways I could not have asked for. You made my study time unforgettable.

M.F. Legêne Gouda, June 19, 2018

Abstract

Vehicle automation has the potential to disrupt the status quo of urban transportation, because it adds a new mode of transportation by taking away the task of the driver. The projections of estimations of the impacts of this new technology are based on many uncertainties and are thus largely unknown. A literature review showed that a wide number of effects is possible with automated driving and that no straightforward method to assess future impacts of this new technology exists yet. This thesis developed a method that provides insights into the impacts of vehicle automation in urban areas, without preconceived ideas about the impacts of the different scenarios. Existing knowledge from literature, transportation and land use data, and sociodemographic information were combined in a geographically disaggregated System Dynamic model. This model explored the effects of vehicle automation on the performance of the transportation and spatial system of the case-study city of Copenhagen, Denmark. Different model runs provided insight in the possible range of outcomes. Considerable problems may arise in the transportation network with the introduction of automated driving because, using the car might become very attractive. A city's land use does, however, not change as much as many could expect. The causes of (un)desirable outcomes were identified with the Patient Rule Induction Method. The ranges of uncertainties in the value of time in an automated vehicle and in the level of adoption of car-sharing were found to influence desirable versus undesirable futures the most. Mitigating measures should focus on these scenarios to prepare for a future with automated driving.

Executive summary

Introduction

Transportation technologies historically shaped urban form. The car made it possible to live further away from work, resulting in urban sprawl. By taking away the task of the driver, automated vehicles are potentially adding a new mode of transportation to the current system, which could result in a new revolution of transportation and land use systems.

Research about long-term large-scale impacts regarding automated driving is still a field that is rather inexperienced. Some research has already been done, but most of it on specific effects of vehicle automation in isolated form. The availability of information is moving in the right direction; several organizations are starting joint research projects to discover and share information about changes and implications of the future of accessibility and spatial development of mobility with respect to automated driving.

Research objectives

The introduction of self-driving vehicles creates numerous challenges, as not only the vehicle itself, but also the way we perceive and use mobility is likely to undergo a radical change. This research started with a literature review of the effects of transportation technologies on urban form. Next, it focused on the car's potential changes regarding accessibility components and finished with policy recommendations on how to smoothen the transition towards automated driving.

This research explored to what extent automated vehicles could transform the way cities are spatially organized and how cities can start preparing for this transformation. This is done by first finding the mechanisms through which automated driving can influence accessibility in urban areas according to the literature. Subsequently a method on how to measure the transportation and spatial impact of automated driving was sought. This method was applied to the Greater Copenhagen Area. Within the results in Copenhagen, desirable and undesirable effects of automated vehicles were defined. And lastly, mitigating measures were explored to steer the introduction of automated vehicles towards desirable future situations.

Literature review

Current literature in this field of research focuses mainly on the technology inside the car, on specific impacts in isolation, or on the implications of self-driving on highways; the information about the impacts on urban regions is very scarce. The attention to self-driving and the necessity to generate and share information is increasing rapidly. Futurists expect the development of vehicle automation to drastically change the outline of cities. Road transportation could become more efficient, resulting in a decrease in road surface needed to facilitate the transportation demand. Improved accessibility and a decrease in land needed for infrastructure enhances the attractiveness of living in cities. Car traffic could, however, increase by longer acceptable travel times and more trip purposes. This could lead to urban sprawl, congestion problems, and increased space consumption of roads.

A wide variation of effects is possible with automated driving. It is hard to quantify the extent to which new vehicle features, new user groups, new trip purposes and its effect on the location choice of households will influence urban form. Ranges of uncertain input values were used to explore the effect of changes caused by the penetration rate of automated vehicles, the efficiency of vehicle operation, the value of time in automated vehicles, the increased mobility per capita, the idle time of automated vehicles, the parking density rate, and the car-sharing rate.

Research method

This research explored the impacts of new technological functions, new trip purposes, and new user groups in terms of accessibility, traffic volume, land used for infrastructure, and the population density in urban areas. The attractiveness of a household location depends on its accessibility and the land use characteristics of surrounding areas. The impact of vehicle automation on these aspects depends on future developments.

The impact of a new vehicle technology with a large amount of uncertainties has not been analyzed and mapped on their topographic location to this date. The future depends strongly on the variation of uncertain input: each combination of uncertainties could lead to different outcomes. It is thus necessary to develop a method that assesses uncertainties as widely and user-friendly as possible; a method of which this research is an important first step.

An urban area was studied by integrating existing knowledge of new traffic technologies, land use, transportation, case specific socio-demographic data, and all uncertainties into a System Dynamics model. This model was programmed into the Exploratory Modelling and Analysis Workbench, where it was combined with spatial data to allocate the effects in an urban area to their respective geographic location. This Workbench additionally allowed to control the model, to adjust parameters, and to discover scenarios in the outcomes. No casespecific policy measures were used and no likelihoods were attached to the probabilities of the scenarios to prevent a biased research approach.

Figure 3.1 shows a graphical abstract of the research method. The population, the number of jobs and an origin-destination matrix in the base year 2015 were the main input values. Differential equations described the state of the land use, transportation, and sociodemographics. The geographic location of the road network and the coordinates of a zone system allowed the model to be applied to each of the zones and to map the results over the case study area.



Figure 1: Schematic overview methodology

Possibilities and combinations of uncertainties were explored based on a high number of model runs. Different statements of literature determined the ranges in which to pick a value for an uncertain factor. Each run used a value within this range as an input value for a specific uncertainty and combines them into a representative sample of possible input options. This allowed for investigation of a very wide range of possible outcomes. These ranges of outcomes were categorized in desirable and undesirable outcomes. The values affecting possible hazards and values encouraging desired outcomes were traced back accordingly with the Patient Rule Induction Method. The analysis was performed until the year 2070 in order to explore the path towards future scenarios and to get insight into uncertain impacts of innovations over time.

The Patient Rule Induction Method related the desired and undesired outcomes to their respective input values. The threshold of desired versus undesired outcomes could be specified by the users themselves.

Results and (un)desired scenarios could be made insightful from the perspective of a complete city, but also per zone. A large number of zones increases the level of detail in the results. Policy interventions could be implemented for the entire city, but also per zone or per district like a city center, other urban areas, suburbs, and rural areas.

Results

Automated vehicles could enhance the attractiveness of living in specific areas by an improved accessibility and a possible decrease of road and parking surface needed. These effects are higher in dense urban areas than in suburbs. A higher attractiveness leads to more population, indicating an increased urbanization in the Greater Copenhagen Area. If the maximum capacity for population has been reached in dense urban areas, further population growth has to be accommodated in suburbs and rural areas.

Vehicle automation could cause a decrease of 4% of the current road space while satisfying the future demand for transportation on the network. This sounds less promising than the expectations where a city is changing into a major green and attractive region, where large parts of the current transportation network become superfluous.

If automated vehicles become very attractive to use, traffic volume could increase extremely by a lower value of time, longer commutes, more trip purposes, and an increased mobility of the population that is unable to drive today. Current transportation networks, generally already performing at their maximum capacity, will face congestion problems and the need for more road surface rises to facilitate even a small growth of traffic volume. The positive effects of automated vehicles, caused by a higher efficiency of vehicle operation, could be diminished by the growth of traffic volume. Cars thus become more attractive for individuals, but the transportation system as a whole might face enormous problems caused by an increased vehicle usage.

The value of time and the car-sharing ratio were found to be the causes of most differences between an ideal situation, where a city's accessibility is improved and no extra road space is required, versus a future where a city is totally congested. Values of time lower than \notin 7.40 in the city center, \notin 7.88 in other urban districts, and \notin 8.16 in suburbs were found to decrease accessibility by an increased attractiveness of the car and thus an increased traffic volume. Decreases in road surface in the city center are possible at a value of time over \notin 8.37 in combination with at least 27% of car-sharing. 4% decrease of road surface in other urban districts is possible at a value of time not lower than \notin 7.20 in combination with at least 18% of car-sharing. This indicates that the city center is more sensitive to changes in the value of time and the car-sharing ratio.

The leading scenarios that give insight in the difference between desirable versus undesirable scenarios of automated vehicles thus vary in the value of time in an automated vehicle and in the car-sharing rate. This could be translated into (1) a scenario where the car becomes very attractive for private use, increasing the comfort of an individual passenger, and (2) a scenario where the automated vehicle enhances the efficiency of the entire transportation system by means of a totally integrated, shared, public vehicle system, such as mobility as a service.

Mitigating measures should focus on increasing car-sharing and decreasing the relative attractiveness of automated vehicles. The population could get used to car-sharing systems starting today and does not need to wait for the introduction of automated driving. The attractiveness of the car versus other modes could be decreased by decreasing the comfort and utility of a car, or by increasing the comfort and utility of other modes. Automated vehicles could even be integrated into the public transportation network, enhancing its quality.

Conclusions

A city with the characteristics of Copenhagen does not seem to change as much as many futurists expect. A small decrease in space used for road infrastructure is possible, but does not allow for the construction of massive parks and green areas. A decrease of road space is scraped of along a long strip of road and could result in wider sidewalks or a slight increase in the backyard of the population. It, however, does not create gigantic free space.

Automated vehicles could enhance the quality and performance of urban transportation and contribute to a more attractive city with the right corrective measures. Automated vehicles could disrupt the current transportation network and cause an immense growth in the demand for transportation because the use of private vehicles becomes too attractive without the right corrective measures. If the automated vehicle becomes very attractive, a car-sharing ratio of at least 27% is needed in the city center and 18% in other urban areas to ensure that vehicle automation will not cause unwanted futures. If mitigating measures could reach these ratios, automated driving is expected to improve the performance of the transportation network and to make cities more attractive to live. A wait-and-see attitude is risky and could cause the automated vehicle to implement itself, with an insurmountable growth in traffic volume and a large increase in congestion as a result.

Further research

This research is an important step towards a new method to develop transportation and land use models. Further research is needed in order to connect the zones and create a form of communication between them. This allows zones to determine from which other zones they want to receive information that, in turn, models the first dependencies between them.

Policy measures could be assessed by implementing them into the model, running the model, and applying the Patient Rule Induction Method again. A new iteration will point out new troublesome values in the uncertainty space, which will ask for more detailed mitigating measures. More detail in public transportation data and available plans for Copenhagen could additionally be implemented and tested in the model. If more policies are to be developed based on the outcomes of this research, a close collaboration with planners and policy makers in the case study is needed.

Contents

Pr	eface	9	iii
At	ostra	ct	v
Ex	ecut	ive summary	vii
Li	st of	Figures	xv
Li	st of	Tables	xix
Li	st of	Abbreviations	xxi
1	Intro	oduction	1
	1.1	Background.	. 1
	1.2	Problem statement	. 1
	1.3	Research questions	. 2
	1.4	Research methods	. 3
	1.5	Thesis outline	. 4
2	Cur	rent knowledge on automated driving	5
	2.1	Background of automated vehicles	. 5
	2.2	New technological features of AVs	. 6
	2.3	New uses of AVs	. 8
	2.4	Shared AVs	. 9
	2.5	Expectations in the literature on AVs in urban areas	. 9
	2.6	Conclusion literature study.	. 14
3	Sys	tem Dynamics and spatial results	15
	3.1	A dynamically complex problem	. 15
	3.2	Model setup.	. 17
	3.3	Model components	. 19
	3.4	Dealing with uncertainties	. 25
	3.5	Applying the method to a zone-based system	. 26
	3.6	Model validation	. 26
	3.7	Conclusion research method	. 27
4	Арр	plication to Copenhagen	29
	4.1	Case demographics	. 29
	4.2	Transportation and spatial planning	. 30
	4.3	Application of the System Dynamics model	. 32
	4.4	Input parameters	. 33

	4.5	Experimental factors AVs	. 40
	4.6	Uncertainties not assigned to vehicle automation.	. 42
	4.7	Model validation	. 43
	4.8	Experimental setup	. 46
	4.9	Results of Key Performance Indicators	. 47
	4.10	Conclusion accessibility analysis	. 60
5	Sce	nario discovery	61
	5.1	Solution space boundaries.	
	5.2	PRIM on the restrictions of outcome of KPIs	
	5.3	Conclusion scenario discovery.	. 70
6	Poli	cy recommendations	73
	6.1	Possible policy measures implemented in the model	
	6.2	Policy measures in next model iterations	
	6.3	Policy measures compared to the outcomes of PRIM	. 76
	6.4	Policy recommendations for the Greater Copenhagen Area	. 78
7	Con	clusion and recommendations	79
	7.1	Overall conclusion	
	7.2	Transportation and spatial impacts of AVs in literature	
	7.3	A method to assess the impacts of AVs in urban areas	
	7.4	Transportation and spatial impacts of AVs in the model	
	7.5	AVs leading towards a desirable future	
	7.6	Steering measures	
	7.7	Recommendations for further research	. 84
Re	ferer	nces	85
Ap	penc	dices	93
A	Dist	ricts in OTM region	95
в	Data	a preparation procedures	107
С	Reg	ression analysis for trip distribution	113
D	Syst	tem Dynamics model	115
Е	Mod	lel variables	121
F	Sen	sitivity runs	123
G	PRII	M scenario selection	129

List of Figures

1	Schematic overview methodology	ix
2.1	Ripple effect of automated driving (Milakis, van Arem, & van Wee, 2017)	10
2.2	Market penetration AV (Nieuwenhuijsen et al., 2018)	12
3.1	Schematic overview of methodology	17
3.2	Sector diagram of System Dynamics model	18
3.3	Land use sub-model	20
3.4	Traffic sub-model	21
3.5	Parking sub-model	23
3.6	Population sub-model	24
3.7	Illustration PRIM	25
4.1	The case study area (Fertner, Jørgensen, & Nielsen, 2012)	30
4.2	OTM zone system and main road network	38
4.3	Representation of lane simplification (OTM Zone 388)	39
4.4	Comparison population density and urban fabric	44
4.5	Comparison fraction road and road network	45
4.6	Maps attractiveness 2018(L) and 2050(R)	47
4.7	Uncertainties in population density (Person / km^2)	48
4.8	Maps population density (Person / km^2) 2018(L) and 2050(R)	49
4.9	Uncertainties in accessibility to jobs (Jobs/hour)	50
4.10	Maps accessibility to jobs (Jobs/hour) 2018(L) and 2050(R)	50
4.11	l Uncertainties in distance to reach within acceptable travel time (Km) \ldots	51
4.12	2 Maps distance within acceptable travel time (Km) 2018(L) and 2050(R) \ldots	52
4.13	3Uncertainties in traffic volume	52
4.14	Maps traffic volume 2018(L) and 2050(R)	53
4.15	5Uncertainties in capacity saturation (congestion)	54
4.16	5 Maps capacity saturation (congestion) 2018(L) and 2050(R)	54
4.17	7 Uncertainties in fraction road surface	55
4.18	Maps fraction road surface 2018(L) and 2050(R)	56
4.19	OUncertainties in fraction parking surface	57
4.20	Maps fraction parking surface 2018(L) and 2050(R)	58
4.21	Uncertainties in fraction other land surface	59
4.22	2 Maps fraction other land surface 2018(L) and 2050(R)	59
5.1	Scenarios population density	63
5.2	Scenarios increased accessibility to jobs	64

5.4 Scenarios acceptable commuting distance 66 5.5 Scenarios raction road surface 67 5.6 Scenarios fraction parking surface city center 69 5.7 Scenarios fraction parking surface city center 69 5.8 Scenarios fraction parking surface other urban districts 70 5.9 Two leading scenarios (Tillema et al., 2015) 71 6.1 Fraction road surface with different values of time and car-sharing ratios 77 A.1 Amager 95 A.2 Christianshavn 96 A.3 Frederiksberg 96 A.4 City center 97 A.5 Narebro 98 A.6 Østerbro 99 A.7 Vesterbro 99 A.8 Northern Suburbs 100 A.9 Vesterbro 102 A.10Comparison Copenhagen 102 A.11Eastern Zealand 104 A.13Comparison Northern Zealand 106 B.2 NTM versus OTM 109 B.3 Traffic loads in the OmniTRANS model 111	5.3	Scenarios decreased accessibility to jobs	5
5.6 Scenarios fraction road surface 68 5.7 Scenarios fraction parking surface city center 69 5.8 Scenarios fraction parking surface other urban districts 70 5.9 Two leading scenarios (Tillema et al., 2015) 71 6.1 Fraction road surface with different values of time and car-sharing ratios 77 A.1 Amager 95 A.2 Christianshavn 96 A.3 Frederiksberg 96 A.4 City center 97 A.5 Nørrebro 98 A.6 Østerbro 99 A.7 Vesterbro 99 A.8 Northern Suburbs 100 A.9 Vestergnen 101 A.10Comparison Copenhagen 102 A.11Eastern Zealand 103 A.12Northern Zealand 105 B.1 Zone system OTM plus center of gravity per road segment 108 B.2 NTM versus OTM 109 B.3 Traffic loads in the OmniTRANS model 111 D.1 Land use submodel 119 F.1	5.4	Scenarios acceptable commuting distance	3
5.7 Scenarios fraction parking surface city center 69 5.8 Scenarios fraction parking surface other urban districts 70 5.9 Two leading scenarios (Tillema et al., 2015) 71 6.1 Fraction road surface with different values of time and car-sharing ratios 77 A.1 Amager 95 A.2 Christianshavn 96 A.3 Frederiksberg 96 A.4 City center 97 A.5 Nørebro 98 A.6 Østerbro 99 A.7 Vesterbro 99 A.8 Northern Suburbs 100 A.9 Vestegnen 101 A.10Comparison Copenhagen 102 A.118astern Zealand 104 A.13Comparison Northern Zealand 105 B.1 Zone system OTM plus center of gravity per road segment 108 B.2 NTM versus OTM 109 B.3 Traffic loads in the OmniTRANS model 111 D.1 Land use submodel 116 D.2 Traffic submodel 112 F.2 Sensi	5.5	Scenarios capacity saturation	7
5.8 Scenarios fraction parking surface other urban districts	5.6	Scenarios fraction road surface	3
5.9 Two leading scenarios (Tillema et al., 2015) 71 6.1 Fraction road surface with different values of time and car-sharing ratios 77 A.1 Amager 95 A.2 Christianshavn 96 A.3 Frederiksberg 96 A.4 City center 97 A.5 Nørrebro 98 A.6 Østerbro 99 A.7 Vesterbro 99 A.7 Vesterbro 99 A.8 Northern Suburbs 100 A.9 Vesterbro 99 A.10Comparison Copenhagen 101 A.10Comparison Northern Zealand 103 A.12Northern Zealand 104 A.13Comparison Northern Zealand 105 B.1 Zone system OTM plus center of gravity per road segment 108 B.2 NTM versus OTM 109 B.3 Traffic loads in the OmniTRANS model 111 D.1 Land use submodel 116 D.2 Traffic submodel 117 D.3 Parking submodel 118 D.4	5.7	Scenarios fraction parking surface city center	9
6.1 Fraction road surface with different values of time and car-sharing ratios 77 A.1 Amager 95 A.2 Christianshavn 96 A.3 Frederiksberg 96 A.4 City center 97 A.5 Nørrebro 98 A.6 Østerbro 99 A.6 Østerbro 99 A.7 Vesterbro 99 A.8 Northern Suburbs 100 A.9 Vestegnen 101 A.10Comparison Copenhagen 102 A.112Northern Zealand 103 A.12Comparison Northern Zealand 104 A.13Comparison Northern Zealand 105 B.1 Zone system OTM plus center of gravity per road segment 108 B.2 NTM versus OTM 109 B.3 Traffic loads in the OmniTRANS model 111 D.1 Land use submodel 116 D.2 Traffic submodel 117 D.3 Parking submodel 118 D.4 Population submodel 119 F.1 Sensitivity access	5.8	Scenarios fraction parking surface other urban districts)
A.1 Amager 95 A.2 Christianshavn 96 A.3 Frederiksberg 96 A.4 City center 97 A.5 Nørrebro 98 A.6 Østerbro 99 A.7 Vesterbro 99 A.7 Vesterbro 99 A.8 Northern Suburbs 100 A.9 Vestegnen 101 A.10Comparison Copenhagen 101 A.11Eastern Zealand 103 A.12Northern Zealand 104 A.13Comparison Northern Zealand 105 B.1 Zone system OTM plus center of gravity per road segment 108 B.2 NTM versus OTM 109 B.3 Traffic loads in the OmniTRANS model 111 D.1 Land use submodel 117 D.3 Parking submodel 118 D.4 Population submodel 112 F.1 Sensitivity attractiveness per district type 124 F.3 Sensitivity opulation per district type 124 F.3 Sensitivity oragestion per district	5.9	Two leading scenarios (Tillema et al., 2015)	1
A.2 Christianshavn 96 A.3 Frederiksberg 96 A.4 City center 97 A.5 Nørrebro 98 A.6 Østerbro 99 A.7 Vesterbro 99 A.7 Vesterbro 99 A.8 Northern Suburbs 100 A.9 Vestegnen 101 A.10Comparison Copenhagen 102 A.11Eastern Zealand 103 A.12Northern Zealand 104 A.13Comparison Northern Zealand 105 B.1 Zone system OTM plus center of gravity per road segment 108 B.2 NTM versus OTM 109 B.3 Traffic loads in the OmniTRANS model 111 D.1 Land use submodel 116 D.2 Traffic submodel 117 D.3 Parking submodel 118 D.4 Population submodel 112 F.1 Sensitivity attractiveness per district type 124 F.3 Sensitivity average trip distance per district type 125 F.5 Sensitivity o	6.1	Fraction road surface with different values of time and car-sharing ratios 77	7
A.3 Frederiksberg 96 A.4 City center 97 A.5 Nørrebro 98 A.6 Østerbro 99 A.7 Vesterbro 99 A.8 Northern Suburbs 100 A.9 Vestegnen 101 A.10Comparison Copenhagen 102 A.11Eastern Zealand 103 A.12Northern Zealand 104 A.13Comparison Northern Zealand 105 B.1 Zone system OTM plus center of gravity per road segment 108 B.2 NTM versus OTM 109 B.3 Traffic loads in the OmniTRANS model 111 D.1 Land use submodel 116 D.2 Traffic submodel 116 D.2 Traffic submodel 117 D.3 Parking submodel 118 D.4 Population submodel 119 F.1 Sensitivity attractiveness per district type 123 F.2 Sensitivity accessibility to jobs per district type 124 F.4 Sensitivity onal surface per district type 125	A.1	Amager	5
A.4City center97A.5Nørrebro98A.6Østerbro99A.7Vesterbro99A.7Vesterbro99A.8Northern Suburbs100A.9Vestegnen101A.10Comparison Copenhagen102A.11Eastern Zealand103A.12Northern Zealand104A.13Comparison Northern Zealand105B.1Zone system OTM plus center of gravity per road segment108B.2NTM versus OTM109B.3Traffic loads in the OmniTRANS model111D.1Land use submodel116D.2Traffic submodel117D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity accessibility to jobs per district type124F.4Sensitivity congestion per district type125F.5Sensitivity road surface per district type126F.7Sensitivity road surface per district type126F.7Sensitivity road surface per district type126F.7Sensitivity parking surface per district type127G.1Peeling and pasting trajectories population density129	A.2	Christianshavn	ŝ
A.5Nørrebro98A.6Østerbro99A.7Vesterbro99A.8Northern Suburbs100A.9Vestegnen101A.10Comparison Copenhagen102A.11Eastern Zealand103A.12Northern Zealand104A.13Comparison Northern Zealand104A.13Comparison Northern Zealand105B.1Zone system OTM plus center of gravity per road segment108B.2NTM versus OTM109B.3Traffic loads in the OmniTRANS model111D.1Land use submodel116D.2Traffic submodel117D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity accessibility to jobs per district type124F.3Sensitivity accessibility to jobs per district type125F.5Sensitivity congestion per district type126F.7Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.7Sensitivity road surface per district type126F.8Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	A.3	Frederiksberg	5
A.6Østerbro99A.7Vesterbro99A.8Northern Suburbs100A.9Vestegnen101A.10Comparison Copenhagen102A.11Eastern Zealand103A.12Northern Zealand104A.13Comparison Northern Zealand105B.1Zone system OTM plus center of gravity per road segment108B.2NTM versus OTM109B.3Traffic loads in the OmniTRANS model111D.1Land use submodel116D.2Traffic submodel117D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity accessibility to jobs per district type124F.3Sensitivity congestion per district type125F.5Sensitivity congestion per district type125F.6Sensitivity congestion per district type126F.7Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.7Sensitivity road surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	A.4	City center	7
A.7Vesterbro99A.8Northern Suburbs100A.9Vestegnen101A.10Comparison Copenhagen102A.11Eastern Zealand103A.12Northern Zealand104A.13Comparison Northern Zealand105B.1Zone system OTM plus center of gravity per road segment108B.2NTM versus OTM109B.3Traffic loads in the OmniTRANS model111D.1Land use submodel116D.2Traffic submodel117D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type124F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity congestion per district type125F.5Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.7Sensitivity ongestion per district type126F.7Sensitivity accessibility to jobs per district type126F.7Sensitivity ond surface per district type126F.7Sensitivity ond surface per district type127G.1Peeling and pasting trajectories population density129	A.5	Nørrebro	3
A.7Vesterbro99A.8Northern Suburbs100A.9Vestegnen101A.10Comparison Copenhagen102A.11Eastern Zealand103A.12Northern Zealand104A.13Comparison Northern Zealand105B.1Zone system OTM plus center of gravity per road segment108B.2NTM versus OTM109B.3Traffic loads in the OmniTRANS model111D.1Land use submodel116D.2Traffic submodel117D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type124F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity congestion per district type125F.5Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.7Sensitivity ongestion per district type126F.7Sensitivity accessibility to jobs per district type126F.7Sensitivity ond surface per district type126F.7Sensitivity ond surface per district type127G.1Peeling and pasting trajectories population density129	A.6	Østerbro	9
A.8Northern Suburbs100A.9Vestegnen101A.10Comparison Copenhagen102A.11Eastern Zealand103A.12Northern Zealand104A.13Comparison Northern Zealand105B.1Zone system OTM plus center of gravity per road segment108B.2NTM versus OTM109B.3Traffic loads in the OmniTRANS model111D.1Land use submodel116D.2Traffic submodel117D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity accessibility to jobs per district type124F.3Sensitivity accessibility to jobs per district type125F.5Sensitivity congestion per district type125F.6Sensitivity road surface per district type126F.7Sensitivity road surface per district type126F.7Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129			9
A.9Vestegnen101A.10Comparison Copenhagen102A.11Eastern Zealand103A.12Northern Zealand104A.13Comparison Northern Zealand105B.1Zone system OTM plus center of gravity per road segment108B.2NTM versus OTM109B.3Traffic loads in the OmniTRANS model111D.1Land use submodel116D.2Traffic submodel117D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity accessibility to jobs per district type124F.3Sensitivity incoming traffic volume per district type125F.5Sensitivity congestion per district type125F.6Sensitivity road surface per district type126F.7Sensitivity ongestion per district type126F.7Sensitivity ongestion per district type126F.7Sensitivity ongestion per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129			0
A.10Comparison Copenhagen102A.11Eastern Zealand103A.12Northern Zealand104A.13Comparison Northern Zealand105B.1 Zone system OTM plus center of gravity per road segment108B.2 NTM versus OTM109B.3 Traffic loads in the OmniTRANS model111D.1 Land use submodel116D.2 Traffic submodel117D.3 Parking submodel118D.4 Population submodel119F.1 Sensitivity attractiveness per district type123F.2 Sensitivity accessibility to jobs per district type124F.3 Sensitivity average trip distance per district type125F.5 Sensitivity congestion per district type126F.7 Sensitivity road surface per district type126F.7 Sensitivity road surface per district type126F.8 Sensitivity polation per district type126F.7 Sensitivity other surface per district type127F.9 Sensitivity other surface per district type127G.1 Peeling and pasting trajectories population density129			1
A.11Eastern Zealand103A.12Northern Zealand104A.13Comparison Northern Zealand105B.1 Zone system OTM plus center of gravity per road segment108B.2 NTM versus OTM109B.3 Traffic loads in the OmniTRANS model111D.1 Land use submodel116D.2 Traffic submodel117D.3 Parking submodel118D.4 Population submodel119F.1 Sensitivity attractiveness per district type123F.2 Sensitivity population per district type124F.3 Sensitivity average trip distance per district type125F.5 Sensitivity incoming traffic volume per district type126F.7 Sensitivity road surface per district type126F.7 Sensitivity road surface per district type126F.7 Sensitivity road surface per district type126F.7 Sensitivity other surface per district type127F.9 Sensitivity other surface per district type127<		-	2
A.12Northern Zealand104A.13Comparison Northern Zealand105B.1 Zone system OTM plus center of gravity per road segment108B.2 NTM versus OTM109B.3 Traffic loads in the OmniTRANS model109B.3 Traffic submodel111D.1 Land use submodel116D.2 Traffic submodel117D.3 Parking submodel118D.4 Population submodel118D.4 Population submodel119F.1 Sensitivity attractiveness per district type123F.2 Sensitivity population per district type124F.3 Sensitivity accessibility to jobs per district type125F.5 Sensitivity incoming traffic volume per district type125F.6 Sensitivity congestion per district type126F.7 Sensitivity road surface per district type126F.8 Sensitivity parking surface per district type127F.9 Sensitivity other surface per district type127G.1 Peeling and pasting trajectories population density129			3
A.13Comparison Northern Zealand105B.1 Zone system OTM plus center of gravity per road segment108B.2 NTM versus OTM109B.3 Traffic loads in the OmniTRANS model119D.1 Land use submodel111D.1 Land use submodel116D.2 Traffic submodel117D.3 Parking submodel117D.3 Parking submodel118D.4 Population submodel119F.1 Sensitivity attractiveness per district type123F.2 Sensitivity population per district type124F.3 Sensitivity accessibility to jobs per district type125F.5 Sensitivity incoming traffic volume per district type125F.6 Sensitivity congestion per district type126F.7 Sensitivity road surface per district type126F.8 Sensitivity road surface per district type127F.9 Sensitivity other surface per district type127G.1 Peeling and pasting trajectories population density129			4
B.2NTM versus OTM109B.3Traffic loads in the OmniTRANS model111D.1Land use submodel116D.2Traffic submodel117D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity population per district type124F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity average trip distance per district type125F.5Sensitivity congestion per district type125F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129			
B.2NTM versus OTM109B.3Traffic loads in the OmniTRANS model111D.1Land use submodel116D.2Traffic submodel117D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity population per district type124F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity average trip distance per district type125F.5Sensitivity congestion per district type125F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	D 1	Zono system OTM plus conter of gravity per read corment 10	0
B.3Traffic loads in the OmniTRANS model111D.1Land use submodel116D.2Traffic submodel117D.3Parking submodel117D.4Population submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity population per district type124F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity average trip distance per district type125F.5Sensitivity incoming traffic volume per district type125F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129			
D.1Land use submodel116D.2Traffic submodel117D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity population per district type124F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity average trip distance per district type125F.5Sensitivity incoming traffic volume per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127G.1Peeling and pasting trajectories population density129			
D.2Traffic submodel117D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity population per district type124F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity average trip distance per district type125F.5Sensitivity incoming traffic volume per district type125F.6Sensitivity road surface per district type126F.7Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	В.3		I
D.3Parking submodel118D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity population per district type124F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity average trip distance per district type125F.5Sensitivity congestion per district type125F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	D.1	Land use submodel	6
D.4Population submodel119F.1Sensitivity attractiveness per district type123F.2Sensitivity population per district type124F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity average trip distance per district type125F.5Sensitivity incoming traffic volume per district type125F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	D.2	Traffic submodel	7
F.1Sensitivity attractiveness per district type123F.2Sensitivity population per district type124F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity average trip distance per district type125F.5Sensitivity incoming traffic volume per district type125F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127G.1Peeling and pasting trajectories population density129	D.3	Parking submodel	3
F.2Sensitivity population per district type124F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity average trip distance per district type125F.5Sensitivity incoming traffic volume per district type125F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	D.4	Population submodel	9
F.3Sensitivity accessibility to jobs per district type124F.4Sensitivity average trip distance per district type125F.5Sensitivity incoming traffic volume per district type125F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	F.1	Sensitivity attractiveness per district type 123	3
F.4Sensitivity average trip distance per district type125F.5Sensitivity incoming traffic volume per district type125F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	F.2	Sensitivity population per district type	4
F.4Sensitivity average trip distance per district type125F.5Sensitivity incoming traffic volume per district type125F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	F.3	Sensitivity accessibility to jobs per district type	4
F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	F.4		5
F.6Sensitivity congestion per district type126F.7Sensitivity road surface per district type126F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	F.5	Sensitivity incoming traffic volume per district type	5
 F.7 Sensitivity road surface per district type	F.6		6
F.8Sensitivity parking surface per district type127F.9Sensitivity other surface per district type127G.1Peeling and pasting trajectories population density129	F.7		
F.9 Sensitivity other surface per district type			
	G.1	Peeling and pasting trajectories population density	9

G.3	Peeling and pasting trajectories decreased accessibility to jobs	130
G.4	Peeling and pasting trajectories acceptable commuting distance	131
G.5	Peeling and pasting trajectories capacity saturation	131
G.6	Peeling and pasting trajectories fraction road surface	132
G.7	Peeling and pasting trajectories fraction parking surface	132

List of Tables

2.1	Values of time (VOT) (€/hour) per mode of transportation	7
2.2	Indication of private versus shared AVs	12
4.1	Districts	32
4.2	Districts per district type	33
4.3	Socio-demographic input values	33
4.4	Coefficient of importance for attributes influencing the attractiveness of a zone	
	(derived from Skifter Andersen (2011))	34
4.5	Average scores for proximity to nature and city (derived from Skifter Andersen	
	(2011))	34
4.6	Mean values road transportation network	37
4.7	Level of Service (Gajjar & Mohandas, 2016)	38
4.8	Delays	40
4.9	Sensitivity in scale factors, each variable is changed with -10% to +10% \ldots .	40
4.10	Uncertain variables assigned to AVs	40
4.11	Different diffusion curves AV	41
4.12	Average values of global uncertainties	42
6.1	Policy measures	74
6.2	Maximum steering factors in the zone districts	74
C.1	Results regression analysis of trip generation with gravity model	114

List of Abbreviations

- AON All-or-Nothing (assignment), page 35
- AV Automated Vehicle, page 1
- CLD Causal Loop Diagram, page 17
- EMA Exploratory Modelling and Analysis (Workbench), page 16
- GCA Greater Copenhagen Area, page 29
- KPI Key Performance Indicator, page 18
- LHS Latin Hypercube Sampling, page 46
- NTM National Traffic Model, page 35
- OD Origin-Destination, page 35
- OTM Øresund Traffic Model, page 32
- PCU Passenger Car Unit, page 13
- PRIM Patient Rule Induction Method, page 25
- SD System Dynamics, page 15
- V2I Vehicle to Infrastructure (communication), page 7
- V2V Vehicle to Vehicle (communication), page 7
- VKT Vehicle Kilometers Traveled, page 8
- VOT Value of Time, page 6

Introduction

1.1. Background

Urbanization is increasing rapidly worldwide, creating many implications in the planning of infrastructure and land use. According to the World Urbanization Prospects, by 2050, 66 percent of the world's population is projected to be urban (United Nations, 2014). Urban transportation and land use planning are in general already more complex than in rural areas, seeing as in urban transportation, the traffic is mixed and space is limited.

Accessibility is the mechanism through which transportation technology and thus automated driving could cause spatial implications in our cities. Transportation technology has historically shaped urban form from first urban settlements (walking city), to the industrial rail-based city and the post-industrial sprawled agglomerations (automobile city). Faster and more comfortable modes of transportation allowed longer travel distances and changed the demand for mobility (Schafer & Victor, 1997). Where previously the introduction of barges, coaches, cars, rail and air transportation all caused major disruptions in society, automated vehicles (AVs) appear as the next potential disruptive innovation for mobility, as it introduces a new mode of transportation (Silberg & Wallace, 2012).

1.2. Problem statement

A breakthrough of the fully automated vehicle and thus a major change in the urban environment is near (Except Integrated Sustainability, 2017b). This breakthrough needs much attention and will not automatically implement itself perfectly. The introduction of AVs requires preparation of the current infrastructure and spatial organization and it is important to deploy it in such a manner that it brings equal opportunities to the entire society. The adjustments to the introduction of a new vehicle technology and its mix with existing transportation modes will become more of a challenge if research to its effects is postponed. Automated transportation is not completely new. A few existing examples are freight transshipment, self-driving rail transportation, and drone-delivery. However, automated urban passenger transportation is a development that has not been widely investigated yet (Milakis, van Arem, & van Wee, 2017; Öztürker, Milakis, & van Arem, 2016). Newly published literature on this topic focuses mainly on the implications inside the vehicles, its effects on highways or on specific issues in isolation (Gruel & Stanford, 2016). Some knowledge about short-term, small-scale impacts of less advanced automated driving does exist, but research about long-term large-scale urban impacts regarding automated driving is still a field that is rather inexperienced (STAD, 2017). The scarce literature on accessibility effects of AVs in urbanized regions published no policy reports so far (Milakis, van Arem, & van Wee, 2017) and spatial effects are mostly overlooked.

The sharing and availability of information is moving in the right direction: where previously information existed in isolated form, most of these information silos are being broken down to create a greater availability of data (ERTRAC, 2017). Several organizations are starting joint research projects to discover and share information about changes and implications of the future of accessibility and spatial development of mobility with respect to automated driving. SAE International and Costlow (2018) state that being able to use relevant data is one of the biggest challenges concerning the impacts and planning of self-driving technologies.

It is important to publicly debate the effects of AVs, seeing as this will generate awareness and give the feeling that it will become accessible to all users equally and thus allows for a better anticipation in urban society (CARE-North plus, 2015). Additionally, the trust in AVs will increase if the expectations about the development and performance of this technology are realistic beforehand (Nees, 2016). An expectant attitude is risky if the AV becomes available in the near future. A fast adaptation and market penetration limits the uncertainty about integrating the technology of automated driving in current systems. Imposing corrective measures that promote the benefits, repress the hindrances, and fasten the process of research and development cannot be postponed much longer (Gruel & Stanford, 2016).

The trends of generating separate information on isolated effects of vehicle automation are broken and the impacts of development combinations are explored in this research. This helps to smoothen the transition from a conventional manual system with public transportation and privately owned vehicles as separate modes towards possible future situations where the AV has all the potential or risk to create a new transportation revolution.

1.3. Research questions

The introduction of self-driving vehicles creates numerous challenges, as not only the vehicle itself, but also the way we perceive and use mobility is likely to undergo a radical change. This research starts with a literature review of the effects of transportation technologies on urban form. Subsequently, it focuses on AVs' potential changes regarding accessibility components and finishes with policy recommendations on how to smoothen the transition towards automated driving. This research was applied to a case study of the Greater Copenhagen Area. The main question that this research aims to answer is:

To what extent could automated vehicles transform the way cities are spatially organized and how can cities start preparing for this transformation?

In order to answer the main question, the following questions, related to the aim of the project, follow logically from the problem description and help to fill the knowledge gaps. The five questions each represent their own category and report chapter, stated in brackets after the question.

- 1. What are the mechanisms through which automated driving can influence accessibility in urban areas according to the literature? (Literature review)
- 2. How can we measure the transportation and spatial impact of automated driving on urban form? (Research method)
- 3. To what extent can automated vehicles change the accessibility and use of space in the Greater Copenhagen Area? (Application)
- 4. Under what circumstances are the effects of automated vehicles desirable in urban areas? (Scenario development)
- 5. What are the most effective measures to steer the introduction of AVs towards a desirable situation in the future? (Policy recommendations)

1.4. Research methods

This thesis assumes that self-driving technologies will be successfully developed and functioning properly. It explores how municipalities can deal with this breakthrough in their urban transportation and spatial planning. The Greater Copenhagen Area is used as a case study.

The first research question explores the features of the self-driving vehicle that could produce crucial change in accessibility measures of an urban transportation network. The answer to this question was established through literature review. It investigates what changes in technological driving features are possible with the introduction of AVs. Additionally, it gives insight into what types of usage scenarios can be distinguished and how the behavior of its users could change. Reports on planning predictions and impacts on shared and self-driving vehicle concepts give insight into the likely impacts of AVs on transportation planning and its implementation projections. Where different scientific sources have significantly different predictions, uncertainty ranges are developed in order to explore future impacts of AVs.

The second research question explores what methods can be used to measure the impacts of automated driving on urban form. This will be done through a literature review on comparable research. Their input, outcomes, and methods are investigated to explore the most logical method to identify the effects and relations around automated driving in urban areas. The third research question applies the research method to the Greater Copenhagen Area with a System Dynamics (SD) model. The uncertainties of the introduction and possibilities of self-driving vehicles are explored with the Exploratory Modeling and Analysis (EMA) Workbench. The results are projected onto a map of Copenhagen, which allows for the viewing of the major effects on the key performance indicators and land use patterns.

The fourth question finds desirable and undesirable scenarios in the results of this research and connects it to the reasons behind these outcomes. Variabilities in adoption, purpose, and operation of AVs are explored by creating easily adjustable input variables. These scenarios are linked to multiple trends as such as sharing economy, automation, mobility as a service (MaaS), and smart infrastructure (Except Integrated Sustainability, 2017a). The scenarios are used to sketch perspectives for planners, designers, and politicians to be able to anticipate change and challenge the current status quo on urban mobility.

The fifth and last research question investigates the subranges of uncertain aspects of AVs that are crucial to differences between desired versus undesired scenarios of automated driving. It additionally gives options to steer the results of this research. The results were discussed with the municipality of Copenhagen and local research institutions. Involving these parties in this thesis increased the relevance and usefulness, and, eventually, the consensus and motivation for implementing the results (Vennix, 1996).

1.5. Thesis outline

This section describes the structure of this thesis. The existing information on spatial and transportation impacts of automated driving is explored and reviewed in chapter 2. It gives insights into what is new and what is possible with the introduction of AVs, how the vehicles can be used, and what the most important assessment factors are. Chapter 3 explains the method of System Dynamics in combination with the Exploratory Modeling and Analysis Workbench. Chapter 4 describes the application regarding the Greater Copenhagen Area. A zone-based model explores the impact of automated driving on small areas within the case study area. According to the uncertainties which have emerged in the first three chapters, an exploration on different possible scenarios gives direction to future expectations in chapter 5. Chapter 6 explores the wishes of the municipality of Copenhagen and compares these to the model output and input. Possible policy instruments are proposed and a final conclusion of this research and recommendations for future directions are given in chapter 7.

 \sum

Current knowledge on automated driving

Hansen (1959) describes the accessibility of a place as the sum of all available social and economic opportunities weighted by their generalized costs of reaching them. These opportunities and costs are expected to change with the introduction of automated vehicles, which thus results in a change in accessibility. The existing literature on AVs is reviewed in this chapter, exploring the mechanisms through which vehicle automation can influence accessibility in urban areas. First, some background information on automated driving is explored in section 2.1. Section 2.2 answers what change in features and trip purposes fully automated vehicles might cause in comparison to conventional driving. Section 2.3 describes new types of usage being introduced by automated driving and section 2.4 describes the expectations and impact of shared automated driving on transportation and spatial planning in urban areas. These expectations lead to ranges for uncertain values that are used as experimental factors in the analysis of the impacts of automated driving. Section 2.6 describes what is learned from literature and how this is used in the rest of this research.

2.1. Background of automated vehicles

The transition to the self-driving future is an incremental process. A transportation system with self-driving vehicles can be seen as a combination of an evolution of private transportation together with a car-sharing society (Tillema, Berveling, Gelauff, van der Waard, & Moorman, 2017). The evolution of private transportation develops over two paths: the autonomous path and the cooperative path. The autonomous path focuses on the driving technologies of the car and the cooperative path focuses on the communication with other road users and the infrastructure system (Milakis, Snelder, van Arem, van Wee, & Correia, 2015). The gradual process of vehicle automation is reflected in five levels, besides level 0 which is the basic level where the driver performs all tasks (SAE International, 2016):

• Level 1: most functions are controlled by the driver, some specific functions such as steering or accelerating can be taken over by the car.

- Level 2: a driver system uses information from the environment to automate tasks as lane-centering. The human driver must still perform all remaining aspects of the dynamic driving task.
- Level 3: some safety critical functions can be taken over by the car under certain traffic or environmental conditions. The driver has to intervene if necessary.
- Level 4: the first level of full automation. All safety critical driving functions and monitoring can be done by the car. However, it does not cover every driving scenario.
- Level 5: the fully autonomous system is superior to the performance of a human driver in every driving scenario.

Today, cars can publicly drive on level 2, which means that the car can drive itself in certain simple circumstances but the driver must always keep his hands on the steering wheel while driving to take over control whenever needed. This research explores possible accessibility changes and identifies potential long-term impacts on urban form induced by AVs on level 4 and 5, where the human error is thus reduced to a minimum and features like a steering wheel and pedals are no longer needed. Dedicated lanes for AVs are not necessary, as the vehicles are expected to operate in mixed traffic at normal city traffic speed.

2.2. New technological features of AVs

The AV is capable of handling all driving aspects, without any input from the passenger, under all conditions that can be managed by a human driver. The new technological features of fully automated driving are investigated for both public and private transportation.

2.2.1. Autopilot

The luxury of not spending any focus on the task of driving is one of the major expected benefits of vehicle automation. Level 4 vehicles will be able to drive automatically in normal conditions. Human drivers can override or switch the system off at any given time, but do not have to monitor the system constantly. Level 5 should not ask for any manual control at all and the control features of a car thus become unnecessary (SAE International, 2016). The autopilot is likely to increase the productiveness and comfort during a trip, which results in a lower value of travel time. Automated taxis could become cheaper because the monetary compensation for the cabdriver is no longer required. A cheaper, driverless taxi system may eventually discourage car ownership and increase the utility of a shared vehicle system (Bagloee, Tavana, Asadi, & Oliver, 2016). This aspect is described in more detail in section 2.4.

Taking away the task of the driver means that the utility of commuting will change. The value of time (VOT) is measured according to its utility and can be used to explore travel behavior and to assess the performance of a transportation system in terms of acceptable travel time. It monetizes the travel time and differs when time is spend in congestion, during parking, or in other transportation modes.

Table 2.1 gives an overview of the values of time per type of car. The VOT is expected to decrease with AVs, depending on the in-car-environment. de Looff (2017) estimated a VOT of \notin 5.39 per hour in an office environment and a VOT of \notin 10.84 for leisure users. An office environment facilitates the passenger to work while commuting, hence the drastic decrease in VOT. Gains in utility in a shared vehicle are less evident. Passengers of shared conventional vehicles and shared AVs are assumed to have a similar VOT of \notin 12.49 (Fosgerau, Hjorth, & Lyk-Jensen, 2007). The VOT in congestion and the VOT while looking for a parking spot are higher than the VOT while driving. Gössling and Choi (2015) estimated this VOT at \notin 22.86 per hour, which is 1.5 times the VOT in a private car.

Mode	VOT (€/hour)	Notes	Source
Private car	€15.19	Danish VOT	Gössling and Choi (2015)
Private AV	€5.39	Office-AV	de Looff (2017)
Shared car	€12.49	VOT car passenger (93DKK) ¹	Fosgerau et al. (2007)
Shared AV	€12.49	VOT car passenger (93DKK)	Fosgerau et al. (2007)

Table 2.1: Values of time (VOT) (€/hour) per mode of transportation

2.2.2. Cooperative driving

Cooperative AVs are able to communicate with each other and road equipment, which harmonizes their driving behavior. Self-driving vehicles cannot only enhance the efficiency with vehicle-to-vehicle (V2V) communication to streamline their road usage in terms of headways, speed and lane changes (Martens & van Loon, 2015), but also by vehicle-to-infrastructure (V2I) communication if an intelligent network is added to the transportation system. This means that vehicles are not only aware of their fellow road users, but also of their driving environment and the road condition of their trip (Talebpour & Mahmassani, 2016).

Traffic efficiency improves most when AVs are cooperative (Babeş, 2017). This statement is not only true for the efficiency on an individual road segment, but also for the road network as a whole, because connected AVs have the ability to avoid congested areas and thus reduce the stress on bottlenecks in the system (Levin, 2017). Cooperative driving additionally improves routing reliability and predictability, and traffic flow stability, which will increase the throughput and reliability of traffic management (Talebpour & Mahmassani, 2016). A reservation-based system at intersections with connected vehicles can double, or even triple, the intersection's capacity compared to traffic lights in a conventional signal operation scheme (Dresner & Stone, 2004; Sun, Zheng, & Liu, 2017). Finding a parking space will also get easier and car trips might therefore even become more attractive.

2.2.3. Platooning

A platoon is a convoy of automated cooperative vehicles and can increase the throughput in urban roads significantly (Lioris, Pedarsani, Tascikaraoglu, & Varaiya, 2017). The front car is in charge of a fleet of vehicles behind it. This smoothens the flow of a number of vehicles as a whole, instead of improving the efficiency per vehicle individually. Platooning is a measure of

¹Values in DKK are converted to Euros according to the 2018 exchange rates.

cooperative driving, but not necessarily applicable to all vehicles. Platooning is thus a great example of how AVs can increase efficiency on roads where both automated and conventional vehicles operate.

2.2.4. Automated parking

Automated parking reduces the effort and time of looking for a parking spot. This feature is expected to be very valuable in urban transportation systems as it reduces the costs of driving. A possible effect of automated parking is increased empty vehicle mobility. The car can drive out of expensive parking zones and park in a cheaper location further away. For a short period of time, it could even cruise around empty until called back for a trip, avoiding parking entirely. The ability of vehicles to park themselves additionally takes out the necessity to park a car in front of a house, jobsite, or other activity, which reduces the need for parking space in expensive city centers or attractive areas.

2.3. New uses of AVs

The AV has many possibilities that can change the use of cars and the behavior of its passengers. With great imagination, one can think of infinite examples. The new possibilities are sorted into two categories in this section: new user groups and new trip purposes of AVs.

2.3.1. New user groups

Self-driving technologies promise an increased mobility for many groups, including those unable to drive today. The fraction of population that is able to drive increases when the tasks and responsibilities of a car driver are taken out of the vehicle. Examples of additional user groups to commute individually in motorized transportation are children, handicapped, elderly, or others without permission to drive. The light-duty vehicle kilometers traveled (VKT) could increase greatly with the increased mobility of the non-driving, elderly and people with travel-restrictive medical conditions (Harper, Hendrickson, Mangones, & Samaras, 2016; Wadud, MacKenzie, & Leiby, 2016). The expectation to drive more in a situation with self-driving vehicles is greatest among those who are unable to drive today and those that do not enjoy driving. A survey by the Danish Road Directorate & Wilke (2017) indicates that 40-50% of the currently non-driving population plan to use AVs.

2.3.2. New purposes

Resulting behavioral changes are very likely, considering the possibilities automated driving introduces to society. If new uses for cars are introduced, for example driverless delivery, errands, and self-parking, the empty vehicle mobility increases and results in a significant rise in traffic volumes. With these new trip purposes, public transportation becomes less adequate and AVs could contribute to greater stress on traffic systems, instead of contributing to a more sustainable system. More efficient combinations of freight and passenger transportation and reservation-based shared vehicle systems increase the utilization of the vehicle and could decrease the amount of vehicles on the road (Bouw, 2014; Llorca, Moreno, & Moeckel, 2017).

2.4. Shared AVs

The growth of shared mobility is increasing (Tillema et al., 2015). One of the major effects expected of AVs is that the gap between private and public transportation will disappear. A shared system could be used in two different ways: a car sharing system where the same car is used sequentially; or where travelers share time and space resources by traveling in the same car simultaneously (International Transport Forum, 2015).

Much literature focuses on the effects of a system with solely shared AVs. The utility rate per vehicle will be higher than in a scenario where the AV is privately owned, indicating a higher VKT. Because of increased vehicle utilization, the costs per km traveling per person are likely to decrease. The total traveled distance and the travel time for both automated and conventional trips could increase when AV fleets are operating. It, however, spreads the peak pressure; reducing the congestion in peak hours (Llorca et al., 2017). A reduction in car ownership and increase in vehicle utilization would reduce the idle time per vehicle, which thus reduces the need for parking space. A shared fleet could strengthen public transportation by providing transportation to and from transit stations. This potentially replaces high-cost, underutilized routes (Gruel & Stanford, 2016) and supplements the existing service, improving the attractiveness of public transport.

Several studies indicate that shared AVs will largely decrease the number of vehicles needed to satisfy the same travel demand, if passengers are willing to accept a slight increase in travel time. Agent-based models by the International Transport Forum (2015) explore different self-driving vehicle concepts and conclude that a fleet of shared AVs could reduce the number of vehicles needed to 10% of the current amount in order to deliver the same mobility. Fagnant and Kockelman (2014) support this conclusion and indicated that it is possible to satisfy the same travel demand with each shared AV replacing around 11 conventional vehicles. Rigole (2014) came to similar results in a research where commuter trips are allocated by a fleet of AVs: less than 10% of today's cars could facilitate the same travel demand. To reach this drastic decrease in vehicle-numbers, users are asked to accept ride-sharing, an average of 15% increase of their travel time, and a start waiting time of 10 minutes.

If ride sharing and increased travel time are unacceptable, shared AVs will still contribute to a solution to congestion problems and other network and environmental impacts. The cost difference between shared AVs and other modes are expected to be small and the competition by other modes, even the private car, will remain. Conventional public transportation is expected to face the strongest competition with the introduction of self-driving technologies (Bösch, Becker, Becker, & Axhausen, 2017; Meyer, Becker, Bösch, & Axhausen, 2017).

2.5. Expectations in the literature on AVs in urban areas

System changes of automated driving could either change the entire urban area, or limit its focus on changes in the transportation network. Smolnicki and Soltys (2016) explore effects of the decision to make the urban transportation system pedestrian-friendly, or to make it

driver-friendly. The first option has the objective to improve the entire urban area and has a mixed structure with low traffic speeds which is focused on mass transit. This system is slow for long distance and most suitable for short distance trips, which could be provided by driverless shuttles. The urban core is expected to become denser, especially as the facilities in the dense areas improve. The second option, driver-friendly system, tries to limit the improvements to the transportation network. This facilitates a high-speed, individual transportation system where longer distances are easier to cover. The urban area is expected to expand, as a larger area becomes more accessible.

Automated driving can support several objectives and societal challenges. Possible benefits that automated driving brings to society are an increase in mobility of those that are not able to drive today, a better utilization of the vehicles and infrastructure, automatic parking and the possibility to perform other activities than paying attention to the task of driving (Anderson et al., 2014; ERTRAC, 2017). The effects of AVs are, however, highly uncertain and not expected to be equally distributed among different social groups (Milakis, Kroesen, & van Wee, 2017). To conceptualize the sequential spreading of the impacts a so-called 'ripple model' (Milakis, van Arem, & van Wee, 2017) is visualized in Figure 2.1. This section explores literature's expectations regarding the most relevant impacts in this figure.

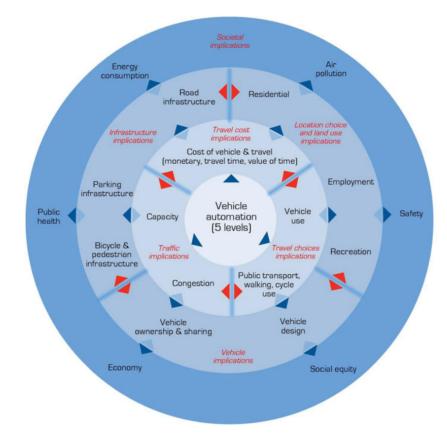


Figure 2.1: Ripple effect of automated driving (Milakis, van Arem, & van Wee, 2017)

2.5.1. Year of introduction and penetration rate

When assessing the impacts of automated driving, it is important to explore the driving factors behind these impacts. In this case, these factors are the year of introduction and penetration rate of AVs. Technological and legal issues and public perceptions as well as the safety and acceptance of self-driving vehicles are covered in the penetration rate of AVs. The effect of all other experimental factors of AVs depend on its share in the transportation system.

If AV implementation follows the patterns of other vehicle technologies, it will take one to three decades to dominate vehicle sales, plus one or two more decades to dominate vehicle travel (Litman, 2014). Cooperative, connected driving could become available much earlier than automated driving itself; Toyota announced at the Consumer Electronics Show 2018 that all US' Toyota-brand models will be enabled with cellular or Internet connectivity by 2020 (SAE International & Visnic, 2018).

The extent of the replacement of conventional systems depends on the development of the technology and the public acceptance. The expected market launch of automated vehicles differs widely in various sources (Underwood, 2014), but are highly dependent on the explored scenarios. Scenarios by Milakis et al. (2015) show combinations of the driving forces of technological development and supportive or restrictive policies influencing the introduction of automated driving. AV in standby describes a rapid technological development and AVs become publicly available in 2030. The government, however, sees many risks and the development is mostly industry-driven. AV in bloom offers a positive context for the development of AVs, which becomes available in 2025. High subsidies allow for a fast increase in the penetration rate of AVs and the government is taking measures to facilitate the highest potential of this technology in their society. AV in demand copes with a slow technological development. The government, however, promotes AVs because they are optimistic about the societal benefits. AVs become available in 2040. AV in doubt describes a path where both technological as well as political support is almost nonexistent. The customers' attitudes towards automated driving is generally negative. AVs are available in 2045, but are only available for the upper class due to high prices. The penetration rate of AVs thus increases very slowly and most trips are still made with conventional transport.

Nieuwenhuijsen, Correia, Milakis, van Arem, and van Daalen (2018) explores both a progressive and conservative version of *AV in bloom* by Milakis et al. (2015), which is the scenario with the highest likelihood and describes supportive policies and high technology development of automated driving. The progressive scenario estimates a penetration rate of 35% in 2025, which is not yet considered feasible. Puylaert, Snelder, van Nes, and van Arem (2018) advised to shift the starting point in time, but states that there is enough evidence to trust the curves for fully automated driving. The curves of the conservative scenario in Figure 2.2 by Nieuwenhuijsen et al. (2018) estimate the share of AVs in the transportation system and comply with the expectations in Copenhagen (Danish Road Directorate & Wilke, 2017; municipality of Copenhagen, 2017a).

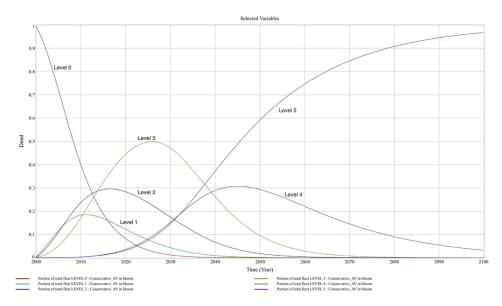


Figure 2.2: Market penetration AV (Nieuwenhuijsen et al., 2018)

2.5.2. Vehicle ownership and sharing

The outcome of a mobility system with AVs depends largely on the behavior of its users. Possible trends with the introduction of AVs are a more silent and safer transportation system, an increase in the difference between urban and rural areas, sharing mobility, an increase in traffic density, bundling of freight and passenger transportation, lower use of space by traffic, an optimal utilization of the road network, greater attraction of car use, and multipurpose land use (Bouw, 2014). Benefits are expected to be apparent for both AVs and the conventional fleet, meaning that benefits are not constrained to only one class of users.

An important decisive factor for the impact of self-driving vehicles on cities is whether the vehicles are privately owned and thus primarily used by individuals or if they are part of a publicly available shared fleet scheme. Shared vehicles are likely to enhance the positive impacts of vehicle automation. Some effects of private versus shared AVs are explored by Tillema et al. (2015) and shown in Table 2.2.

Table 2.2: Indication of private versus shared AVs

Variable	Private AV	Shared AV
Road capacity	+	+
Traffic volume	++	+
Public transportation		
Bike use	0/+	-
Urban sprawl	++	+
Equal mobility	+	++
Livability	-	+
Parking reduction	0	++

2.5.3. Location choice and land use implications

Self-driving vehicles could affect the commuting and settlement patterns in addition to the city's physical structure and its urban planning. The impact of automated driving depends on the perspective and focus of the study. From a land use perspective, the adoption of AVs could develop denser urban cores with more buildings and less surface devoted to transportation and parking, as self-driving vehicles can distribute themselves more efficiently and park away from dense areas (Rodoulis, 2014). A transportation perspective could claim that the ability to perform other activities while driving results in longer acceptable travel times and longer trips because passengers could now utilize their time in a vehicle better (Gruel & Stanford, 2016). This encourages urban sprawl (Anderson et al., 2014; Zakharenko, 2016).

Historical data suggests that personal income and the demand for mobility grow in tandem (Schafer & Victor, 1997). The average daily time people spend on traveling also remains constant. This means that if transportation becomes more efficient, they take more trips, select faster transportation modes, or pick a transportation mode where they spend a lower value of travel time to cover more distance in the same time as opposed to reducing the time they spend traveling (van Wee, Rietveld, & Meurs, 2006). With increased mobility people do not only move around, but also away (Gibbs, 1997); cities sprawl along with the accessible region, dispersing urban areas. More efficient public transportation facilities could, per contra, result in a more concentrated population in cities (Gelauff, Ossokina, & Teulings, 2017).

AVs can additionally reduce the need for parking space. The current idle time of a car in peak hours is around 84% (Alessandrini, Campagna, Site, Filippi, & Persia, 2015). Changes in the vehicle utility and inversely the idle time of the car are related to the increased mobility for those unable to drive and new uses for cars. Shared vehicle scenarios could decrease the idle time drastically to only 5.5% (Rigole, 2014). Besides a decreased idle time, parking robots can save parking space per vehicle by 60% (Heinrichs, 2016).

2.5.4. Traffic volume and infrastructure implications

The greatest impacts on mobility are expected to be a decreased value of time and an increased road capacity (Boston Consulting Group, 2016). If the public's behavior does not change, AVs will most likely lead to a more efficient mobility system, because of an increased efficiency of individual vehicle operation (Gruel & Stanford, 2016). Especially cities are expected to enjoy improvements in the efficiency and sustainability of road traffic (Rodoulis, 2014).

A measure of the efficiency of vehicle operation is the Passenger Car Unit (PCU) per hour per lane. A car or standard sized taxi is 1 PCU, bicycles 0.2 PCU, and buses and trucks between 1.8 and 3.5 PCU. Puylaert et al. (2018) estimates a PCU of 0.95 for an AV, meaning that AVs will take less space on the road than conventional vehicles. Cooperative driving needs enough support to be effective, so the benefits increase exponentially at higher penetration rates. Cooperative driving could decrease the PCU to 0.7 at 100% AVs (Atkins, 2016) or even to 0.5 in cases of vehicle platoons (Talebpour & Mahmassani, 2016).

System Dynamics and static models show an increase in trips with self-driving vehicles. The congestion is expected to decrease because of a reduction in vehicle crashes and an enhanced vehicle throughput, but could also possibly increase because of changes in VKT (Anderson et al., 2014). Reasons for an increased VKT are, for example, longer commutes due to lower (perceived) travel costs (Childress, Nichols, Charlton, & Coe, 2015; Madadi, van Nes, Snelder, & van Arem, 2018), self-fueling, self-parking, increased mobility of those unable to drive, and increased empty vehicle mobility (Bagloee et al., 2016). The VKT per AV is expected to increase with 10 to 20% because of an induced demand (Fagnant & Kockelman, 2015; Wadud et al., 2016), or even up to 75% because of trip overlaps, vehicle requirement changes, and an expected reduction of more than 40% in vehicle ownership (Schoettle & Sivak, 2015). Correia and van Arem (2016) confirm the lower value of travel time, higher number of trips and because of more efficient, harmonized driving, congestion does not necessarily increase. The network benefits dependent on the capability and the penetration rate of AVs (Atkins, 2016).

2.6. Conclusion literature study

Literature taught that a wide variation of effects is possible with automated driving. Fully automated driving is expected to make an introduction between 2030 and 2045. It will have a positive impact on road capacity, but because of more trip purposes and possible longer acceptable distances, the total traffic volume could increase. This will lead to urban sprawl, congestion problems, and increased space consumption of road transportation and parking surface (CARE-North plus, 2015). Shared AVs can harmonize the entire transportation system, depending on its support. The biggest advantages of a shared fleet are expected decreases in the number of vehicles, a higher utility per vehicle, and thus a decrease in necessary road and parking space.

It is hard to quantify the extent to which new vehicle features, new user groups, new trip purposes and its effect on the location choice of households will influence urban form. Therefore, a range of uncertain values is used to explore future possibilities for automated driving as accurately as possible. The learnings from this chapter are summarized in uncertainty ranges for the penetration rate of AVs over time, the efficiency of vehicle operation, the value of time in AVs, the increased mobility of the population, the idle time of AVs, the parking density rate, and the car-sharing rate. Literature states different expectations for these mechanisms through which automated driving can influence accessibility in urban areas. Section 4.5 explains how the uncertainties for these values are used in this research.

Current literature findings assign the transportation and spatial effects of automated driving to a transportation system or to a complete city as a whole. It is not yet subdivided in many smaller parts of a region, to allocate the effects to a specific geographic location. Besides concluding that the information on transportation and spatial effects of automated driving is scarce and varies widely among sources, a method to assess these effects over time on a spatial level has not yet been developed. This adds a challenge, seeing as no straightforward method to perform this research exists.

3

System Dynamics and spatial results

The future depends on the variation of uncertain input factors; every combination of factors can lead to a different outcome. A user-friendly method is needed to analyze these uncertainties and their respective effects as widely as possible. This chapter describes the method to assess transportation and spatial impacts of automated driving on urban form. Section 3.1 introduces the method of System Dynamics. Section 3.2 describes the general model setup and section 3.3 elaborates on the complete model and its components. Uncertainties are explained in section 3.4 and the application to a spatial system is explained in section 3.5. Section 3.6 deals with the model validation and section 3.7 concludes the research method.

3.1. A dynamically complex problem

System Dynamics (SD) (Forrester, 1958) maps the causal relations of the key variables to build a better understanding of the interdependencies and feedback processes of a complex system. These maps are used to conceptualize the system, define the problem, and, eventually, to communicate the results (Sterman, 2000). After the system components are pointed out and connected according to their causal relations, mathematical integrals and time delays are added. This results in a model that is able to simulate and quantify the behavior of the system over time and to explore different policies and future scenarios (Sterman, 2000).

Feedback loops assume that the behavior of a system is largely caused by its own structure (Pruyt, 2013). It occurs when outputs are ultimately routed back as inputs for the same variable, creating a circular argument. This prevents reasoning with a top-down approach and the risk that existing knowledge becomes too dominant (Adviesgroep voor verkeer en vervoer, 1995). This enhances innovative thinking and is essential in transportation research when exploring the future of new technologies. Time delays accumulate and temporarily store the difference between input and output in a variable. It could represent a physical flow of material (construction time of buildings), or the adjustment of information (time to make decisions and the time for decisions to affect the state of the system) (Sterman, 2000).

Cities are seen as self-organizing systems in which SD could explain the causes and effects relations between the variables in such a system. SD is the appropriate method as it is designed to handle a lot of complex information in an intuitively understandable way (Pfaffenbichler, Emberger, & Shepherd, 2010). The different aspects in the transportation and land use system are interdependent, so modeling feedback between these entities is essential. Additionally, SD's advantage is the possibility to cope with temporal effects: time-varying policies can be tested and uncertainty can conveniently be included and used to develop a broad range of scenarios. The mechanisms that impact the performance of the transportation network and the distribution of land use categories are used to detect quantitative correlations, which indicate where input parameters need to be adjusted in order to achieve the desired result.

The ability to bring in soft issues, such as impact of social exposure, and to quickly demonstrate the sensitivity of results to assumed parameters are major strengths of the SD approach. Because of the immaturity of theory on quantified effects of automated driving and the low number of feasible experiments, a high level of uncertainty is expected in many model components. SD is a good method to deal with uncertainties, but a system consisting of many different zones and uncertainties that have to be explored by running thousands of experiments, favors an additional and stronger tool.

Exploratory Modeling aims at exploring implications of various combinations of uncertainties (Kwakkel, 2017). Exploratory Modeling does not include a base case and no probabilities are attached to the likelihood of any outcomes or scenarios. The Exploratory Modelling and Analysis (EMA) Workbench offers computational support for making decisions by constructing a set of plausible models that are consistent with the available information (Kwakkel, 2013). It reveals how the system will behave based on various uncertainties, rather than making a prediction based on a potentially falsely consolidated single model. It enables controlling a simulation model by setting parameters, picking a simulation setup, run the model, and provide output. EMA can sample over a high number of models, given a priori knowledge. The EMA workbench is implemented in Python and is compatible with models developed in Vensim®.

Figure 3.1 provides a schematic overview of the methodology used to assess the transportation and spatial impacts of automated driving on urban form. This figure explains the duplication of the model in each of the zones in a land use system. The results are modeled over time and compared to specifications of desired and undesired outcomes. The Patient Rule Induction Method (PRIM) is used to connect a cause to the outcome and to deduct the input values that have the most influence on either wanted or unwanted outcome. This allows policy makers to get insight into the most influential values; policy measures should focus on the outcome of the PRIM. How to deal with many uncertainties and the application of PRIM is explained in section 3.4.

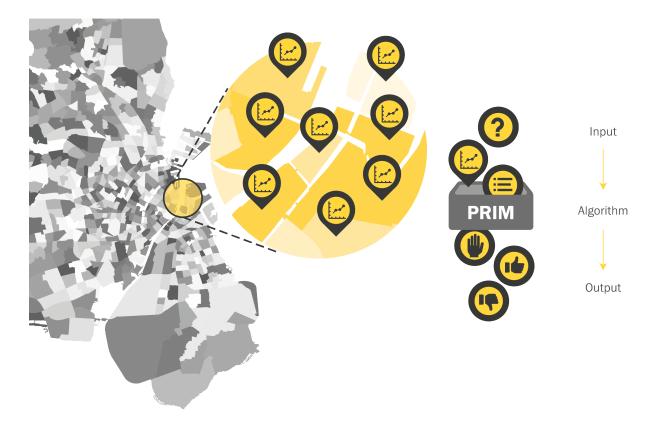


Figure 3.1: Schematic overview of methodology

3.2. Model setup

Most transportation studies in SD are performed with the Causal Loop Diagramming (CLD) technique. CLDs consist of variable names and their causal links (Gruel & Stanford, 2016). This technique explores directions of behavior based on feedback loops. Causal loop diagrams are used to identify the variables, the relations between them, and the main feedback loops to set up basic structures of the subsystems and modules in this research.

Figure 3.2 shows the basic model structure in this research. Each rounded box describes a sub-model and the arrows indicate their interrelations. This general structure is based on the dynamics between transportation and land use systems in the Metropolitan Activity Relocation Simulator (MARS) (Pfaffenbichler et al., 2010), models of traffic and congestion (Sterman, 2000), and models incorporating self-driving technologies to Sterman (2000) to assess the long-term effects of AVs (Gruel & Stanford, 2016). Differential equations are added to the CLDs and modified further according to logical and theoretical considerations. The methodology of research into the mobility effects of early forms of automated driving (SAE level 1, 2, and 3 by Puylaert et al. (2018), and SAE level 3 and 4 by Meyer et al. (2017)) supports the investigation of the potential of automated vehicle technologies in reference to transportation and land use systems. Main modifications to these models are an elaboration of parking, population, and land use aspects and a simplification of the public transit aspects.

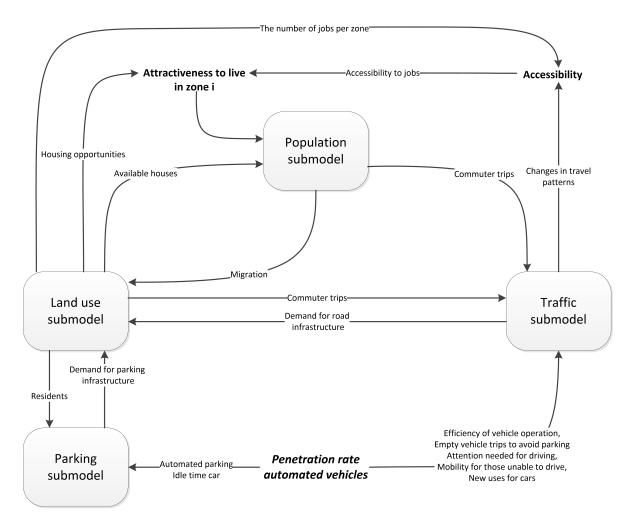


Figure 3.2: Sector diagram of System Dynamics model

The implications of automated driving related to policy and society by Milakis, van Arem, and van Wee (2017) are used to explore the various system components that are expected to be key to evaluate societal challenges addressed by automated driving. The following list of key performance indicators (KPIs) provides a complete coverage of the effects AVs could have on a transportation and land use system:

Attractiveness to live in a certain area
 Congestion (capacity saturation)

Road surface

- Population
- Accessibility to jobs
- Average trip distance (urban sprawl) Parking surface
- Incoming traffic volume (incoming trips) Other land surface

The reallocation of population depends on the attractiveness to live in an area. The attractiveness is the result of land use characteristics and the accessibility to jobs. Decreases in road and parking surface result in an increase of other land applications in a zone which ideally creates free space to use for improving the attractiveness of an area. The amount of space needed for road depends on the capacity saturation, which is a result of traffic volume divided by the road capacity. Other assessment criteria all have influence on one of the KPIs and are thus not listed as key outcomes.

3.3. Model components

To create general understanding of the model, each of its components and the relations between them are explained in this section. The complete submodels are shown in Appendix D. The main endogenous and exogenous variables are shown in Appendix E. The endogenous variables are influenced by the system and exogenous variables are mostly input variables, coming from literature or databases. Many of the variables have unknown values. Section 3.4 explains how to deal with these uncertainties. The model represents the transportation and land use section of a single zone within an urban system. All zones combined thus represent an urban region. Section 3.5 explains how this zone-based system is implemented.

Polarities are added to each of the sub-models to show either a positive relation (+) or a negative relation (-) between two connected variables, or a relation that is either positive or negative (+/-) depending on uncertain characteristics of AVs or where allocated land has both a positive and a negative influence, depending on the fractions of each land use category.

3.3.1. Land use

Figure 3.3 shows a representation of the land use sub-model. Land use categories are residential surface, business surface, road transportation surface, and parking surface. The surface that is not used for any of the four previously mentioned categories is considered 'other land'. These categories form a closed system where land use is being reallocated to unallocated land which reversely can be constructed back into one of the land use categories (Havelaar & Jaspers, 2017). All categories are assumed to decay over time, which introduces a period of time of renovation, that causes some parts of the land to be temporarily unavailable.

The allocation of new land depends on the available space (unallocated land), the demand, and the allocation priority for each type of land. If the demand for a land use category is higher than the allocated land, more land is required. If the demand is lower, this type of land could be reallocated to another type of land. The allocation priority is a normalized measure regarding the demand for each type of land and could be guided by governmental institutions. It is limited by the current maximum fraction of each land use category to maintain the distribution of several categories. In the event that the total of demands for each land use category is less than the unallocated land, the rest will be allocated to other land.

Newly allocated space for housing, jobs, road, parking, or other land can only become available by reducing the space required for for housing, jobs, road, or parking. Other land can only increase and remains untouched when constructing new parking, road, residential, or business facilities. The sub-models of traffic, parking, and population explain the dynamics in demand for each of the respective land use categories.

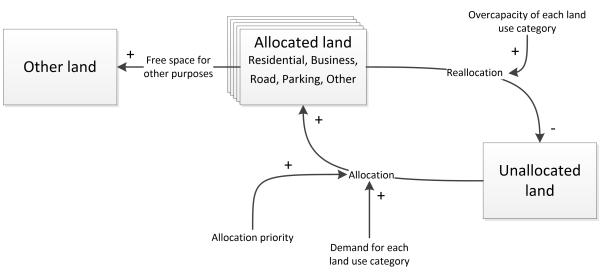


Figure 3.3: Land use sub-model

3.3.2. Traffic

Figure 3.4 represents the traffic sub-model. The number of road lanes is used to estimate the road capacity, which, together with the traffic volume, estimates the capacity saturation. The over- or under-capacity of road surface is connected to the allocation and reallocation of the land use sub-model, which, in turn, initiates lane construction from newly allocated land for roads, or allows for lane decommissioning. AVs influence the traffic system (1) by changing the efficiency of vehicle operation, which is the amount of road space needed per vehicle; (2) by changing travel behavior because of new uses for cars and increased mobility for those unable to drive; and (3) by changing the value of time, which changes the acceptable travel time for a trip. These three measures are expected to influence the traffic volume and road capacity, and thus the capacity saturation and demand for road surface.

Traffic volume is measured in the number of trips entering and moving through a zone per hour. AV effects on the road are most evident during peak hours, so only the morning peak traffic volume is modeled. The most popular ways to derive the number of trips are based on gravitational, time-space or utility measures (Xu, Zhang, & Li, 2017). In this case, a gravitybased approach is chosen because it requires relatively simple and easily-obtainable input data. It is, however, not as detailed as the other two measures. The other two measures need case specific data on a high level of detail. This will limit the model's possibility to be generalized for other urban regions.

The gravity-based approach is used under the assumption that the number of trips between an origin and a destination zone is proportional to a production ability factor for the origin zone (population able to drive), an attraction ability factor for the destination zone (jobs), and a factor depending on the travel costs between the zones (travel time). The mathematical expression of the gravity model is reformulated to a doubly constrained version, where both trip productions and trip attractions are known (van Nes, 2014b):

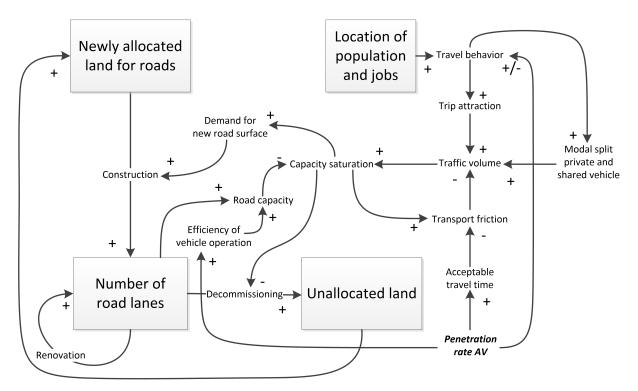


Figure 3.4: Traffic sub-model

$$T_{ij} = \alpha \cdot \frac{P_i \cdot A_j}{TT_{ij}^{\beta}}$$
(3.1)

Where:

 T_{ij} = Number of commuter trips from origin i to destination j;

 P_i = Trip production potential in origin i (Population able to drive);

 A_j = Trip attraction potential in destination j (Jobs);

 TT_{ij} = Travel time between origin i and destination *j*;

 α = *Proportionality constant related to the rate of event;*

 β = Parameter of transportation friction related to the efficiency of transportation between locations.

Regression analysis is used to estimate the parameters α and β to establish the relation between the dependent variable *Incoming commuter trips* and independent variables *Population able to drive* multiplied with *Jobs* and the natural logarithm of *Travel time*. The multiplicative model is converted into a linear form by taking logarithms of these values (Stynes, 1989).

The modal split is used to get insight in the total number of commuter trips in the morning peak. AVs can influence the modal split, as it introduces new, self-driving modes of transportation and it can change the costs of already existing modes. Cost changes are, for example, a reduction of driver costs in taxis or buses, but also a lower value of time, and a reduced effort to find a parking spot. The modal split is subdivided in six categories: Private car, Private AV, Shared car, Shared AV, Public Transportation and Active Modes (Biking and Walking). The probability to use each of these six categories is estimated using a logit model which considers a trade-off between the utilities of each mode in Equation 3.2, assumed that travelers act rationally, have well-defined preferences and select the alternative with the highest utility (van Nes, 2014a). The utility is based on the travel time and travel costs, where travel time is scaled to a cost-factor, according to the comfort and value of time for traveling with each mode. Only the systematic component of the utility function is used, as the random component will be explored by uncertainty analysis in the SD model.

Public transportation and active modes are not modeled in detail and their utilities are initially unknown. The number of trips per mode with unknown utilities, in this case public transportation and active modes, are calculated based on the share of all modes in the base year (EPOMM, 2014) and the number of trips by car. The estimation of trips for all modes allows to compute the initial utilities of public transportation and active modes. The costs and utilities of the known modes are compared to its respective share in the transportation system, which is used to find the relation between number of trips and utility of public transportation and active modes. AVs influence the utility of the car, which thus causes changes in the modal split of the car versus the modal split of other modes.

$$P_{i} = \frac{e^{V_{i}}}{\sum_{r=1}^{n} e^{V_{(r)}}}$$
(3.2)

Where: P_i = Probability of using mode i; V_i = Utility of mode i; $V_{(r)}$ = Utilities of all modes r; n = Number of modes in consideration

3.3.3. Parking

Figure 3.5 represents the parking sub-model. The value for cars per person is used to estimate the number of vehicles in an area and when multiplied with the idle time, it can estimate parking demand. The parking demand is compared to the parking capacity, which determines the capacity saturation and the demand for new parking surface, or the possibility to decommission parking surface. The model will decide to construct more parking spaces according to the unallocated space and the allocation priority.

The idle time of a car and the car ownership rate are both highly dependent on the penetration rate of AVs. New uses for cars change the idle time of a car, which thus changes parking demand. New uses for cars can additionally change the time and effort in finding a parking place, which changes the need to park the car close to home, work or other destinations. Changes in VKT by the mobility for those unable to drive and car-sharing influence car ownership and the number of cars per person. If car ownership changes, the demand for parking changes as well. AVs can additionally increase parking capacity because it requires less parking space per vehicle (Alessandrini et al., 2015; Heinrichs, 2016).

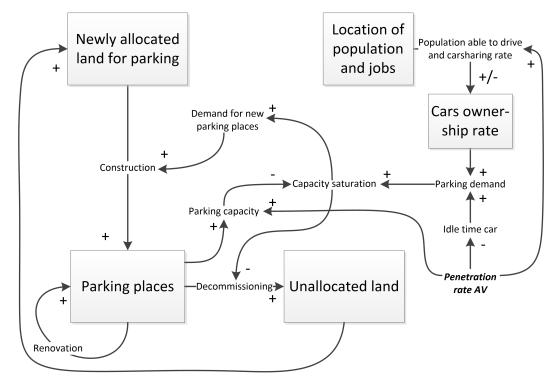


Figure 3.5: Parking sub-model

3.3.4. Population

Figure 3.6 represents a simplification of the population sub-model. The population is influenced by immigration and births, emigration and deaths, and interregional migration. Interregional migration is the population that is relocating within the case study area. The reallocation over the area depends on the relative attractiveness of each location. The migrating population is constrained by the amount of vacant houses and the unallocated land that can be developed into residential space to create more available houses. The allocation algorithm is used to allocate a scarce supply to a number of requests, based on their respective priority (Ventana Systems Inc., 2017). The maximum request of a zone is thus the amount of available houses. The excess demand is taken up by the next most attractive zone if the capacity is reached (Pfaffenbichler et al., 2010). The population supply is the number of people moving out of their current house each year, which depends on the amount of years one stays in a house. If this is, for example, ten years, one tenth of the population moves out each year. If the supply is bigger than the sum of the requests, then all requests are fulfilled. If supply is smaller, the priority determines where to relocate the population. The population is only subdivided by age cohorts, not by differences in family situation, income, culture, and lifestyle.

The attractiveness of each zone influences the allocation priority and the intraregional migration accordingly. The attractiveness is influenced by a series of factors regarding the location quality that compare the value for the concerned zone with the average value for the whole study area. The land use characteristics are a fraction of road surface (unattractive because of traffic noise and pollution), a factor of vacancy (which is considered unattractive

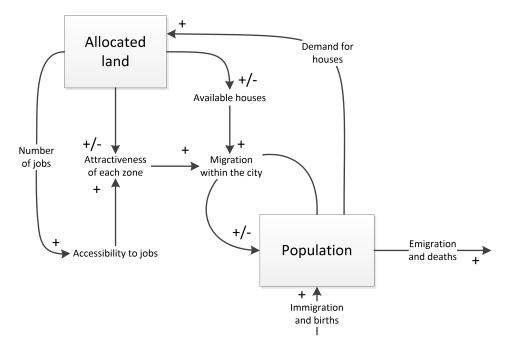


Figure 3.6: Population sub-model

if it exceeds a certain threshold, because it is related to unwanted social activities as crimes), the amount of other land (which includes facilities as access to public transport, education, shopping sports, parks, and other leisure or communal facilities, and thus influences the attractiveness in a positive manner) and proximities to nature as well as to the city center.

Besides land use characteristics, the accessibility to jobs influences the attractiveness of a zone. The accessibility to jobs in a section gives a value to the number of jobs that can be reached from a specific zone within a maximum acceptable travel time. This value is not constrained by the total number of jobs in the area in cases where the hypothetical number of jobs to be reached within the maximum acceptable travel time exceeds the total number of jobs in the case study area, because the population could also work outside the Greater Copenhagen Area. The accessibility to jobs is calculated with the same method as trip generation: a gravitational approach as in 3.3. The measure is derived from the traditional gravity model by Hansen (1959) and has the following form, assuming the total number of jobs as opportunities in all zones divided by a distance decay function of reaching that zone:

$$A_i = \sum_{j=1}^{N} \left(\frac{J_j}{TT_{ij}^{\beta}} \right)$$
(3.3)

Where:

 A_i = Accessibility to jobs from zone i;

 J_j = Number of jobs in all zones j (j = 1,2,...,N);

 TT_{ij} = Travel time between origin i and destination j;

 β = Parameter of transportation friction related to the efficiency of transportation between locations.

3.4. Dealing with uncertainties

Missing information and differences in literature findings are explored by varying the uncertain input variables and running the model a high number of times. Uncertain input values may result in unlikely or undesired future situations. The Patient Rule Induction Method (PRIM), originally proposed by Friedman and Fisher (1999), identifies combinations of uncertainties that achieve desired targets and explores uncertainties that are responsible for generating possible hazards (Groves & Lempert, 2007; Hamarat, Kwakkel, & Pruyt, 2013; Kwakkel, 2018; Kwakkel, Haasnoot, & Walker, 2016). PRIM not only finds the most important driving forces, it also provides evidence that the other uncertainties are less important (Bryant & Lempert, 2010).

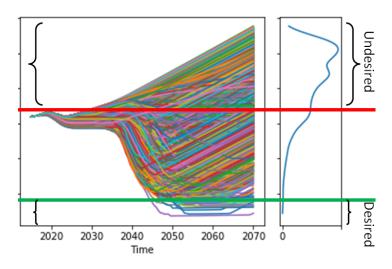


Figure 3.7: Illustration PRIM

Figure 3.7 shows an example of the selection of results. The graph on the right represents the density of the outcomes. If the red line is the threshold for undesired results, all outcomes above this line are considered undesirable. The algorithm seeks out the input values that have the most impact on these outcomes. Cases of interest are separated as much as possible, which is sequentially conducted until the number of remaining observations falls below a specified stopping parameter (Chong & Jun, 2008; Kwakkel & Cunningham, 2016).

Each set of simultaneous constraints is called a box, which can be interpreted as a scenario. A case of interest is an observation with a specified (un)desired outcome. The quality of the scenario discovery is explained by the coverage and density of a box. The coverage shows the proportion of the cases of interest in a certain box compared to the total cases of interest. A coverage of one means that all cases of interest are present in a certain box and a coverage of zero means that none of the cases of interest are present in a certain box (Kwakkel & Cunningham, 2016). The density explains the fraction of cases of interest compared to the total number of cases in a box. A density of one means that all cases in a box are of interest and a density of zero means that none of the cases in a box are of interest (Kwakkel & Cunningham, 2016). An ideal set of scenarios combines high coverage with high density and is easily interpreted (Bryant & Lempert, 2010).

The EMA Workbench includes PRIM algorithms and is accessible from an easy to use, open source application. The Jupyter Notebook supports the EMA Workbench through Python language and is used to code the uncertainty analysis and to visualize the results. Future scenarios are found by giving directions to uncertain inputs and by specifying desirable model outcomes. These desirable outcomes depend on the case study area. Desirable outcomes can thus be provided as an input for the analysis in order to discover likely scenarios towards this desirable future.

3.5. Applying the method to a zone-based system

The case study area is divided into many different zones. This enhances the level of detail in the conclusions and allocates the effect of automated driving to specific locations instead of coming up with general conclusions for a large area. Vensim reads zone-specific input from an Excel file and by programming the SD model in the EMA Workbench, it is possible to visualize the effects in all zones in their geographic location. The EMA Workbench allows for control of the SD model from an external source and for it to be combined with resources such as geographic information and scenario discovery applications. The combination of Vensim and the EMA Workbench allows for dealing with many model uncertainties and comes up with the most relevant insights for each zone as a result.

The combination of SD in a zone-based system and exploratory modeling has not been applied to transportation and land use studies before. This makes this research not only relevant for exploring the effects of automated driving in urban areas, but also for finding new methods to assess the impacts of the introduction of new technologies to urban form in general. SD alone cannot handle a geographic representation of networks and handles each zone as an isolated system. The method in this research creates a platform for showing the results and for exploring scenarios of all these isolated systems combined.

The results and (un)desired scenarios can be explored from the perspective of a city in general, but also per individual zone. A high number of zones increases the level of detail in the results. Specific policy plans can be implemented for the entire city, or per individual zone, but also per district, such as a city center, other urban areas, suburbs and rural areas.

The different zones in the model cannot interact with each other. The parking demand in each zone is, for instance, estimated independently from the parking facilities in surrounding zones; roads are not connected and not influenced by the infrastructure of adjacent zones; and the attractiveness to live in a zone is not increased or decreased by the attractiveness of zones nearby.

3.6. Model validation

Validation tests the model's fit for its purpose. This checks if the correct and accurate model has been built for this research. The validity of an SD model has a major influence on its trustworthiness and thus needs a lot of attention. Shepherd (2014) reviews SD studies that

optimize strategic transportation policies for cities and deals with the validation of transportation models using an SD approach. The evaluation should be designed in the model from the beginning of the project. This is done by adding several variables that sum up the values over all zones. This monitors the totals in the Greater Copenhagen Area and prevents them from exceeding realistic values.

There is a wide variety of methods that uncover flaws, and improve and validate SD models. Sterman (2000) describes twelve tests of model validation, reformulated from Forresters confidence-building tests. The confidence in an SD model accumulates gradually as it passes more tests and new points of correspondence between the model and empirical reality are identified (Forrester & Senge, 1980). The model is scientifically useful if it generates insight into the structure of real systems, makes correct predictions and stimulates meaningful questions for further research. The model is politically useful if it explains the reasons behind important problems and provides a basis for designing policies that can improve behavior in the future (Forrester & Senge, 1980).

3.7. Conclusion research method

The most logical method to assess the transportation and spatial effects of automated driving in urban areas is a method that is able to perform analyses for a time period of several decades from now. It should handle many uncertainties in a manner that can be easily understood. The effects should be allocated to their respective geographic location to show the effects in the entire urban region over time in one overview.

An urban area is divided into many different zones to increase the level of detail in the results. SD is able to handle many different sub-systems, but cannot include dependency between them. The separate zones cannot interact with each other in this first version of the model, which means that the effects of AVs only depend on what happens in each zone separately and on variables that apply to the entire region, such as the population growth and economic prosperity.

Programming the SD model into the EMA Workbench and combining it with spatial data, makes it possible to allocate the effects in an urban area to their respective geographic location. This Workbench additionally allows for controlling the model in a manner that can be easily understood, which is an important requirement of handling and exploring many uncertainties.

An important step has been made to explore the effects of a new technology in a city subdivided in a high number of zones, while handling future uncertainties in an easily understandable manner, and visualize the effects over time on their geographic location. Next steps in this type of research should be to connect the zones in order to increase the realism in conclusions.

4

Application to Copenhagen

This chapter describes an application of the method to the Greater Copenhagen Area (GCA). Section 4.1 contains a short introduction of the demographics of the GCA. Current and future transportation and spatial planning in the area are described in section 4.2. The model is applied to the GCA in section 4.3 and validated in section 4.7. Section 4.8 describes the experimental setup. Model behavior and the results on the key performance indicators are discussed in section 4.9. Section 4.10 concludes the analysis.

4.1. Case demographics

Copenhagen, situated on the east coast, is the Danish capital and its most populous city with approximately 1.3 million inhabitants in its urban area and just over 2 million in its metropolitan area. The Øresund region is the metropolitan region covering the areas of both Copenhagen in Denmark and Malmö in Sweden. This research includes only the Danish part, which is also named the Greater Copenhagen Area or the Copenhagen metropolitan area. This region includes the capital region of Denmark and a small north-eastern part of the region Zealand. The urban area covers 86.5 square kilometers and the GDP per capita is \$60,000. The city is the cultural, economic, and governmental center of Denmark and one of the major financial centers of Northern Europe. Especially in the service sector, information technology, and clean technology, Copenhagen's economy is developing rapidly.

Copenhagen ranks high for its quality of life. Its cityscape is characterized by parks, waterfronts, and several walking areas and is a popular place for tourists. Despite Copenhagen being one of the world's most expensive cities, stable economy, education services and social safety together with public transport, facilities for cyclists and environmental policies make it an attractive place to live. The case study area is shown in Figure 4.1. This image gives an overview of the land use types over the area, in which the finger structure of the urban area is clearly visible.

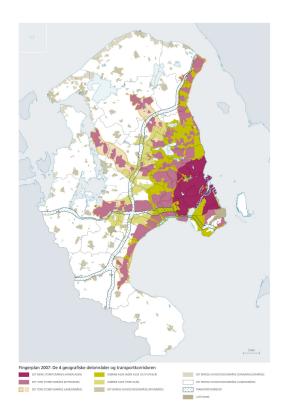


Figure 4.1: The case study area (Fertner et al., 2012)

4.2. Transportation and spatial planning

The Copenhagen metropolitan area has a very well-established transportation infrastructure which makes the area an important hub in Northern Europe. Its road network connects the city to other parts of Denmark and to Sweden over the Øresund Bridge. The car represents two-thirds of all distances traveled. However, if categorized by number of trips, the bicycle is nowadays the most popular form of transportation in the city. The bicycle is especially popular for trips to work, school or university. The city's bicycle network of 400 kilometers of dedicated cycle lanes is extensive and well-used. The public transportation network facilitates 750,000 passengers every day. Half of these passengers uses the city's bus services.

4.2.1. The Fingerplan

The Fingerplan originates from the 1940s and establishes a main structure with the stationary principle, urban areas, and green wedges for the capital region of Copenhagen. The urbanized region metaphorically shows a hand on the map in Figure 4.1. The city is the palm and the peripheral area develops along its fingers with green wedges in between. The key element in the Fingerplan is that it ensures continued housing and business development in the region. This supports the current urban structure and maintains the stationary principle, which provides guidelines for the location of workplaces and other important destinations according to the accessibility of well-serviced public transportation stations. Since 2007 the Danish Law states that only the national government has authority to make adjustments to the Fingerplan. Until this day, this plan provides a robust structure in which urban development is closely linked with the development of road infrastructure and public transportation (Danish Business Authority, 2017).

4.2.2. Future planning

The Danish land use system, the local plans, and their documentation are publicly available (Danish Business Authority, 2018a, 2018b). The availability of plans indicate transparency in decision-making and that Copenhagen wants to share its information so that researchers may use it. An important note is that the main goal of the improvements to the transportation system of Copenhagen is to maintain or improve the generalized costs of traveling by car, while improving the alternative transportation modes as public transportation and active modes. Plans of the city fit in the model to see which variables the city can influence and to find out how this influences their criteria to reach future goals. Insights in the ambitions and opportunities of the municipality of Copenhagen make the model more useful and determine the major influential variables of the model.

4.2.3. Copenhagen's attitude towards self-driving

Copenhagen is known for its bicycle policies and is proud of what they have achieved in the modal split of active modes and in becoming one of the most green and sustainable cities worldwide. Can this be sustained, or should they be concerned that self-driving vehicles will make the car more popular and reduces the share of bicycles and public transportation.

The Danish parliament announced that experiments with self-driving vehicles on public roads in Denmark have been possible since July 2017. They analyze the opportunities and challenges of self-driving vehicles as well as the importance of the future of accessibility. The municipality of Copenhagen (2017c) wants pilots and results to support the current composition of traffic between pedestrians, cyclists, public transport, and motorists. Self-driving should also cooperate with the existing climate and community plans.

The Danish Road Directorate & Wilke (2017) expect that the development will affect city life and urban spaces and that it will make the current public transportation system redundant if all these vehicles are used as a part of a shared collective system. It is expected to increase traffic capacity and safety, reduce the need for parking in the city, and improve the mobility of goods and people. They also expect that this development will generate increased traffic and congestion, CO_2 emissions and therefore negatively impact the climate, as well as reduce public health. However, the technology and knowledge is still young, so its decisive impact is questionable.

The driving needs and the traffic situations are affecting the interest in self-driving vehicles. Those who often drive long trips, often drive on the highway or are stuck in traffic, are more interested in using and buying automated vehicles than others. 25% of the respondents expect to drive more using the car in a situation with self-driving vehicles, while only 9%

expect to drive less. 25% of the respondents said to not see any benefits in self-driving vehicles. These concerns probably reflect the fact that technology, the legislation, user interface, and associated security is largely unknown and thus has not gotten a known and final form (Danish Road Directorate & Wilke, 2017).

Copenhageners generally expect hindrance with AVs in their region in terms of increased traffic and increased travel times compared to a situation with manual vehicles (Danish Road Directorate & Wilke, 2017; municipality of Copenhagen, 2017a). The development of AVs should be steered towards a situation with a reduction of need for parking and road surface, which means that Copenhagen will gain space for outdoor activities; a development they like to encourage in the future.

4.3. Application of the System Dynamics model

To explore the different effects on the KPIs and land use categories in more detail, the Greater Copenhagen Area is subdivided in 860 different zones according to the Øresund Traffic Model (OTM). This model is developed to calculate future traffic flows in the GCA. It uses OTM version 5.4 and its GIS data. Preparations prior to processing data from different sources are also explained in this section.

4.3.1. Zone districts in the GCA

Scenario discovery per OTM zone is too detailed for viable conclusions. Therefore, the 860 zones in the GCA are subdivided according to an unofficial but widely perceived district division of Copenhagen (Wikivoyage, 2017). These districts are mapped behind the zone shape of the OTM region to extract the number of zones per district. The maps of each region with its corresponding zones is shown in Appendix A. The population, jobs, and the average size of a place in each of the districts are shown in Table 4.1.

#	District	# Zones	Population (person)	Jobs (job)	m² /place	Reference OTM zone
1	Amager	89	160181	58318	33.16	312
2	Christianshavn	12	10487	10768	26.21	35
3	Eastern Zealand	68	201475	60413	189.31	802
4	Frederiksberg	44	97530	31662	23.61	353
5	Indre By	36	38154	88207	12.31	25
6	Nørrebro	30	74665	13914	33.47	93
7	Northern Suburbs	222	408503	174983	52.01	247
8	Northern Zealand	115	379739	113362	125.66	694
9	Østerbro	50	71461	39574	23.90	65
10	Vestegnen	144	350374	141688	52.88	243
11	Vesterbro	50	81466	43423	18.91	131
	Total	860	1874035	776312		

Table 4.1: Districts

District types are used to aggregate the districts. This is needed for input data that depends on different types of districts and to draw conclusions for different parts of the city. A distinction is made between the city center, other urban areas, suburbs, and rural areas. The districts of the Greater Copenhagen Area in each of these types are shown in Table 4.2.

Table 4.2: Districts per district type

District type	Districts
City center	Christianshavn, Indre By
Urban districts	Amager, Frederiksberg, Nørrebro, Østerbro, Vesterbro
Suburbs	Northern Suburbs, Vestegnen
Rural areas	Eastern Zealand, North Zealand

4.4. Input parameters

4.4.1. Socio-demographics

OTM data provides the initial population and jobs per zone. The number of houses is estimated by the population divided by an average household size of 2.1 persons (Elmeskov, 2015) and by adding a vacancy rate of 3.9% (Newsec, 2016) to maintain a housing buffer. The jobs per zone change according to the availability of developable land and a factor depending on the Danish economic growth of 1.5% (Trading Economics, 2018). Table 4.3 shows an overview of the socio-demographic input values in the start of the simulation in 2015.

Table 4.3: Socio-demographic input values

District type	Population (person)	Person /km ²	Jobs (job)	Job /km ²	Fraction road	Fraction parking	Fraction other
City center	48640	5653	98980	11500	6.12 %	10.77 %	54.78 %
Urban districts	485300	3711	186900	1429	4.16 %	10.95 %	61.32 %
Suburbs	758800	1854	316700	768	3.15 %	3.96 %	77.55 %
Rural areas	581200	259	173800	78	0.96 %	0.70 %	88.44 %

The population and jobs density are estimated by dividing these respective values for each of the district types by the surface of the respective districts. Estimation of the initial fraction road is explained in subsection 4.4.4 and the initial fraction parking in subsection 4.4.5. Data of the initial land used for residential and business purposes was not available and is calculated based on the other types of land use. The total zone surface minus the surface of road and parking infrastructure is divided by the amount of jobs plus the amount of houses in a zone to determine the surface per place. The surface of workplaces and houses are assumed to be equally large and only differ per district. The surface per place is an estimate of the land needed per place if everything is built on one level. This value is thus lower in high density districts with higher buildings. The minimal surface per place is used as the average surface per place in each district. In the zone where the surface per place is smallest, it is thus assumed that the zone is filled with the land use types for road transport, parking, residential and business purposes. No *other land* exists in these zones. This ensures that the sum of the surface of all land use categories will not exceed the total zone surface.

4.4.2. The attractiveness of living in each zone

The housing location choice depends on the attractiveness of living in each zone. However, if a zone is very attractive, but there are no available houses, it cannot receive population. A proxy is used because area quality is difficult to measure (Pfaffenbichler et al., 2010). Table 4.4 shows the preferences for qualities in the surroundings and for the location of the home as a result of a survey of a large sample of randomly selected Danish population over 15 years old (Skifter Andersen, 2011). The right column is the coefficient of importance which is used to weigh the influence of each attribute on the attractiveness. Each index has a value between 0 and 1, where 1 means that all respondents believe that attribute to be very important, 0 means that all respondents believe it to be no impact at all. Factors including social mixture, access to public transportation and proximity to social relations are considered equal among all zones and thus are not taken into account regarding the attractiveness of each zone.

Attribute	Coefficient
Proximity to nature	0.76
Proximity to the city	0.36
Fraction wasteland and vacancy ¹	0.72
Fraction other land (Communal facilities)	0.25
Accessibility to jobs (Proximity to workplace)	0.45
Fraction road (Traffic noise and pollution)	0.64

Table 4.4: Coefficient of importance for attributes influencing the attractiveness of a zone (derived from Skifter Andersen (2011))

The factors of proximity to nature and the city attempt to explain patterns between the differences in preferences for living in the countryside versus living in the city center and all options in between. The estimated factor scores for proximity to green spaces and the city center are shown in Table 4.5 for each district. The proximity to nature is formed by a dominant factor for the urge to live close to green spaces, but also, to some extent, to avoid noise. The proximity to the city includes the importance to stay close to the city's pulse, communal facilities, and good public transportation links. The most right column shows the distribution of respondents on their preferred location. The preference of each attribute is divided by the preference of a location to estimate the value for the proximity to nature or to the city per zone district and explains the stated preference for these qualities (Skifter Andersen, 2011). These factors are used as a value per zone in each district in order to give it a score for proximity to nature and city.

Table 4.5: Average scores for proximity to nature and city (derived from Skifter Andersen (2011))

District type	Nature	City	Preferred location
City center	-28.1	60.4	17%
Urban districts	-22.9	42.5	5%
Suburbs	-2.6	12.9	26%
Rural areas	15.6	-33.4	52%

¹Related to unwanted social activities such as crimes.

4.4.3. Traffic volume

The network capacity is assumed to be designed to handle traffic at the busiest times, e.g. during the morning peak. An origin-destination (OD) matrix was not available, so OD data is composed from the traffic loads of the OTM model with the OmniTRANS system. OmniTRANS can allocate the traffic counts to the OTM zones to obtain an OD matrix. This is converted to the morning peak in order to match it to the current network capacity.

The OTM traffic is counted per 24 hours and has distinction in time-frames. A morning peak fraction is needed to convert the 24-hour-based model to a morning peak model. The national traffic model (NTM) OD file has trips in 10 time frames. The NTM, however, uses coarser zones; 265 NTM zones cover the same area as the OTM region of 860 zones. Small groups of OTM zones are assigned to the respective NTM zones in the OTM region in order to use the correct morning peak ratio per zone. Appendix B.3 describes the procedure to derive the data from commuter trips in the morning peak by combining the OTM traffic counts with the NTM OD matrix. The time frames for the morning peak are extracted and divided by the total trips to get a morning peak ratio. Multiplying this ratio per zone results in the traffic counts for all OTM OD pairs in the morning peak with a duration of two hours.

The provided OTM data makes no distinction in trip purposes. The commuter trips are derived from the total number of trips in the same way as the morning peak trips. The NTM data provides the trips for six types of purposes. The commuter trips are extracted and divided by the total trips over all purposes to get a ratio of commuter trips. This ratio is used as a multiplier to derive the distance and travel times for commuter trips in the morning peak. The ratio multiplied with the OTM morning peak results in an OTM commuter trip OD matrix.

Matrix estimation has its limits, but it suits short-term analysis and is very useful to set initial data up for further analysis. As the traffic counts from the road network are available, OmniTRANS is able to draw a matrix estimation on this system. The procedure in Appendix B.4 describes how to obtain the OD matrix for the OTM region from the traffic counts. An (uncongested) All-or-Nothing (AON) Assignment based on the links in the OTM network estimates an OD matrix where the total travel time experienced by all travelers is minimized, as shown in Equation 4.1.

$$\min_{q_a} Z = \sum_a t_a q_a \tag{4.1}$$

Subject to:

$$\sum_{s} q_a^s = q_a; \quad T_{ms} + \sum_{a \in M^-} q_a^s = \sum_{a \in M^+} q_a^s; \quad \forall m \neq s \quad Flow \text{ conservation}$$
(4.2)

$$q_a^s \ge 0$$
 Non-negatives (4.3)

Where: $q_a = Traffic flow on link a;$ $q_a^s = Traffic flow on link a with destination s;$ $t_a = Travel time on link a;$ $T_{ms} = Number of OD trips from node m to node s (where m is an origin);$ $M^- = Outgoing trips;$ $M^+ = Incoming trips.$

A skim matrix is retrieved in OmniTRANS to get the values of trip distance, travel times, traffic speed, and network capacity in Appendix B.5. The network capacity in the OmniTRANS model is found insufficiently detailed to draw viable conclusions. This is caused by the removal of a random number of traffic counts in order to allow OmniTRANS to estimate the OD matrix. Therefore, the network capacity in OmniTRANS is dismissed and the capacity as described in 4.4.4 is used. The traffic speed depends on the capacity saturation (V/C ratio). The nature of flow in Table 4.7 determines the network speed. Free flow and stable flow allow for the designed speed. A higher capacity saturation gradually decreases the speed to 95% of the designed speed at an unstable flow and to 70% or even 50% at a forced flow.

The incoming trips per zone are derived from the OD matrix by using the gravitational model. Appendix C gives the procedure and summary of the results when Excel's regression procedure is applied to estimate the incoming traffic volume for the OTM zones, which generates the constant α and the coefficient β in Equation 3.1. The R-squared of this analysis is 0.072, which is not a very strong fit. 7.2% of the variation in incoming commuter trips is explained by the independent variables adult population, jobs and travel time. The significance F is very close to zero, indicating that the results are statistically significant and thus reliable. The P-values are below 0.05 and indicate significance at both the estimated constant and the coefficient. Converting the natural logarithm back to Equation 3.1 results in an estimation of the constant $ln(\alpha) = -4.65$; thus $\alpha = e^{-4.65} = 9.54 \times 10^{-3}$ and the coefficient $\beta = -1.46$. The low R-squared is considered not to be a problem, as it based on a very large set of OD pairs and an adjustment is made to scale the estimated values to the observed values.

SD does not model the trips in realistic fashion. A trip leaves origin zone i and pops up in destination zone j, without passing through the zones located in between. This lowers the traffic volume, as through-traffic is not included. The difference between the outcome of the gravitational model and the observed initial trips varies widely in some cases. A multiplier for the number of zones that need to be crossed between origin and destination of a trip is applied to include through-traffic. The number of zones that need to be crossed is the average trip distance to a destination divided by the average length of a zone, as in Equation 4.4. The average length of a zone is the square root of the average zone surface. High traffic volumes are generally allocated to zones with highways or big crossings while low volumes are allocated to zones that are difficult to pass through. Zones in the city center are used by through traffic as well. This is caused by much smaller zone sizes in the city center, so a trip of only a couple of kilometers still crosses several zones before reaching its destination.

$$Z_j = \frac{\overline{D}_j}{\sqrt{\overline{S}_N}} \tag{4.4}$$

Where:

 Z_j = Number of zones to cross before reaching destination zone j;

 \overline{D}_{ij} = Weighted average trip distance from any origin to destination *j*;

 \overline{S}_N = Average zone surface of all N zones in between an OD pair.

4.4.4. Road surface and road capacity

The OTM main road network is shown in Figure 4.2b. The initial road transportation surface is calculated with the *Sum line length* tool in QGIS. This tool calculates the total sum of line lengths for each polygon (Zone) of a polygon vector layer (Road network). The length of the roads is multiplied with the respective number of lanes and the lane width per type of road. This data is processed in the procedure described in Appendix B.1. The zones that were not estimated according to the data processing procedure received the mean values of their respective district as shown in Table 4.6. The OTM is modeled on the level of regional roads. Low-density and low-speed roads are not taken into account and were thus not calculated into the amount of land used for roads. These types of roads are assumed to contribute very little to the noise in comparison with more important, regional roads. The allocated space for roads in the model thus only determines the amount of space needed to facilitate the regional and higher levels of transportation networks.

Table 4.6: Mean values road transportation network

Attribute	Value
Width (m)	6.8
Designed speed (km/h)	44.0
Observed speed (km/h)	40.3
Capacity (veh/h)	934.2

The initial road capacity is the average lane capacity per zone times the number of lanes entering a zone. The number of lanes per zone is not determined by the OTM value for number of lanes per road segment, because several road segments could be allocated to one zone and other zones receive no road segments at all. The model does not use a geographic representation of the road network, but a simplified structure of a detached system that is not connected to its geographically neighboring zones and roads. This system is illustrated in Figure 4.3, where the transparent lines represent the OTM network.

The initial number of lanes is estimated under the assumption that the current road capacity is sufficient. It is designed to facilitate the road capacity needed for the total of incoming traffic per zone in the base year 2015. This is calculated by the initial car traffic volume, divided by the lane capacity according to OTM data. Table 4.7 indicates that traffic conditions depend on traffic volume versus the network capacity. The traffic volume in the morning peak is assumed to flow through the network at a stable flow, approaching an unstable flow (Gajjar

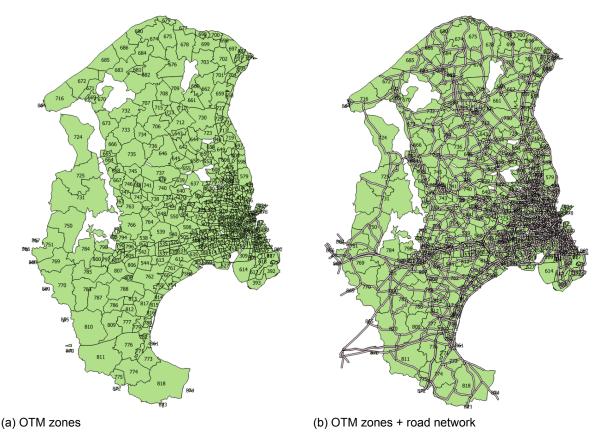


Figure 4.2: OTM zone system and main road network

& Mohandas, 2016). This is Level of Service D, where 70% of the road capacity is used. The road capacity is designed with a maximum capacity of 1/0.7 times the traffic volume in the morning peak. When the traffic volume exceeds the V/C ratio of 0.7, a signal to reduce congestion is sent to the land use sub-model, asking for more road space in certain areas.

Table 4.7: Level of Service	(Gajjar &	Mohandas,	2016)
-----------------------------	-----------	-----------	-------

Level of Service (LOS)	Volume/Capacity Ratio (V/C)	Level of Comfort	Nature of flow
А	< 0.30	Highest	Free Flow
В	0.30 - 0.50		Reasonably free flow
С	0.50 - 0.70		Stable flow
D	0.70 - 0.90	Threshold	Approaching unstable flow
Е	1.00		Unstable flow
F	>1.00	Lowest	Forced flow

4.4.5. Parking surface

The demand for parking spaces depends on the population and jobs in a zone, the idle time of a car and the number of cars per person. The initial number of cars per person is 0.37 based on averages of the city of Copenhagen, the suburbs and the rest of the GCA (Statistics Denmark, 2012). Parking spaces are, just as houses and jobs, designed with an initial overcapacity, so the current parking capacity is sufficient. The parking data is obtained from a shape file which maps the on-street parking locations and its capacity throughout Copen-

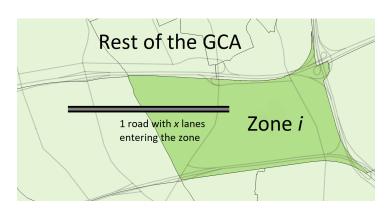


Figure 4.3: Representation of lane simplification (OTM Zone 388)

hagen, following the procedure described in Appendix B.2. The zone structure of the OTM model is placed behind the parking map in order to allocate the parking areas to specific zones. This is done by allocating the closest zone center to either one of the two ends of a parking strip. The parking places are allocated to the OTM zone closest to one of these points. This generates a list of all parking strips with their corresponding zones. Adding the parking capacities with the same zone number results in a matrix in which the parking capacity for each zone is calculated.

Several parking garages disrupt the distribution of parking capacity per zone. The municipality of Copenhagen provides a map of the city to visualize the locations of on-street parking and indoor parking areas (Danish Business Authority, 2018b). The location of 19 indoor parking areas is compared to the map with the zone structure of the OTM region with GIS software. The extra capacity of the indoor parking areas is manually added to the parking capacity of its respective zone.

4.4.6. Delays

The variables in Table 4.8 make the model more realistic by creating delays. One cannot assume that the demand and supply of buildings or infrastructure adapts immediately, so decision-making, preparation, and construction times need to be included. Aging buildings and infrastructure are not demolished to reallocate for other land use, but are renovated to be used for the same land use category. In times of renovation, it cannot be used for its respective purpose. The construction aging is different in the city center, as the historical buildings do not age in 80 years but have remained for centuries. For the time frame in this research, it is thus assumed that buildings in the city center do not need large-scale renovation work.

The delay functions return the value of the input, delayed by the delay time and a delay order. The delay order should be seen as a number of steps between input and output, thus smoothing the flow in higher order delays. First-order delays provide output immediately, which is the input value divided by the delay time; the yearly output with a delay time of ten years is thus one-tenth of the stock content. Higher-order delays are a sequence of first-order delays where the output is initially zero, builds to a maximum, and then decreases again.

Variable	Value	Comment
Construction aging	80 years	No aging in city center
Road aging	20 years	Short lifetime, quality needs to be guaranteed
Parking aging	50 years	Bad quality parking can mostly still be used
Construction time buildings	1.5 years	Time to construct buildings until use
Construction time roads	5 years	Time to construct roads until use
Construction time parking	0.5 year	Time to construct parking until use
Allocation delay	1 year	Time to decide on reallocation
Decommissioning delay buildings	1 year	Time needed to clear land from buildings
Decommissioning delay infrastructure	0.5 year	Time needed to clear land from infrastructure

Table 4.8: Delays

Infinite order, or fixed delays represent a pipeline where the input is shifted in time with the delay time and then gives the same value as an output (Sterman, 2000). In general, a third order delay is chosen to represent real world delays.

4.4.7. Scale factors

The scale factors in Table 4.9 are needed to specify relations between variables and are determined based on literature or case data. A sensitivity analysis explores the robustness of these scale factors and takes data insufficiencies or errors into account.

Variable	Value	Comment
Constants attractiveness to relocate	see Table 4.4	
Constant trip generation	$9.54 imes 10^{-3}$	Result regression analysis in Appendix C
Exponent travel time	-1.46	Result regression analysis in Appendix C
Car traffic management	10%	Increased efficiency of current infrastructure

4.5. Experimental factors AVs

The variables in this section are the result of the literature review in chapter 2. Table 4.10 gives the ranges of the uncertain variables assigned to AVs. The uncertainties that are not assigned to AVs are explained in section 4.6.

Table 4.10: Uncertain variables assigned to AVs	Table 4.10:	Uncertain	variables	assigned to AVs	
---	-------------	-----------	-----------	-----------------	--

Variable	Range	Comment
Penetration rate AV	0 - 100%	Dynamic over time
Efficiency of vehicle operation	0.7 - 1 PCU	0.95-1 at <40%; 0.8-0.95 at >40% AVs
Value of time in private AV	5.39 - 10.84 €/h	Depends on in-vehicle environment
Increased mobility per person	0 - 50%	0 - 10% of adults; 0 - 50% of teens and elderly
Idle time car	5.5 - 84%	Fraction of time, depends on new uses of cars
Parking density rate	100 - 160%	Fraction of change in parking capacity per m^2
Car-sharing rate	0 - 100%	Fraction of vehicles used for sharing

4.5.1. Penetration rate AVs

The penetration rate of AVs follows a curve over time and is modeled according to Nieuwenhuijsen et al. (2018), with input from other sources to vary possibilities. Where Nieuwenhuijsen et al. (2018) expects a market introduction of fully automated driving around 2040, the municipality of Copenhagen (2017a) and experts at the Automated Vehicles Symposium in 2014 expect a market introduction of full vehicle automation earlier, in 2030 (Underwood, 2014). The Danish Road Directorate & Wilke (2017) expects that by 2035 all vehicle sales in Denmark will be at level 3 or higher and that it will have a penetration rate of at least 80% in 2040 and 100% in 2055. All Danish traffic is expected to be self-driving at level 5 in 2065.

The diffusion of AVs is included in the model by varying the adoption curve of AVs in traffic, besides a scenario without any AVs at all. The year of introduction (2030 or 2035) and the slope of the curve in the first years (fast or slow adoption) are modified to sketch different adoption scenarios. The curves go through the points stated in specific years by literature as shown in Table 4.11 and are coded 0, 1, 2, 3, or 4. Table 4.11. The year of introduction is shifted as there is not enough trust to base it solely on the research of Nieuwenhuijsen et al. (Puylaert et al., 2018). The slope of the curve is adjusted, because Nieuwenhuijsen et al. estimates the percentage of AVs owned and not the percentage of trips made by AVs. The number of trips made by AVs is higher than its ownership rate because the VKT is much higher in the first years of a vehicle's lifespan (Litman, 2014).

Table 4.11: Different diffusion curves AV

Introduction	Adoption	2040	2050	2060	2070	
0	2030	Fast	30%	50%	60%	70%
1	2030	Slow	15%	30%	40%	50%
2	2035	Fast	15%	40%	55%	65%
3	2035	Slow	7.5%	22.5%	35%	45%
4	No AV					

4.5.2. Efficiency of vehicle operation

The upper bound of the PCU of AVs is set to 1 in the year of market penetration, as the first vehicles have the same behavior as manual drivers. Later, more developed variants could drive more efficiently, so the PCU gradually decreases to 0.95 with a penetration rate of 40% (Puylaert et al., 2018). Then cooperative driving starts to play a role and gradually decreases the PCU to 0.7 at 100% AVs (Atkins, 2016).

4.5.3. Value of time

As the commuting trips in the morning peak are modeled, the value of time of $\notin 5.39$ in an office environment by de Looff (2017) is determined to be a minimum value of time possible in an automated system. The value of time of $\notin 10.84$ in a leisure environment is the upper bound of the uncertainty in value of time, indicating that at least a small change is expected.

The values of time for public transportation and active modes are not used in this research as no detailed zone-based data was available for these modes. The modal split of these zones is thus less detailed and based on a generic modal split tool for the entire GCA (EPOMM, 2014).

4.5.4. Mobility for those unable to drive

The range for an increased mobility for those unable to drive is set to vary between 0% and 10% for the adult population and between 0% and 50% for the population of teens and elderly (Danish Road Directorate & Wilke, 2017; Wadud et al., 2016). Young children are not able to use a self-driving vehicle individually, as they are currently not allowed to perform other types of trips unaccompanied.

4.5.5. Parking demand

The idle time of a car is the result of new uses for cars. As the current idle time of a car in peak hours is around 84% (Alessandrini et al., 2015), the current usage rate of a vehicle is 16%. New uses and new users change the vehicle utility and inversely the idle time of the car. 100% shared vehicle scenarios could decrease the idle time drastically to only 5.5% (Rigole, 2014). The maximum increased parking efficiency of AVs is 60% (Heinrichs, 2016).

4.5.6. Shared AVs

All options for shared AVs are explored by using a range for a car-sharing rate from 0% to 100%. Shared AVs are characterized in scenarios with extreme values for car ownership, passengers per vehicle and idle time car in combination with slight increases in travel time.

4.6. Uncertainties not assigned to vehicle automation

Many uncertainties around the expected effects of self-driving technologies make it difficult to model this technology and to draw valid conclusions. The uncertainties and the experimental factors of AVs are modeled with an uncertainty analysis implemented in the EMA Workbench to explore its ability to influence the outcomes on KPIs. The Workbench sets the range for these variables and makes it run a high number of times to get insight in probable values. The uncertainties explained in this section, as listed in Table 4.12, are not assigned to effects of AVs and count for the entire case study area.

Variable	Default value	Range	Comment
Average time in house	20 years	5 - 40 years	Varying per age group
Migration to and from GCA	0.21%	0 - 0.42%	Migration rate 2018
Construction rate houses	3.9%	2 - 6%	Initial vacancy rate 2015
Construction rate jobs	1.5%	0 - 3%	Economic growth rate 2018

Table 4.12: Average values of global uncertainties

4.6.1. Average time in house

The average time in a house determines the fraction of relocating population. If the population spends on average 20 years in a house, 5% of the population leaves a zone each year. The average time in a house strongly depends on differences in the populations income and social mixture, and is thus uncertain in this case. The average time in a house differences between 5 and 40 years, covering the differences between young people, who stay in their house for a relatively short time, and older people who like to spend a longer period of time in their house. The average time in a house thus involve social differences in the population and is therefore the only social factor taken into account in the uncertainty analysis.

4.6.2. Migration to and from the Greater Copenhagen Area

The Greater Copenhagen Area is modeled as a closed system, which is not completely realistic, as migration to and from the area plays a big role in the numbers of the population in an area. Since no distinction is made in the populations income and social mixture, the migration is modeled in the uncertainty analysis based on the total population in the GCA. The migration for the base year is +0.21% (Index Mundi, 2018).

4.6.3. Construction rates

The initial construction rate for business places is set at the economic growth rate of 1.5% (Trading Economics, 2018) and the initial construction rate for houses is set at the initial vacancy rate of 3.9% (ERTRAC, 2017) in order to maintain some vacant places that are immediately ready for use. For suburbs and rural areas, the initial vacancy rate is set at 10%, which means that the model assumes there is more place available to allocate residents to suburbs or rural areas. This vacancy stays within the vacancy threshold for housing demolition.

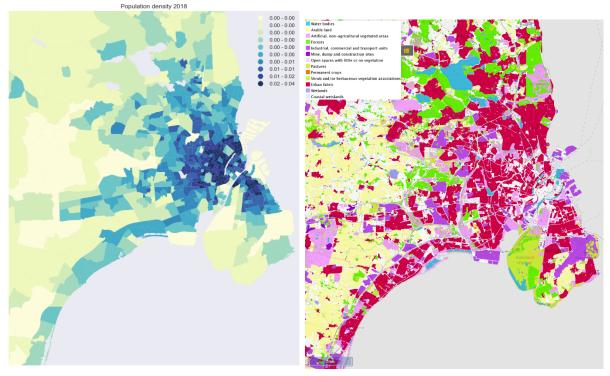
4.7. Model validation

4.7.1. Behavior reproduction

Complex estimations of the model are compared to trends in historical data, future predictions of other trusted research, and case-specific transportation and land use prospects. Behavior reproduction cannot guarantee that a model is correct or reliable. It is used to uncover flaws in the structure or parameters of the model and focuses on the places where the model does not fit the data. These discrepancies are the points of discussion for model revision.

The allocation of population of the case study area is subject to several complex equations. The sum of the population in all zones follows a smooth curve over time and is not influenced by the redistribution of population over the zones, regardless the level of detail in the model. The estimation of the population is considered valid as it is robust under complex equations for redistribution. The absolute number and growth rate, however, differ slightly from the population prospects by Danmarks Statistics (2018) and need to be improved by more detailed information about the population.

The map of population density estimated by the model is compared to the location of urban fabric by OSM (2018) in Figure 4.4. It can be seen that the dark red areas, indicating urban fabric, also have a high population density in the model of this research. This indicates that the model estimates the population density in the zones correctly.

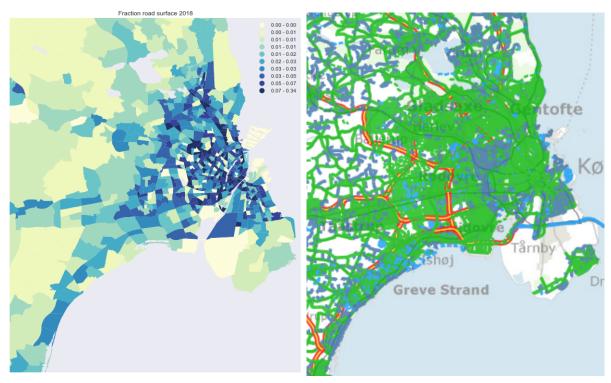


(a) Population density in 2018 by the modelFigure 4.4: Comparison population density and urban fabric

(b) Land cover 2018, urban fabric in red (OSM, 2018)

The estimation of the initial number of lanes and the fraction of road surface is validated by comparing it to the OTM network and maps of the GCA (Danish Business Authority, 2018b) in Figure 4.5; the zones with higher fractions of land use dedicated to roads received a higher number of lanes and are indeed located in the dense parts of the transportation network. The initial length of the road network calculated in this research is 2921 km. Danmarks Statistics (2017) calculated a length of 3019 km in the same region. This shows that the current road transportation network, the model's estimation of incoming traffic volume, and the resulting road surface match properly.

The OmniTRANS model's transportation characteristics are checked by comparing them to the demand estimate of an other transportation model for the Greater Copenhagen Area: OTM 6 (Fox, Bhanu, & Daly, 2013). The average trip distance of a car driver in OTM 6 is 26.2 km and for a car passenger 19.1 km, and on average 25.6 km in the OmniTRANS model. The observed fraction of commuter trips in OTM 6 was 51% and, in the SD model, an average of 58% was used. These estimated transportation characteristics are very similar to the observed variables in OTM 6, so the OmniTRANS estimations are also considered to be valid. More detailed transportation data could replace the OmniTRANS estimations, which improves the correlation of the SD model to real world data.



(a) Fraction road surface in 2018 by the modelFigure 4.5: Comparison fraction road and road network

(b) Road network (Danish Business Authority, 2018b)

4.7.2. Sensitivity analysis

Sensitivity analyses test the robustness of the conclusions. It was performed on a small-scale in the boundary adequacy and structure assessment tests. Sensitivity analysis to explore the robustness of the scale factors and delays was performed in Vensim. The ranges were set according to Table 4.8 and Table 4.9 and changed with -10% to +10% in a random uniform distribution. 200 simulations were performed with a Latin Hypercube Sampling. Each of the KPIs was assessed in the sensitivity analysis and the results are shown in Appendix F.

The attractiveness of a district is most sensitive to the use of scale factors. Sensitivity of attractiveness results in sensitivity in population per district type, but to a much smaller extent because the population also depends on the available houses. The accessibility to jobs is not at all sensitive to changes in scale factors of delays, because the impact of changes in scale factors influencing the accessibility is diminished by the use of exponential functions. The sensitivities on the average trip distance are small and remain constant after the equilibrium is found. The sensitivities in surface for road, parking, and other land use are very small because optimums are sought. This optimum is slightly different at changes in scale factors and delays. The sensitivities are strongest in rural areas, which is explained by a lower level of detail in calculations in these areas. Sensitivities are thus very small. Conclusions and recommendations of this research are focused on the city center, other urban districts, and the suburbs, so sensitivities in rural areas are not considered a problem.

4.7.3. Conclusion validation

The important concepts for addressing the problem are all endogenous to the model. The model structure is based on existing knowledge of the transportation and land use system and other comparable SD studies to make sure the model is consistent with the knowledge of the real system. The behavior and outcomes of the model were monitored and constantly checked for plausibility in each increment of model building. This prevented the final model from ending up with a giant set of errors and not much time had to be spent on debugging the model. The model debugger (Kwakkel, 2018) is used to trace model errors caused in runs controlled by the EMA Workbench. The sources used in the model provide comprehensive evidence that the model is built on a strong scientific foundation.

Unknown values for scale factors are estimated by statistical methods such as regression analysis. This explores many different options and is a good method to establish constants and coefficients for relations in the model. Sensitivity analysis tests the validity of these scale values and other uncertain input values. This shows that the sensitivities of the model are very small, which indicates that the model is stable and robust when it comes to estimating the results on all KPIs.

The model's behavior is similar to existing land use and transportation systems in the Greater Copenhagen Area. Comparisons of several maps and transportation characteristics conclude that the model has a good grasp on existing information. The model is generating symptoms of difficulty in order to motivate the study by using a simplified structure of the modal split. The model focuses only on different types of car transportation. Zone-based information on active modes and public transportation was inadequate to realistically include these modes and has to be taken into account in future research to improve the motivation of conclusions.

4.8. Experimental setup

The model is built in Vensim® DSS 7.1 for Windows (x32). The set up for the model has initial time for the simulation = 2015, final time for the simulation = 2070, frequency with which output is stored = 0.25 year, time step for the simulation = 0.03125 year, and the integration type = Euler. The final year of computation is 2070 to take the last expected change of AVs into account. Computing far beyond this point cannot include reliable data or system changes and will be based solely on assumptions.

The SD model and the map of Copenhagen are loaded in EMA Workbench version 1.1.3 to adjust input parameters, plot the results, and perform the scenario discovery. The scenario discovery uses the experimental factors of AVs from section 4.6 and global uncertainties from section 4.5, which adds up to twelve uncertainties in total. 5000 experiments are run in an Latin Hypercube Sampling (LHS) experimental design to provide an efficient sample of the system's behavior (Kwakkel, 2017). The frequency of output storage is changed to 0.5 year to decrease the runtime. A repository with the model, the source code, and all relevant data can be retrieved from GitHub: https://github.com/martijnlegene/Thesis.

4.9. Results of Key Performance Indicators

The results of each of the nine KPIs are explained in graphs with outcome space per district type and in plots on the map of Copenhagen. The effects over time are presented by pasting the maps of all years in videos in the digital Appendix on GitHub. The results clearly show a conversion time where the model is searching for an equilibrium. This is the warm-up period of the model. Input data starts the model in 2015 and it takes approximately 2 years to reach equilibrium state, which is generally close to the initial values of the KPIs. Some outcomes vary greatly, depending on the uncertainties influencing these KPIs. The graphs on the right side of the results indicate the density of experiments. Extreme cases are only shown in the graphs. The maps are based on average values of the experiments.

4.9.1. Attractiveness to live in a certain area

Attractiveness is a measure to describe the livability of areas. The attractiveness of zones is not explored in the uncertainty analysis and scenario discovery because restrictions were not applied to this variable.

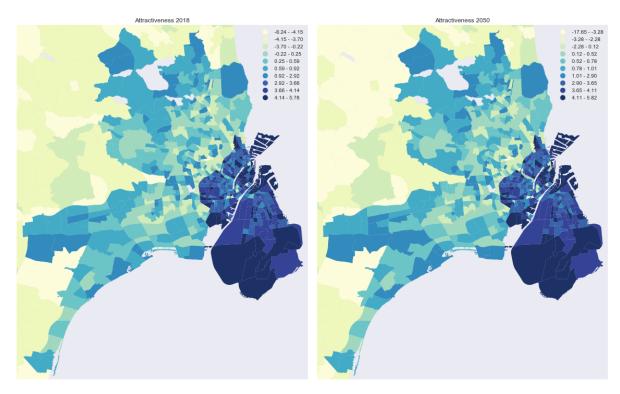


Figure 4.6: Maps attractiveness 2018(L) and 2050(R)

The attractiveness remains highest in the city center, followed by other urban districts, suburbs, and rural areas, as seen in Figure 4.6. Individual zones in the city center or in other urban districts with much other land have the highest attractiveness. This is caused by the initial ranking of attractiveness as explained in subsection 4.4.2. The results over time show that the attractiveness in the city center decreases slightly, but remains similar to its initial value in other urban districts and suburbs, and generally decreases in rural areas. The latter is shown by lighter colors in the rural areas and much lower values in the legend. These developments are caused by the influence of the fraction roads and the fraction of other land on the attractiveness. The fraction road increases in a large portion of the experiments in the city center, but it generally remains the same or decreases in other urban districts. The fraction of road decreases in the suburbs in all experiments. The fraction of other land could increase the most in the city center, followed by other urban districts and suburbs.

4.9.2. Population

The reallocation of population is initiated by the attractiveness of each zone. The graphs in Figure 4.7 show that in a high fraction of experiments, the population in the city center and other urban districts is increasing until a certain limit is reached. At this limit, the maximum possible number of houses is reached, the zone is considered full, and no more residents are accommodated. The population in these districts remains stable once the limit is reached, because they remain more attractive than the suburbs and rural areas. This indicates more urbanization. Lower attractiveness of suburbs and rural areas explains the depopulation in the first years. Suburbs and rural areas have more space for new houses, so an increase in the total population can only be accommodated in these areas after the other areas have become full.

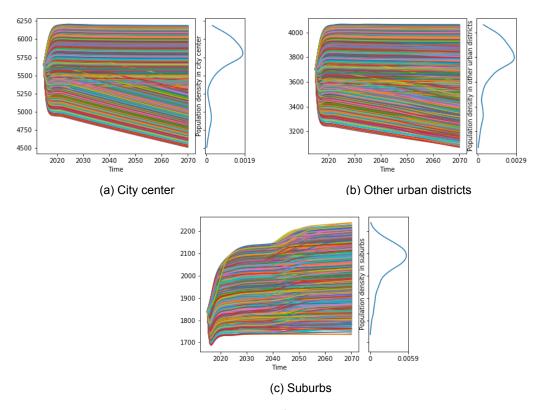


Figure 4.7: Uncertainties in population density (Person / km²)

Around 2040, some disruptions are shown in the population density in the suburbs. Figure 4.17 shows that from 2040 onwards, the fraction of road space is generally increasing in the city center and decreasing in suburbs, caused by the introduction of AVs. This increases the relative attractiveness of suburbs and thus causes a steeper population growth.

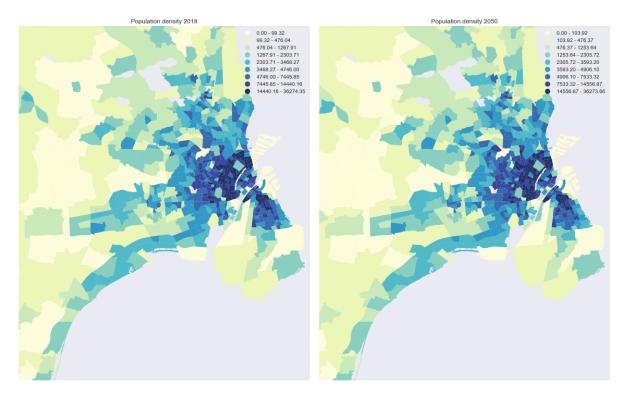


Figure 4.8: Maps population density (Person / km²) 2018(L) and 2050(R)

The maps show very little difference in population density. Only a small number of zones in the rural areas become darker. Not all attractive zones within the urban areas also have a high population density. This is caused by the location of the airport on the east of the map, or by zones primarily consisting of industry on the east, northeast, and south of the city.

4.9.3. Accessibility to jobs

Accessibility to jobs is measured in travel time, not in desired travel time. This gives an objective view of the performance of the transportation network and is not covered up by changes in value of time. The decreased accessibility to jobs is not necessarily problematic for individuals if the value of time decreases, but it will increase the traffic volume because vehicles spend more time on the network.

AVs are expected to influence the accessibility to jobs as seen in the graphs in Figure 4.9, in which the outcomes start varying after the introduction of AVs. Most cases indicate only very little changes. This generally consists of experiments without AVs or without extreme changes caused by AVs. A second peak in experiments shows large decreases in accessibility to jobs. This is caused by a high attractiveness of AVs, which results in more vehicles on the road and a higher capacity saturation. Higher capacity saturation has a negative influence on the traffic speed, which means that less jobs can be reached in the same amount of time.

The maps in Figure 4.10 show that the accessibility of suburbs and rural areas is not drastically changing. Some zones become slightly less accessible and other zones enjoy a higher accessibility in the future. The accessibility generally decreases in the city center and other

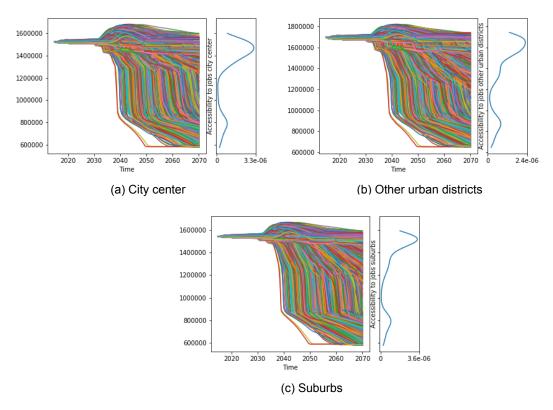


Figure 4.9: Uncertainties in accessibility to jobs (Jobs/hour)

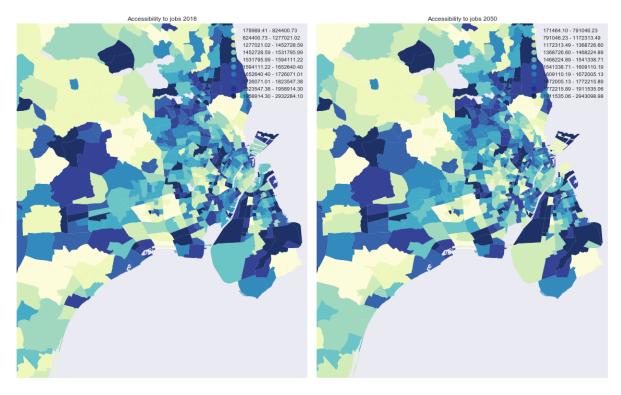


Figure 4.10: Maps accessibility to jobs (Jobs/hour) 2018(L) and 2050(R)

urban districts. The zones with the highest accessibility to jobs are areas with a high density of jobs, such as, for example, the area of the airport or industrial zones.

4.9.4. Average trip distance

Figure 4.11 shows that the distance that can be traveled within the acceptable time is increasing in all district types. The high fraction of runs on the bottom of the graphs indicates experiments without AVs. The distance that can be traveled within acceptable time does not change because the acceptable travel time does not change in cases without AVs. The influence of traffic speed on the distance is thus negligible in a system with only conventional vehicles.

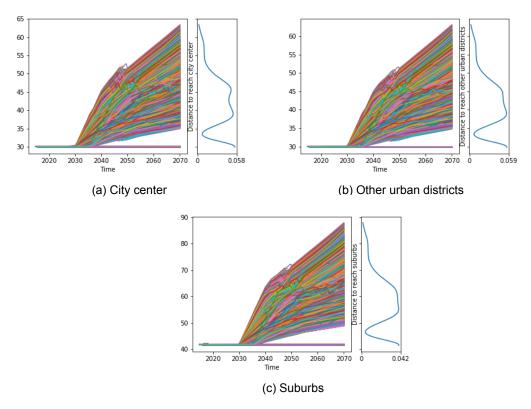


Figure 4.11: Uncertainties in distance to reach within acceptable travel time (Km)

The results do not show a smooth curve over time. Increased congestion results in shorter distances. Bumps in the output curves are caused by the mechanisms of demand and supply of the transportation network. This mechanism is explained in subsection 4.9.7 and leads to fluctuating performances of the transportation network. The decreased value of time compensates the increased congestion in all cases with AVs, which means that the distance that can be traveled within the acceptable travel time increases.

Figure 4.12 shows that some zones in the suburbs and rural areas have an extremely high distance to reach within their accessible travel time. These extreme values are caused by a very large initial acceptable travel time. The initial travel time is assumed to be the acceptable travel time. Zones with lower accessibility thus have a higher initial acceptable travel time. The rest of the city shows a general increase in travel distance within acceptable travel time.

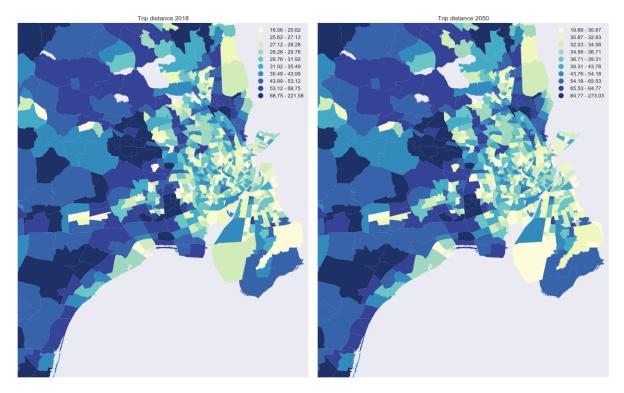
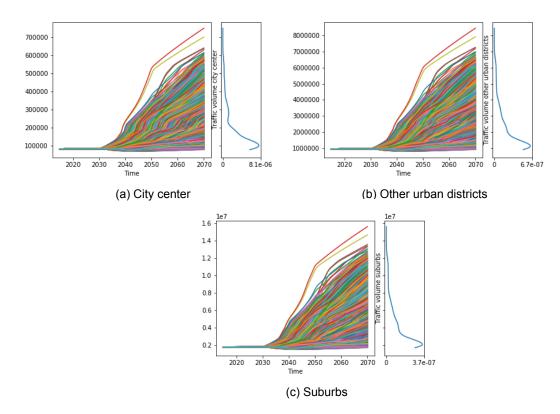


Figure 4.12: Maps distance within acceptable travel time (Km) 2018(L) and 2050(R)



4.9.5. Incoming traffic volume

Figure 4.13: Uncertainties in traffic volume

Incoming traffic volume increases due to increased trip attraction and reduced transportation friction. Trip attraction is enhanced by an increase in jobs and an increased population able to drive, transportation friction decreases by increasing the acceptable travel time. The graphs in Figure 4.13 show that the traffic volume increases in equal proportions in all district types. The high fraction of experiments on the bottom of the graph are the result of no AVs and an increase in the total population and the total number of jobs in the GCA.

The incoming traffic volume varies widely from the moment AVs are introduced. The experiments show runs with a decreased traffic volume, but also cases with extreme increases in traffic volume in all district types. Small decreases are caused by decreases in jobs or population, or by an increased transportation friction. A decrease in traffic volume generally includes experiments without AVs. Extreme increases in traffic volume are caused by a combination of lower values of time, an increased mobility for those unable to drive, more trip purposes, and little car-sharing. The traffic volume could increase up to seven times the initial value.

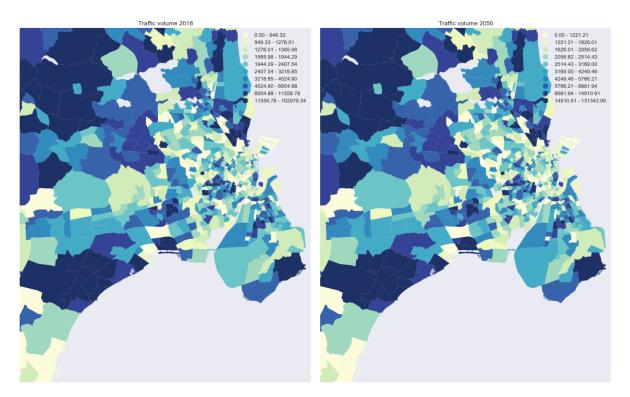


Figure 4.14: Maps traffic volume 2018(L) and 2050(R)

Figure 4.14 shows that zones in the rural areas and suburbs have the highest traffic volume. This is caused by highways surrounding the urban areas. The traffic volume increases equally for all regions and does not cause extreme differences over the region.

4.9.6. Congestion

Capacity saturation is a result of traffic volume over the network capacity. Figure 4.15 shows a slight increase in a system without AVs, caused by the trends in traffic volume. An in-

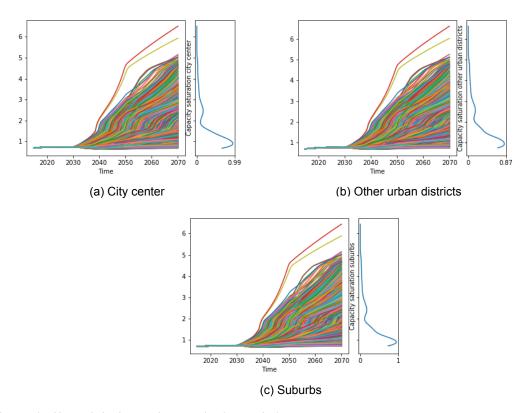


Figure 4.15: Uncertainties in capacity saturation (congestion)

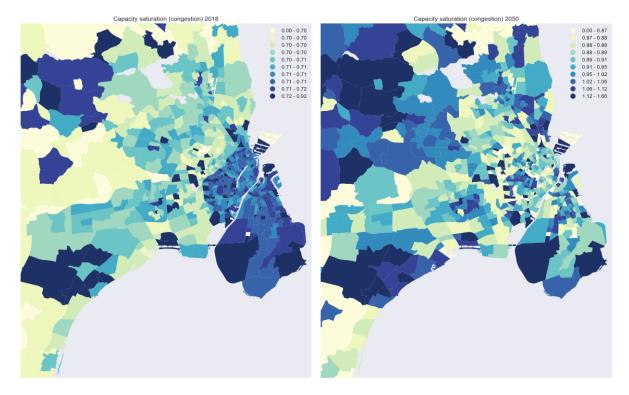


Figure 4.16: Maps capacity saturation (congestion) 2018(L) and 2050(R)

creased efficiency of vehicle operation could decrease the capacity saturation and allows for a higher number of vehicles on the same road network without the need for capacity expansion. In case the capacity saturation exceeds the congestion threshold, the road capacity is expanded to mitigate the undercapacity.

The undercapacity cannot always be mitigated in systems with AVs. The traffic volume could increase up to six times the road capacity. This will lead to many problems, as AVs are in no case expected to drive six times as efficient as conventional vehicles. There is not enough space available to build new roads to facilitate the extreme increases of traffic volume.

The maps in Figure 4.16 show that high capacity saturations in 2018 generally occur in dense urban areas and in some cases in the rural areas because of dense highways. The congestion seems to decrease in dense urban areas, but this is skewed by a changed legend. Capacity saturation increases in all areas and yields similar patterns as the traffic volume.

4.9.7. Road surface

The model is allowing for small increases in road surface each year. The land available for allocation for new road surface is mostly the result of a decrease in surface required for parking. If less road space is needed, road lanes are decommissioned and the land can be used for other purposes. The reason the road surface is stable in the first years is because no roads are decommissioned immediately. The surface is only reallocated if there is an overcapacity in several subsequent years.

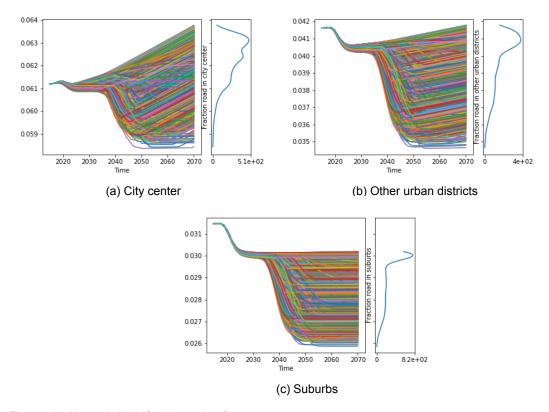


Figure 4.17: Uncertainties in fraction road surface

Figure 4.17 shows that the fraction of road in city centers is expected to increase, which means that there will be surface available to allocate to roads. This surface is the result of a stronger decrease in required parking space in city centers. The fraction of road in other urban districts is decreasing until AVs are introduced. Then the surface could either increase or decrease, depending on the usage of AVs. Most cases lead to a slight further increase in road surface, but this will not exceed the initial fraction of road surface in 2015. The fraction of road surface in suburbs has a very strong limit of approximately 3%. The limit is a result of the allocation priority of all types of land. There is always a demand for housing and business surface in suburbs, so the newly allocated land for roads is limited due to its lower priority. Fluctuations occur because of the alignment of demand and supply of road surface. If capacity saturation is too high, more roads need to be built and if capacity saturation is low, roads are decommissioned. This leads to construction or decommissioning.

The zones in the city center have a higher fraction of road surface, in decreasing order followed by other urban districts, suburbs, and rural areas. Zones in the dense urban areas are much smaller than in regions further outside the city. If less road space is needed, a small proportion of the total road surface in a zone is decommissioned. In larger zones, the absolute decrease in road space is thus larger if this space is not needed anymore. The combination of a high fraction of road surface in zones in the city center and relatively small absolute numbers of decrease make the proportion of decrease in road surface smaller in city centers.

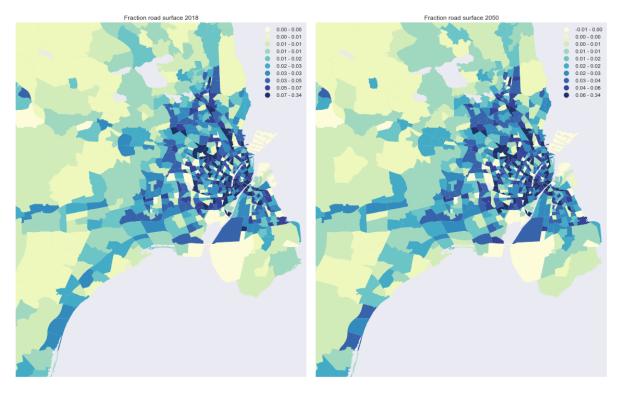


Figure 4.18: Maps fraction road surface 2018(L) and 2050(R)

The maps in Figure 4.18 clearly show resemblance with the Finger-plan and the population density. Due to the fact that allocation priorities prevent large increases in road surface, very little difference is shown between 2018 and 2050. The city center has little room for changes in land use and the other dense areas mostly need the available space to accommodate residents. Small changes can be found in suburbs and rural areas. The fraction of road space increases in some zones where a dense highway already exists and decreases in areas where there is more demand for residential or business surface.

4.9.8. Parking surface

The graphs in Figure 4.19 only show results for the city center and other urban districts. Parking facilities in suburbs and rural areas are included in the space that is used for residential or business purposes, because many residential areas already include parking space and business areas often have parking space available for their employees. Conclusions on changes in parking surface in these two districts cannot be solely based on the results of this research.

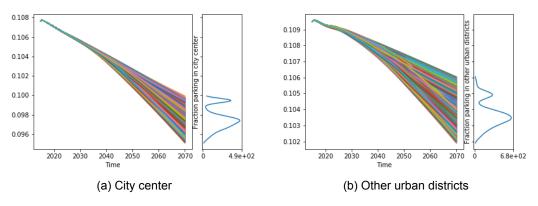


Figure 4.19: Uncertainties in fraction parking surface

The parking surface in the city center is decreasing in higher proportion than in other urban districts. The upper peak of the experiments in both district types is explained by the constant aging of parking surface. The lifetime of a parking space is set to 50 years, which means that 2% of the parking space have to be either renovated or demolished each year. If the need for new parking space is low and the allocation priority is lower than 2%, the parking surface will generally decrease. The lower peak indicates a demand for parking caused by an increased vehicle utility. This effect is enhanced by AVs.

Figure 4.20 shows that the fraction of parking surface per zone is in some cases slightly decreasing and otherwise remaining the same. Highest fractions of parking are found in the areas with high fractions of road surface. This is caused by the trend that parking strips are generally constructed along road lanes. Large parking garages disrupt this trend, but only in the city center or other urban areas.

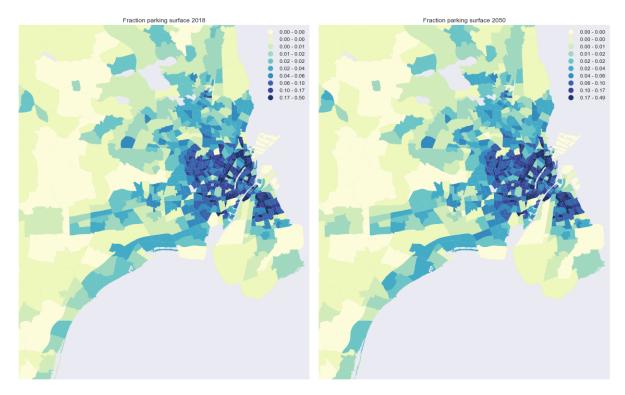


Figure 4.20: Maps fraction parking surface 2018(L) and 2050(R)

4.9.9. Other land surface

Other land can only increase, but its degree of increase differs per district type. Figure 4.21 shows that the increase in city centers is quite constant and proportionally larger compared to the other district types. This is caused by the decrease in surface needed for parking. The increase of other land in all districts has a slight bump until 2020. This bump is caused by the stable fraction of road during these years. Fractions of road are reallocated in the period from 2020 to 2025, leading to a stronger increase in other land surface in those years. After 2025, the decommissioning of roads decreases and only parking surface is decreasing at a constant rate. This causes the decreasing growth of other land surface between 2025 to 2040. A steep growth occurs from 2040 to 2050. Much road surface is reallocated, due to the introduction of AVs. A solid fraction of this land is reallocated to housing and business surface and if the need for road and parking spaces is low, much of the unallocated land becomes other land.

The fraction of other land in Figure 4.22 is the result of the location of residents, workplaces, roads, and parking spots. The fraction of other land is an inverse of locations with high proportions of any of the previous four categories. The city center and dense urban areas logically have less other land, followed by suburbs, and rural areas have the most other land. An outlier is the location of the airport, which has much other land allocated. The average size for a workplace per person is used to determine the amount of space allocated to business, which is incorrect at an airport.

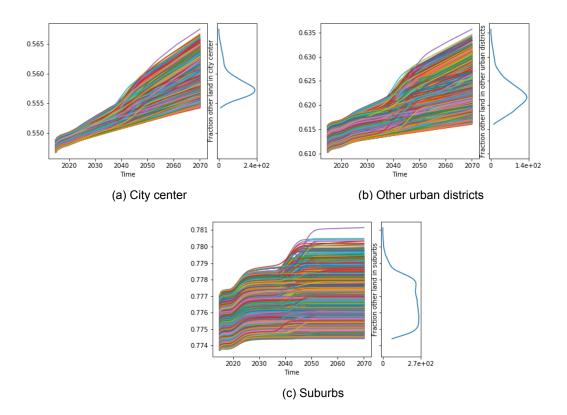


Figure 4.21: Uncertainties in fraction other land surface

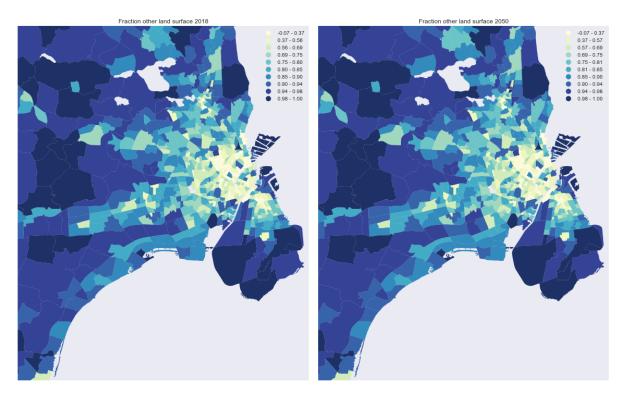


Figure 4.22: Maps fraction other land surface 2018(L) and 2050(R)

The increase in other land might be smaller than expected. This is mainly caused by the fact that city centers have very little space for reallocations and the effect of automated driving is smaller in less-dense areas that already have a high fraction of other land.

4.10. Conclusion accessibility analysis

The model is showing stable and consistent output and can be used to explore future directions of the implementation of AVs in urban areas. Several adjustments have been made to prepare the data in this research. This decreased the level of detail, especially since traffic data was simplified. The level of detail in conclusions can be enhanced by more detailed transportation data.

The zones in the city center, other urban districts, as well as suburbs in particular allow for conclusions on zone-level, because the level of detail on area surface is very high. The effects of AVs are explored for each individual zone. In the presentation of the results, it is chosen to aggregate the conclusions to different district types, in order to decrease the number of graphs required for the explanation. Differences in behavior in all zones are visualized on the maps. The results could be presented on a more detailed zone-level by zooming into the maps when such level of detail is desired.

AVs enhance the attractiveness of zones by improved accessibility and a possible decrease of road surface needed. These effects are higher in dense urban areas than in suburbs or rural areas. A higher attractiveness leads to more population in dense urban areas, indicating increased urbanization. At some point, dense urban areas reach their maximum capacity. Further population growth has to be accommodated in suburbs and rural areas.

The performance of the transportation network depends on the usage of AVs. Traffic volume could multiply by seven in extreme cases. The performance of each vehicle individually will thus improve by the introduction of AVs. The total transportation network could, however, perform worse.

The city does not change as much as expected. The maximum gains in space because of a decrease in road and parking surface are generally low. The most striking result is the possibility of extreme increases in traffic volume. Such an increase is obviously problematic and needs mitigating measures.

5

Scenario discovery

It is not yet possible to quantify the effects of automated driving in the current state of available data. Long-term planning regarding the impact of automated vehicles is currently impossible, but scenarios can be estimated quite well (Bouw, 2014). Scenarios are usually seen as input to explore the effects of an uncertain future. PRIM, however, uses a wide range of possibilities with AVs in an uncertain future to discover scenarios as a result.

5.1. Solution space boundaries

Existing knowledge from literature does not always match among different sources. Especially when discussing scenario discovery, the results vary widely. Scenarios are explored by varying the diffusion of automated driving, the way it can be used, and the way it could change the status quo of the transportation network.

In some studies, stakeholders can have well-defined preferences in order to distinguish the cases of interest. In this research, the difference between undesirable versus desirable situations is based on global research on urban areas and not on opinions of stakeholders in Copenhagen. The possible results for the case of Copenhagen are explored in section 4.9. Desirable and undesirable outcomes are sought within this solution space. The graphs with results per district type and the distribution of the experiments determine where to apply PRIM to explore scenarios.

Not all results are explored based on differences between desirable versus undesirable outcomes. The attractiveness is not explored, because restricting the attractiveness would be done with an objective to restrict the population in certain areas. Instead, the population density is explored and the maximum population to enter a zone could be restricted. Increases in the fraction of other land are explored by decreases in fractions of land needed for road and parking. Land use in suburbs is not restricted in order to keep as many possibilities open as possible.

5.2. PRIM on the restrictions of outcome of KPIs

PRIM is applied to the results of the population density, accessibility to jobs, acceptable travel distance, congestion, fraction of road surface, and fraction of parking surface. PRIM locates the restricted dimensions that have a significant influence on exceeding the specified preference threshold of each KPI. In some cases, all values are on one side of the initial value, indicating that this value is either increasing or decreasing independently of the values for uncertainties. A more detailed investigation is performed to not only find the direction of future possibilities, but also to point out the degree of changes. This gives insight into the strength of the influence specific uncertainties can have and points out focusing areas for future objectives.

The peeling and pasting trajectories in Appendix G graphically visualize the coverage, the density, and the number of restricted dimensions. The x-axis shows the number of boxes that could describe scenarios in the specified solution space. The peeling and pasting trajectory helps to find the scenarios with the highest combination of coverage and density, which improves the significance of conclusions. The restricted ranges become smaller when a higher box number is picked, but this decreases the significance of a scenario. The scenarios of restricted dimensions of uncertainties that significantly affect the outcome of KPIs are explained in this section.

5.2.1. Population density

If urban sprawl is undesirable, the population density in city centers and other urban districts should increase, hence more than the initial value is desired. The scenarios with an increased population in respectively the city center, other urban districts, and the suburbs are explored. For all three district types, the number of cases leading to a decrease is lower than the number of cases where the population density increases. This indicates that the population density in these three districts is likely to increase. This can be explained by an increase of the total population of the GCA and a decrease in population in rural areas. As indicated by the density curves in the graphs in Figure 4.7, decreased population occurs in too few experiments to make significant statements. In this case, the results of PRIM indicate how to attract more population to each of the respective district types.

The population density is not significantly influenced by the impact of AVs. Figure 5.1 shows that the average time in a house and the initial vacancy rate are the only significant influences on an increased population density. The value in brackets after the restricted range of uncertainties provides the statistical significance (p-value). The lines indicate which part of the uncertainty space is causing an increased population density. In this case, the uncertainty space for the average time in a house ranges between 5 years and 40 years and the initial vacancy rate in the city between 2% and 6%. Population increases in the city center and other urban districts are caused by time spend in a house of longer than 14.29 years and an initial vacancy rate over 2.2%. Population increases in suburbs are caused by an average time spend in a house longer than 8.42 years.

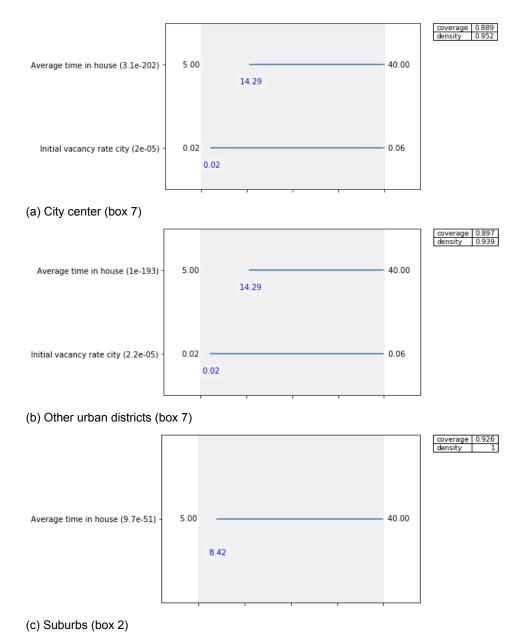


Figure 5.1: Scenarios population density

The average time in a house determines the pool of the moving population. An increase in population density in city centers and other urban districts is caused by the long period of time spend in a house, meaning the population moves around within the area each 14 to 40 years. The population density in the city center and in other urban districts are restricted by the exact same ranges of uncertainties, indicating the population is expected to behave the same in both district types. The threshold is lower for suburbs, because there is generally more available space in suburbs because there is more surface available to construct new houses on. This is also the reason that the initial vacancy rate is not restricting the population density in suburbs. If more population is moving each year, there is not enough space in the city center and other urban districts to move to, causing the population to settle in less attractive areas. The threshold of vacancy rate leading to a higher population density is

explained by the increasing attractiveness of city centers and other urban districts. A higher attractiveness leads to more population willing to move to these areas, but is constrained by the amount of available houses, which, in turn, is determined by the initial vacancy rate and the migrating population. The vacancy rate and the migrating population depend of the average time spend in a house.

5.2.2. Accessibility to jobs

The accessibility to jobs should increase in desired scenarios. Both an increase and a decrease of accessibility to jobs in the city center, other urban districts, and suburbs are investigated and shown in Figure 5.2 and Figure 5.3. Mitigating the causes of a decreased accessibility is essential for maintaining the current level of accessibility to jobs.



Figure 5.2: Scenarios increased accessibility to jobs

Increases in accessibility are related to less extreme changes in the value of time (over $\notin 8.05$ in the city center, $\notin 8.99$ in other urban districts, and $\notin 8.32$ in suburbs) in addition with a car-sharing population above 5%. The higher side of the value of time indicates that an AV increases the level of comfort, but to a limited extent.

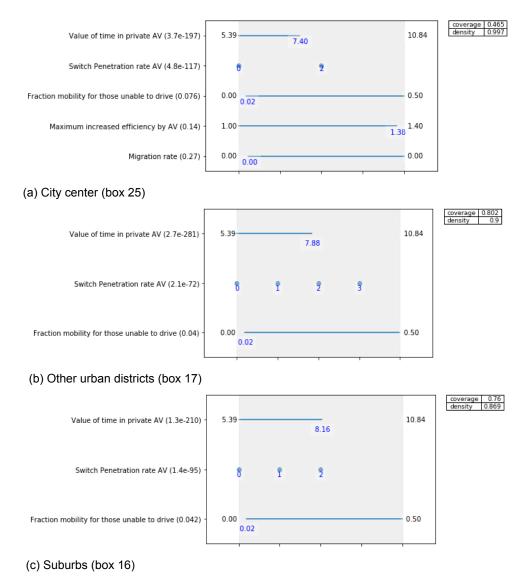
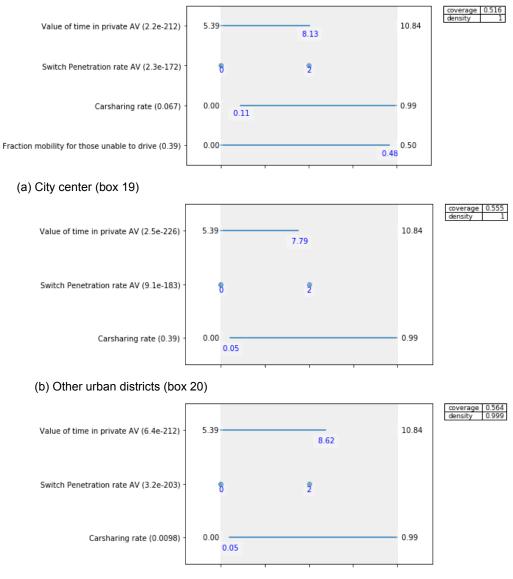


Figure 5.3: Scenarios decreased accessibility to jobs

A decrease of accessibility is caused by a low value of time in a private AV, which indicates a high attractiveness to use this vehicle. Scenarios with an early introduction or fast adaptation of AVs cause problematic scenarios in the city center and in suburbs. A high fraction of AVs results in stronger impact of this new technology. In other urban districts, all scenarios with AVs are problematic. A low value of time and an increase in mobility for those unable to drive result in longer commutes and more trips. Vehicles thus spend a longer period of time on the road or there are simply more vehicles, which increases the capacity saturation and the travel time. An increased travel time results in less jobs that can be reached within an hour, thus a decreased accessibility. A slight increase of the mobility per capita and an increase in attractiveness of AVs could thus result in a decreased accessibility.

5.2.3. Average trip distance

If the expenses people devote on traveling remain the same and the value of time becomes twice as low, the acceptable travel distance could, hypothetically, become twice as long. The acceptable travel distance is expected to increase in all cases with AVs. An increase in travel distance does not necessarily have a negative impact on travelers, as it could be compensated by the value of time. Increased travel distance is, however, putting more stress on the transportation network, because the vehicle kilometers increase. The causes for an increase in average trip distance of 50% are explored and shown in Figure 5.4.



(c) Suburbs (box 14)

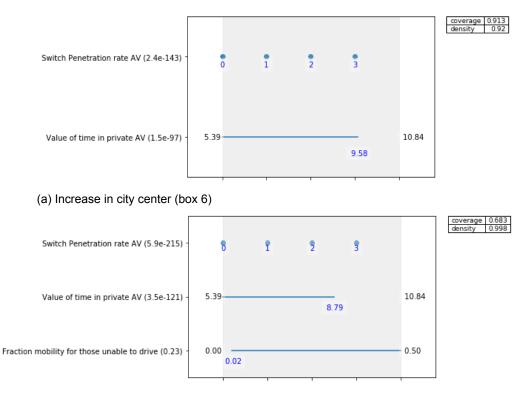
Figure 5.4: Scenarios acceptable commuting distance

Increases in travel distance are related to decreases in value of time, a higher car-sharing rate and systems with a fast adoption of AVs. A lower value of time leads to a longer but acceptable time in the car and a longer distance can thus be covered within that time. Car-sharing decreases the amount of vehicles on the road. A decreased number of vehicles on

the road decreases the capacity saturation, which increases speed. A higher speed indicates that a larger region can be accessed in the same amount of travel time.

5.2.4. Capacity saturation

Traffic performance should increase in desired scenarios. Capacity saturation is allowed to increase slightly, but it should not exceed 100%. In scenarios where the traffic volume is more than the road capacity, extreme congestion occurs, which makes it an unwanted scenario for city centers and other urban districts. The capacity saturation in city centers and urban districts increases if the road capacity is not extended. An increased capacity saturation does not necessarily cause problems, because AVs could space more efficiently and increase the road capacity without constructing more road surface. A capacity saturation of more than 100% is very problematic, which is explored in Figure 5.5. This indicates that the current road network is not sufficient, even if the AVs use the space more efficiently. In the city center, around 62% of the cases lead to a capacity saturation higher than one, and in other urban districts, this is almost 70% of the cases.



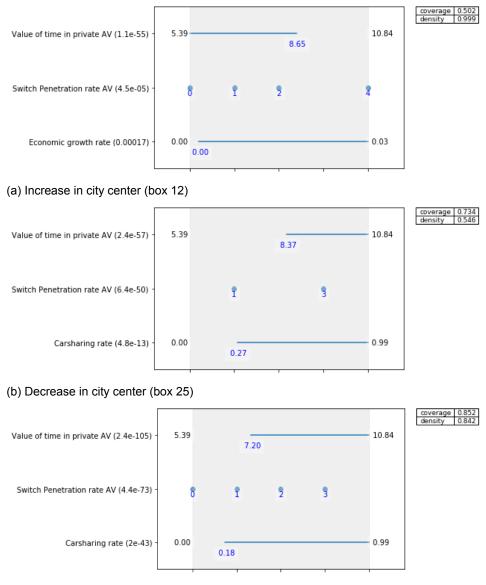
(b) Increase in other urban districts (box 11)

Figure 5.5: Scenarios capacity saturation

The increased capacity saturation occurs in all scenarios with AVs and is related to a low value of time. A value of time lower than $\notin 9.58$ leads to extreme congestion in the city center. Problematic congestion in other urban areas will occur at a value of time below $\notin 8.79$. Increased attractiveness of the vehicle could go hand-in-hand with an increased efficiency of vehicle operation. The increased efficiency is, however, not found in the PRIM analysis and is thus not compensating for the increased traffic volume.

5.2.5. Fraction road

The fractions for road and parking surface should decrease in desired future situations, to create surface that can be used for other purposes. The causes of impacts on the fraction of road space in city centers and other urban areas are shown in Figure 5.6. Scenarios asking for more road space in city center occur in about 90% of the cases. More road space is required if the value of time decreases below &8.65. This happens in scenarios with an early introduction of AVs or in scenarios with a fast adoption process. More road space is also needed in a scenario without any AVs at all. This is caused by the fact that the city center is already performing at its maximum capacity. A scenario with conventional cars and a slight increase in trip attraction will already result in problems on the current road network. The economic growth rate causes an increase in jobs, which, in turn, causes a higher trip attraction; thus more trips; thus more road space is required in order to facilitate these trips.



(c) Decrease to 4% in other urban districts (box 13)

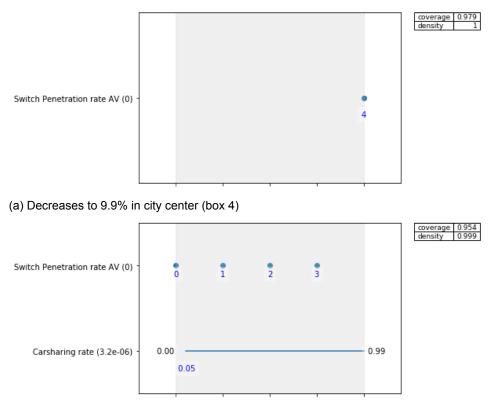
Figure 5.6: Scenarios fraction road surface

Scenarios with a slow adoption of AVs and a value of time above €8.37 result in a decreased need for road space in the city center. Additionally, at least 27% of the population should share their car. The already dense core of cities is expected to face many problems in cases with increased traffic volume. The scenarios leading to a decrease in required road space indicate that positive impacts of AVs are possible if the AV does not become too attractive for private or empty trips and car-sharing is promoted.

All cases indicate a lower fraction of road needed in other urban districts. This means that the uncertain ranges have no restrictions regarding a decrease in the road space whatsoever. The current road surface in city centers is 4.16%. PRIM analyses the causes resulting in a decrease to 4% of the total areas surface needed for roads, which is a decrease of 4% of the current road space. This decrease is possible if the value of time will not go below \notin 7.20 and if at least 18% of the population is sharing their car in any scenario with AVs. Further decreases are possible, but need a higher value of time and an increase in car-sharing.

5.2.6. Fraction parking

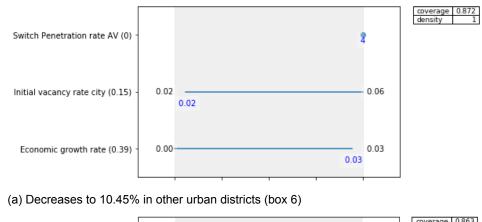
Figure 5.7 and Figure 5.8 show a very clear distinction in scenarios with only conventional cars and scenarios with AVs. Scenarios without AVs lead to a slight decrease in required parking space. This is caused by the mechanisms in the model, where the parking spaces are decaying over time and have a low allocation priority for new surface. Stronger decreases of parking surface needed are only caused in scenarios with AVs.

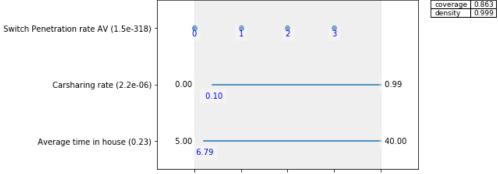


(b) Decreases to values lower than 9.9% in city center (box 3)

Figure 5.7: Scenarios fraction parking surface city center

The fraction of land used for parking in city centers is expected to decrease from 10.8% to a fraction between 10% and 9.9% in scenarios without AVs. The fraction of land could decrease further than 9.9% in cases with AVs if a minimum of 5% of the population is sharing their car. This means that the impact of AVs cause at least a possible reduction of 8.3% of the land used for parking in city centers. A higher penetration rate of AVs, a further increase in car-sharing, an increased parking density rate per vehicle, and a limitation of new uses for cars could decrease the fraction of land needed for parking even further.





(b) Decreases to values lower than 10.45% in other urban districts (box 5)

Figure 5.8: Scenarios fraction parking surface other urban districts

The fraction of land used for parking in other urban districts is expected to decrease from 11.0% to a value between 10.6% and 10.45% in scenarios without AVs. Scenarios with AVs could result in a fraction of land needed for parking below 10.45% if at least 10% of the population is car-sharing. This indicates that AVs cause a decrease in the land used for parking in other urban districts of at least $5\%^{1}$.

5.3. Conclusion scenario discovery

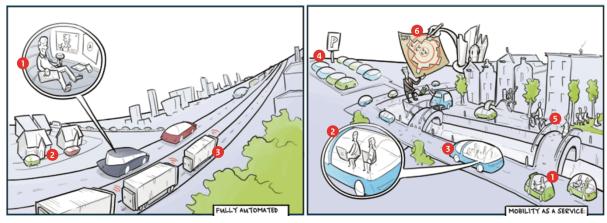
This chapter gives insight in many different scenarios based on different adoptions and different uses of AVs in combination with some uncertain global variables. The uncertainties for the penetration rate of AVs, value of time, and car-sharing are atop most of the lists of restricted areas causing a difference between desired and undesired futures. The danger of the AV becoming too attractive could result in very extreme increases in traffic volume be-

 $^{^{1}10.45/11 = 0.95}$, thus a decrease of 5%.

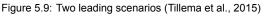
cause of more trip purposes, a higher mobility of the population, and longer trips. This effect could be compensated by increased car-sharing.

Besides changes in accessibility, the spatial organization of cities could change in terms of land allocated for road and parking. At least 4% of the current road space could be decommissioned and used for other purposes in other urban districts. At least 8.3% of the land currently used for parking space in city centers and 5% in other urban districts can be taken back and used for other purposes.

The leading scenarios that give insight in either desired or undesired scenarios of AVs vary in the value of time in an AV and in the car-sharing rate. This could be translated into increasing the comfort of a passenger individually, as shown in Figure 5.9a versus improving the efficiency of the entire transportation system, as shown in Figure 5.9b.



(a) Fully automated private luxury



- 1. No need for manual controlling measures
- 2. Cars spend their idle time in front of your door
- 3. Platoons of freight transport

(b) Mobility as a service

- 1. Door-to-door trips
- 2. Ride sharing economy
- 3. Traditional public transport mostly replaced
- 4. Vehicles park themselves out of town
- 5. Biking and walking are popular
- 6. Increased price per km transport

A value of time over $\notin 8.05$ in the city center, $\notin 8.99$ in other urban districts, and $\notin 9.03$ in suburbs increase accessibility. Values of time lower than $\notin 7.40$, $\notin 7.88$, and $\notin 8.16$ decrease accessibility in these respective districts. Additionally, an increase in accessibility needs at least 5% of car-sharing. Congestion increases in city centers at a value of time below $\notin 9.58$ and in other urban districts at a value of time below $\notin 8.79$. The fraction of road surface increases in city centers at a value of time below $\notin 8.65$. It decreases at a value of time over $\notin 8.37$ in combination with at least 27% of car-sharing. 4% decrease of road surface in other urban districts is possible at a value of time not lower than $\notin 7.20$ in combination with 18% of car-sharing. Large differences are thus expected in the ranges for value of time between $\notin 7.20$ and $\notin 9.58$. A car-sharing ratio of 5% could compensate many of the unwanted effects of AVs. The carsharing ratio should be at least 27% in city centers and 18% in other urban districts to compensate for the unwanted effects caused by AVs and to facilitate a decrease in required road and parking space.

6

Policy recommendations

The best parameters for policies are found by optimization methods. In this case, that method is the Patient Rule Induction Method. Scenario discovery reveals insight into the causes of two types of futures: one where the use of the private car becomes too attractive, which leads to extreme congestion and a greater need for road space; and one indicating a shared system enhanced by AV technologies. The most effective steering measures should focus on the variables that proved to be key in the scenario discovery.

The transition to automated driving is a process that will require continuous adaptation. It is one in which governments will continue to have significant authority. The role of the government is to steer the mobility system, allow innovation to flourish, and simultaneously ensure enhancement of public value (Docherty, Marsden, & Anable, 2017). Policy makers should focus less on the development of the technology and more on measures that promote the application of automation in reference to socially desirable objectives (Wadud et al., 2016). This way, they are able to mitigate possible negative outcomes from vehicle automation, while encouraging its benefits in an early stage. In a city like Copenhagen, many opportunities for smart mobility solutions arise, as the cities perspective on new, green, and more efficient manners are privileged. Mobility solutions are not only focused on improving (road) transportation, but also on improving livability as a whole. By including failures of policies in the scenarios, the policy makers are given a sense of impact when behavior is not as they expect. Possible policy measures and their establishment according to PRIM are explained in this chapter.

6.1. Possible policy measures implemented in the model

Possible policy interventions are included while building the model and testing for reliable parameters. The following variables are used as mitigation measures that can be taken by the municipality of Copenhagen. These measures and their respective range of realistic values are shown in Table 6.1 and can be used to steer a future with AVs towards a desired situation.

Variable	Range	Comment
Allocation priority residential	0 - 58.9%	Maximum fraction residential
Allocation priority business	0 - 89.6%	Maximum fraction business
Allocation priority road	0 - 10%	Maximum fraction road space
Allocation priority parking	0 - 10%	Maximum fraction parking space
Allocation priority other	0 - 100%	Fraction of unallocated land
Building demolition threshold	5 - 15%	Demolish houses until vacancy threshold
Building demolition delay	1 - 10 years	Demolish after x years of vacancy
New lane construction	0.1 - 0.4 lane	Construct 1 lane if there is x shortage
Lane decommissioning threshold	1.1 - 1.3 lane	Demolish one lane when there is x excess
Lane decommissioning delay	1 - 10 years	Demolish after x years of unused lanes
Parking decommissioning threshold	5 - 15%	Demolish parking until threshold is reached
Parking decommissioning delay	1 - 3 years	Demolish after x years of unused parking

Table 6.1: Policy measures

6.1.1. Allocation priority per land use category

New land is awarded according to the allocation priority per type of land. This priority depends on the demand for each type of land, but can be steered by policy makers. Adjustments to the allocation priorities are modeled based on the maximum fraction of each land use category in each district type. These values are calculated according to the zone with the highest ratio of surface used in a district. The maximum fractions for residential and business are found in Table 6.2 and the limits for infrastructure is 10% of the zone's surface. The allocation of other land is unrestricted in order to get insight in the amount of space that becomes available and to ensure no land is allocated to a category that does not need more surface.

District type	Max. fraction residential	Reference zone residential	Max. fraction business	Reference zone business
City center	23.3%	35, Christianshavn	64.9%	35, Christianshavn
Other urban	58.9%	99, Nørrebro	89.6%	353, Frederiksberg
Suburbs	47.1%	244, Vestegnen	70.0%	553, Northern Suburbs
Rural areas	37.0%	694, Northern Zealand	65.6%	802, Eastern Zealand

Table 6.2: Maximum steering factors in the zone districts

The composition of land use could be changed by zone- or district-specific policies. Copenhagen can, for example, attract or repel population to or from zones by changing the attractiveness in specific zones or districts. Drastic changes are not always possible. City centers mostly follow very strict building policies where historic buildings and parks have to be maintained. In industrial or high-density urban areas and rural areas, it is considered possible to construct new buildings or create more open space. Increasing the building density allows for more houses or workplaces on the same surface. If the land use composition remains the same, building density and creation of more open space is possible if the demand allows to do so. This contributes to the attractiveness of zones, as it realizes more space for bigger residential lots or other types of land use.

6.1.2. Building demolition

A large amount of empty buildings in a zone is considered unattractive. If zones become largely vacant, the municipality can decide to either increase the attractiveness of a zone, trying to attract residents, or demolish the overcapacity of buildings. Attractiveness could be increased by reducing the space needed for infrastructure and rebuilding it into land that is considered attractive, as extensions of leisure areas, parks, or backyards. A vacancy rate is needed in order to facilitate migrating population as quickly as possible, without the need for constructing new houses immediately. The initial vacancy rate of 3.9% (Newsec, 2016) is maintained in the construction of new houses. A maximum value for empty houses in a zone is 10% of the total houses in a zone. If the fraction of empty houses exceeds this limit, houses are demolished until this threshold is satisfied. A delay time of five years is added to make sure no immediate demolition is triggered in case of sudden time-specific events, but to ensure that buildings will only be demolished after a vacancy of five years. As noted before, this is not possible in the city center where buildings will not be demolished.

6.1.3. New lane construction

In the event that the difference between the traffic volume and the road capacity is too great, new road surface is needed to facilitate the transportation demand according to the pressure in order to reduce congestion. An under-capacity-threshold is used for constructing an entire new lane in a zone. This means that if the number of lanes needed to facilitate road capacity, minus the current lanes available but including the lanes under construction, is larger than the threshold value for new lane construction, a new lane is constructed. This threshold ranges between 0.1 and 0.4 lanes shortage in order to manage the traffic more actively when the current capacity is insufficient. Roadworks are included in an additional expansion of the current road capacity by 10% to increase the efficiency of the current road surface. Parts of the current infrastructure cannot be used in times of roadworks.

6.1.4. Lane decommissioning

Opposed to the threshold value for new lane construction, lanes are decommissioned when proved that not all road capacity is needed. When 1.2 lanes are not needed anymore, one lane will be removed. A delay of five years is added to make sure no lanes are removed too soon in case a time-specific event that causes a sudden decrease in the demand for road transport surface. This means that a lane will only be removed when it is out of commission for at least five years.

6.1.5. Parking decommissioning

The number of parking spaces is divided by a delayed parking demand. Parking spaces are decommissioned if this value exceeds a certain threshold. This threshold is set to 10% of the current parking spaces and the delay time is two years. This means that after two years of more than 10% overcapacity, parking places are demolished. The delay time for parking spaces is shorter than for buildings and roads, as parking spaces are relatively easy to construct and to reallocate, which allows for better responses to its actual demand and supply. Examples are empty lots that can temporarily be used to take in extra parking spaces.

6.2. Policy measures in next model iterations

The model's current policy measures are only relevant for car transportation and land use aspects of the system. Policies influencing social aspects, other modes of transportation, or parking are not included. Including more types of policy measures is advised in future research. This section explains mitigation measures that are easy to implement if the required data is available in future iterations of this model.

Insight in the city's prospected goals regarding transportation and land use provides information about developments that can be included into the next iterations of the model. Policies dealing with public transportation are needed to compare the attractiveness of traveling by car to other modes and to explore the possibilities of connecting AVs to public transportation. Additional restrictive policies about limitations for the amount of driving per household, or about limitations for certain uses of AVs, could be implemented and tested whether that would have a significant impact in order to reduce the congestion problems. Zone-specific policies could be implemented in their prospected year of commissioning.

If zones are able to communicate with each other, they can exchange data regarding parking demand and supply. High-density city centers, shopping zones, or business districts need space-saving parking solutions. Cheap parking hubs just outside these areas are a great solution to satisfy the parking demand and reduce the parking surface in attractive areas. These parking hubs would increase the time spend looking for a parking spot, but it could reduce the parking costs. AVs would not have problems with an increased time spend looking for a parking spot. Automated driving thus enhances solutions with parking hubs out of attractive areas. A negative effect is an increase in traffic volume due to empty vehicles looking for a parking spot.

6.3. Policy measures compared to the outcomes of PRIM

The outcomes of the scenario discovery by PRIM conclude that mitigating unwanted future scenarios caused by AVs should focus on increasing car-sharing and decreasing the relative attractiveness of AVs. These mitigations can be made with adjustments to a social perspective or with adjustments regarding public transportation. Adjustments as described in section 6.1 could only mitigate the problems caused by too much vehicles on the road, but will not tackle the problem from the source. A higher allocation priority for road space decreases the congestion problems. This will, however, lead to higher fractions of road surface, decreasing the attractiveness of an area.

Car-sharing should be promoted when trying to reach the threshold that could mitigate the increased number and distance of trips caused by AVs. Car-sharing with conventional vehicles makes the population already aware of the benefits now. Increasing car-sharing does not need to wait for AVs to be introduced. An increased car-sharing rate could not only compensate the increased number of vehicles, it would have an additional impact on the value of time because sharing a car is not as attractive as driving privately.

The attractiveness of using the car versus the attractiveness of using other modes could be decreased by either decreasing the attractiveness of a car, or by increasing the attractiveness of the other modes. Limiting the comfort and utility of a car, or road use charges, reduces the attractiveness of using the car. Increasing the attractiveness of other modes could be done by lowering costs or increasing comfort when using these modes. AVs could enhance the use of public transportation by providing access and egress to public transit stations. This would make the AV a part of the public transportation network.

An expectation of policy measures is made based on plots with a variation in value of time in AVs and in car-sharing rates. Experiments are categorized with a value of time below $\notin 7.20$ versus over $\notin 9.58$ and with car-sharing rates below 5% versus over 27%. Figure 6.1 points out the differences in results among experiments with input values below or over the thresholds found with PRIM. A low value of time is causing the highest fractions of road surface, even in combinations with a high car-sharing. This indicates that 27% car-sharing rates do not result to desired scenarios in any of the experiments. This indicates that the ranges found with PRIM are adequate and are indeed the most important focusing points when developing mitigating measures against undesired scenarios caused by vehicle automation.

0.042

0.041

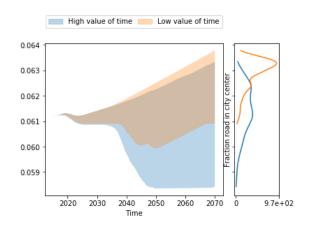
0.040

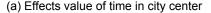
0.039

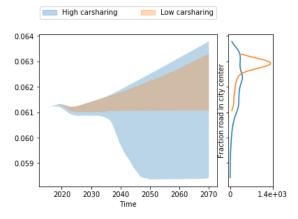
0.038

0.036

0.035





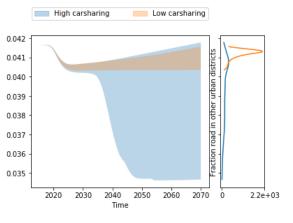


2020 2030 2040 2050 2060 2070 0 7.9e+02 Time

Fraction road in other urban districts

(b) Effects value of time in other urban districts

High value of time Low value of time



(c) Effects car-sharing in city center

(d) Effects car-sharing in other urban districts

Figure 6.1: Fraction road surface with different values of time and car-sharing ratios

6.4. Policy recommendations for the Greater Copenhagen Area

Copenhagen's strongest long-term instrumentality is the possibility to strive for an early introduction year by promoting research and development of automated driving technologies and by informing the public about its impacts. By facilitating a smooth transition, they can influence the impact of automated driving.

The current plans and the results of this research should be discussed with the policy makers in Copenhagen to see what aspects of the current system they can influence and what aspects they wish to influence. This will lead to possible changes in the current plans and realistic advice based on the model's outcome and the possibilities for change in the current system. The city should embrace exploratory research like this thesis and participate in pilot projects with self-driving vehicles if funds are available for this purpose (municipality of Copenhagen, 2017a).

The municipality is currently seeking partnerships in attempts to obtain knowledge and experience about opportunities and barriers for self-driving vehicles. They like to steer towards green, shared, electric vehicles and wants to know how this interacts in public transportation systems (municipality of Copenhagen, 2017a). The advantage of partnerships in this regard is that when innovative work is to be done and new products and services are created, the parties' resources are better utilized and new joint knowledge is created. The role of the municipality needs to be proactive to ensure their influence on how the pilots are planned, performed, and followed up. Public authorities have the responsibility of adapting infrastructure and making it suitable for the development and testing of self-driving vehicles.

The requirement that pilots and results should support the current composition of traffic between pedestrians, cyclists, public transportation, and motorists (municipality of Copenhagen, 2017c) indicates that Copenhagen is expecting the AV to adapt to the status quo. This is an awkward approach to exploring uncertain futures, whereas a municipality might not have the ability to influence the development of a new transportation technology. Cities should be open for radical changes caused by AVs, because AVs could diminish the current problems caused by the conventional cars and enhance an integration between private and public transportation. If radical changes in mobility patterns are explored, new opportunities open up to steer a future with automated driving towards their objective goals: one where the AV enhances sustainable transportation and maintains the attractiveness of a city.

Copenhagen has an image as the city of innovation and should be the driving force behind green development, including driver-less cars and buses. The city has succeeded in being a role model as a cycling city (municipality of Copenhagen, 2017b), and now it can repeat that success and become a leader as a smart city with sustainable, intelligent traffic systems.

Conclusion and recommendations

This chapter concludes the study and answers the research question: to what extent could automated vehicles transform the way cities are spatially organized and how can cities start preparing for this transformation? Each section answers one of the research questions and provides recommendations for further research.

7.1. Overall conclusion

From a transportation perspective, immense problems could be caused by AVs; the traffic volume and the stress on the transportation network could undergo extreme increases. From a land use perspective, the city's outline does not change as much as many expect. Early consideration for the effects of vehicle automation is critical in the development of such innovations. To leverage the full potential of AVs, it is important that possible hazards of this technology are explored. This allows for the mitigation of unwanted effects before AVs are introduced into society.

The introduction of AVs will most likely not solve the problems of clogging cities itself; it could even decrease the performance of current mobility systems. Analysis of possible hazards and exploring the key issues that are encouraging desirable outcomes helps to identify mitigation measures that are needed to leverage the full potential of AVs.

Two scenarios are the result of this thesis: one where cars become so attractive, so much easier to use, and more readily available for a broader public and for multiple purposes, that more vehicles are bought and used, which results in more vehicles on the road, longer trips, and increased urban sprawl. Problems with scarcities in urban areas will grow as the need for road surface increases.

The second scenario describes a shared system enhanced by automated driving technologies. The utilization of vehicles increases, which decreases their idle time and their need for parking. A lower number of vehicles is needed to facilitate the transportation demands, leading to decreases of required road surface. A shared system helps to clear space from parking and road infrastructure and makes the city more attractive. The freed land can be used for other purposes.

AVs could be key to a more sustainable transportation system, but without corrective measures it could lead to overwhelming congestion problems. Low acceptance of sharing vehicles and AVs becoming too attractive are the main causes of most future problems. The introduction of AVs enhances urban sprawl in systems without mitigating measures. In the right development, AVs make city centers and other urban districts more attractive by a reduced need for road and parking surface.

Increasing the acceptance of shared systems will reduce the need for a high number of vehicles in the future, increasing the attractiveness of urban areas and creating a more sustainable transportation system. This research shows that when 27% car-sharing is feasible in the city center and 18% in other urban districts, the future of AVs will lead to increased accessibility and a decreased need for road and parking space.

Relatively little and simple data was needed to come up with the results of this research. This information can easily be provided by stakeholders and policy makers and could be transformed into the desirable format based on the data preparations as described in this research. The method used in this research takes a great step towards a new tool to explore the impacts of new vehicle technologies.

7.2. Transportation and spatial impacts of AVs in literature

A review of literature has shown that automated vehicles are expected to enter the transportation system between 2030 and 2045. For Copenhagen, this transition is expected to take place between as early as 2030 and 2035. An individual AV should have a positive effect on the road capacity because it can space itself more efficiently. All AVs together could greatly increase traffic volume due to an increased mobility for the population that is currently unable to drive, increased trip purposes, and because of a lower value of time longer travel times. This could diminish the positive effects of AVs and results in an increase in total vehicle kilometers and also increases the stress on the road network. An increase in the attractiveness of using an (automated) car decreases the use of other modes of transportation. If the acceptable travel time and distance increase, urban sprawl is encouraged. A shared system could decrease the number of vehicles needed to facilitate transportation demand, which would decreases the need for parking. The livability in a city increases due to a higher accessibility and if less road and parking surface are needed.

The measures through which AVs could influence accessibility in cities have uncertain effects. Literature review did not identify a straightforward method to assess these effects and their respective uncertain range and to show the results over time on its geographic location.

7.3. A method to assess the impacts of AVs in urban areas

The impacts of new vehicle technologies and transportation or land use studies are generally performed by agent-based modeling or System Dynamics. System Dynamics proved to be a good method to model the effects of self-driving vehicles and other traffic measures regarding the dynamics of land use. It enables researchers to explore the dynamic complexity of an entire system by constructing feedback loops between cause and effect. This emphasizes the analysis of relationships between system components, which is essential when exploring uncertainties of AVs and measures to regulate it.

Exploratory modeling is a great method to deal with uncertainties in a system like the future of automated driving. It can analyze long-term consequences of uncertainties, which is of interest for long-term urban planning. Additional geographic information and scenario discovery applications are attached to the model. The model is programmed into an external source to vary the input parameters, control the model runs, and visualize the effects on the map of the case study. Many results can be viewed simultaneously, which improves the overview of research that deals with many uncertainties. System Dynamics models isolated systems, but in combination with exploratory modeling, it becomes possible to visualize these isolated systems in their geographic location and show an overview of the effects in the entire case study area in one glance. Several algorithms in the Exploratory Modelling and Analysis Workbench are useful when analyzing the output data of the System Dynamics model. The EMA Workbench is compatible with Vensim, which makes it very suitable for this thesis.

This combination of methods is new in transportation studies. Therefore, an assessment of the effects of automated driving is not the only main objective in this research; it also focuses on an assessment of the method.

This research provides insight in how to model the dynamic complexity of impacts of AVs in urban areas. In this case, it concerns self-driving technologies, but this can be changed to electric vehicles, car-sharing systems, or many other technological developments. The case specific information of Copenhagen can be changed to input from other cases, where the input data has to satisfy certain requirements. This thesis showed that even without satisfying the data requirements, a detour and great data analysis allows data from another geographical level to be converted and used as input in a zone-specific urban model.

The level of detail in archetyping the zones provides good insight into the characteristics and effects of each zone. By adding more detail to the archetypes, the applicability on small geographical zones increases. This allows to establish policies per zone and insights can be gathered under zone-specific circumstances. Each zone can thus be made unique, which is great when implementing detailed policies and analyzing the land use based on an individual zone. The absence of the geographical component leads to some adjustments in the transportation data. Simplifications were needed to include the through-traffic in certain zones. Facilities such as parking spaces in adjacent zones have no influence on the parking demand and supply of a specific zone, which is not realistic. The model is showing stable and consistent output and can be used to explore future directions of the implementation of AVs in urban areas and to visualize the impact over time on its geographic location. The model outcomes should not be interpreted to describe exact future changes, but to show a range and direction of possible futures caused by AVs. The reliability of model outcomes could be improved by using a method that both explores the dynamic complexity of a system, as well as represents the spatial system in more detail. This could replace some of the assumptions and simplifications made in this thesis. This first step of a new method does not include interaction between zones about the demand and supply of facilities. This has to be advocated in further research.

7.4. Transportation and spatial impacts of AVs in the model

The attractiveness of zones in dense urban areas is increasing. This effect is stronger in cases with more AVs. A higher attractiveness results in a greater number of people who want to settle in these areas. At some point, the zones have reached their maximum population, which remains stable over time because the attractiveness remains highest in these areas. The population in rural areas decreases during the period where the population in the city center, other urban districts, and suburbs increases. AVs could enhance the attractiveness of areas by improving accessibility to jobs and by decreasing the amount of required road space. These effects are higher in denser urban areas than in suburbs.

The performance of the transportation network dependents strongly on the use of AVs. Traffic volume could increase up to seven times the initial value if AVs becomes more attractive. This will obviously create many implications, thus steering measures are needed to mitigate this effect. These extreme increases in traffic volume are caused by an increased mobility of the population that is currently unable to drive, more trip purposes such as driver-less delivery and self-parking, and longer acceptable travel times caused by a lower value of time in AVs.

Extreme congestion is the result of this increased traffic volume when no extra roads are built, or a wait-and-see approach is applied to prepare for AVs. Longer travel times are not necessarily a problem for individual travelers because a decrease in value of time makes the time more useful and thus compensates for longer commutes. From a broader social perspective, a totally clogged transportation network is not a desirable future.

Higher capacity saturation will lead to a higher demand for road surface. The model allows for small increases in road surface each year, depending on the allocation priority for road surface and the available land. The land that is used for allocating new road surface to, is mostly the result of declines in the need for parking surface. This model does not allow land used for other categories to be reallocated for road and parking surface. This choice is made to maintain green spaces, residential areas, and business districts. Especially city centers face a strong decrease in required parking surface. This is caused by a high attractiveness to live in city centers, thus the allocation for new residential surface has a higher priority.

7.5. AVs leading towards a desirable future

Not all effects of AVs are desirable. Higher attractiveness of using the car increases the stress on the transportation network, which is already performing at its limit in urban areas. Increased traffic volume decreases the attractiveness of zones by a decreased accessibility caused by congestion. More road space decreases the attractiveness due to noise and pollution and it decreases space available for other purposes. Higher car-sharing rates would decrease the number of vehicles needed, which decreases congestion problems. This creates positive outcomes because less road and parking space is needed and more land can be used for other land use categories. AVs will contribute to a less sustainable transportation system if car-sharing does not increase. Mitigating measures are needed to either decrease the attractiveness of AVs or to enhance car-sharing.

Besides changes in accessibility, the spatial organization of cities could change in terms of land allocated to roads and parking. As much as 4% of the current road space could be decommissioned and used for other purposes in other urban districts. At least 8.3% of the land that is currently being used for parking in city centers and 5% in other urban districts can be decommissioned and used for other purposes.

The leading scenarios that provide insight in either desirable or undesirable scenarios of AVs vary in the value of time spend in an AV and in the car-sharing rate. This could be translated into increasing the comfort of a passenger individually versus improving the efficiency of the entire transportation system.

Large differences are expected between a value of time lower than $\notin 7.20$ versus a value of time over $\notin 9.58$. A car-sharing ratio of 5% could compensate many of the unwanted effects of AVs. The car-sharing ratio of 27% in the city center and 18% in other urban districts could compensate for the unwanted effects of AVs and allow a decrease in required road and parking space. Car-sharing would influence the value of time, seeing as a shared vehicle is not considered as attractive as a private vehicle. Enforcing car-sharing thus seems to be the most effective measure to mitigate the potential hazards of AVs.

7.6. Steering measures

A wide possibility of steering measures can be developed to reach those desirable outcomes. Many of them are already known from other transportation studies and are not further investigated here. This research shows that there is an important relation between attractiveness of AVs according to their value of time, and car-sharing. Increased attractiveness could lead to undesirable outcomes, while car-sharing leads to more desirable outcomes in the performance of the transportation system and in the distribution of land use categories in urban areas.

There are many ways to steer towards a desired implementation of AVs. Reducing the attractiveness of traveling by car compared to other modes can be done by charging for road use, limiting the comfort in and utility of a car, or by increasing the attractiveness of other modes. Urban sprawl and long commutes could be discouraged by land use regulations. The amount of trips could be decreased by limiting certain uses and the amount of trips per household. The mitigating strategy that is expected to be most effective is to make car-sharing more popular, starting today, in a system without AVs. This allows people to get used to a shared system and eases implementation of a future with shared automated transportation.

7.7. Recommendations for further research

The impacts and synergy effects of combined policy measures can be tested over time by implementing them into the model and performing the analyses again (Pfaffenbichler et al., 2010). More detailed, or geographic specific policy measures are easily implemented in the model to explore the effects on zone-level. The model can be used with a very high level of detail, which is great for the analysis of mitigating measures that should only be implemented in specific zones. Policies to mitigate unwanted uncertainties are set up after PRIM indicates the troublesome values. PRIM can be applied once again to find out if there are new troublesome scenarios when applying the policies. This monitors the path towards intended outcomes and identifies vulnerabilities in proposed mitigation policies by finding out in what scenarios proposed strategies might fail.

More detailed regional transportation data will leave out some of the simplifications made in this research and improves the reliability of conclusions. This research used traffic counts from a regional model based on a 24-hour period which did not include different trip purposes or different time frames. The trip purposes and time frames are extracted from a national traffic model. Information on other modes besides the car should be added in further research to explore the role of AVs in combination with public transportation.

Available plans for Copenhagen (Danish Business Authority, 2018a) could be implemented and tested in the model. If more policies are to be developed based on the outcomes of this research, a close collaboration with planners and policy makers in the municipality of Copenhagen is needed. Testing policy measures is considered beyond the scope of this thesis, as it is a very time-consuming procedure where the opinion of stakeholders should be taken into account in more detail.

Combining more detailed input data and a method where zones can interact with each other are key points in improving the reliability of conclusions. If zones could transfer information, the zones are not seen as isolated systems any longer, which will improve the realism of the representation of an urban system.

References

- Adviesgroep voor verkeer en vervoer. (1995). Systeem-dynamische Verkenning Verkeer en Vervoer met het oog op verkeersveiligheid (Tech. Rep.). Rotterdam: Ministerie van Verkeer en Waterstaat.
- Alessandrini, A., Campagna, A., Site, P. D., Filippi, F., & Persia, L. (2015). Automated vehicles and the rethinking of mobility and cities. , 5.
- Anderson, J. M., Kalra, N., Stanley, K. D., Sorensen, P., Samaras, C., & Oluwatola, O. A. (2014). Autonomous Vehicle Technology - A Guide for Policymakers. Santa Monica, California: RAND Corporation.
- Atkins. (2016). Research on the impacts of connected and autonomous vehicles (CAVs) on traffic flow Stage 1: Evidence Review (Tech. Rep. No. March). ATKINS, Department for Transport. Retrieved from https://www.gov.uk/government/uploads/ system/uploads/attachment_data/file/530091/impacts-of-connected-and -autonomous-vehicles-on-traffic-flow-summary-report.pdf
- Babeş, V. (2017). *Self-driven MRDH* (Unpublished master's thesis). Delft University of Technology.
- Bagloee, S. A., Tavana, M., Asadi, M., & Oliver, T. (2016). Autonomous vehicles: challenges, opportunities, and future implications for transportation policies. *Journal of Modern Transportation*, 24(4), 284–303. doi: 10.1007/s40534-016-0117-3
- Bösch, P. M., Becker, F., Becker, H., & Axhausen, K. W. (2017). Cost-based analysis of autonomous mobility services. *Transport Policy*(February), 1–16. Retrieved from http://linkinghub.elsevier.com/retrieve/pii/S0967070X17300811 doi: 10.1016/j.tranpol.2017.09.005
- Boston Consulting Group. (2016). Impactanalyse Zelfrijdende Voertuigen.
- Bouw, M. (2014). Smart Cities: What if? Retrieved from https://prezi.com/ e3e8vqkyhfth/140903-plenaire-presentatie-smart-city-what-if-ienm/ ?utm campaign=share&utm medium=copy
- Bryant, B. P., & Lempert, R. J. (2010). Thinking inside the box: A participatory, computerassisted approach to scenario discovery. *Technological Forecasting and Social Change*, 77(1), 34–49. doi: 10.1016/j.techfore.2009.08.002
- CARE-North plus. (2015). Autonomous vehicles impacts on mobility of the future. *Journal ID: 35-2-4-13.* Retrieved from http://archive.northsearegion.eu/files/ repository/20160113160412_CN+FactSheet_AutonomousTransport.pdf
- Childress, S., Nichols, B., Charlton, B., & Coe, S. (2015). Using an Activity-Based Model to Explore the Potential Impacts of Automated Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*. doi: 10.3141/2493-11
- Chong, I. G., & Jun, C. H. (2008). Flexible patient rule induction method for optimizing process variables in discrete type. *Expert Systems with Applications*, *34*(4), 3014–3020.

doi: 10.1016/j.eswa.2007.05.047

- Correia, G. H. d. A., & van Arem, B. (2016). Solving the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility. *Transportation Research Part B: Methodological*, 87, 64–88.
- Danish Business Authority. (2017). *Fingerplan 2017* (Tech. Rep.). Copenhagen: Erhvervsstyrelsen.
- Danish Business Authority. (2018a). *Lokalplaner, PlansystemDK*. Retrieved 8-4-2018, from http://visplaner.plansystem.dk/lokalplaner.html
- Danish Business Authority. (2018b). *PlansystemDK*. Retrieved 2018-01-08, from http://kbhkort.kk.dk/spatialmap?

Danish Road Directorate & Wilke. (2017). Danskernes forventninger til selvkørende biler.

- Danmarks Statistics. (2017). *Road Network.* Retrieved 23-5-2018, from https://www.dst .dk/en/Statistik/emner/geografi-miljoe-og-energi/infrastruktur/vejnet
- Danmarks Statistics. (2018). Population projections by region and time. Retrieved 2018-05-23, from http://statistikbanken.dk/statbank5a/default.asp?w=1680
- de Looff, E. J. (2017). Value of Travel Time Changes as a result of Vehicle Automation (Unpublished master's thesis). Delft University of Technology.
- Docherty, I., Marsden, G., & Anable, J. (2017). The governance of smart mobility. *Transportation Research Part A*. doi: 10.1016/j.tra.2017.09.012
- Dresner, K., & Stone, P. (2004, July). Multiagent traffic management: A reservation-based intersection control mechanism. In *The third international joint conference on autonomous agents and multiagent systems* (pp. 530–537).
- Elmeskov, J. (2015). *Denmark in figures 2015. Statistics Denmark* (Tech. Rep.). Copenhagen: Statistics Denmark.
- EPOMM. (2014). TEMS The EPOMM Modal Split Tool. Retrieved 21-01-2018, from http://www.epomm.eu/tems/result_city.phtml?city=227&list=1% 2520gives%252047%25%2520active,%252020%25%2520PT,%252033%25%2520car

ERTRAC. (2017). Automated Driving Roadmap (Tech. Rep.). Brussels.

- Except Integrated Sustainability. (2017a). De zelfrijdende stad (Tech. Rep.). Rotterdam: Except. Retrieved from http://media.except.nl/media/uploaded_files/ asset_files/SDC__vision_book_V15_AS_web.pdf
- Except Integrated Sustainability. (2017b). Self-Driving City (Tech. Rep. No. March). Rotterdam: Except. Retrieved from http://media.except.nl/media/uploaded_files/ asset files/SDC Research Book V15 AS web.pdf
- Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy* and Practice, 77. doi: 10.1016/j.tra.2015.04.003
- Fagnant, D. J., & Kockelman, K. M. (2014). The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies*, 40, 1–13. doi: 10.1016/j.trc.2013.12.001
- Fertner, C., Jørgensen, G., & Nielsen, T. S. (2012). Land Use Scenarios for Greater Copenhagen : Modelling the Impact of the Fingerplan. *Journal of Settlements and Spatial*

Planning, 3(1), 1-10. Retrieved from http://jssp.reviste.ubbcluj.ro

- Forrester, J. (1958). a major breakthrough for decision makers. *Harvard Business Review*, 36, 37–66.
- Forrester, J., & Senge, P. (1980). Tests for Building Confidence in System Dynamics Models. TIMS Studies in the Management Sciences, 14, 209–228.
- Fosgerau, M., Hjorth, K., & Lyk-Jensen, S. V. (2007). The Danish Value of Time Study (Tech. Rep.). Lyngby.
- Fox, J., Bhanu, P., & Daly, A. (2013). OTM 6 Demand Model Estimation. , 119.
- Friedman, J. H., & Fisher, N. I. (1999). Bump hunting in high-dimensional data. Statistics and Computing, 9(2), 123–143. doi: 10.1023/A:1008894516817
- Gajjar, R., & Mohandas, D. (2016). Critical Assessment of Road Capacities on Urban Roads
 A Mumbai Case-study. *Transportation Research Procedia*, 17(December 2014), 685–692. doi: 10.1016/j.trpro.2016.11.124
- Gelauff, G., Ossokina, I., & Teulings, C. (2017). Spatial effects of automated driving: dispersion, concentration or both? (Tech. Rep.). KIM Netherlands Institute for Transport Policy Analysis, Eindhoven University of Technology, University of Cambridge, University of Amsterdam. doi: 10.1007/11597018_1
- Gibbs, W. W. (1997). Transportation's Perennial Problems. Scientific American, October, 32–35.
- Gössling, S., & Choi, A. S. (2015). Transport transitions in Copenhagen: Comparing the cost of cars and bicycles. *Ecological Economics*, 113, 106–113. doi: 10.1016/j.ecolecon .2015.03.006
- Groves, D. G., & Lempert, R. J. (2007). A new analytic method for finding policy-relevant scenarios. *Global Environmental Change*, 17(1), 73–85. doi: 10.1016/j.gloenvcha.2006 .11.006
- Gruel, W., & Stanford, J. M. (2016). Assessing the Long-term Effects of Autonomous Vehicles: A Speculative Approach. In *Transportation research procedia* (Vol. 13).
- Hamarat, C., Kwakkel, J. H., & Pruyt, E. (2013). Adaptive Robust Design under deep uncertainty. *Technological Forecasting & Social Change*, 80(Future-Oriented Technology Analysis), 408–418. Retrieved from http://10.0.3.248/j.techfore.2012.10.004% 5Cnhttps://login.e.bibl.liu.se/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=edselp{&}AN=S004016251200248X&site=eds -live{&}scope=site
- Hansen, W. (1959). How accessibility shapes land use. *Journal of the American Institute of Planners*, 25, 73–76.
- Harper, C. D., Hendrickson, C. T., Mangones, S., & Samaras, C. (2016). Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. *Transportation Research Part C: Emerging Technologies*, 72. doi: 10.1016/j.trc.2016.09.003
- Havelaar, M., & Jaspers, W. (2017). Long-term planning of large interventions within complex and dynamic infrastructure systems (Unpublished master's thesis). Delft University of Technology.

Heinrichs, D. (2016). Autonomous Driving and Urban Land Use. Autonomous Driv-

ing, May, 213-231. Retrieved from https://link.springer.com/chapter/10.1007/ 978-3-662-48847-8 11/fulltext.html

- Index Mundi. (2018). Denmark Demographics Profile 2018. Retrieved 22-01-2018, from https://www.indexmundi.com/denmark/demographics profile.html
- International Transport Forum. (2015). Urban Mobility System Upgrade: How shared self-driving cars could change city traffic (Tech. Rep.). Paris: OECD. Retrieved from http://www.internationaltransportforum.org/Pub/pdf/15CPB Self-drivingcars.pdf
- Kwakkel, J. H. (2013). Exploratory Modelling and Analysis (EMA) Workbench. Delft: Delft University of Technology. Retrieved from http://simulation.tbm.tudelft.nl/ema -workbench/contents.html#exploratory-modeling-and-analysis-ema
- Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling and Software*, 96, 239–250. doi: 10.1016/j.envsoft.2017.06 .054
- Kwakkel, J. H. (2018). EMA Workbench documentation release 1.1.
- Kwakkel, J. H., & Cunningham, S. C. (2016). Improving scenario discovery by bagging random boxes. *Technological Forecasting and Social Change*, 111, 124–134. doi: 10 .1016/j.techfore.2016.06.014
- Kwakkel, J. H., Haasnoot, M., & Walker, W. E. (2016). Comparing Robust Decision-Making and Dynamic Adaptive Policy Pathways for model-based decision support under deep uncertainty. *Environmental Modelling and Software*, 86, 168–183. Retrieved from http://dx.doi.org/10.1016/j.envsoft.2016.09.017 doi: 10.1016/j.envsoft .2016.09.017
- Levin, M. W. (2017). Congestion-aware system optimal route choice for shared autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, 82, 229–247. doi: 10.1016/j.trc.2017.06.020
- Lioris, J., Pedarsani, R., Tascikaraoglu, F. Y., & Varaiya, P. (2017). Platoons of connected vehicles can double throughput in urban roads. *Transportation Research Part C: Emerging Technologies*, 77(April), 292–305.
- Litman, T. (2014). Autonomous Vehicle Implementation Predictions: Implications for Transport Planning (Vol. 42; Tech. Rep.). Victoria Transport Policy Institute.
- Llorca, C., Moreno, A., & Moeckel, R. (2017). Effects of Shared Autonomous Vehicles on the Level of Service in the Greater Munich Metropolitan Area. International Conference on Intelligent Transport Systems in Theory and Practice, mobil.TUM, 00(2016).
- Madadi, B., van Nes, R., Snelder, M., & van Arem, B. (2018). Network Design and Impacts of Automated Driving: An Explorative Study. *2018 TRB Annual Meeting*.
- Martens, M., & van Loon, R. (2015, jan). Automated Driving and its Effect on the Safety Ecosystem: How do Compatibility Issues Affect the Transition Period? *Procedia Manufacturing*, 3, 3280–3285. doi: 10.1016/J.PROMFG.2015.07.401
- Meyer, J., Becker, H., Bösch, P. M., & Axhausen, K. W. (2017). Autonomous vehicles: The next jump in accessibilities? *Research in Transportation Economics*.
- Milakis, D., Kroesen, M., & van Wee, B. (2017). Implications of automated vehicles for

accessibility and location choices: a conceptual model and evidence from an expertbased experiment.

- Milakis, D., Snelder, M., van Arem, B., van Wee, B., & Correia, G. H. d. A. (2015). Development and transport implications of automated vehicles in the Netherlands: scenarios for 2030 and 2050 (Tech. Rep.). Delft: Delft University of Technology.
- Milakis, D., van Arem, B., & van Wee, B. (2017). Policy and society related implications of automated driving: a review of literature and directions for future research. *Journal of Intelligent Transportation Systems*, 0(0), 1–25. doi: 10.1080/15472450.2017.1291351
- municipality of Copenhagen. (2017a). Analyse af Københavns Kommunes Muligheder og Udfordringer i Forbindelse med Udviklingen af Selvkørende Køretøjer (Tech. Rep.). Copenhagen.
- municipality of Copenhagen. (2017b). *Medlemsforslag om forsøg med førerløse kommunale biler og busser (2017-0068218).*
- municipality of Copenhagen. (2017c). Selvkørende køretøjer i København (2017-0113442). Copenhagen. Retrieved from https://www.kk.dk/indhold/ teknik-og-miljoudvalgets-modemateriale/19062017/edoc-agenda/5e1a7bb6 -baad-491b-804d-b115a1b6b9d4/642e6cbb-9d02-4b7a-b25b-1bbd0c761a5f
- Nees, M. A. (2016). Acceptance of Self-driving Cars: An Examination of Idealized versus Realistic Portrayals with a Self- driving Car Acceptance Scale. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 60(1), 1449–1453. doi: 10.1177/1541931213601332
- Newsec. (2016). Greater Copenhagen & Skåne Property Market. Stockholm: Tysk-Svenska Handelskammaren. Retrieved from http://www.handelskammer.se/sites/default/ files/MarketPresentation RealEstateInvestorsSummit NEWSEC.pdf
- Nieuwenhuijsen, J., Correia, G. H. d. A., Milakis, D., van Arem, B., & van Daalen, E. (2018). Towards a quantitative method to analyze the long-term innovation diffusion of automated vehicles technology using system dynamics. *Transportation Research Part C: Emerging Technologies*, 86(November 2017), 300–327. Retrieved from http:// linkinghub.elsevier.com/retrieve/pii/S0968090X17303339 doi: 10.1016/j.trc .2017.11.016
- OSM. (2018). OSM Landuse Landcover. Retrieved 23-5-2018, from osmlanduse.org
- Öztürker, M., Milakis, D., & van Arem, B. (2016). Towards a methodology to identify design changes for urban transport infrastructure in the era of automated driving and vehicle sharing. Delft.
- Pfaffenbichler, P., Emberger, G., & Shepherd, S. (2010). A system dynamics approach to land use transport interaction modelling: the strategic model MARS and its application. *System Dynamics Review*, 26, 262–282.
- Pruyt, E. (2013). Small System Dynamics Models for Big Issues: Triple Jump towards Real-World Complexity (Vol. 18) (No. 5). Delft: Delft University of Technology. Retrieved from http://mitsloan.mit.edu/group/system-dynamics/%5Cnhttp:// linkinghub.elsevier.com/retrieve/pii/S0278612599901012 doi: 10.1016/ S0278-6125(99)90101-2

Puylaert, S., Snelder, M., van Nes, R., & van Arem, B. (2018). Mobility impacts of early forms

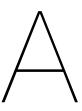
of automated driving – A system dynamic approach. *Transport Policy*(February), 1–9. doi: 10.1016/j.tranpol.2018.02.013

- Rigole, P.-J. (2014). Study of a Shared Autonomous Vehicles Based Mobility Solution in Stockholm (Master's thesis, Royal Institute of Technology, Stockholm). Retrieved from http://www.diva-portal.org/smash/record.jsf;jsessionid= kS81CXqhOs0_dmrLKUFTDaNVPVCycHsxfNNBxBRF.diva2-search7-vm?pid=diva2: 746893&dswid=4734
- Rodoulis, S. (2014). The Impact of Autonomous Vehicles on Cities. *Journeys Sharing Urban Transport Solutions*(12), 12–20. Retrieved from http://www.lta.gov.sg/ltaacademy/ doc/Journeys_Issue_12_Nov_2014.pdf#page=14
- SAE International. (2016). Surface Vehicle Recommended Practice.
- SAE International, & Costlow, T. (2018). SAE Connect2Car: Smart cities bring connectivity challenges. Retrieved 21-01-2018, from http://articles.sae.org/15844/
- SAE International, & Visnic, B. (2018). All U.S. Toyotas to be 'connected' by 2020. Retrieved 2018-01-19, from http://articles.sae.org/15827/
- Schafer, A., & Victor, D. (1997). The Past and Future of Global Mobility. Scientific American, October, 36–39.
- Schoettle, B., & Sivak, M. (2015). Potential Impact of Self-Driving Vehicles on Household Vehicle Demand and Usage (Tech. Rep. No. February). University of Michigan Transportation Research Institute.
- Shepherd, S. (2014). A review of system dynamics models applied in transportation-finalsubmission-White rose (Tech. Rep.). Leeds: University of Leeds.
- Silberg, G., & Wallace, R. (2012). Self-driving cars: The next revolution (Tech. Rep.). KPMG. Retrieved from www.caragroup.com%5Cnwww.kpmg.com doi: 10.1007/978-3 -642-21381-6-16
- Skifter Andersen, H. (2011). Explaining preferences for home surroundings and locations. *Urbani Izziv*, 22(1), 100–114. doi: 10.5379/urbani-izziv-en-2011-22-01-002
- Smolnicki, P. M., & Soltys, J. (2016). Driverless Mobility: The Impact on Metropolitan Spatial Structures. Procedia Engineering, 161, 2184–2190. Retrieved from http://linkinghub .elsevier.com/retrieve/pii/S187770581633048x doi: 10.1016/j.proeng.2016.08 .813
- STAD. (2017). Spatial and Transportation impacts of Automated Driving. Retrieved 26-4-2017, from http://stad.tudelft.nl/
- Statistics Denmark. (2012). Transport (Tech. Rep.). Copenhagen.
- Sterman, J. D. (2000). Business Dynamics: Systems Thinking and Modeling for a Complex World. Cambridge: Jeffrey J. Shelsfud. Retrieved from http://www.lavoisier.fr/ notice/frJWOAR6SA23WLOO.html
- Stynes, D. (1989). Gravity Model. East Lansing: Michigan State University.
- Sun, W., Zheng, J., & Liu, H. X. (2017). A capacity maximization scheme for intersection management with automated vehicles. *Transportation Research Procedia*, 23(2016), 121–136. doi: 10.1016/j.trpro.2017.05.008
- Talebpour, A., & Mahmassani, H. S. (2016). Influence of connected and autonomous vehicles on traffic flow stability and throughput. *Transportation Research Part C: Emerging*

Technologies, 71, 143-163. Retrieved from http://www.sciencedirect.com/ science/article/pii/S0968090X16301140?_rdoc=1&_fmt=high&_origin= gateway&_docanchor=&md5=b8429449ccfc9c30159a5f9aeaa92ffb&dgcid=raven sd recommender email doi: 10.1016/J.TRC.2016.07.007

- Tillema, T., Berveling, J., Gelauff, G., van der Waard, J., Harms, L., & Derriks, H. (2015). *Chauffeur aan het stuur*? (Tech. Rep.). Den Haag: Kennisinstituut voor Mobiliteitsbeleid. doi: 978-90-8902-137-3
- Tillema, T., Berveling, J., Gelauff, G., van der Waard, J., & Moorman, S. (2017). Paden naar een zelfrijdende toekomst (Tech. Rep.). Den Haag: Kennisinstituut voor Mobiliteitsbeleid.
- Trading Economics. (2018). Denmark Economic Indicators. Retrieved 22-01-2018, from https://tradingeconomics.com/denmark/indicators
- Underwood, S. (2014). Automated Vehicles Forecast Vehicle Symposium Opinion Survey. San Francisco: Graham Institute for Sustainability. Retrieved from http:// www.automatedvehiclessymposium.org/avs2014/program/tuesday
- United Nations. (2014). World Urbanization Prospects 2014 (Tech. Rep.). New York. doi: (ST/ESA/SER.A/366)
- van Nes, R. (2014a). Choice Modelling. Delft: Delft University of Technology. Retrieved from https://blackboard.tudelft.nl/bbcswebdav/pid-2617771-dt-content -rid-8753273 2/courses/35161-151601/Lecture4%20Choice%20modelling.pdf
- van Nes, R. (2014b). Trip Distribution. Delft: Delft University of Technology. Retrieved from https://blackboard.tudelft.nl/bbcswebdav/pid-2619105-dt-content -rid-8753274_2/courses/35161-151601/Lecture5Tripdistribution.pdf
- van Wee, B., Rietveld, P., & Meurs, H. (2006). Is average daily travel time expenditure constant? In search of explanations for an increase in average travel time. *Journal of Transport Geography*, 14(2), 109–122.
- Vennix, J. (1996). Group Model Building. New York: Wiley.
- Ventana Systems Inc. (2017). Vensim ® Version 7.2.
- Wadud, Z., MacKenzie, D., & Leiby, P. (2016). Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy* and Practice, 86, 1–18. doi: 10.1016/j.tra.2015.12.001
- Wikivoyage. (2017). Copenhagen. Retrieved 01-08-2018, from https://en.wikivoyage .org/wiki/Copenhagen
- Xu, W. A., Zhang, W., & Li, L. (2017). Measuring the expected locational accessibility of urban transit network for commuting trips. *Transportation Research Part D: Transport* and Environment, 51, 62–81. doi: 10.1016/j.trd.2016.12.002
- Zakharenko, R. (2016). Self-driving cars will change cities. Regional Science and Urban Economics, 61, 26 - 37. Retrieved from http://www.sciencedirect.com/science/ article/pii/S016604621630182X doi: http://dx.doi.org/10.1016/j.regsciurbeco .2016.09.003

Appendices



Districts in OTM region

In this Appendix, the zone numbers per district are shown, which are used to make zone archetypes for policy intervention.

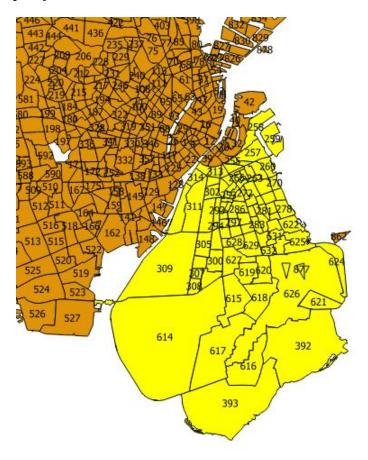


Figure A.1: Amager

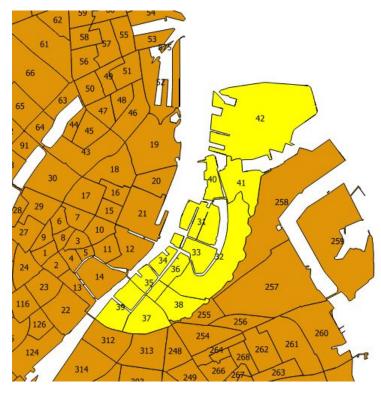


Figure A.2: Christianshavn

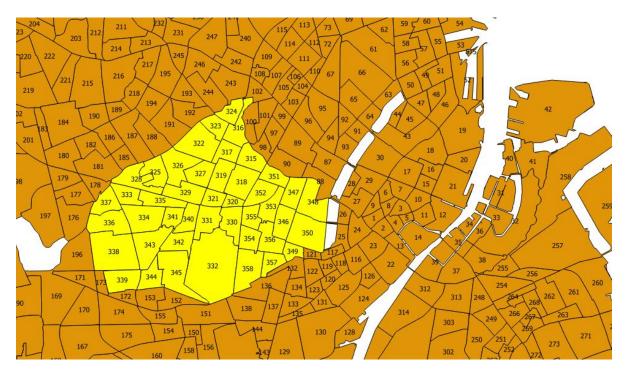


Figure A.3: Frederiksberg

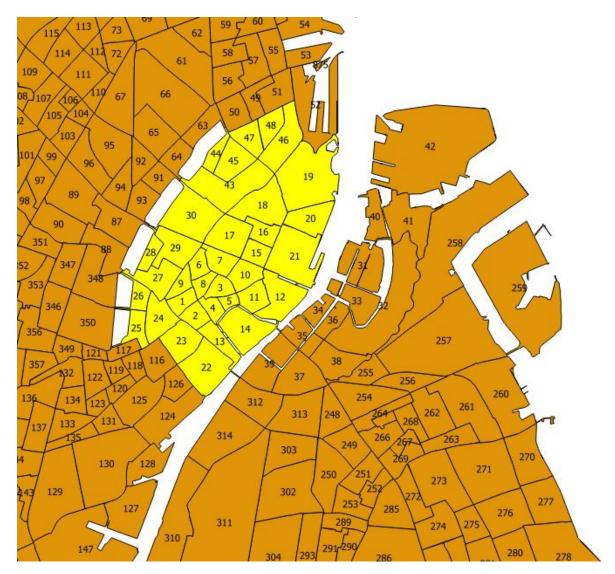


Figure A.4: City center

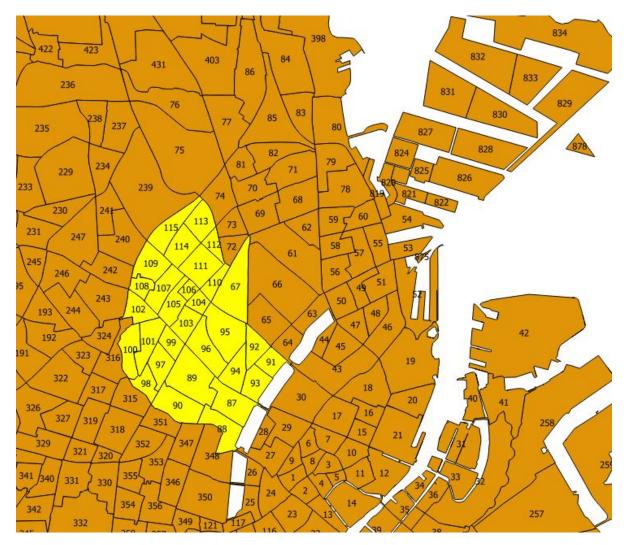


Figure A.5: Nørrebro

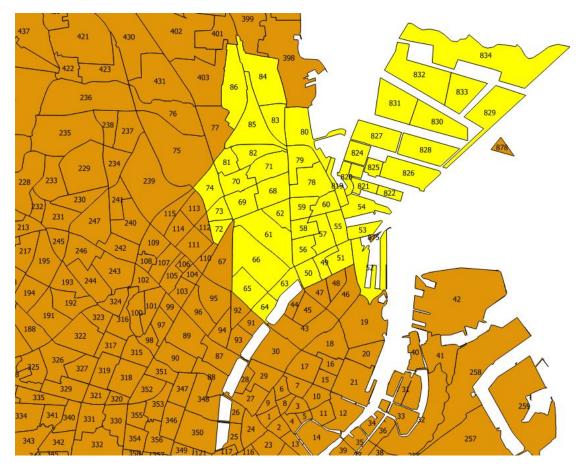


Figure A.6: Østerbro

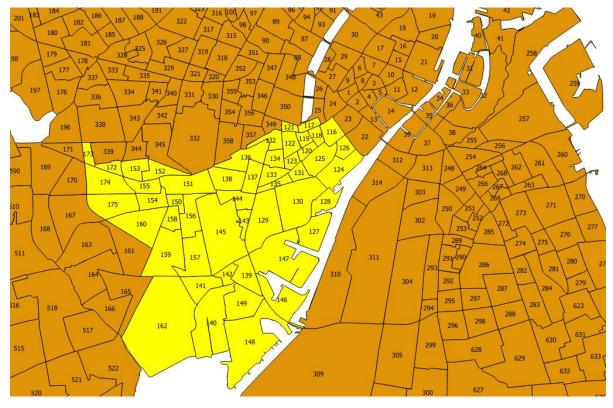


Figure A.7: Vesterbro

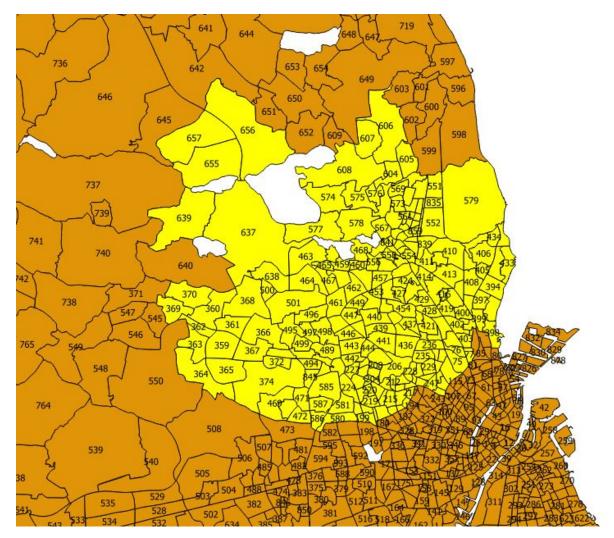


Figure A.8: Northern Suburbs

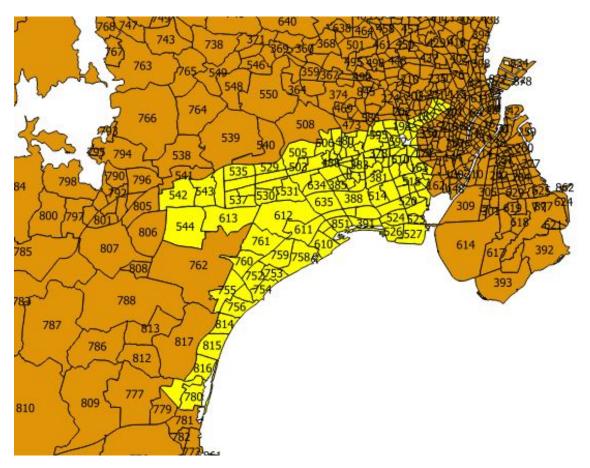


Figure A.9: Vestegnen



Figure A.10: Comparison Copenhagen

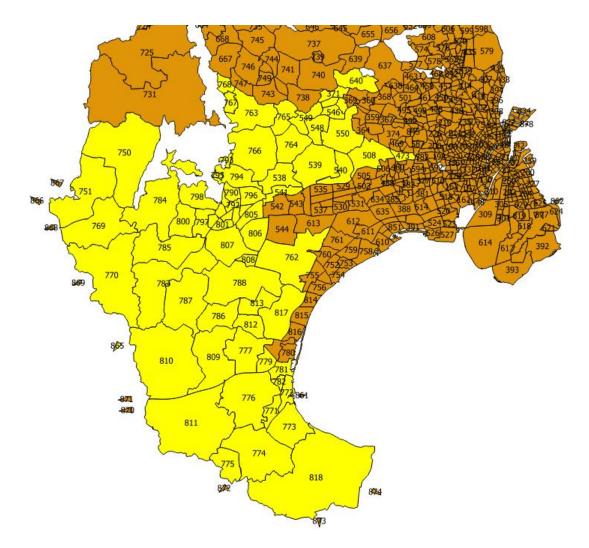


Figure A.11: Eastern Zealand

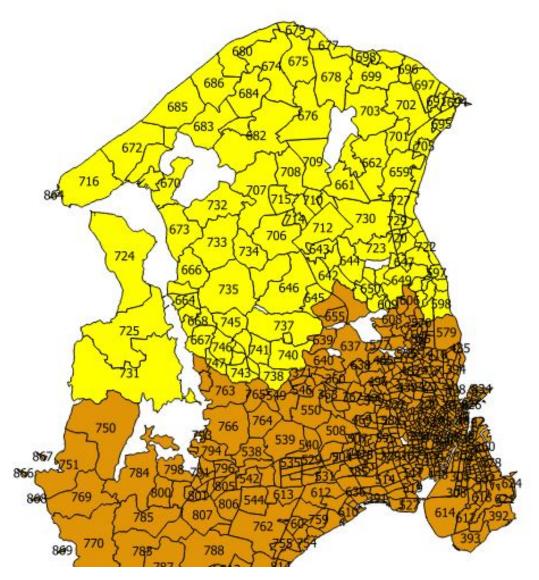


Figure A.12: Northern Zealand



Figure A.13: Comparison Northern Zealand



Data preparation procedures

B.1. Road surface

- 1. With GIS software (QGIS), calibrate the road network over the OTM zone shapes.
- 2. In the Geometry tools, select the function *Lines to polygons* to convert the road infrastructure vector network to a polygon network.
- 3. For each road polygon, calculate the centroid in the center of gravity.
- 4. Map the centroids from step 3 on the OTM zone shape.
- 5. Assign each centroid from step 3 to the zone it is located in.
- 6. Extract the attributes Road width, Designed speed, Observed speed, Number of lanes and Road capacity per road segment into Excel.
- 7. Match the ID of each road segment to the assigned zone from step 5.
- 8. Sum the values over their respective number of times a zone ID occurs in the file.
- 9. Check all zones that did not get road segments allocated, in case an error has been made and a road is visible on the map, replace the zero-values of these zones with the mean values as shown in table Table 4.6.
- 10. 300 zones have been replaced with the average values. The other 560 zones received the values from the OTM road network¹.
- 11. The replacement of the unassigned zones is justified with the assumption that several road segments cross multiple zones, especially in the small zones in the city center. The center of gravity is located in only one of these zones. It is thus not possible to argue that surrounding zones receive no road surface. To make sure it has no impact on the

¹The error of 300 zones occured because 300 zones only have straight roads, QGIS was unable to draw polygons from straight (one-dimensional) vectors.

average values of the entire system, average values of road width, , designed speed, observed speed, number of lanes and capacity are assigned to the 'empty' zones.

12. Note that the road length per zone is calculated with the tool *Sum line length* and gives accurate values for each zones, it is thus not calculated according to this procedure. In case the road length is missing, while a road is clearly present, recalculate the line lengths according to the values from the national traffic model.

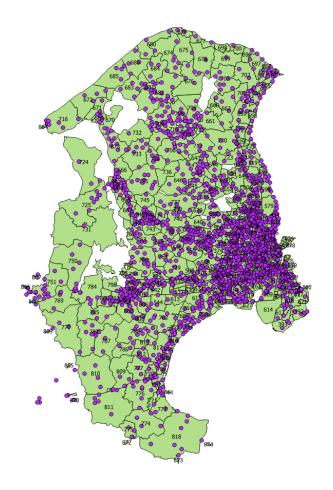
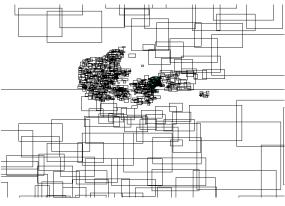


Figure B.1: Zone system OTM plus center of gravity per road segment

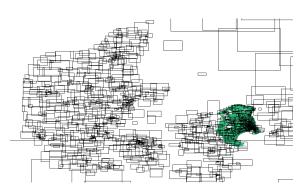
B.2. Parking surface

- 1. Import the shapefile with the on-street parking locations in OmniTRANS.
- 2. Import the shapefile of the OTM zones.
- 3. Add a centroid in the center of gravity for all OTM zones.
- 4. Use a special script to allocate the closest zone center to either one of the two ends of a parking strip.

- 5. A list of parking strips with their corresponding zones is now generated.
- 6. Add the parking capacities with the same zone number.
- 7. A list with the on-street parking capacity per zone is now obtained.
- 8. Find the locations of parking garages with QGIS.
- 9. Manually allocate the capacity of the 19 parking garages to their respective zones in the list created in step 7.
- 10. A list with the full parking capacity per OTM zone is now obtained.



(a) Denmark in NTM zones



(b) Denmark in NTM zones zoomed

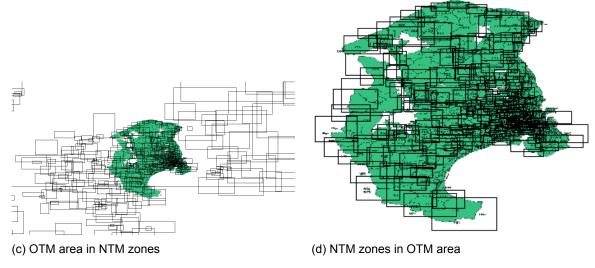


Figure B.2: NTM versus OTM

B.3. Morning peak and commuter trips

- 1. With GIS software (QGIS, OmniTRANS), calibrate the NTM and OTM shapes to find the NTM zones that cover the OTM region as in Figure B.2a to B.2d.
- 2. Extract only the rows where both the origin and the destination is an NTM zone in the OTM region and save the file (1).

- 3. In file 1, extract only the two time frames for the morning peak to an other file (2).
- 4. In file 2, extract only the commuter trip category and save it to an other file (3).
- 5. In file 1, sum all different time frames to one category.
- 6. In file 1, sum all different trip purposes to one category.
- 7. Perform step 6 for file 2.
- 8. Divide the result from step 7 by the result of step 6; this means dividing the morning peak trips by the total number of trips and results in a morning peak ratio.
- 9. Validate the results. In a case where all trips are made in the morning peak, these trips are expected to return at some point. A maximum of 50% of the trips is considered likely to travel in the morning peak and values > 0.5 are considered unlikely.
- 10. 10262 values > 0.5; this gives an error of $\frac{10262}{860^2} = 1.4\%$.
- 11. Replace unlikely values with the average value of the matrix: 0.212534.
- 12. With Excel formulas, for each OTM OD pair, find the morning peak ratio of the respective NTM OD pair and place it in an OTM OD matrix.
- 13. A matrix with the OTM morning peak fractions is now obtained.
- 14. To find the commuter trip ratio in the morning peak, divide the result of step 4 by the result of step 7.
- 15. Validate the results, no odd values found.
- 16. A matrix with the OTM commuter trip fractions in the morning peak is now obtained.

B.4. OD matrix

- 1. Convert the shapefile of OTM traffic counts to a coordinate system that corresponds with the layout of OTM zones. This calibrates the road map and the map of the OTM zones.
- 2. Import the shapefile of the traffic counts and save the road section loads from the shapefile in the OmniTRANS road sections.
- 3. Import the shapefile of the OTM zones.
- 4. Add a centroid in the center of gravity for all OTM zones.
- 5. Use a special script² to add zone-connectors between a zone and the closest road section.
- 6. Use a special script to convert all road section loads in OTM to traffic counts in the entire OmniTRANS traffic network. Two countpoints are assigned to each road section and count the loads according to the OTM.

²Edwin Mein is a former software architect of OmniTRANS, his experience helped converting the data and writing the scripts within OmniTRANS.



(a) Traffic loads urban core

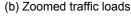


Figure B.3: Traffic loads in the OmniTRANS model

- 7. Create an OD matrix of ones.
- 8. Use a standard script to generate a screenline-matrix³ which determines which counts belong to each OD pair, it is used to define the OD's passing a count.
- 9. Use a standard script to calibrate the matrices from step 7 and 8, based on (uncongested) AON-Assignment⁴. Characteristics in an AON assignment are not influenced by the amount of traffic on the network. Congestion is not taken into account in the OmniTRANS model and is modeled in Vensim.
- 10. Failed step 9, because the number of countpoints exceeds the OmniTRANS memory (out-of-memory error).
- 11. Manually remove a logical set of counts that add little or nothing to the final result.
- 12. Repeat step 9, again out-of-memory.
- 13. Use a script to randomly remove 50% of the counts.
- 14. Repeat step 9, now succeeded.
- 15. A new OD matrix for the OTM zones is now obtained.
- 16. Validate the results, the allocation of the previous counts in a basic all-or-nothing traffic assignment seems to match with the OTM results.
- 17. A useful OD matrix for the OTM region is now obtained, shown in Figure B.3.

³A screenline in OmniTRANS is a measure to group multiple counts together

⁴AON-assignment is a fast and easy to interpret method in OmniTRANS, it is however very sensitive to small changes. Since a high number of zones is modeled the errors can average out, therefore it is considered a valid method.

- 18. Multiply the OTM OD matrix with the OTM morning peak fractions.
- 19. An OTM morning peak OD matrix is now obtained.
- 20. Multiply the OTM morning peak OD matrix with the OTM commuter trip fractions.
- 21. An OTM morning peak commuter trip OD matrix is now obtained.

B.5. Skimmatrix

- 1. Open the OmniTRANS model from the procedure in Appendix B.4.
- 2. Use a standard script that uses the built-in class OtTraffic. This generates shortest paths for all OD pairs and stores the impedance of these paths into a skim matrix. The script to generate the skim matrices needs to be invoked within the assignment job in OmniTRANS.
- 3. Generate the matrix only for distance and travel time.
- 4. If desired, set skim factors for [distance, travel time] to [1000,60] to convert the values to respectively meters and minutes.
- 5. The average distances and the average travel times to/from each zone are derived from the matrices generated in step 3.

\bigcirc

Regression analysis for trip distribution

Gravitational Model

$$T_{ij} = \alpha \cdot \frac{P_i \cdot A_j}{T T_{ij}^{\beta}} \tag{C.1}$$

$$T_{ij} = \alpha \cdot P_i \cdot A_j \cdot TT_{ij}^{-\beta} \tag{C.2}$$

$$\frac{T_{ij}}{P_i \cdot A_j} = \alpha \cdot TT_{ij}^{-\beta}$$
(C.3)

$$ln\left(\frac{T_{ij}}{P_i \cdot A_j}\right) = ln(\alpha) + ln\left(TT_{ij}^{-\beta}\right)$$
(C.4)

$$ln\left(\frac{T_{ij}}{P_i \cdot A_j}\right) = ln(\alpha) - \beta \cdot ln(TT_{ij})$$
(C.5)

Linear regression analysis estimates values in the format: y = a + bx, where $a = ln(\alpha)$ and $b = \beta$

Regression analysis results: $ln(\alpha) = -4.65$; $\beta = -1.46$

Procedure regression analysis

The following sequence of steps performed the regression analysis based on the number of trips between zones(i and j), the travel time between zones(i and j), the population in zones(i) and the jobs in zones(j). The gravitational model from C gives the formula to convert the exponential relation into a linear relation.

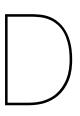
- 1. Take all OD pairs, this generates a datafile with 860*860 = 739600 pairs.
- 2. Multiply the population in zone i with the fraction adults to estimate the trip production.
- 3. The number of jobs in zone j gives the trip attraction.

- 4. Multiply trip production and attraction.
- 5. The OD matrices contain the amount of trips and travel times between all zones (i-j).
- 6. Take the natural logarithm of the 'Production' Attraction', 'Trips' and 'Travel time'.
- 7. Divide LN(Trips) by LN(Production*Attraction).
- 8. Filter out the results of zone i to i (because intra-zonal trips are not used in the estimation of the gravity model).
- 9. Filter out all OD pairs with less than 10 trips, because less than 10 is considered too little to draw conclusions.
- 10. Filter less than 90 minutes travel time (more than 90 minutes is considered improbable in an urban environment as the GCA) and more than 10 minutes (less than 10 minutes is considered taking an other mode than the car).
- 11. The remaining 3644 pairs are used to perform the regression analysis.
- 12. Regression analysis LN((Population*Jobs)/Trips) versus LN(Time), according to C.
- 13. Use the coefficients α and β for respectively the *Constant trip generation* and *Exponent travel time*, subscripted for each zone in the Vensim model.

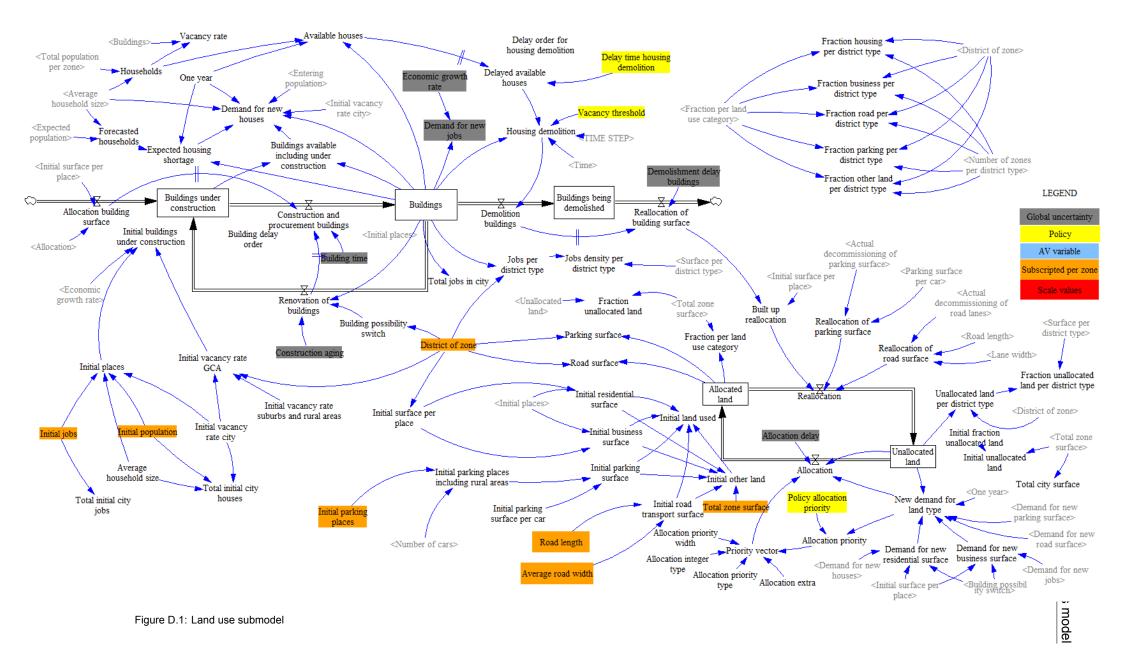
Results regression analysis

Table C.1: Results regression analysis of trip generation with gravity model

SUMMARY OUTPU	Т					
Regression Statistics						
Multiple R R Square Adjusted R Square Standard Error Observations	0.268425 0.072052 0.071797 2.512044 3644					
ANOVA	df	SS	MS	F	Sig. F	
Regression Residual Total	1 3642 3643	1784.499 22982.34 24766.84	1784.499 6.310363	282.7886	3.56E-61	
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept LNTime	-4.65206 -1.45714	0.2985 0.086651	-15.5848 -16.8163	4.61E-53 3.56E-61	-5.2373 -1.62703	-4.06681 -1.28726



System Dynamics model



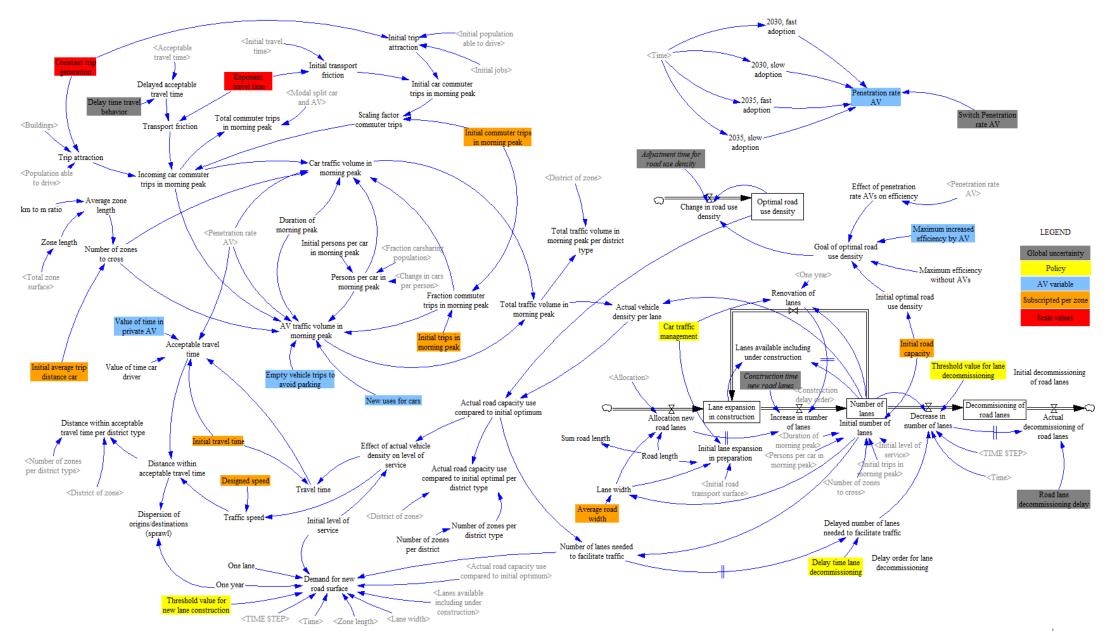
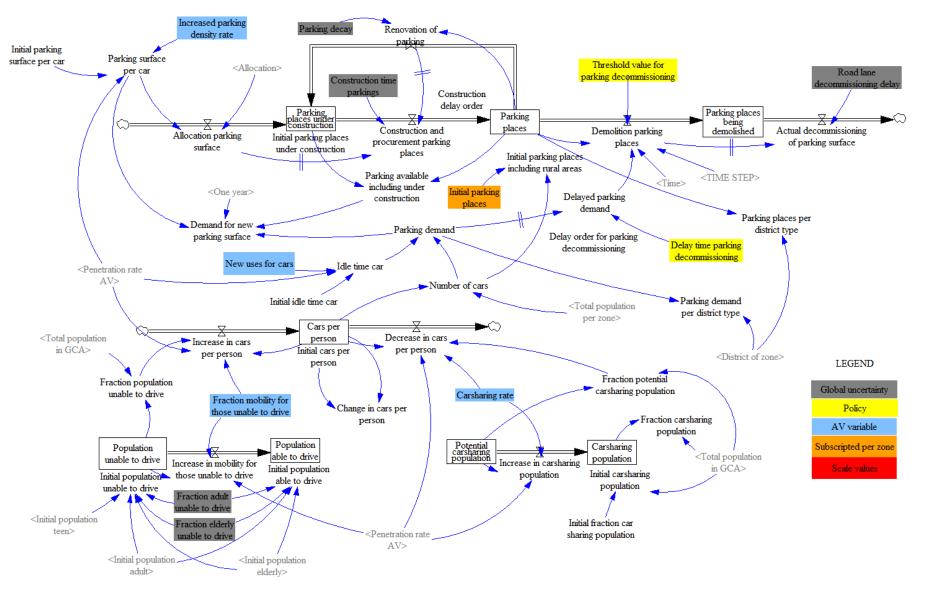


Figure D.2: Traffic submodel



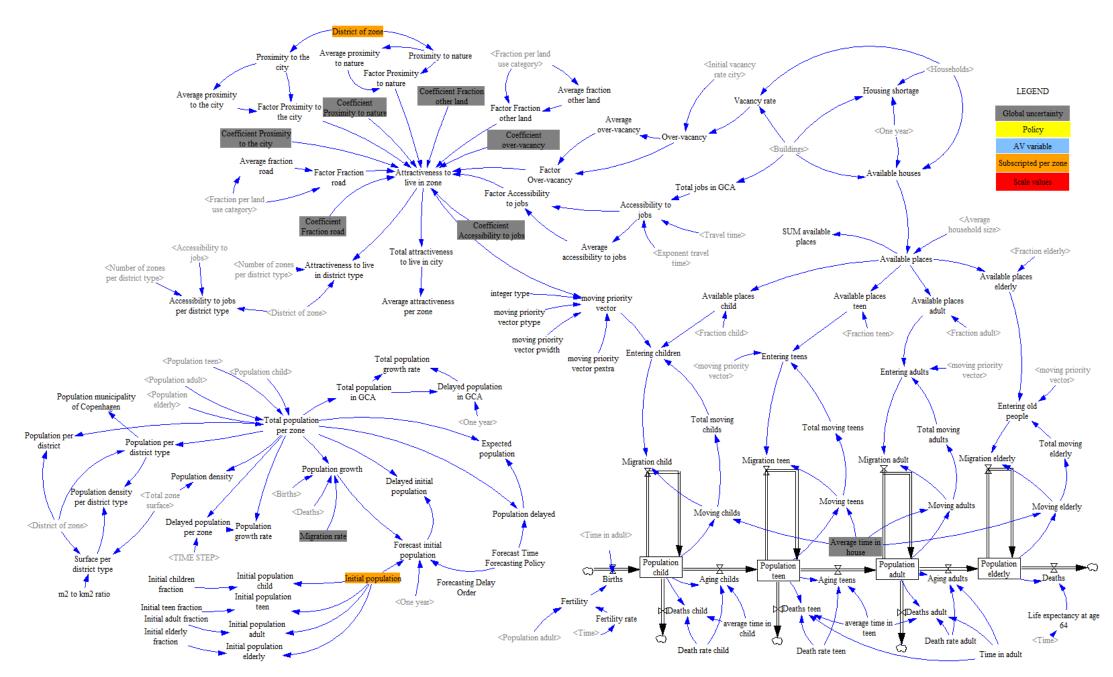


Figure D.4: Population submodel

Model variables

Endogenous

- Attractiveness to live in zone: The factors for Accessibility to jobs, Over-vacancy, Fraction other land, Proximity to nature, Proximity to the city and Fraction road multiplied with their respective coefficients.
- Population and population density
- Migrating population within the Greater Copenhagen Area: A set fraction of population leaves a zone each year: 1 divided by the average time one spends in a house. The population is relocated according to the attractiveness per zone.
- Surface per land use category: Residential, Business, Road, Parking, Other
- Allocation of land: Allocates the unallocated land according to the priority for each land use category.
- Gained free space: Unallocated land that can be used for Other land. Especially changes in the need for road and parking surface are important indicators of the effects of AVs on urban form.
- Renovation of land: Constructions and infrastructure are aging, but this is not broken down and reallocated to other types of land use. Instead, the aging land use categories are temporarily unusable until fully constructed again. Aging land is thus input for 'land under construction'.
- Construction of land: According to the allocation of surface for each land use category.
- Traffic volume: Trip attraction times trip production, divided by transport friction. Transport friction is the travel time to the power of the exponent travel time as calculated in the gravitational model.

- Road capacity: Initial road capacity is subscripted, but could change because of changes in road use density by AVs.
- Road capacity saturation: Traffic volume divided by the road capacity, if this exceeds a certain limit, pressure to reduce congestion is sent to demand for newly allocated road surface.
- Effect of actual vehicle density on road use efficiency: Lookup variable showing that at low capacity saturations, the effect on road use efficiency could increase the traffic speed and at high capacity saturations it will decrease the traffic speed.
- Travel times: Dependent on the effect of actual vehicle density on road use efficiency.
- Acceptable travel time: Initial travel time equals the acceptable travel time, this can change due to changes in value of time.
- Region within desired travel time: The distance to be reached within the acceptable travel time; The acceptable travel time multiplied with the Traffic speed.
- · Accessibility to jobs
- Cars per person: Initially set, dependent on new technological features and possible shared vehicle systems.
- Number of cars: Cars per person times the population per zone.
- Parking capacity: Current on-street parking capacity from database. Parking garages are added to this parking capacity. The zones out of the city gets a parking capacity awarded with is sufficient to facilitate the number of cars in each respective zone.
- Parking demand: Land needed for parking.

Exogenous

- All initial values subscripted per OTM zone: Jobs, Population, Zone districts, Parking places, Road length, Road width, Number of road lanes, Zone surface, Commuter trips in morning peak, Total trips in morning peak, Road capacity, Trip distance, Travel time, Actual speed, Designed speed, Parking price, Time looking for a parking spot.
- Delays: Construction aging, Road aging, Parking aging, Construction time buildings, Construction time roads, Construction time parking, Allocation delay, Decommissioning delay buildings, Decommissioning delay infrastructure.
- Scale factors: Constants attractiveness to relocate, Constant trip generation, Exponent travel time, Car traffic management.
- All effects caused by the introduction of AVs: Penetration rate AV, Efficiency of vehicle operation, Value of time in private AV, Mobility for those unable to drive, Idle time car, Parking density rate, Carsharing rate.
- Uncertainties not assigned to AVs: Average time in a house, Migration to and from GCA, Construction rate houses, Construction rate jobs (Economic prosperity).

Sensitivity runs

2043 Time (Year)

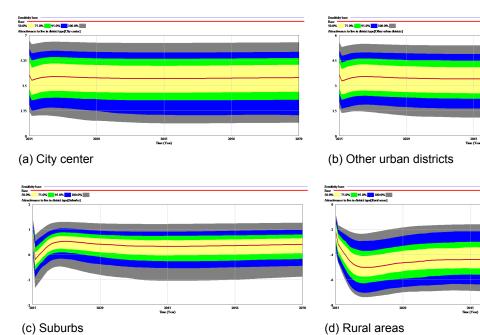
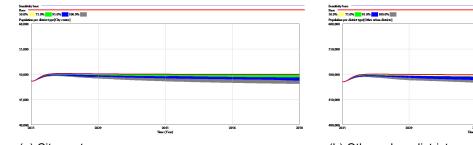
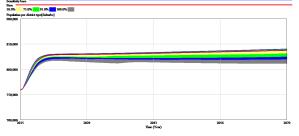




Figure F.1: Sensitivity attractiveness per district type

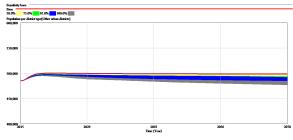


(a) City center

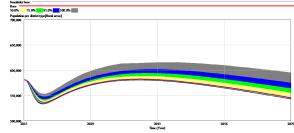


(c) Suburbs

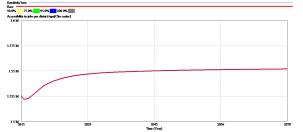
Figure F.2: Sensitivity population per district type



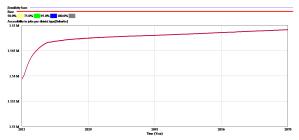
(b) Other urban districts



(d) Rural areas

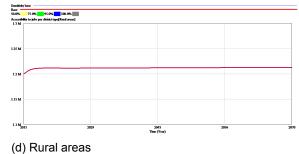






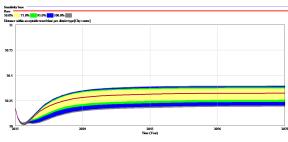
Sensitis Base 50.0% Access 1.8 M .0% 95.0% 100.0% 1.75 M 1.6 M 2043 Time (Year)

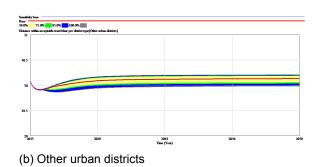
(b) Other urban districts



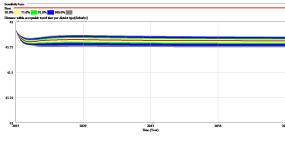
(c) Suburbs

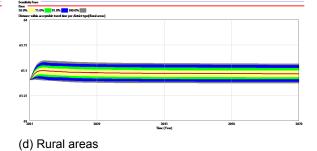
Figure F.3: Sensitivity accessibility to jobs per district type





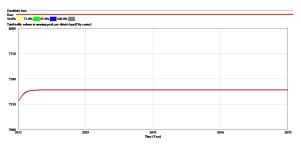
(a) City center

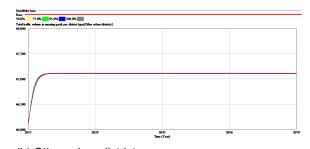




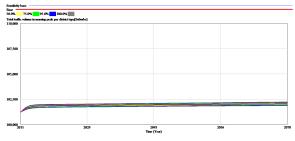
(c) Suburbs

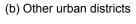
Figure F.4: Sensitivity average trip distance per district type



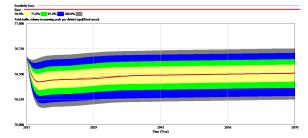


(a) City center



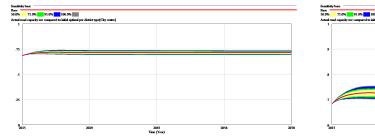


(d) Rural areas

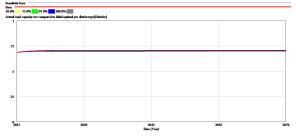


(c) Suburbs

Figure F.5: Sensitivity incoming traffic volume per district type

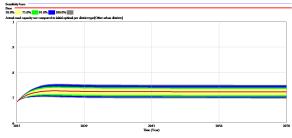


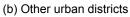
(a) City center

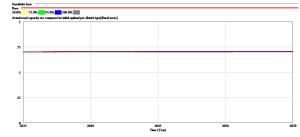


(c) Suburbs

Figure F.6: Sensitivity congestion per district type





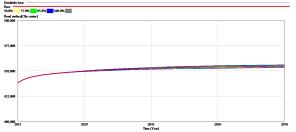


(d) Rural areas

95.0%

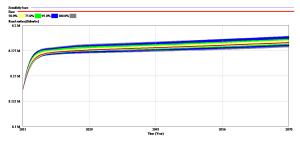
Base 50.0%

2.75





(a) City center



(b) Other urban districts

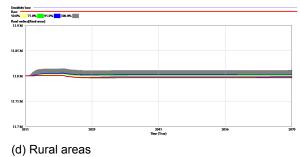
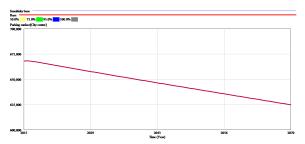
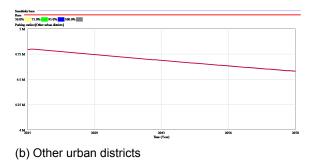




Figure F.7: Sensitivity road surface per district type









Sensitis Base 50.0% Packing

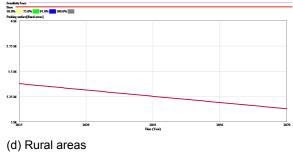
7.75 M

7.25 M

7 м,

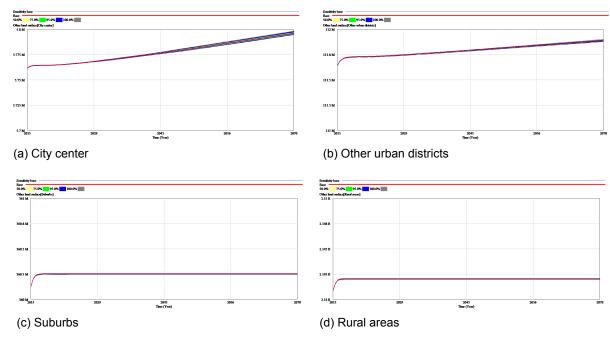


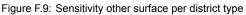
2043 Time (Year)



(c) Suburbs

Figure F.8: Sensitivity parking surface per district type





\bigcirc

PRIM scenario selection

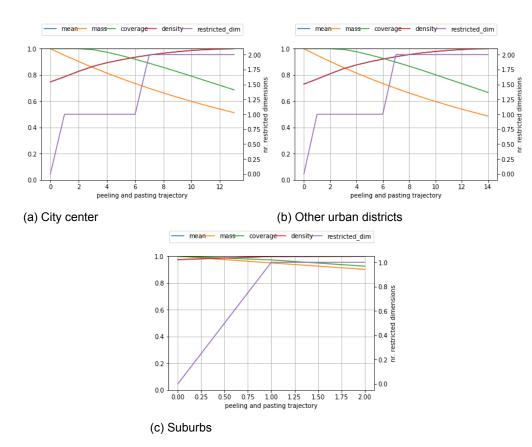


Figure G.1: Peeling and pasting trajectories population density

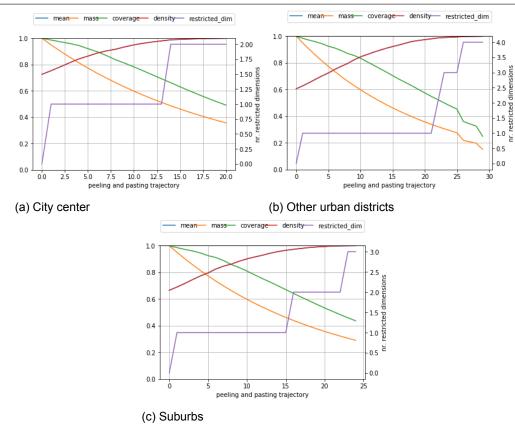


Figure G.2: Peeling and pasting trajectories increased accessibility to jobs

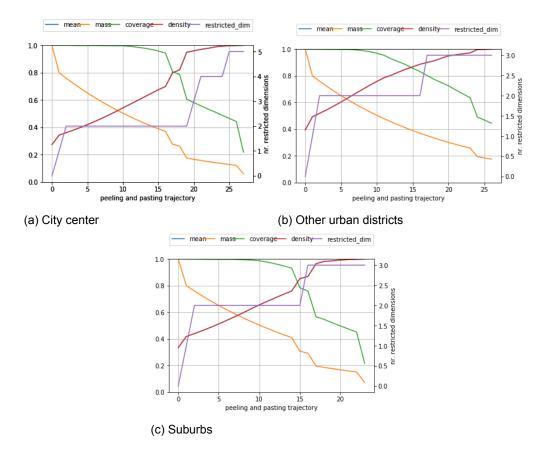


Figure G.3: Peeling and pasting trajectories decreased accessibility to jobs

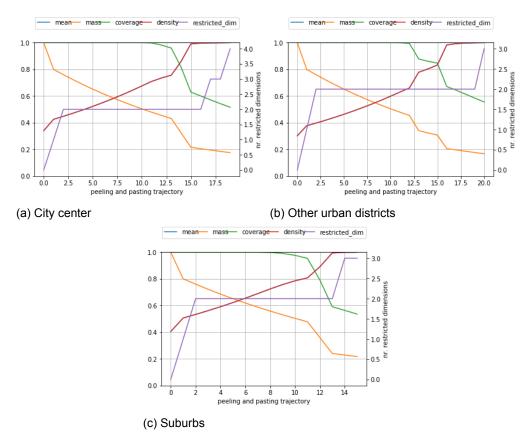


Figure G.4: Peeling and pasting trajectories acceptable commuting distance

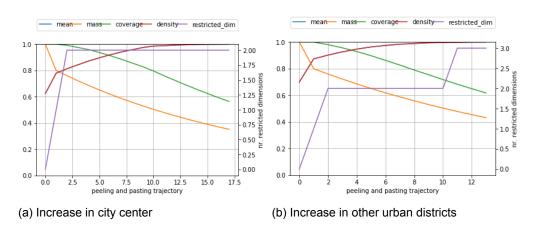


Figure G.5: Peeling and pasting trajectories capacity saturation

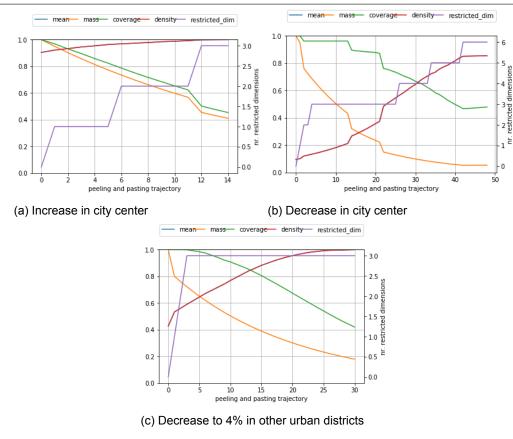


Figure G.6: Peeling and pasting trajectories fraction road surface

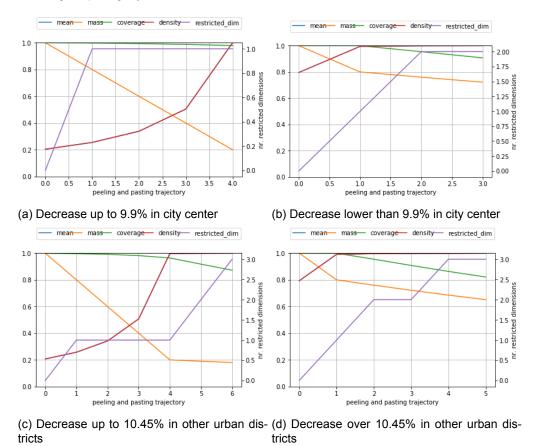


Figure G.7: Peeling and pasting trajectories fraction parking surface