Jurgen Nieuwenhuijsen

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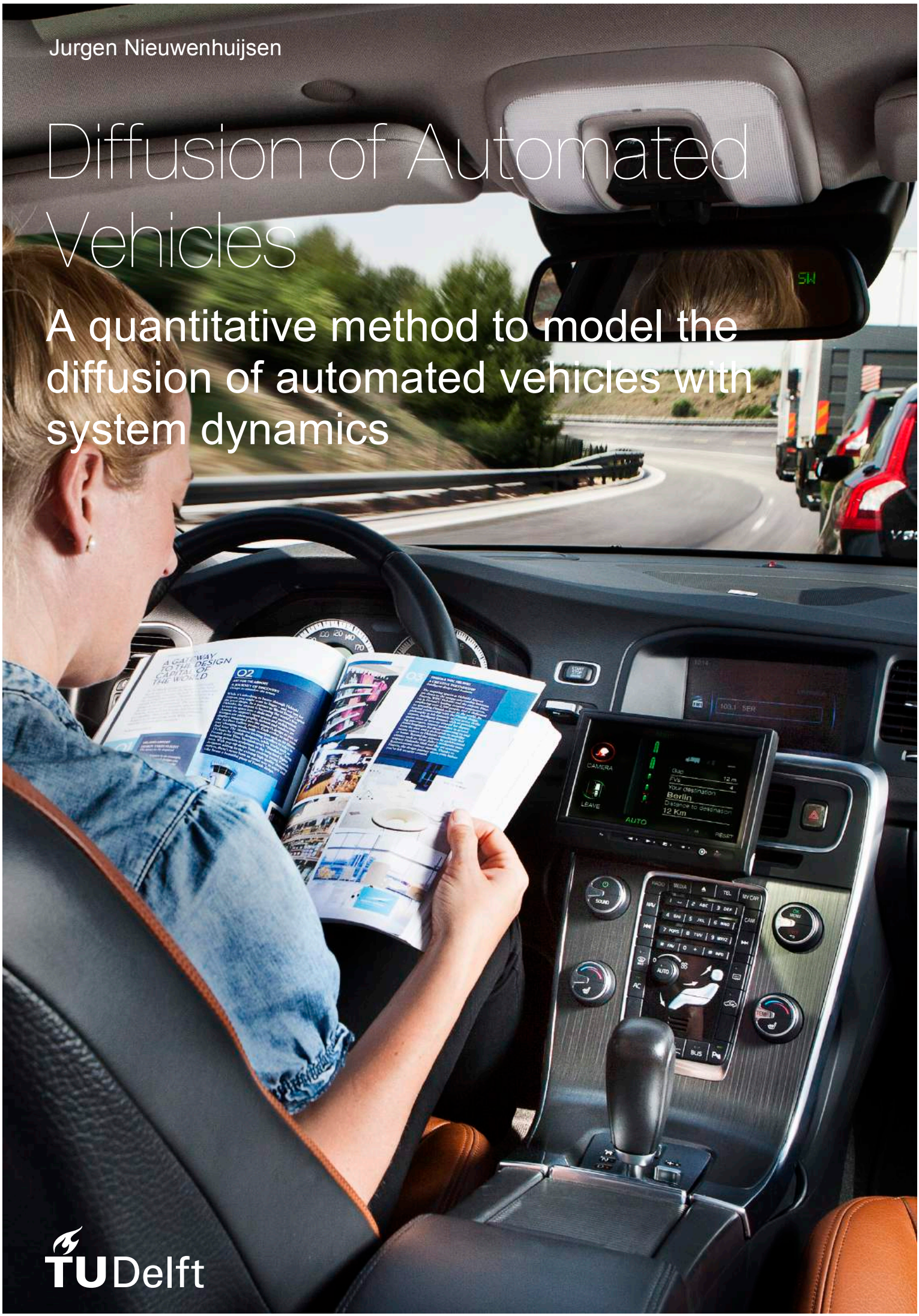
A quantitative method to model the diffusion of automated vehicles with system dynamics



TU Delft

Diffusion of Automated Vehicles

A quantitative method to model the diffusion of automated vehicles with system dynamics

By

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Preface

This document represents the results of the Master Thesis Project of the master program Transport, Infrastructure and Logistics at the Delft University of Technology. This thesis has been conducted in context of the company Connekt, located in Delft. The thesis covers the topic of automated vehicles and the diffusion of the innovation into society. My gratitude goes to my thesis committee members who have given me great guidance during the process. I want to thank Connekt for the welcome environment and rich context they provided, full of stakeholders that are in the middle of the developments concerning automated vehicles in The Netherlands. All people that are involved in this research as experts are thanked for their perspectives. A special thanks goes to Tom Alkim of Rijkswaterstaat who made it possible for me to collect empirical data with experts at the Automated Vehicle Symposium 2015 in Michigan, USA. At last I want to thank all my friends and family who are close to me, including the people at Erasmus Centre for Entrepreneurship, which made it possible for me to work on this project with my full focus.

Jurgen Nieuwenhuijsen

Delft, 8 September 2015

Abstract

This research presents a novel simulation model that shows the dynamic and complex nature of the innovation system of vehicle automation in a quantitative way. The model looks at the system of automated vehicles from a functional perspective and therefore categorizes vehicle automation into six different levels. Each level is represented by its own fleetsize, its own technology maturity and its own average purchase price and utility. These components form the core of the model. The feedback loops between the components form a dynamic behavior that influences the diffusion of automated vehicles. The model can be used with different datasets and can be enriched with new data in the future. Policymakers and the industry can use the model with their own dataset to gain insight in the speed and direction of the diffusion of automated vehicles.

To test and use the model in this study a dataset has been collected through a literature review and expert interviews. Through an uncertainty analysis on this dataset the input parameter have been calibrated, which forms a base simulation run. The outcome of this base simulation run shows a dominant market penetration after 2040 for conditionally automated vehicles. This run also shows a low adoption rate and market penetration for highly and fully automated vehicles. Within the model the technology development is lacking behind of both highly and fully automated vehicles.

Various policy instruments have been tested in the model. The model outcome shows that if knowledge sharing and collaborative projects in the industry are stimulated and a public and private technology fund is created the technology development will grow faster. These policy instruments together lead to a market introduction of highly and fully automated vehicles between 2025 and 2030. In 2030 partially and conditionally automated vehicles mainly dominate this market with a market penetration of 60%. In 2050 highly and fully automated vehicles with a market penetration of 75% mainly dominate the market.

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1. Introduction

The automobile industry is gigantic in terms of production, revenue and amount of workforce and has an enormous impact on the economy. In the US alone more than 734,000 Americans work in the automobile industry (IHS, 2013), which makes up 3% of the national GDP (AAPC, 2014). However the market is changing and technology is advancing in an accelerating pace. This requires new business models and innovation in both products and internal processes. The automobile industry spends around €77 billion (ACEA, 2015) worldwide on R&D in order to boost innovations and stay competitive. According to a study by the European Commission (2014) the automobile industry in Europe has the highest R&D expenditure compared to all other sectors like pharmaceutical, technology hardware and aerospace & defense. One of the changes that will have a major impact on the industry is vehicle automation.

Automated vehicles seem to have a much wider impact on the system that reaches further than the automobile industry alone. The transportation and mobility sector as a whole will be affected by the possibilities that vehicle automation can bring. It will be hard to tell the difference between a leasing-company, a rental company, a taxi company or a peer-to-peer carsharing company when vehicles are able to operate themselves without any human driver. The underlying business model that supports this system is not crystalized yet. Whether people will buy a car, rent it or have a subscription to a monthly mobility-'bundle' all depends on the opportunities that are created due to vehicle automation and the value proposition that arises from this.

Research by McKinsey Global Institute (2013) calls vehicle automation as one of the ten disruptive technologies of the future. It estimates the direct societal value that will be created between 0.2 - 1.9 trillion dollars annually by 2025. The possible beneficial effects of automated vehicles on society are summed up by Anderson et al. in the 2014 RAND report (Anderson et al., 2014). Vehicle automation can increase the mobility of people that can't drive themselves because of a disability or due to their age. Land use and urban planning could be improved due to a decreased number of parking spaces that are required. Smarter cars can increase the fuel efficiency. Furthermore automated vehicles are considered safer than conventional cars, so lighter materials can be used, which also saves fuel. People can be more productive in the vehicle if it is automated, this can cut societal costs of traveling or congestion delay.

Currently there are driver support systems and partially automated vehicles on the market. A study by Kyriakidis et al. (2015) shows the significant impact that these systems already have on decreasing the number of accidents. According to Anderson there are 5,3 million automobile crashes in the USA alone, resulting in 2,2 million injuries and 32.000 fatalities. If these numbers can be brought down, this could save society a lot of lives and billions of euros. A study by Snelder et al. (2014) show the impact that automated vehicles can have on traffic efficiency, highway capacity and congestion reduction. Current literature, simulation studies and field tests combined form an extensive amount of data on the possible effects of automated vehicles. Though because of a lack of common terminology a clear distinction between different types of automated driving is not always made. This makes it hard to have a clear overview on this available data. Milakis et al. do make this distinction and show in a study that there are causal connections between the different effects of vehicle automation (Milakis, van Arem, & van Wee, 2015). They also show qualitatively by means of a ripple model what the impact of vehicle

automation is over different time spans. Their model originates from the ripple effect theory, which is used in other fields of research as well to show the effects of a certain impactful event over the short-, medium- and long-term. Figure 1 shows this ripple effect of the impact of vehicle automation once it is being deployed and available on the market. In the short term this model shows mostly traffic and travel implications. The second ripple shows effects in the way people plan their activities and location, effects in the way people think about vehicle ownership and effects on the infrastructure planning. The effects in the long term are wider spread. Through more productivity, a higher accessibility and the formation of new markets the economy could be highly impacted. Our health could be impacted through the possible reduction of accidents and emissions. The urban planning could be changed drastically through a different allocation of parking spaces, living areas and green strokes. And also our transportation system could be largely impacted through a possible reduction in congestion, changes in mode choices and a higher level of mobility of people that are currently not able to travel individually without help, like blind and elderly people. As part of this model Figure 2 shows that higher levels of automation cause a stronger ripple, which has more impact on society over the long-term. In his study Milakis shows that there still is a lack of data on most of the medium- the long-term effects. This makes the system very uncertain.

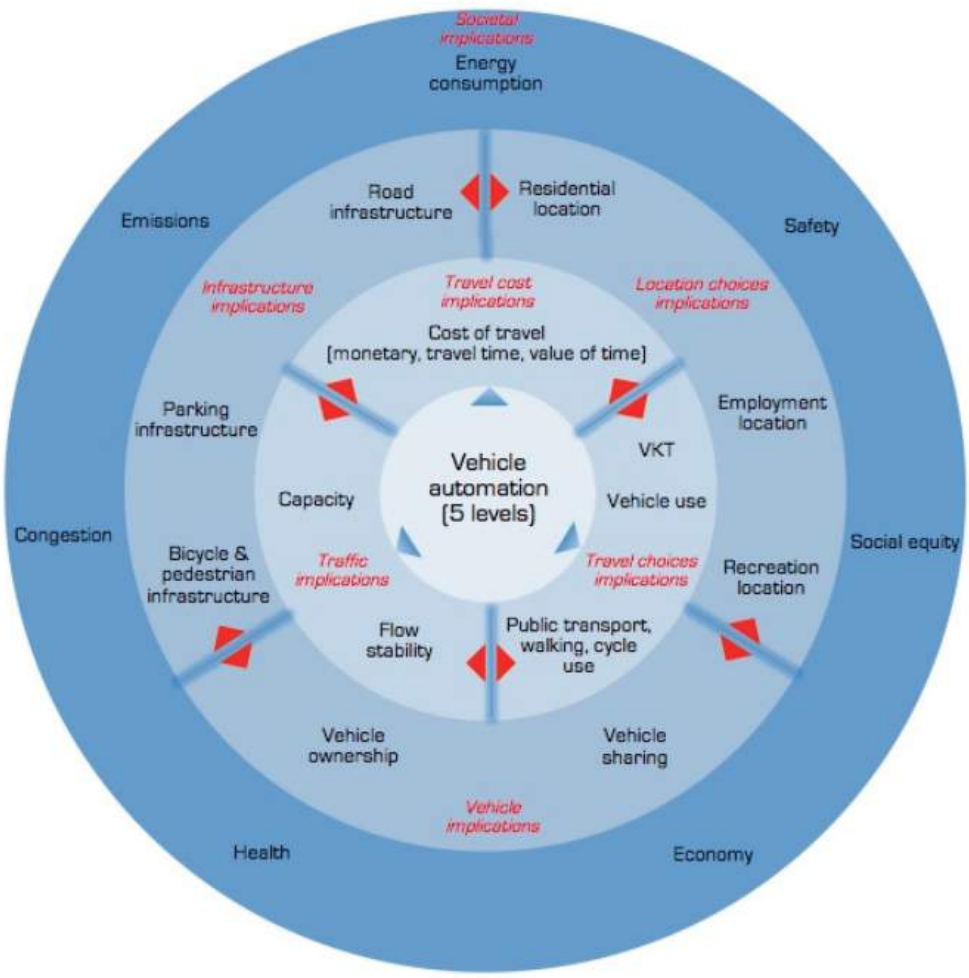

Figure 1 Ripple Model by Milakis et al. (2015)

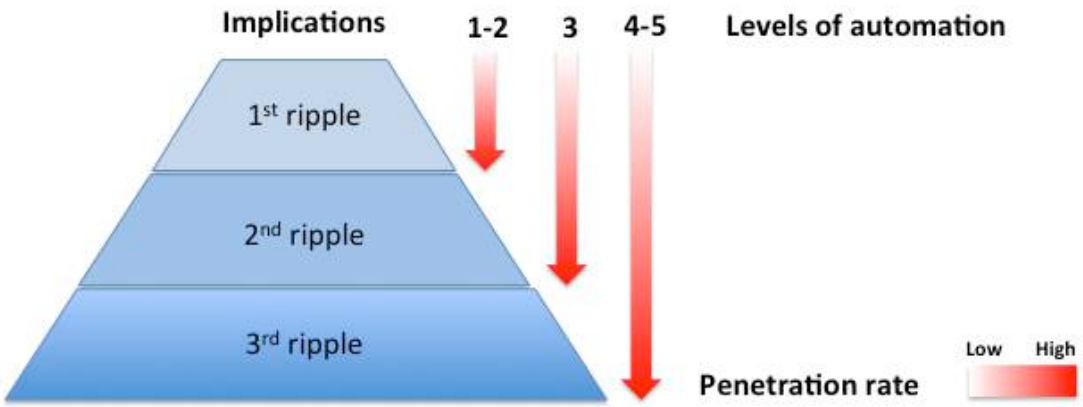

Figure 2 Magnitude of the impact along higher levels of vehicle automation.

The ways that the business models in this new system of vehicle automation will turn out to be have a large impact on the adoption rate of automated vehicles and on the type of impact automated vehicles will have on society. If the model changes from ownership to 'usership', this will largely decrease the number of cars in operation. This has impact on the number of required parking spaces and thus on urban planning. This change also likely will increase the utilization of vehicles and might even create more traffic. If however people will massively adopt automated vehicles and own them, this will create more operational cars and thus more parking spaces are required. These changes however are highly unknown and unpredictable.

Due to the beneficial effects of vehicle automation there is a high incentive by policy makers to stimulate the development and diffusion of automated vehicles. The value that is being created by vehicle automation is often looked at in a third-person perspective, meaning that mainly the overall societal benefits are being mentioned. However Howard & Dai claim that: "the ability of automated vehicles to affect transformative change depends largely on how successful the vehicles are in attracting drivers from automobiles. Once a critical mass of automated vehicles has been established, network benefits and other economies of scale enable environmental, safety, and travel time improvements". In order to attract a large consumer-base towards vehicle automation, it has to have a clear value proposition. The magnitude of the societal changes is determined by how consumers will adopt automated vehicles into their lives. This statement is supported by Figure 2, which illustrates that in order to impact the system on the long-term, on a 3rd order ripple, a high market penetration is needed. The adoption of vehicle automation is seen from a first-person perspective. In order for policy makers to support the adoption of automated vehicles and its diffusion in society they have to take this first-person perspective into account.

As Rosenberg already wrote in 1983: "One of the most important unresolved issues is the rate at which new and improved technologies are adopted". The difficulty of deployment is also underlined by Shladover as he states that: "one of the most vexing problems has always been that of determining how to advance from the present-day manually-controlled vehicles to the future fully automated vehicles." (Shladover, VanderWerf, Millee, Kourjanskaia, & Krishnan, 2001). Many studies have been conducted upon the deployment of automated vehicles. Litman (2015) identifies a possible deployment pathway by comparing vehicle automation to similar innovations. Underwood (2014) conducted a study in which expert estimated the year of the introduction of vehicle automation into the market. Bierstedt (2014)

identifies barriers for massive market adoption of self driving vehicles. These barriers are a low maturity of the technology; the high costs in the early stage; the readiness of the infrastructure; liability issues and personal preferences of the user. The diffusion of automated vehicles into society seems to be subject to an interdependency of many factors. Above-mentioned studies do not take the dynamics of the system into consideration. As the diffusion of automated vehicles is part of one or more feedback loops, this phenomenon cannot be explained in a linear equation.

1.1 Aim of this research

Vehicle automation could have a large impact on society. Governments from various European countries like UK (KPMG, 2015), Finland and the Netherlands (Dutch Ministry of Infrastructure and Environment, 2014) have already indicated to put extra focus on stimulating the development of vehicle automation in their country. Policymakers should have insight in the interaction between technology development, personal preferences of the end-consumer and entrepreneurial activities of vehicle automation. Either to be more adaptive to changes in society due to vehicle automation or even to guide the direction and speed of this innovation system of automated vehicles. The system is too complex with too many interrelated components to simply see the dynamics. This system overview and quantitative approach to analyze the future adoption and diffusion of automated vehicles is currently missing in literature. What is needed is a framework that can grasp the different aspects of the system in an unambiguous way and relate these aspects to each other. The data that is available on the different aspects can be used to quantify the relations within the framework. The aim of this research is to create this framework and gain more knowledge about the factors that influence the diffusion of automated vehicles so that we can better understand the interaction of complex policies and their potential effects on the diffusion of automated vehicles. This leads to the following research question:

What can we learn quantitatively about the speed and direction of the diffusion of automated vehicles given its dynamic and uncertain complexity?

In order to answer this research question the following sub-questions are defined:

1. How could the adoption rate and market penetration of vehicle automation evolve over time?
2. How can we change the direction and the speed of the adoption rate of automated vehicles?
3. How can we increase the speed of technology development?
4. What is the influence of high economic growth on the model?
5. What is the influence of a supportive AV policy and a High technological development?

In the next Chapter the best-suited research methodology for this research question will be explored.

2. Methodology

In this Chapter it is reviewed why system dynamics is chosen as the appropriate method for the research question. Furthermore the steps of this method that will be done in this research will be discussed.

2.1 Method requirements

When analyzing the system of automated vehicles three characteristics can be identified about this system. First of all the system is unknown because the components lack a lot of data in literature. Studies can be found on the impact of automated vehicles, but this research still has a lot of unknowns about the magnitude of the impact. There is still a lot unknown about the factors that have an effect on the development and diffusion of automated. This lack of knowledge about the structure of the system and a lack of data about the magnitude of specific factors make the system **uncertain**. A second characteristic is that the factors in the system of automated vehicles are very interrelated. An example is the possible impact of the use of automated vehicles on traffic and congestion. Congestion has an impact on travel behavior, which on its turn has an impact on the usage of automated vehicles. Various feedback loops can be identified, which makes the system **complex**. The factors that affect the diffusion or adoption rate are part of the system of automated vehicles. They are endogenous to the system and thus have a tendency to change over time. This is in contrast to static factors that are exogenous to the system. A multitude of these endogenous factors make the behavior the system unpredictable and **dynamic**.

The research question that has been identified in the previous chapter is: "What can we learn quantitatively about the speed and direction of the diffusion of automated vehicles given its dynamic and uncertain complexity?" A method needs to be found that is **available** and can be applied in uncertain, complex and dynamic systems. As stated in the research question the method needs to be **quantitative**. Automated vehicles are totally new products that are in the **beginning of the product lifetime cycle**. This needs to be taken into account when studying the future demand and diffusion into society. The diffusion of automated vehicles is something that did not occur before in history, but needs still to be happening in the **future**. This creates a **lack of data** that needs to be accounted for in a method. In order to really learn from this study, the method should be able to show **future behavior** of the speed and direction of the diffusion of automated vehicles. This way relations between factors might come to light that have a strong influence on one and another. Due to the many factors that are involved with the diffusion of automated vehicles, a **large time horizon** needs to be taken into account. To learn more about the speed and direction of the diffusion of automated vehicles over this long time horizon the general **averaged behavior** on a **aggregated level** of the system is more interesting than detailed information on a disaggregated level. Aggregated behavior gives more information about the relations between factors in the system, while disaggregated behavior gives more information about individual components in the system.

2.2 Forecasting techniques

The adoption rate of an innovation is closely related to the future demand of this product. An often-used method to predict future demands is forecasting. There are various techniques of forecasting methods available that can be classified in three basic types: qualitative techniques, time-series analysis and causal models. Chambers (1971) gives a breakdown of the appropriate application of these forecasting techniques. A selection of a forecasting technique depends on the

availability of data, the available knowledge about the system, the required accuracy of the forecast and the type and context of the product of which the demand ought to be forecasted.

An important aspect of forecasting studies is that they relate to the stage of the lifetime cycle that the product is in. A product that has matured through the lifetime cycle has a lot of historical data. The characteristics of these products are known and through these characteristics it can be measured what the past and current demand of these products is. Chambers (1971) states, that "different forecasting techniques are appropriate to forecast sales, say, at different stages of the life cycle of a product—for example, a technique that relies on historical data would not be useful in forecasting the future of a totally new product that has no history."

2.2.1 Qualitative methods

Different qualitative techniques exist for forecasting of new products. The Delphi method takes a group of experts of which each expert is interviewed. The answers of one expert are input for questions to the next expert or collective iteration. This technique is very useful when the system and its possible behavior is known to the experts but still unknown to the researcher. It is a good method of getting into a new field of research and getting to know the system. As identified before the system of automated vehicles however still has a lot of unknowns. The opinions about the system are widespread among the experts.

Another technique is visionary forecasting or expert estimations. In this technique experts estimate the likelihood that a certain event will occur and at what time horizon. However these expert estimations cannot be treated as very reliable. The reason for this is that the potential diffusion of vehicle automation can be considered as an exponential growth. According to Scott Armstrong (1985) exponential growth is hard to handle for people, even for experts on a topic. People are used to handle "percentagewise" growth and can't grasp the impact that exponential growth can have on a system. According to studies by Wagenaar and Sagaria (1975) expert forecasts of exponential growth are highly conservative. These forecasts could therefore underestimate the real phenomenon. According to Armstrong the level of expertise (measured in education, experience, reputation, previous success and self-identification) only improves the accuracy of a forecast up to a certain threshold E_j. Above this threshold the level of expertise doesn't add to an improved accuracy anymore. The height of this E_j depends on the complexity of the forecast one is doing. The theory of Armstrong is depicted in Figure 3.

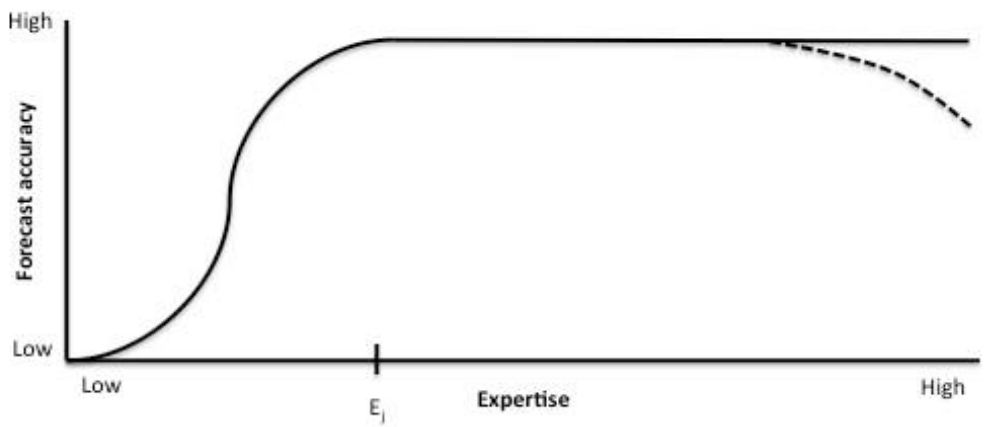

Figure 3 Relationship between expertise and accuracy in forecasting. Source (Armstrong, 1985)

Both mentioned forecasting techniques are qualitative. These techniques might give a good insight in certain qualitative relations and qualitative behavioral aspects. However this research aims at gaining a quantitative insight in the diffusion of automated vehicles.

2.2.2 Time-series analysis

Quantitative approaches are time-series analyses like moving averages and trend projection. These methods require a set of historical data that can be used to extrapolate. If one cannot work with historical data or product characteristics of a product because the product is new and not on the market, like in the case of vehicle automation, Rogers (2003) proposes to use extrapolation from the rate of adoption of similar past innovations. These adoption rates can be extrapolated into the future for the new product under investigation. Useful past innovations that represent characteristics of the innovation of automated vehicles could be: the introduction of the steam engine for locomotives or the introduction of the automobile by Henry Ford. Litman (2015) has conducted research similar to this method by extrapolating the adoption rate of airbags, navigation systems and hybrid vehicles to the possible diffusion of automated vehicles. The system of automated vehicles seems much more interrelated with travel behavior, car ownership vs. car-usage, traffic conditions and macro economical factors like industry and policy decisions. Furthermore Milakis (2015) has shown that automated vehicles have a very high impact on the system around them. This makes the system of automated vehicles much more complex than innovations like airbags and navigation systems. The adoption of hybrid vehicles seems complex as well. However this innovation doesn't have as much of an impact on travel behavior, traffic conditions and urban planning as automated vehicles do. It is therefore hard to find a suitable innovation from the past that can be extrapolated to forecast the adoption of automated vehicles.

In order to get an insight in the possible demand or acceptance-to-buy of automated vehicles, one could conduct a market research. By describing the possible characteristics of automated vehicles to respondents stated preference research could be used to identify a possible demand. However automated vehicles don't exist yet and it is highly uncertain what the exact characteristics and value proposition will be like. It also seems hard to grasp for people what an automated vehicle really is, so the reliability of a stated preference is doubtful.

2.2.3 Causal models

The last forecasting type that Chambers (1971) identifies is causal modeling. This entails that to gain insight in the diffusion of a new product of which you lack historical data, you can look for relationships of this product with other existing phenomena of which there is historical data. Regression modeling is such a method, in which you relate future demand or future sales to other economic variables. You can estimate an equation that best predicts the behavior of this relation by using the least-square technique. However to use this technique knowledge is needed of the economic factors that drive the diffusion of automated vehicles, which are very uncertain.

To describe the behavior of the diffusion of automated vehicles the theories that exist on lifetime cycle analysis could be use. These theories describe an s-shaped curve for the diffusion of new products. However automated vehicles cannot be seen as just one product. It is a multitude of products and also services that all together form a new system that will be deployed. It is therefore hard to relate the lifetime cycle theory to the system of automated vehicles. Another disadvantage of this method is that it only gives an indication of the shape of the diffusion over time, but not on the speed or impact of this diffusion as required for a method in this study.

2.2.4 Prediction market theory

A forecasting method that has not been discussed yet and that can't be categorized into one of the three forecasting types very easily is prediction market theory. Prediction market theory, also sometimes referred to as "idea futures" or "event futures" (Wolfers & Zitzewitz, 2006) teaches that if you ask the question to a very large number of people to forecast on event, the average answer is fairly accurate (Berg, Nelson, & Rietz, 2003). Some prediction markets can even be more accurate then most benchmark studies says Wolfers (2004). A question that is been asked a lot, by industry leaders, researchers and media is something like "when will automated vehicles be available on the market". A technique like prediction markets theory seems appropriate to be looking for a specific date that the automated vehicles will be available on the market. After all Armstrong's theory shows that the use of experts doesn't always increase the accuracy of the estimation, so a very large group of well-informed people could also be used. Two things should be taken into account however. For prediction market theory to be successful the question should be rather unambiguous and unbiased. Furthermore to have a large accuracy the time-horizon shouldn't be too long. When relating this to automated vehicles various problems might occur. An automated vehicle is still an ill-defined object and could be interpreted by people in many ways. The terms 'mass adoption' or 'deployment' of automated vehicles are also something that people might interpret in many ways and so these terms are not very unambiguous. At last the time horizon before automated vehicles will be available on the market might be also too long for accurate predictions.

Next to that one might ask what really could be learned from a study that looks at a specific moment when automated vehicles will be available on the market? One can only validate this research once the event actually occurs. And by that time the study will lose its value anyway. It is therefore much more interesting to look at what causes the diffusion of automated vehicles and how this can be influenced before the event actually occurs, so that the speed and direction of the diffusion can be steered to a beneficial outcome.

2.3 Simulation

A widespread of forecasting techniques have been looked at. Most of these techniques could be excluded because they don't meet the method requirements. Some methods could be used in parts of this study, like for example expert estimations, to partially fill the lack of data.

Forecasting techniques are considered as deductive research. They estimate a phenomenon from existing theories. Beside inductive and deductive research, simulation can be considered as a third research methodology. Erhentreich (2008) states: "Even though simulation does not prove theorems, it can enhance our understanding of complex phenomena that have been out of reach for deductive theory". This seems to be very applicable for both the system of automated vehicles and seems to meet the method requirements.

In order to model this uncertain, complex and dynamic system there are two simulation techniques that seem appropriate: System Dynamics (SD) and Agent-Based Modeling (ABM). The next few paragraphs will give an overview of both systems, compare them and will give arguments why systems dynamics has been chosen as the most suitable method for this research.

2.3.1 Agent-Based Modeling

Agent-Based Modeling, ABM, is build upon the existence of an agent. Siegfried (2014) defines an agent as "an entity that is situated in some environment, and that

is capable of autonomous actions in this environment in order to meet its objectives". This agent operates in a dynamic environment. The environment consists of various agents that have interactions and relation with each other. Each agent looks at its current state in its environment and alters this state according to its own objective function. In ABM the agents do not simultaneously perform actions at constant time-steps. Rather, their actions follow discrete-event cues or a sequential schedule of interactions powered by the simulation engine (Castiglione, 2006).

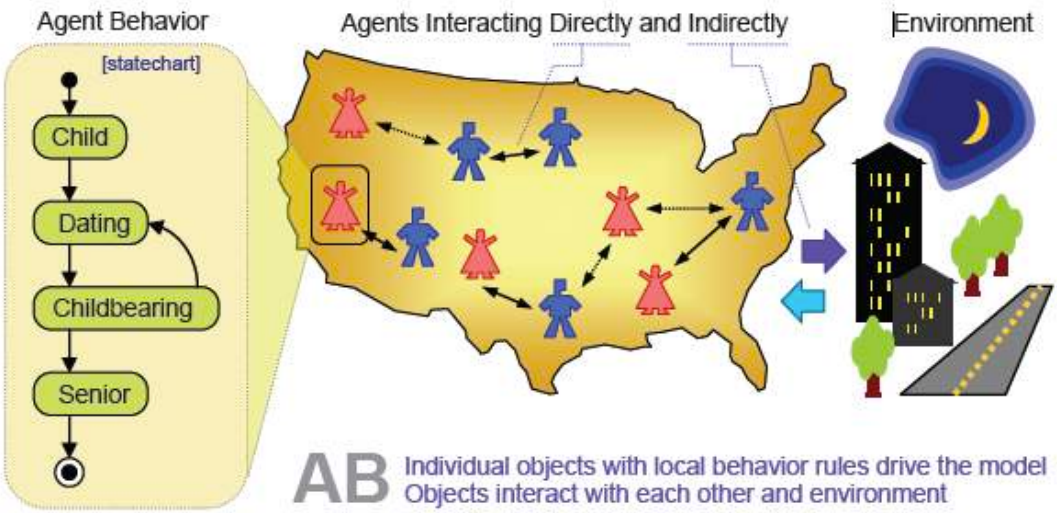

Figure 4 Conceptual illustration of a typical Agent-Based model. Source: (Borshchev, 2004).

ABM is used often to emulate emerging phenomena that transcend the individual agent level. These phenomena are hard to grasp by just looking at the individual agent, because often these phenomena occur because of the relations that agents have with each other. Examples of these emerging phenomena are the behavior of a stock market due to negotiation and trading between agents and emerging traffic congestion due to individual car behavior. Innovation diffusion could also be categorized as an emerging phenomenon. Bonabeau (2002) shows with an example that ABM can indeed be applied to the diffusion of a new product, which has similarities with the topic of this research.

Emerging phenomena occur when fluctuations of nonlinear behavior of individuals are amplified. This nonlinearity consists of thresholds and if-then-else rules. ABM is good for grasping this discontinuous behavior. According to Bonabeau ABM is the most suitable technique to emulate this kind of nonlinear behavior, because averaging this behavior with differential equations smoothens out the fluctuations. According to Bonabeau "a synonym of ABM would be microscopic modeling, and an alternative would be macroscopic modeling". ABM is characterized as microscopic because it shows behavior of agents and their choices on a disaggregate level. However to simulate this microscopic behavior may require a lot of computation power and can be very time intensive with bigger models.

One of the issues with ABM according to Bonabeau is the needed availability of data. As ABM uses agents, this often means that people are simulated in the model. The danger here lies in the fact that sometimes only rational objectives will be taken into account because irrational behavior and other psychological factors are hard to quantify. This may lead to wrongly interpreted outcomes when this model represents a real-world system in which these irrational factors are very influential.

2.3.2 System Dynamics

System Dynamics, SD, was originally used by Forrester (1962, 1969) to model the dynamic phenomena in businesses and industries. Because of the high level of interdependencies and feedback loops of these systems, the dynamics could not be modeled by traditional methods like linear equations. Forrester claimed that in order to solve problems one should have sufficient knowledge about the strategic processes involved in complex systems (Pruyt, 2013). According to Pruyt: SD allows to identify behavior of a system, to design desirable system changes and to test them in a 'virtual laboratory'. Two central concepts of SD are the concept of feedback in a system and stocks and flows.

Two modeling techniques of System Dynamics are Causal Loop models and Stock & Flow models. Causal loop models can be used to emulate the dynamic nature of a system and capturing mental models of a real-world system. It identifies system components and connects them according to their causal relations. Causal loop models are therefore well suited to represent the interdependencies and feedback processes in a system (Sterman, 2000). Stock & Flow models are quantitative models that consist of flows and accumulations of physical materials and of flows of information in between those accumulations. The stocks, or accumulations, are represented by mathematical integrals. These stocks conserve the specific materials that are flowing through the model. The flows of material and information between the stocks are represented by differential equations. A Stock & Flow simulation model takes a set of integrals and differential equations and simulates it over time. For each time step the output of the previous time step is used as input for the equations on the next time step. For the first time step initial values have to be specified. SD modeling requires an aggregated approach over the system components, averaging their behavior over time.

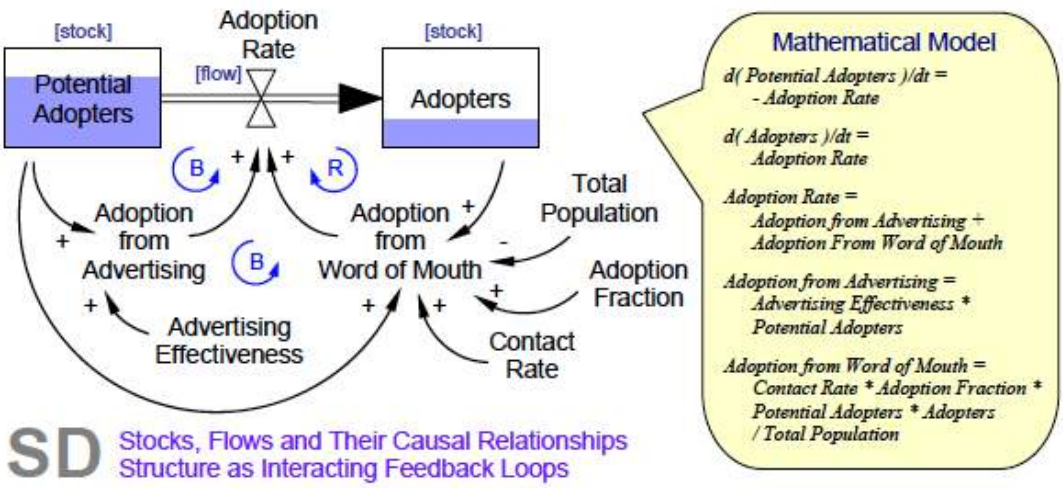

Figure 5 Conceptual illustration of a typical System Dynamics model. Source: (Borshchev, 2004) and Sterman (2000).

SD is a much used research tool to emulate learning behavior. Through the use of feedback loops repetitive learning can be represented and through the use of stocks knowledge can be accumulated. Another phenomenon for which SD is often used is the representation of S-shaped growth like epidemics, innovation diffusion or the growth of new products (Sterman, 2000). The reason for this is that feedback loops and accumulation form the core of S-shaped behavior.

2.3.3 System dynamics vs. Agent Based Modeling

When comparing System Dynamics with Agent-Based Modeling it can be seen that both techniques are capable of simulating complex systems that show nonlinear behavior. SD has a perspective of the system in terms of stocks and flows of material or information. It therefore has a more aggregated perspective on the system. The materials or items that it represents in the model have no individuality. ABM looks at the system in terms of agents and the relations between those agents. This is a much more disaggregated perspective on the system. This distinction can also be categorized as macroscopic (SD) and microscopic (ABM).

SD uses a continuous approach in which it averages the values of variables on a specific time instant towards a behavior of these variables over a time span. The behavior of the system in SD is driven by its feedback loops and accumulations. ABM has a discontinuous approach as it is much more interested in the fluctuations of the values of specific agents. The behavior of the system is driven by the objectives of the agents, their relations and a set of rules that is specified. The disaggregated level on which the AB model operates causes slight fluctuations in the model outcome, which creates a higher level of detail. Table 1 shows an overview of the comparison between System Dynamics and Agent-Based modeling.

	System Dynamics	Agent-Based Modeling
Approach	Continuous	Discontinuous
Level	Macroscopic	Microscopic
Perspective	Aggregated	Disaggregated
Central concept	Feedback loops, information flow and accumulations	Objectives, rules and communication
System components	Stocks and flows of material and information	Agents and their relations
Simulation engine	Integration of time steps using Euler or Runge-Kutta Method	Event based or sequential scheduling
Mathematics	Differential equations	Objective functions
Behavior	Centralized system behavior	Decentralized individual behavior. Emerging phenomena as a result of many individuals.

Table 1 Comparison System Dynamics and Agent-Based modeling

For this research it is important to whether the diffusion of innovation and adoption rate of new products can be modeled by both techniques. Borshchev (2004) confirms in a study how a typical innovation diffusion SD model by Sterman can be rebuild into an AB model. For this re-conceptualization he breaks open the stocks that represent an accumulation of physical items, like people, cars or products. The AB model takes on the perspective of the individual items and redefines them as agents. The stocks (e.g. Potential Adopters and Adopters) are redefined as states that the agent can be in. The flow between the two stocks is redefined as a set of rules for the agents. After rebuilding a simulation run of the AB model with 10.000 agents show the same behavior as the SD model. This can be seen in Figure 6.

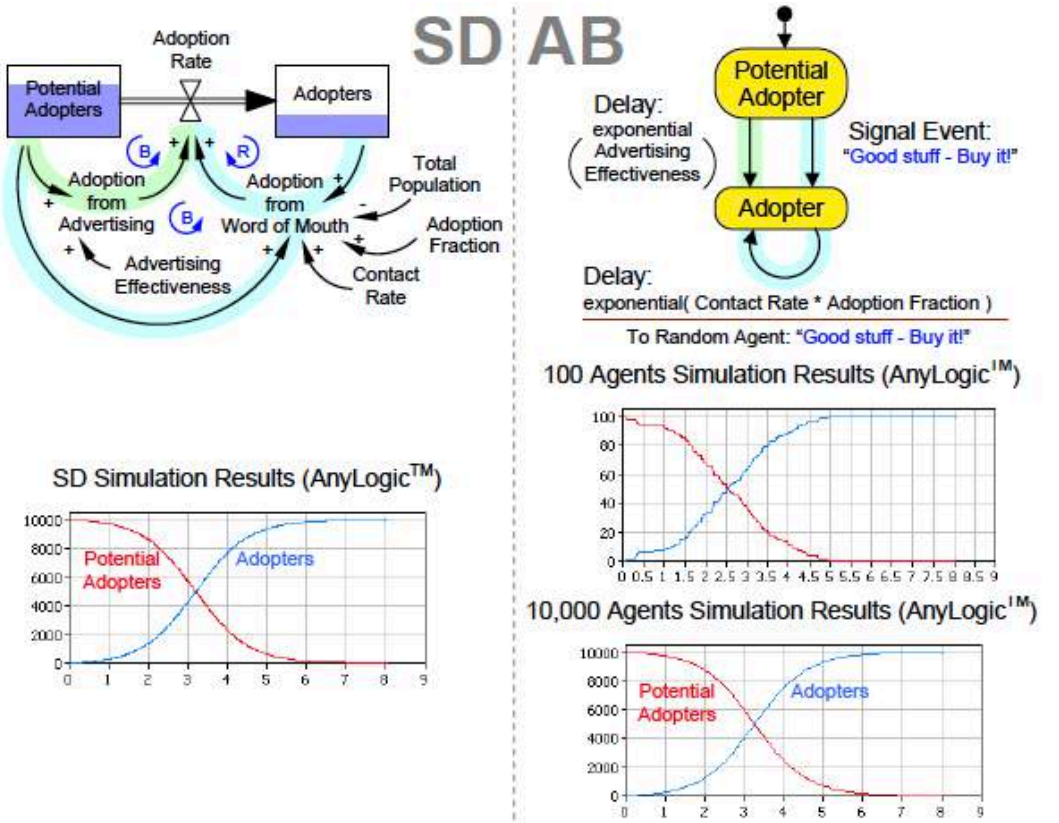

Figure 6 Bass diffusion model converted from System Dynamics to Agent-Based Modeling (Borshchev, 2004).

Borshchev argues that ABM is the most suitable tool to use when not much is know about the macroscopic behavior of the system, but when more information is available about the individual behavior of agents. Building an AB model in this case then requires less work and is less complex than a SD model. It has to be said though that the runtime of an AB model for a similar system is higher than that of a SD model as it has to simulate all the small details on an individual level. If the same smooth behavior as a SD model needs to be reached by a ABM model the run time is significantly higher.

System Dynamics seems the most appropriate research method that meets the method requirements the best. SD seems to be most suitable to capture the complex and dynamic nature of the system. Little knowledge is available about possible future actors, their objectives and their relations over the long term of this system. This knowledge would be needed in order to build a strong AB model. More knowledge seems to be available about possible phenomena that could occur and the overall structure of the system. In order to learn more about the speed and direction of the diffusion of automated vehicles small fluctuations that could occur on a long time horizon and are not so interesting. ABM is too detailed for the purpose of this research. ABM focuses too much on the actions of individual agents in respect to the long time horizon and the global perspective in this research. With SD individual actors are taken out of the picture and a more aggregated view is created, which focuses purely on the behavior and interaction of variables. For these reasons System Dynamics seems to be the most suitable simulation technique to use in research. Both causal modeling and stock & flow modeling will be applied.

2.4 Methodology

In the last paragraphs an appropriate method for the research question has been selected. By using System Dynamics modeling the diffusion of automated vehicles will be emulated. In order to build a good model that represents this system it is needed to gain more knowledge about this system. By a literature review the important components and boundaries of the system in this research will be identified. As a framework for the identification of system components an innovation system model of Marco Hekkert (2007) will be used. By causal loop modeling the relations and feedback loops between the system components will be identified.

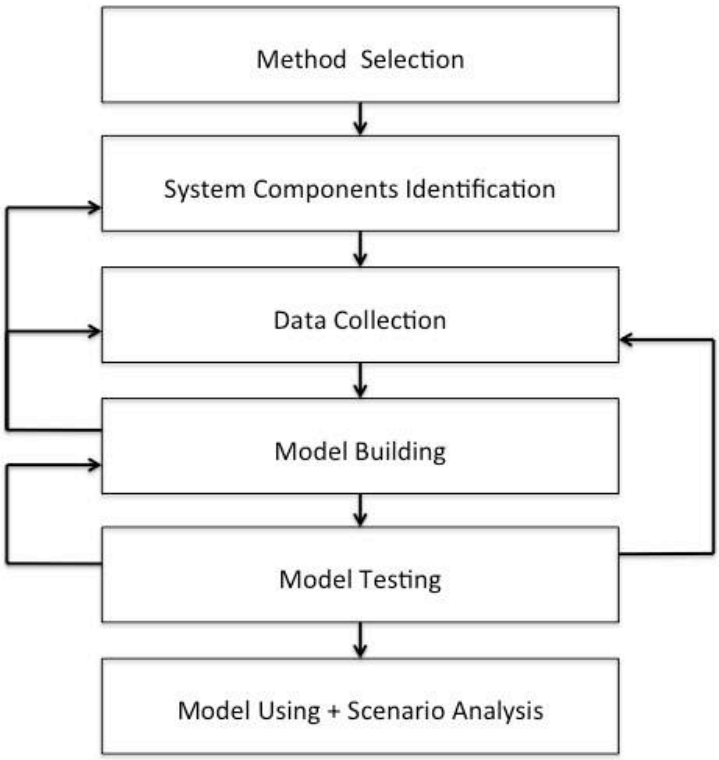

Figure 7 Flowchart representing the methodology steps.

Through a thorough literature review the availability of data about the system components will be assessed. Components that have available data will be described and further explored. If new information is found about relations between system components then the system scope will be revisited and revised. Knowledge gaps in literature that are identified can also be very valuable. Interviews will be held with selected experts to fill these knowledge gaps and to find additional information about the system components and structure. An overview of the selected experts can be found in Appendix F. The interviews will be held at the Automated Vehicles Symposium 2015 in Ann Arbor, Michigan. This is an annual gathering of all the top experts in the field of vehicle automation, which forms a very efficient way of conducting the interviews. The interviews will be semi-structured in order to ask all the experts the same set of questions, but keep the freedom to go into a specialized topic with the expert on that topic. The questionnaire for the semi-structured interviews can be found in Appendix E.

With the knowledge about the system components, their structure and input data a Stock & Flow model can be built. Theory about innovation diffusion, learning curves and demand modeling is used to come up with a set of differential equations that describe the internal structure of the model components. The values for the initial settings and the input parameters are fed by the collected dataset. These settings

will form a simulation base run. After it is being build the model will be tested using seven different steps. The model will be analyzed both statically and dynamically. Among others a sensitivity and uncertainty analysis will be done. Faults that come to light during the testing of the model can be revisited in the model building. By testing the model, more confidence will be gained upon the validity of the model to represent the real-world system.

When the model has been found robust and enough confidence in the model is gained, the model can be used to test different scenarios. The outcomes of these scenarios form a way to answer the research question. A flowchart of the above-mentioned methodology steps can be seen in Figure 7.

3. System scope

In this chapter the system scope of this research will be explained. Through a literature study the various system components will be identified. Furthermore the assumptions and boundaries of the focus of this research will be specified.

3.1 Two game changers

The technology of self-driving vehicles is best described as a movement of two game changers, as introduced by Wilmink (2014): the movement from autonomous towards cooperative systems and the movement from manual control towards automated control of the vehicle. Figure 8 shows an overview of these two game changers.

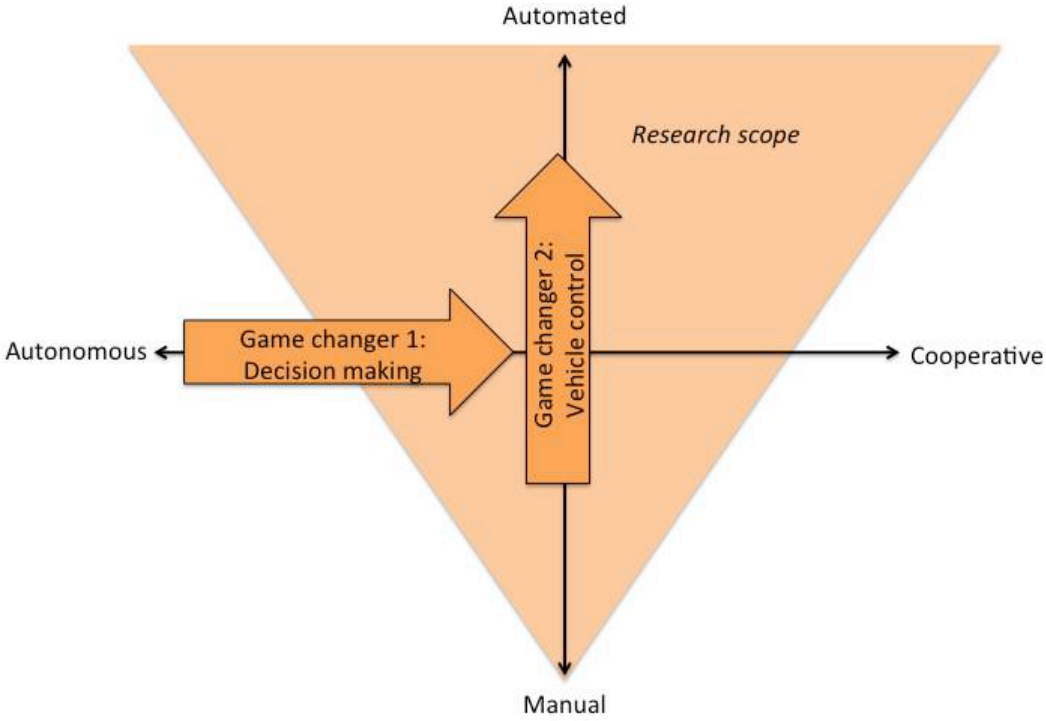

Figure 8 Two game changers of self-driving vehicles and research scope. Adjusted picture from an original by Wilmink (2014).

The first game changer is the movement from autonomous decisions making towards connected systems, which are able to make cooperative decisions through information sharing with other vehicles and infrastructure. Autonomous decisions can be made either by a computer or by a human driver. The information that is shared with cooperative driving could be information about surrounding traffic situations, about the route of the vehicle or about the state of the vehicle. A study by Van Arem (2006) shows that under certain conditions cooperative driving could benefit traffic flows on highways and therefore increase road capacity on the long run. Furthermore cooperative driving could play a beneficial role in decreasing the fuel consumption of the car, because with the enhanced information it can better predict and advice the optimal acceleration and deceleration levels for the car. An important factor in the impact of these benefits is the degree of connectivity, or penetration rate, among the total fleet. If there are limited vehicles and infrastructure equipped with connectivity

devices, the car is only able to receive limited information. The impact cooperative driving can have is thus largely dependent on the penetration rate of connected cars.

The second game changer is vehicle automation. Through sensing of the environment, computation of all the information and actuation of throttle, brakes and steering wheel the vehicles could be able to operate them selves fully automated without any interaction needed from human drivers.

Both the first and the second game changer could happen separately, without the other game changer happening. Within the scope of this research the main focus will be on the movement from manual control towards vehicle automation, either autonomously or more in a cooperative form. The adoption and diffusion of cooperative systems is out of the scope of this research.

When the term '*self-driving vehicles'* is used in this research the technology as a combination of the two game changers is meant. When '*vehicle automation'* or '*automated vehicles'* is used, solely the second game changer is meant.

3.2 Functional vs. Spatial

Van Arem (2015) specifies the transition from manual towards full automation in two different paths: a functional and spatial path. The functional pathway looks at a gradual transition from driver support applications, towards partial automation, high automation and full automation. The spatial pathway describes the transition as a sudden step towards full-automation, but only on dedicated areas. In the spatial transition path this area specific boundary will then gradually expand from campus areas towards mixed traffic with a low(er) operational speed. This research will look at the system with the view of the functional pathway.

The steps in the functional pathway from driver support, partial automation, high automation and full automation are divided in specific levels. Both the National Highway Traffic Safety Administration (NHTSA) and SAE international have standardized these levels of automation. In this research the standard of SAE are being used as this standard offers a higher level of detail (SAE, 2014). These standards range from level 0 (non-automated) to level 5 (full-automation). The levels of automation by SAE are shown in Figure 9.

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Figure 9 Overview of levels of automation by SAE Standard J3016. Source: (SAE, 2014).

3.2.1.1 Level 0 – No Automation:

All the control functionalities of the dynamic driving task are performed by a human driver. Traditional automobiles are categorized within this level. Vehicles that are equipped with systems that do not take over control of any of the primary functions, but solely give warning signals are still considered as level 0.

3.2.1.2 Level 1 – Driver Assistance:

Most of the control functionalities of the dynamic driving task are performed by a human driver. The computer system is capable of performing some driving modes. The monitoring of the environment is the responsibility of the human driver. Systems like cruise control are an example of level 1 automation. These systems perform the de/acceleration of the longitudinal control, but the human driver is expected to monitor the environment and perform braking when changes in the environment occur.

3.2.1.3 Level 2 – Partial Automation:

The execution of the longitudinal and lateral control can be performed by the computer system. The responsibility of monitoring the environment is still the responsibility of the human driver. The driver should be alert to take over control of the vehicle on short notice. At the moments that the systems are operational, the human driver can take hands and feet off. Examples of systems that categorized in level 2 automation are Adaptive Cruise Control (ACC) and Lane Keeping Assist (LKA). These systems need sensors to detect the environment; like other vehicles

and road markings. With this information about the environment the systems can execute the longitudinal and lateral control of the vehicle.

3.2.1.4 Level 3 – Conditional Automation:

Both the execution of the primary control functionalities and the monitoring of the environment are performed by a computer system. The human driver is still "in the loop" of the operation of the vehicle as it functions as a fallback option if the computer system cannot handle specific situations. The biggest difference with level 2 is that the computer system now has a responsibility to monitor the environment. Furthermore an extended number of decisions are now performed by the computer system in comparison with level 2. With level 3 automation the vehicle can drive in automated pilot mode on the highway. Mercedes Benz has released his S-class with these functionalities. The decisions to change lanes are made and executed by the computer system. The human driver has to be able to re-take control over the vehicle within 10 seconds up to a minute. This means that the human driver can take his/her hands, feet and eyes off, while the computer system is operational. There is no spatial separation between the different levels, but it is realistic to say that the level of complexity that the various levels can handle increase with the levels. The level of complexity is much higher on artillery and urban roads than on highways. It can therefore be said that level 3 automation systems mostly operate in less complex environments such as highways.

3.2.1.5 Level 4 – High Automation:

The execution of the primary driving functionalities, the monitoring of the system and also the fallback option can all be performed by the computer system. The human driver can take his/her hands, feet, eyes and even head off. This means that the human driver could be sleeping. Nevertheless the computer system is still not able to perform all the driving modes under all the conditions. This means that a human driver still has to perform some driving modes under some conditions. Within level 4 automation the human driver can take up to 10 minutes to take over control of the vehicle. Systems that are spatially bounded to a specific area are also considered as level 4 automation, as they are almost fully automated, but cannot perform these functionalities under all conditions.

3.2.1.6 Level 5 - Full Automation:

All the driving mode functionalities are executed by the computer system. At level 5 automation it is possible to remove the steering wheel from the vehicle as the driver does not have to intervene with the control of the vehicle at all. With level 5 automation the computer system can perform control of the vehicle under all conditions, everywhere. The vehicle is also able to drive itself, without a human inside the vehicle. A commonly used name for this level of automation is "robot-taxi".

3.3 Enabling technologies

Looking at an automated vehicle from a functional point of view, it can be concluded that such a vehicle does not consist of just one technology. There is a multitude of technologies that enable the automation of a vehicle. Figure 10, by IHS (Juliussen & Carlson, 2014), shows an overview of the functions in a vehicle that need to be automated for a fully automated vehicle.

Functions to be automated		
Function	**Autonomy needed**	**Availability**
Following	Speed control: Fixed ⇄ Variable	ACC: 1995
Stay in lane	Steering within lane	LKA: 2001
Object detection	Detect pedestrian & other objects	PDS: 2010
Read signs	Spot, sense & recognize signs	TSR: 2008
Braking	Sense & recognize when to brake	Multiple systems: 2003
Switch lane	Steering to another lane	Expected 2016
Know position	Always sense accurate position	Expected by 2018
Navigate	Determine driving routes	Expected by 2018
Obey traffic laws	Drive according to traffic laws	Expected by 2018
AP: Traffic Jam	Follow traffic flow at all speeds	TJA: 2013
AP: Highway	Drive, pass at highway speeds	Expected by 2017
AP: Parking	Find parking, park & retrieve	Expected by 2018
Self-driving	All driving functions; Plus driver mode	Expected by 2025
Self-driving only	All driving functions; No driver mode	Expected before 2030

Source: IHS © 2014 IHS

Figure 10 Vehicle functions to be automated. Source (Juliussen & Carlson, 2014)

Some of the technologies are in a different stage of development than others. Some technologies are already available but need higher performance to be reliable for vehicle automation, such as the accuracy of localization. These enabling technologies are a combination of both hardware and software. Development of the hardware profits a lot from investments and developments made in other sectors such as aerospace and robotics. Chips, processors and cameras keep improving according to Moore's law, which state that the performance of these hardware technologies doubles every 2 years. The software however is more specific for the use-case and can therefore profit less from improvements made elsewhere.

3.3.1 Categories for enabling technologies

As mentioned in the introduction of this report a common terminology and definition of vehicle automation is often missing. To get rid of this ambiguity a framework is created in this research to classify the technologies that enable vehicle automation. The functionalities that enable vehicle automation will be divided into five categories:

- **Perception**: This category includes technologies that enable object detection and the situational awareness of the vehicle. Hardware technology like radar, lidar, camera and sonar fall in this category. Software includes pattern recognition, image processing and the creation of digital environments.
- **Localization**: This includes localization both on a microscopic level and on a macroscopic level. On the microscopic level the vehicle needs to know where it is on the road. It needs to connect the perception data with known data points of its surrounding to localize itself. On a macroscopic level the vehicle has to know where it is located on the road to its destination. Technology like digital maps and GPS is used.
- **Planning and decision-making:** This category is very much software driven with a lot of smart optimization and control algorithms. This software processes the sensor data, fuses this data to get a more enriched picture and makes decisions based on this picture of the surrounding. To process all this computation power fast chips and processors are needed.
- **Vehicle motion control:** This category includes the use of the actuators, inside a vehicle, that control the lateral and longitudinal movement of the vehicle, like the brakes, throttle and steering wheel. Other significant actuators that do not influence the lateral or longitudinal movement of the vehicle directly might be shifting the transmission, the windshield wipers and adjustments in the suspension of the vehicle.
- **Driver monitoring.** Besides it's surroundings it is also important for the computer to know what happens inside the vehicle. By monitoring the driver

possible fatigue or distractions can be identified, which may prevent failures from the driver. This is mainly applicable at lower levels when the human driver is still in the loop. At level 4 or level 5, the human driver is less involved with the control of the vehicle. Nevertheless it may be important for the computer to know whether there are humans in the vehicle. Also it might be important for the human to communicate with the computer, for example to alter the destination of the trip.

According to KPMG (2012) there are currently various Advanced Driver Assistance Systems (ADASs) on the market, which can be identified as level 1 and level 2 systems. These systems use a combination of sensors, such as stereo cameras and short- and long-range radars, combined with actuators on the lateral and longitudinal control of the car, and integrated software. Examples of these systems are park assist, lane-keeping and warning systems, and adaptive cruise control. Improvements in the software- and hardware-technology on both the sensor capabilities, actuation and control of the vehicle have to be made to get vehicles of higher level of automation ready for deployment.

3.4 Innovation system

The system of automated vehicles is being viewed in this research as an Innovation System. “The central idea behind the innovation system approach is that innovation and diffusion of technology is both an individual and a collective act” (Edquist, 2001). An innovation system can be defined as all institutions and economic structures that affect both rate and direction of technological change in society” says Hekkert (2007). The innovation system of automated vehicles is not bound to a specific country or region. As the innovation is across borders, the system it is not geographical specific. Hekkert et al. (2007) specifies these systems as a Technology Specific Innovation System (TSIS).

Nevertheless regional differences do determine the adoption of an innovation. Differences in socio-economical characteristics across different geographical regions could determine the speed and direction of the innovation adoption. This can be seen in the different adoption rates across the globe of innovations like mobile phones, solar power and electrical vehicles. The current state of the infrastructure and fleetsize in a specific region can be a determinate factor for the speed of innovation of automated vehicles as well. Statistics show that e.g. the registration of new cars in developing countries in Africa and China grow much more rapidly (annual growth rate of 11.4%) than in Europe and USA (with respectively 1.4% and 0.8%) (Gao, Hensley, & Zielke, 2014). This difference in growth rate has a major impact on various levels on the adoption rate of new technologies in these regions such as automated vehicles. An example of above-mentioned regional differences can also be seen by comparing the market penetration of Automated Driving Assistance Systems (ADASs) across different parts of Europa (Kyriakidis et al., 2015). Countries with a low GDP like Romania, Croatia, Latvia and Estonia have much lower market penetration (between 10% - 15%) than countries with a high GDP like Germany, Sweden Austria and Luxembourg (between 30% - 50% market penetration).

Because of this sensitivity of innovation diffusion to regional differences the model is sensitive for the type of region in which it is specified. The model is intended to be general and have a whole-world perspective within the boundaries of developed countries. However to represent the whole developed world would make the model unnecessary complex. In order to use the new model in a proper fashion, data from a specific region has to be collected for a case study. The Netherlands is chosen as a geographic region for this case study. As the Netherlands is a small country with a relative high availability of data it proves to be a good case study. Furthermore the

Netherlands has shown to be very active in the field of transportation and vehicle automation, so new data is likely to occur in near future on the system components that are used in this research. However the Netherlands misses some components to represent the whole world, as it for example doesn't have a very active automobile industry. As it turned out that a mix of data is available in a mix of countries, which makes it difficult to specify the model for one specific region.

Most of the data found is either from North America, EU28 or the Netherlands. As variables could be inter-related, the data has been carefully chosen from the Netherlands, a variety of countries from EU28 and North America to match the characteristics as a whole. The general socio-economical characteristics in the model are all matched with data from the Netherlands. The selection of the data is further specified in Chapter 4 and at the end of Chapter 5.

Hekkert describes 7 functions that cause the development of any specific technology, such as automated vehicles. These 7 functions are activities that influence the goal of the innovation system. Hekkert describes the goal of an innovation system as "to develop, apply, and diffuse new technological knowledge". A short overview of the 7 functions of a Technology Specific Innovation System is given and applied to the case of automated vehicles in Table 2.

Function	Description
Entrepreneurial Activities	The formation of new startups and existing firms deploying new activities to test the market of automated cars.
Knowledge Development	R&D activities by knowledge institutes, governmental organizations and industry focused on the development of new knowledge in the field of automated vehicles. Simulations and test drives are part of this function.
Knowledge Diffusion and Exchange of Information	As a form of open innovation the gained knowledge should be exchanged to create new interactions with current players in the field of automated vehicles, which can speed up the technological development. For example Google states to have already driven more than one million miles of test-drive in which they gained a lot of information about the technology and the human factor.
Guidance and Vision	To direct and guide the allocation of the limited resources within the innovation system a common vision should created by an overarching organization. A clear example is the letter of the Dutch Minister of Infrastructure and Environment in 2014 to the Dutch Parliament in which the ambition is expressed to make the Netherlands an international front-runner in automated vehicles.
Market Formation	As new technologies often have many risks and uncertainties associated with them, new legislations and regulations have to be formed in order to create a smooth and safe transition. An example of a topic that is often mentioned in the context of automated vehicles is the liability aspect that is shifting from human drivers to a machine.
Resource Allocation	Both financial as human capital have to be made available as input for the knowledge development and field tests.
Legitimize and Lobby	New players within the innovation system should lobby with existing players of the incumbent regime in order to

	create enough resources and direct the market formation in a favorable direction.

Table 2 Application of 7 functions of a TSIS to automated vehicles.

The 7 functions interact with each other in various ways creating a dynamic system, which is shown in Figure 11. Regarding this framework, the focus will mainly be on the dynamics of technology development in this research, which is shown in the illustration by notation 'B'. These dynamics involve the development of new technologies. As entrepreneurial activities are being formed, more resources are allocated to knowledge creation. Through R&D the technology is enhanced further, creating new business opportunities that will further increase the entrepreneurial activities.

Another dynamic loop shown in the framework of Hekkert is the legislation of an innovation. Legislative issues happen through new entrepreneurial activities that arise and challenge the incumbent regime. As innovations have different characteristics than their traditional counterpart new laws have to get into place that did not exist before. This happens through lobbying and market formation, enabling the new entrepreneurial activities to be legit and have all the liabilities covered. A recent example in the field of mobility is the rise of transport network company: Uber (Le Vine, Zolfaghari, & Polak, 2014). Their services are becoming increasingly important as their were last valuated in 2015 at over $50 Billion (Techcrunch, 2015). Still their services are not allowed yet in all countries. They are challenging the traditional taxi market, which is projected by law in various ways. This makes it challenging for an innovation to really breakthrough and diffuse into society. This part of Hekkert's framework will be left out of scope in this research as it is less technology driven and in many cases very specific to a context and region.

The last dynamic loop described in the framework of Hekkert is often a trigger for an innovation to grow, shown in the illustration with the notation 'C'. Because of the many societal benefits of automated vehicles, like increased traffic safety and reduced congestion, policy is trying to guide and direct the development of this innovation. Through programs at knowledge institutions and creating more awareness around the topic, more knowledge is created on the topic. This speeds up the development of the technology. This part of the framework of Hekkert is part of this research, but will not be taken into account in the specification of the simulation model.

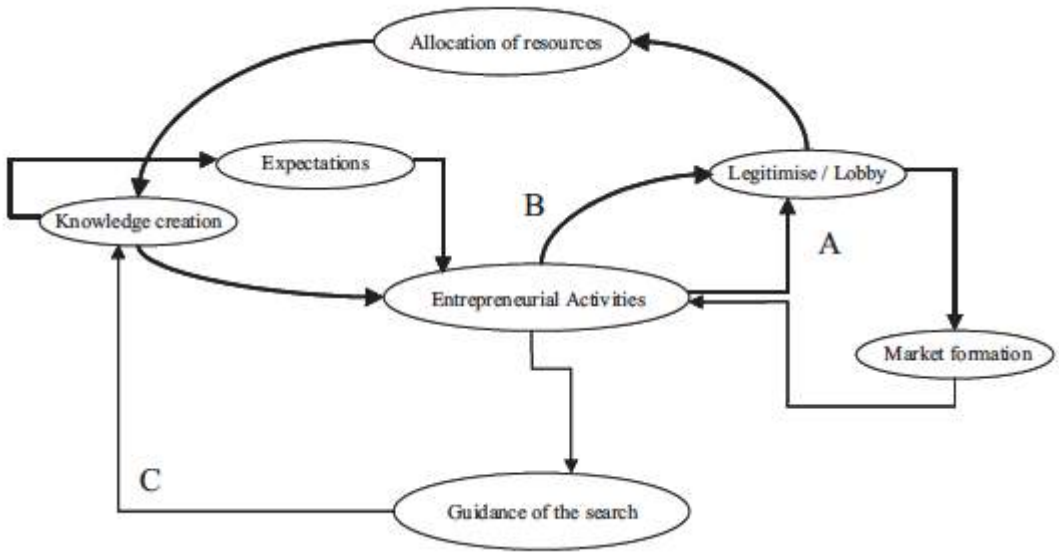

Figure 11 System overview of the 7 functions of a Technology Innovation System. Source (Hekkert, 2007)

3.5 Innovation diffusion

The overall goal of the 7 functions of innovation is the diffusion of an innovation into society. What is missing in this framework is the role of the end user. Howard states that "the ability of automated vehicles to affect transformative change depends largely on how successful the vehicles are in attracting drivers from automobiles" (Howard & Dai, 2013). In his work *Diffusion of innovation,* Everett Rogers describes the five attributes that determine the speed of an innovation in which it is diffused into society (Rogers, 2003). These five attributes of innovation are (1) relative advantage, (2) compatibility (3) complexity (4) triability (5) observability. The adoption rate by society is very much determined by the added value that an innovation or novel technology can bring in contrast to the existing technology, Rogers calls this the relative advantage. Furthermore the added value of this new technology should be easy to understand, should have a low complexity, and should be compatible with the value that currently exist in the society. The last important aspect according to Rogers is the observability, which means whether potential customers can see clear benefits accruing to those who use it. In this research the main focus will be on the first attribute, namely the 'relative advantage' of the innovation over existing technologies.

Christensen and Overdorf (2000) describe the distinction between disruptive and sustaining innovations. "Sustaining technologies are innovations that make a product or service perform better in ways that customers in the mainstream market already value". Disruptive innovations has different values than the product or services that it replaces and therefore serves the needs of new customer segments. In this study the innovation of automated vehicles is seen as a sustaining innovation.

3.5.1 Utility

What can be concluded from this is that the attributes of a technology should consist of a certain added value over its traditional counterpart in order to have a demand by the end user. To summarize these attributes and make them comparable among the different levels of automation, a relative 'utility' will be used for each of the different levels of automation in this research. The utility is specific to a certain level of automation at a certain moment in time and generic to the whole population in the scope of the research. In this research each level of automation will be looked at separately, having a possible higher utility over its technological 'predecessor'. Rogers (2003) states that price and economic effects "may even be the most important single predictor for the rate of adoption". Utility will be seen in this research as a trade-off between the purchase price and the attractiveness of a specific level of automation. The way consumers value the attractiveness of a vehicle and balance this attractiveness with its price determines the customer demand.

Lots of literature can be found about customer choice and demand models in the traditional automotive industry. The foundation of demand models goes back to work of Lancaster (1971) and McFadden (1974). In these models, products are described as bundles of characteristics, and consumers choose the product that maximizes the utility derived from product characteristics. Train (2007) recognizes a shift in market share in the current automotive industry due to a changing customer choice. Train has found in a customer-level model of vehicle choice that this current shift of market-share can be explained by attributes like price, size, power and operating costs. Berry et al. (2004) analyze a rich source of information on customer choice to estimate demand parameters. Models that describe customer choice on the current automotive market cannot be used for innovation diffusion of new technologies though. Vehicle automation is a new technology and an innovation in the existing

incumbent regime of the automotive industry. Other research methods will thus be needed to reliably identify the specific attributes of the attractiveness within the utility function.

Rogers (2003) recognizes the problem in trying to predict the utility attributes that potential users will gain from a new innovation. As the innovation is not yet diffused among the users, the relative utility that causes this diffusion can also not be observed yet. Rogers therefore proposes three sub-optimal research methods that could be used to predict utility attributes of new technologies. These research methods could be used in this research to give data on the utility of automated vehicles. Together these research methods can give a good overview of the available data that can be used for the utility in this research.

- **Extrapolation of the rate of adoption and utility attributes of similar past innovations.**

KMPG (2013) makes a comparison with the early adoption of automobiles in the early 1900s. The value of the automobile upon the horse that was recognized in those days by its adopters was it added level of comfort. The car went faster, had a longer range, took less space and people did not have to worry about feeding it. Furthermore cars were a status symbol for people to show off among their peers.

The same can not be said of electrical vehicles, which have been struggling with their adoption rate into society (Struben & Sterman, 2008). Although electrical vehicles are cleaner, quieter and have lower operating costs, potential users might see no clear added value in them.

- **Describing a future innovation to its potential adopters and ask for their opinion on the subject.**

Both Kyriakidis et al. (2014), Howard et al. (2013) and KMPG (2013) have asked a group of respondents about their opinion on automated vehicles. Kyriakidis (2014) conducted a survey among 4886 respondents. Respondents indicated that they were willing to pay more for fully automated than for no automation, partial automation and high automation.

Howard et al. (2013) investigated public attitudes toward automated cars using the responses of 107 likely adopters. Howard identified six attractive features to automated cars: amenities (e.g. ability to text message or multitask while driving), convenience (e.g. not having to find parking), environmental friendliness, increased mobility, safety, and speed. They found out that people were most attracted to potential safety benefits. Furthermore people were most attracted to the comfort that automated vehicles can offer like the convenience of not having to find parking and the ability to multitask while en route.

KMPG (2013) has conducted a focus group with 41 respondents. Their results give a good qualitative directional insight, but are not statistically valid. According to this report the value proposition of shorter commute times and extra free time inside the car were loudly applauded. According to the same report the two most important aspects that differentiated automated vehicles against traditional vehicles were handling and safety in the eyes of the public.

- **Investigate the acceptability of an innovation in its pre-diffusion stage.**

With vehicle automation various stages among the different automation levels can be identified. Various ADASs have already been implemented in operational systems and are slowly getting adopted by society. By observing the innovation acceptance of

these ADASs more could be learned about the general utility attributes of vehicle automation. Planing (2014) has conducted a study on the innovation acceptance of ADASs including semi-structured interviews with 37 experts and a survey among 400 respondents. The resulting regression model shows that safety and comfort benefits are most decisive (beta value of 1,137) for the acceptance of ADAS among users. When the perceived benefits increase with one point the odds that people will increase their *intention to use* with one point increases with 65%.

3.5.2 Attractiveness

From the literature above it can be learned that there are two value propositions that are most valued by potential adopters, namely safety and comfort. These two attributes form the core of the attractiveness of automated vehicles. Furthermore the aspect of word of mouth and visibility of the new technology is also regarded as an important aspect as stated before. The re-enforcing loop of word of mouth communication is widely described in relation to the diffusion of innovations as can be seen in among many others: Czepiel (1974), Banerjee (1993), Sterman (2000) and Goldenberg (2001). If more people start using a new technology, this strengthens a positive familiarity towards this technology by potential users who are then more likely to also start using the innovation, especially if they can see clear benefits among the existing users according to Rogers. As mentioned before the utility in this research consists a trade-off between purchase price and attractiveness. The attractiveness consists of comfort and safety and is reinforced by the familiarity of people towards vehicle automation.

3.5.3 Learning effects

As it can be learned from literature the purchase price of a new technology is highly affect by its rate of development. In the beginning of an innovation lifecycle knowledge is accumulated through R&D. According to Kamp (2002) “the actors involved in R&D are generally universities, research organizations or research departments of firms.” The knowledge derived from this R&D can be used to develop the technology. By gaining more knowledge through R&D about a certain technology, costs decrease through learning by searching effects. Abernathy and Utterback (1978) show that in this part of the innovation lifecycle the focus of the market is on product innovation. In this phase of product innovation more focus is put on the design and characteristics of a new product and less focus is put on the production process. For this reason the purchase price stays reasonably high in the product innovation phase. Abernathy & Utterback show that through production of the innovation more skills and experience are gained. “Through productive processes many problems, faults and bottlenecks are demonstrated and solved. Furthermore, through trial-and-error practical experience is gained on how to produce the technology,” says Kamp. Rosenberg (1983) shows that this increases the efficiency of production operations. In this second phase the purchase price will decrease more rapidly. This concept of process innovation as Abernathy calls it, is often referred to as learning by doing. “The concept that as the manufacturing process develops over time, costs decrease” (Akiike, 2013).

An example of above mentioned phenomena in the automobile industry is described in Utterback (1996). He mentions that in the early years a big variety of technologies were developed, including electrical and steam engine cars. All of the firms that developed these technologies were eager to add value over existing technologies and thereby capture a part of the customer demand. “In this period of high product innovation, less attention was given to the processes by which products are made, so the rate of process innovation was significantly less rapid,” says Utterback. A parallel can be made with the current days of automated vehicles, where many firms are experimenting with vehicle automation and developing the technology in order to

be the first on the market to capture customer demand. The purchase price is still very high, but once a few products really arrive on the market it is likely that a sort of standard will be created. This standard causes efficiencies and economies of scale in the production. Once these learning effects are starting to kick in, the price of automated vehicles could also rapidly decrease.

3.5.4 Adoption rate

The diffusion of automated vehicles in the society will happen gradually over time. Various predictions have been done in research literature about the future adoption rate of autonomous vehicles. These studies use a lot of different terminology when talking about similar phenomenon. Kyriakidis et al. (2015) uses 'adoption rate' as a metric to indicate how fast a technology gains market share. Underwood (2014) uses 'market introduction' to indicate the moment that a technology will be available for the general public. Litman (2015) uses the term 'deployment' to indicate the movement of new technologies into society. Furthermore he uses the term 'market saturation' for the moment that "everybody who wants a automated car, and will pay any extra costs, has one." Bierstedt (2014) uses a variation of terms including 'rate of adoption', 'fleet conversion' and 'market absorption' all indicating the same phenomenon.

In this report the term market penetration will be used when the number of users or vehicles of a new innovation that are already in use compared to the total number of users or vehicles is indicated. *Market penetration* can be compared with *market share*, but in this research solely market penetration will be used. Market penetration has "percentage" as a unit. The term *adoption rate* will be used to indicate the speed of the annual growth of market penetration by a new innovation. The unit of adoption rate is 'percentage per year'. The market penetration and adoption rate of vehicle automation will not just be looked at as a whole, but split it among the 5 levels of automation defined by SAE. The term *diffusion* represents the overall emergent phenomenon of a technology that is being developed and gains market penetration over time.

3.6 System components and dynamics

By using the TSIS framework of Hekkert (2007), the innovation diffusion theory of Rogers (2003) and the Abernathy and Utterback (1978) model five important system components have been identified that will be used in this research. All of these system components are represented by a stock in the model. The system components interact with each other by various dynamic loops.

The five system components are (1) the technology maturity (2) the purchase price, (3) the perceived utility by the end consumer of the various levels of automation, (4) the fleetsize and adoption rate of the various levels of automation and (5) the dynamic interaction between car-ownership and carsharing. A system overview with the components and their dynamic loops is shown in Figure 12.

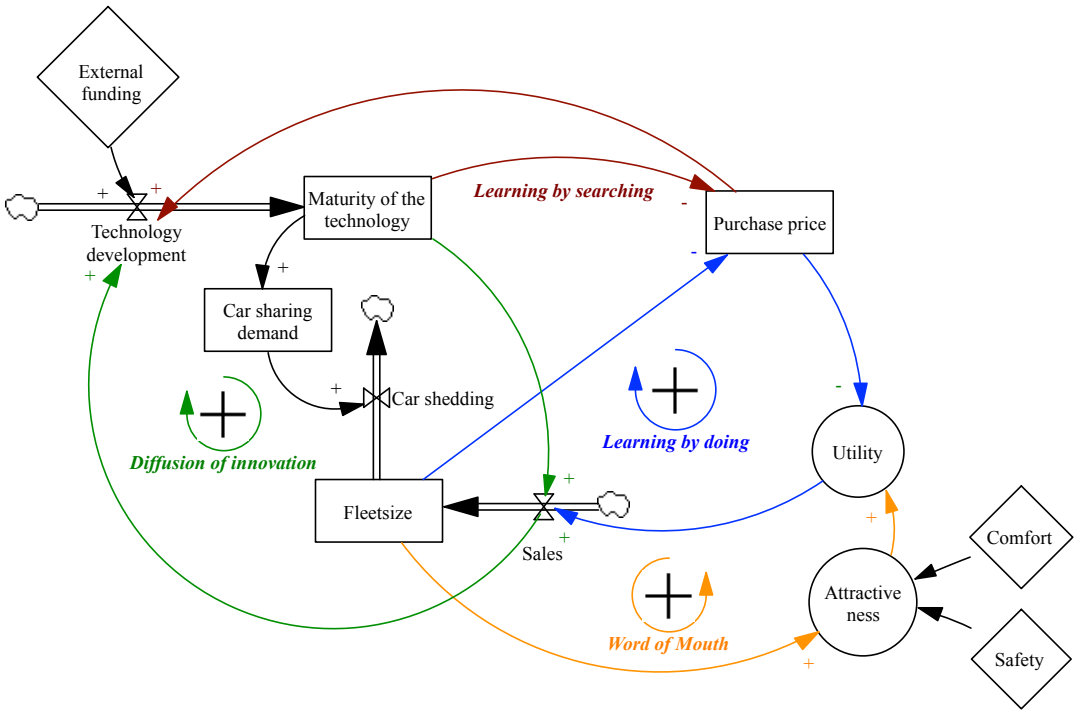

Figure 12 System components and dynamic loops

3.6.1 Technology maturity

The number of vehicles in use at a certain moment in time is specified as the fleetsize. This study will solely look at passenger cars and not at commercial vehicles like trucks. The reason for this is that the dynamics of demand modeling are different with commercial activities than activities of private individuals. Each of the six levels of automation is represented by its own fleetsize and therefore forms it own 'market'. The size of this market is specified as the number of vehicles sold multiplied with the average price of the vehicles. The technology development is driven by the amount of R&D expenditure that is put into the technology. The amount of R&D expenditure is based on the potential gains of a technology and thus on its market size. The state of readiness of a technology will be referred to in this research as the technology maturity, as described in Newes et al. (2011) and Vimmerstedt (2015). The maturity of a technology can be seen as a trade-off between the reliability of a technology and its performance. The maturity is defined within a range of 0 to 100%, although it could be argued that a technology could always improve and never reach 100% maturity. If a technology gets near the 100% maturity asymptote it will only improve very little at very high marginal costs.

3.6.2 Purchase price

As the technology develops through R&D, this will have an effect on the purchase price. As discussed earlier the purchase price will decrease through learning by searching. When the fleetsize of a level of automation grows, this will build up cumulative experience in the industry about this specific level of automation. This concept of learning by doing will build up experience and skills and lower the production costs. An increasing fleetsize will thus lower the purchase price for the end consumer. The purchase price has a negative effect on the utility of a specific vehicle. When the price decreases, the utility will therefore increase. This will further increase the fleetsize.

3.6.3 Utility

Each level of automation will be appointed with a certain level of comfort and safety. This comfort and safety are exogenous to the model and contribute to the attractiveness of this level of automation. If the fleetsize of a certain level of automation grows the odds will grow that people will encounter upon this level of automation on the street. People will get more familiar with the concept of automated vehicles. Likewise interest of the media on the topic of automated vehicles will grow as the sales and fleetsize increase. As people see it more around them, people will gain confidence in the reliability and performance of the technology of a specific level of automation. This positively affects the attractiveness of this level of automation. Furthermore Rogers states through his attribute of *observability* that if people can see clear benefits in this level of automation, this will further speed up the adoption rate. Altogether this concept is referred to as the dynamic feedback loop of word-of-mouth.

3.6.4 Fleetsize and adoption rate

The fleetsize of a specific level of automation increases through sales. 'Sales' represents the flow of vehicles from one level of automation towards another level of automation. This 'sales' is determined by the utility and the state of maturity of a specific level of automation. As the technology of a certain level of automation gets more mature, this gives more confidence to the end consumer and will have a positive effect on the sales. The market penetration of one level is specified as the percentage of the fleetsize of this specific level of automation compared with the total fleetsize.

The diffusion of innovation represents a dynamic feedback loop in the model between the technology development and the fleetsize of automated vehicles. This fleetsize is increased by the sales, of which the relative speed is expressed as the adoption rate.

3.6.5 Carsharing

In this research the fleetsize is assumed to consist of owned vehicles that are in use. These vehicles can either be owned by a fleet-owner or by individuals. Two significant trends could disrupt this ownership of vehicles in the upcoming decades. Bierstedt et al. (2014) talks about a possible significant shift in car ownership over the next decades due to the introduction of automated vehicles. Cars currently are in use for an average of ten years. "With new business model opportunities and car sharing applications this could speed up the car replacement and thus the replacement of new technologies." According to Shaheen et al. (2007) carsharing has a major impact on car ownership. She states that "carsharing provide a flexible alternative that meets diverse transportation needs across the globe, while reducing the negative impacts of private vehicle ownership." In this research the impact will be taken into account that vehicle automation can have on the growth of the carsharing market. The other effect that is taken into account in this research is the effect that carsharing can have an effect on the ownership rate which can lead to shedding of cars by individuals that previously owned a car. A growth in the carsharing market can therefore lead to a decrease in fleetsize over the long haul.

3.7 Other literature

A comparison of the system components used in this research could be made with the specification of the system by Yun et al. (2014). Yun's research question focuses onto the relation of technology and the market in the field of automated vehicles. In their study they show the system dynamics of automated vehicles with the components: technology, market and business model. In their study Yun et al. analyze the gradual change from technology push and market demand theories

towards business model innovation and apply this to the field of automated vehicles. In a sense this reflects the perspective at the system in this study. However the study by Yun is very abstract and general and uses qualitative input gathered from a few dozen interviews. Furthermore the way Yun et al. apply system dynamics to the context is different than in this research. This study will use a more detailed scope and use quantitative input to analyze the dynamics of the system.

In this chapter the research scope is defined and the system components are identified. Chapter 4 will elaborate further upon the system components and explore the availability of data in literature for the variables. In Chapter 5 the system components will be specified into a stock & flow simulation model.

4. Availability of data

This research focuses on the real-world system of automated vehicles. In Chapter 3 the system scope for this research has been defined. In Chapter 5 a model will be build within this system scope that emulates the real-world system. This model consists of endogenous variables and exogenous parameters. The endogenous variables consist of differential equations that represent the real-world system structure. The values of the parameters need to be filled with input data in order to simulate a base run. In Chapter 6 the model will be tested. The input data that is used for the parameter settings will be compared with real-world data. The structure of the model will be compared with known theory about the real-world system structure. The output of the model is a base simulation run over time. The output behavior of the model will be compared with other data that is available about the system. The base run of the simulation model will start in the year 2000 and simulates 100 years. The input that is used therefore represents a situation of the system in 2000. The data that is used to validate the output behavior is from 2000 – 2100. Figure 13 is a conceptualized illustration of the real-world system, the model and the distinction between input data and validation data.

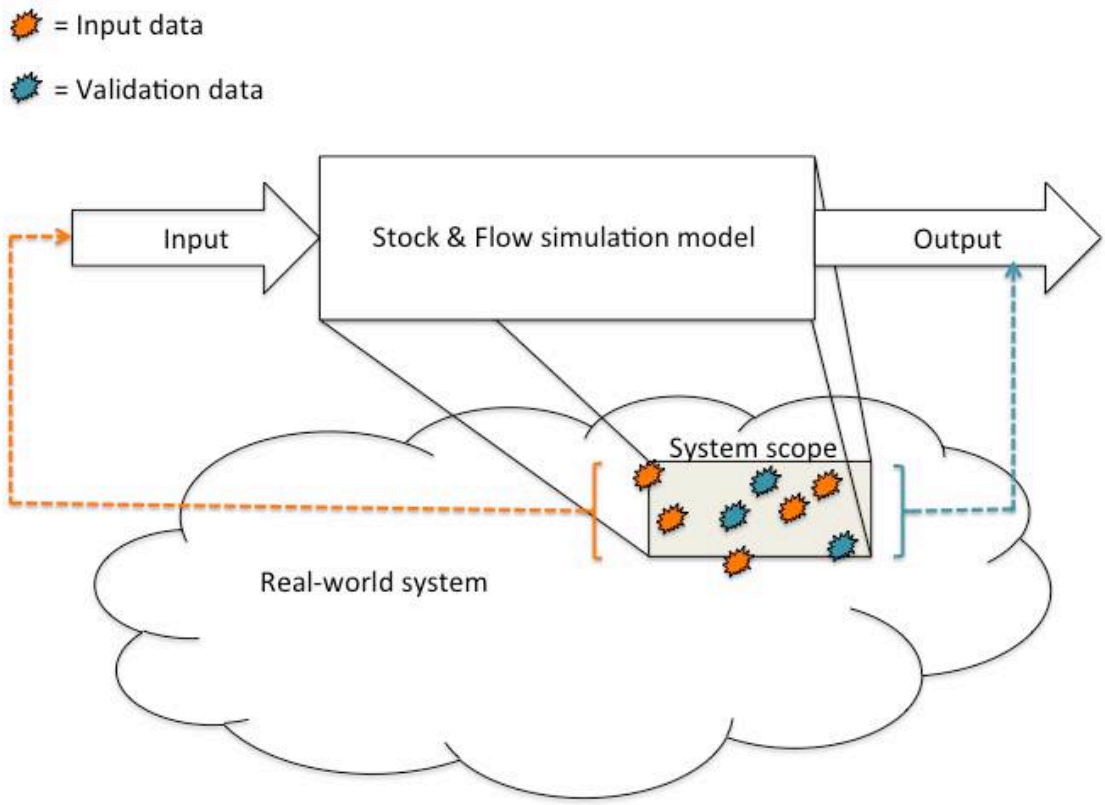

Figure 13 Conceptualization of real-world system, the model and the usage of data.

In this chapter an overview will be presented of the data availability in literature of the system components within the system scope. Both input data and validation data will be gathered. Furthermore there will be looked at studies that are available about the real-world relations between system components. Knowledge about these relations can help by building the model structure. Possible knowledge gaps will be identified. These knowledge gaps will be filled by expert opinions gathered in semi-structured interviews. An elaborate overview of the interviews can be found in Appendix F.

4.1 Technology maturity

As described in the previous chapter, an automated vehicle can be viewed as a multitude of different components, both hardware and software. Some of the technologies are in a different stage of development than others. When assessing the maturity of vehicle automation technologies this has to be taken in mind. Some technologies are already available but need higher performance to be reliable for vehicle automation, such as the accuracy of localization.

As described earlier, the state of readiness of a technology will be referred to in this research as the technology maturity. The maturity of a technology can be seen as a trade-off between the reliability of a technology and its performance. Literature tells us that technology typically develops in a s-shaped curve (Mahajan & Peterson, 1985), (Sterman, 2000). A KPMG (2012) report describes the maturity of various automation sensor technologies in 2012. The GPS systems that enable localization are evaluated highly mature. GPS systems have been in business for a long time and used widely in big markets like turn-by-turn navigation devices and mobile telephones. Baydere et al. (2014) states that GPS system are not completely fool proof yet. The accuracy is sufficient for macro level route planning. The camera and radar systems that are used for perception are evaluated as medium mature.

Lidar (Laser Imaging Detection And Ranging) systems are used to detect the environment and the relative distance of objects. Lidar systems are therefore highly useful for the situational awareness of an automated vehicle. Lidar technology is evaluated with a low maturity by KPMG. The report of KPMG does not mention the maturity of any actuation technologies.

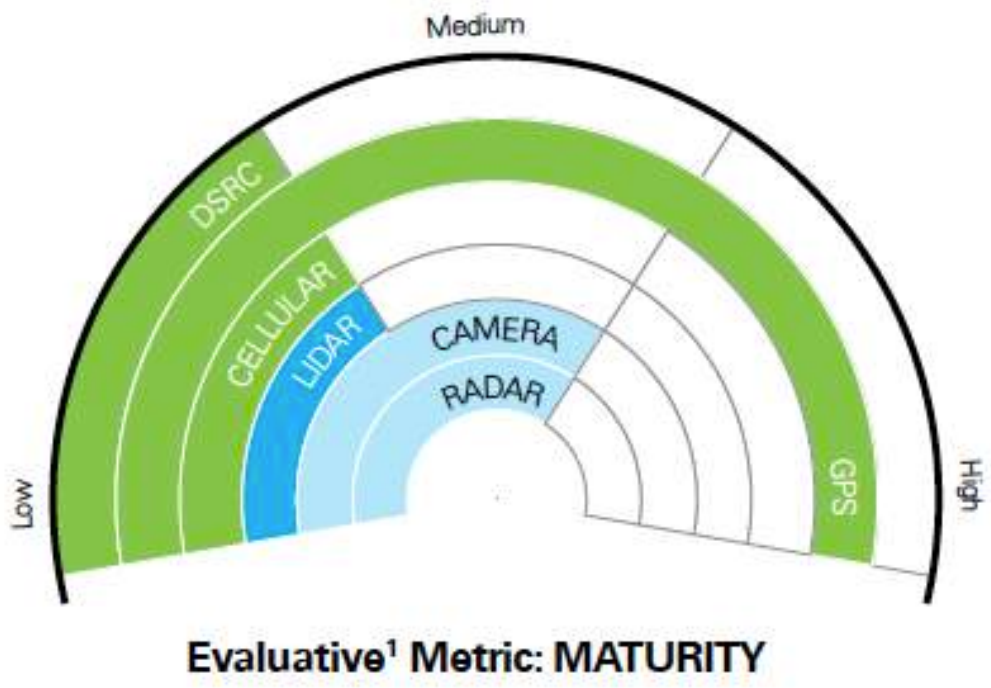

Figure 14 Maturity of enabling technologies for automation. Source (KPMG, 2012)

4.1.1 R&D expenditure

By multiplying the annual sales by the average price it can be concluded that the annual revenue in the European passenger car market is approximately €315B. Of the total R&D expenditure in Europe, about 21% goes to automotive and parts. This accounts for an R&D expenditure on automotive & parts of €41 billion in 2013 in Europe. This makes Europe the largest investor in the automotive industry R&D according to the Automobile Pocket Guide 2015-2016 (ACEA, 2015). R&D expenditure worldwide in the automotive industry is €77 billion (ACEA, 2015). The USA invests around €47B in hardware technology & equipment. Part of these technologies can be used as enabling technologies for automated driving like cameras and processors. It is unknown what part this is of the total hardware and equipment market.

4.2 Purchase price

In this paragraph the literature on the purchase price of vehicle automation is reviewed, specifically at known data on partially-, highly- and fully automated vehicles. There are a lot of different brands, types and sizes on the market. Furthermore vehicles are quite regularly sold with a lot of add-on features. A distinction is made between the base price of a vehicle and the price of the extra features and technology that is added to the vehicle to make it automated. These extra features that enable vehicle automation are being called 'retrofit technologies'. This term is used in general to describe technology that is added to something after it is available on the market. In this context that is possible, but not necessarily meant. The retrofit technologies can also be incorporated with a vehicle during the manufacturing and assembling process. The distinction is made explicitly because one type of vehicle could be on the market both with and without vehicle automation capabilities. The technology that enables these vehicles to be automated has a different learning curve than the base price of the vehicle itself. This distinction is not always very clear, as sometimes the retrofit technologies are incorporated within the vehicle and come together with the base price. All above stated arguments make a difficult to estimate a clear purchase price for the different levels of automation for this research.

The average vehicle price in 2013, including taxes, is €25.000 according to ICCT. In 2001 this was €20.000. Research by the Center for Automotive Research (CAR) state that the base price of a vehicle in 2009 is $28,966 (€20,690 with the exchange rate of 2009 taken into account), in 2025 it is estimated around $39,764 (approx. €34,500 euro with current exchange rates) without inflation taken into account. Kyriakidis et al. (2015) make an comparison between price among the different types of ADASs. "Statistics for the Netherlands, specifically, showed that the more expensive brands, i.e. premium vehicles, are equipped with more than one ADAS." These statistics are supported by Figure 15, which shows an overview of car types that are currently on the market which are equipped with video cameras, radar sensors and very accurate maps. Furthermore Kyriakidis shows a positive correlation between the price of the vehicle and the fact whether it is equipped with one or multiple ADASs.

A report by KPMG (2012) states that the lidar system used in the Google car costs $70,000 (€60,500) in 2013, which is confirmed by both Fagnant (2013) and Baydere (2014). As a comparison Fagnant reports on an additional cost of €10,700 from a base price of €41,000 of a BMW 528i sedan (which can be considered level 2) when added with the full technology package. This technology package consisted of driver-assist features, ACC (adaptive cruise control) and safety options like night vision with pedestrian detection. In a correspondence with Steven Dellenback, director of Southwest Research Institute, Fagnant reports on an estimated drop in added costs

to between $50.000 and $25.000. Furthermore Dellenback expects the “added costs not to fall to $10.000 for at least 10 years” (Fagnant & Kockelman, 2013). Clark (2013) states that “as of 2013, the autonomous driving system costs about $150,000”. In this case by the autonomous driving system Clark means the added costs of the retrofit technologies upon the base price. Estimates by IHS automotive (Juliussen & Carlson, 2014) are that in 2025 retrofit automation technology has an addition cost of around $7K - $10K. By 2030 this will be $5K and by 2035 this will decrease towards $3K. Table 3 gives an overview of the literature on current prices and expected prices of vehicle automation prices. Due to the low availability of European literature on this subject, all the prices found are in dollars.

Figure 15 Overview of cars currently on the market equipped with sensors. Source (Baydere, 2014)

Automation	Type	Price	Year	Source
No (level 0)	Base price	$29K	2009	(CAR, 2011)
		$39,7K	2025	
Partial (level 1 – 2)	Base price	$27K – 80K	2015	Derived from expert interviews
	Retrofit price	$15K	2013	(Fagnant & Kockelman, 2013)
High (Level 3 – 4)	Base price	$70K - 200K	2015	Derived from expert interviews
	Lidar	$70K	2012	(KPMG, 2012)
	Retrofit price	$150K	2013	(Clark, 2013)
		$50K – 25K	~2016	(Fagnant & Kockelman, 2013)
		$7K – $10K	2025	(Juliussen & Carlson, 2014)
		$5K	2030	
		$3K	2035	
Full (Level 5)	Base price	>$150K	2015	Derived from

			expert interviews
	Retrofit price	Unknown	

Table 3 Overview of literature on vehicle automation purchase prices.

4.3 Utility

Utility is a trade-off between price and attractiveness. The attractiveness of automated vehicles is determined by the comfort and safety that automated vehicles can bring to the end user.

By extrapolating the attributes of the early adoption of automobiles in 1900 upon the innovation of automated vehicles it can be stated that people value a level of comfort. A certain level of comfort is definitely added with automated vehicles upon the current automobiles on the market. Level 1 till 3 is mainly represented in the market today by ADASs. “Increasing the perceived benefits (whether related to safety or to comfort effects) will lead towards a stronger intention to use Advanced Driver-Assistance Systems” says Planing. Automated vehicles give people a lot of extra useful time, also referred to as amenities, while they are inside the car, especially at level 3, 4 and 5. A KMPG report stats that “the average commute time in the United States is about 25 minutes. Thus, on average, approximately 80 percent of the U.S. work force loses 50 minutes of potential productivity every workday.” This time can be made productive by automated vehicles. Furthermore a truly automated car can bring the extra convenience of automated ‘valet parking’ functionalities.

The literature seems to agree upon the importance of safety and comfort for the adoption rate of automated vehicles. Nevertheless a clear value for each of the individual levels of vehicle automation cannot be found in literature.

4.3.1 Willingness to pay

In an earlier part of this report the price of the various levels of automation has been discussed. Other literature talks about the willingness to pay by customers for extra automation functionalities. Kyriakidis et al. (2014) and Howard (2013) have already identified in their survey that people are willing to pay more for automation features. According to a report by KPMG customers are willing to pay an extra $4500 over a base price of $30.000 for a vehicle with automated functionalities. Marketing firm J.D. Power and Associates, (J. D. Power, 2012) released a report “2012 U.S. Automotive Emerging” in which they state that 37% of all vehicle owners say they "definitely would" or "probably would" purchase it in their next vehicle. After learning the estimated market price of an extra $3,000 upon the base price the interest dropped to 20%. This data extracted from literature can be used to estimate the willingness to pay for vehicle automation in Paragraph 5.3.

4.4 Fleetsize and adoption rate

The main mode of transportation for people in the EU28 is the passenger car. Passenger cars accounted for 83.3 % of inland passenger transport in the EU-28 in 2012 (Eurostat, 2014). The total fleet of (passenger) cars in use in the EU28 is estimated at 250 million units by ACEA (2015). Between 2005 and 2013, the world motorization rate rose by a fifth. This rapid increase of car ownership is mainly caused by growth in emerging countries like China, India and Africa. In Europe the number of registration of new cars has dropped from 15 million in 2001 to 12.6 million in 2013 (ICCT, 2014). Worldwide the yearly number of registrations of new cars is 70,9 million passenger cars. In The Netherlands a total of 6,4 million passenger cars were in use in 2000. This number has grown to 7,9 million passenger cars in 2014 (CBS Statline, 2015). With a total population in The Netherlands of 15,9 million people in 2000 and 16,8 million people in 2014 (CBS Bevolkingstrends, 2014)

this accounts for a slight growth in vehicle ownership from respectively 0,4 to 0,47 vehicles per person.

4.4.1 Market penetration

Although vehicle automation can be seen as a new development in the market, some of the literature studies found are not all dated very recently. Shladover (1995) published a paper about the then current state of the diffusion of automated vehicle control systems back in 1995. Various features for longitudinal control and lateral control that can be recognized as level 1 automation driver support systems were already implemented in operation systems. No exact numbers on the adoption rate are given in this paper though.

Kyriakidis et al. (2015) studied the diffusion of ADAS in the period 2012- 2015 and compared the market penetration of ADASs among different European countries. The market penetration of ADASs related to safety is limited. Data showed that ADASs are typically installed in less than 5% of the vehicles registered for first time in 2012. These systems can be identified as level 1 and level 2 automation. The Eco Driving systems, on the other hand, are installed in about 25% of the total vehicles first registered in 2012 in Europe.

Victoria Transportation Policy Institute (Litman, 2015) forecasts it takes at least "until 2050/2060 before automated vehicles of level 5 achieve a 50% - 75% market penetration." It won't take until 2070 according to Litman until vehicle automation reaches market saturation with a market penetration of 100%. In order to make this forecast he studied the adoption of airbags, navigation systems, automatic transmission and hybrid vehicles. The analogy was made between these systems and vehicle automation. Which is doubtful, as vehicle automation seems to have a much larger impact on transportation and society than automatic transmission or navigation systems ever had. Litman however does argue that vehicle automation is not a "game changer" and certainly not a "paradigm shift" since it doesn't fundamentally change how society defines transportation problems. Bierstedt et al. (2014) predicts that 25% of all the vehicles are level 5 in 2035, 50% in the period before 2050 and 95% not before 2040. By using policy enforcement of vehicle automation in the market of new vehicles, Bierstedt states that a 50% - 75% market penetration could be reached earlier on by 2035/2045 instead of 2050/2060 as predicted by Litman.

Rangarajan (2014) predicts that by 2020 over 70% of all vehicles will be equipped with ADASs. The type of systems that Rangarajan refers to can be translated to level 3 automation. Furthermore the market penetration of radars and cameras are expected to rise to respectively 63% and 69% in 2020 from a penetration rate of 16% and 11% in 2015.

Milakis et al. (2015) has developed various scenarios in which the market penetration for automated vehicles in the Netherlands between 2030 and 2050 is estimated. In a scenario with restrictive policies and a low technology development they estimate a 1% market penetration for automated vehicles in 2030 and 7% market penetration in 2050. With a high technology development and supportive policy they estimate a market penetration of 11% (mainly level 3) in 2030 and 61% (mainly level 5) in 2050.

4.4.2 Market introduction

Milakis et al. (2015) estimate a market introduction of level 5 in a twenty-year time window between 2025 and 2045, depending on the speed of technology and the supportive nature of policies.

Underwood (2014) conducted a survey among 217 experts in the field of automated vehicle systems, active safety systems, travel behavior and human factors. In this survey they were asked to forecast future market introductions of automated vehicles. These experts expected level 5 to make a market introduction between 2027 and 2035 with the majority expecting it to be in 2030. Nothing is mentioned about the further adoption rate of the technology. Table 4 shows the complete overview of market introduction predictions by the experts.

Level - Spatial	Median [Year]	Lower bound [Year]	Upper bound [Year]
Level 3 – Freeway	2018	2017	2020
Level 4 – Shuttle	2016	2016	2020
Level 4 – Freeway	2019	2018	2024
Level 4 – Freight platooning	2020	2019	2024
Level 4 – Urban	2025	2024	2030
Level 5 – Full automation	2030	2027	2035

Table 4 Average market introduction predictions by 217 experts. Source: (Underwood, 2015)

Shladover (2015) makes a spatial separation among the various SAE levels with his forecasts of the diffusion of vehicle automation. According to his definition, driving with level 5 automation is possible everywhere without any exceptions on terrain or weather conditions. Shladover expects that this is not possible before 2040. Figure 16 shows the further estimates by Shladover. Level 1 up to 4 can already be seen on the road nowadays in fully segregated roads. Level 2 is expected to be available for highway use and some urban streets by 2025. Level 3 and 4 are expected in these same spatial areas around 2030 according to Shladover.

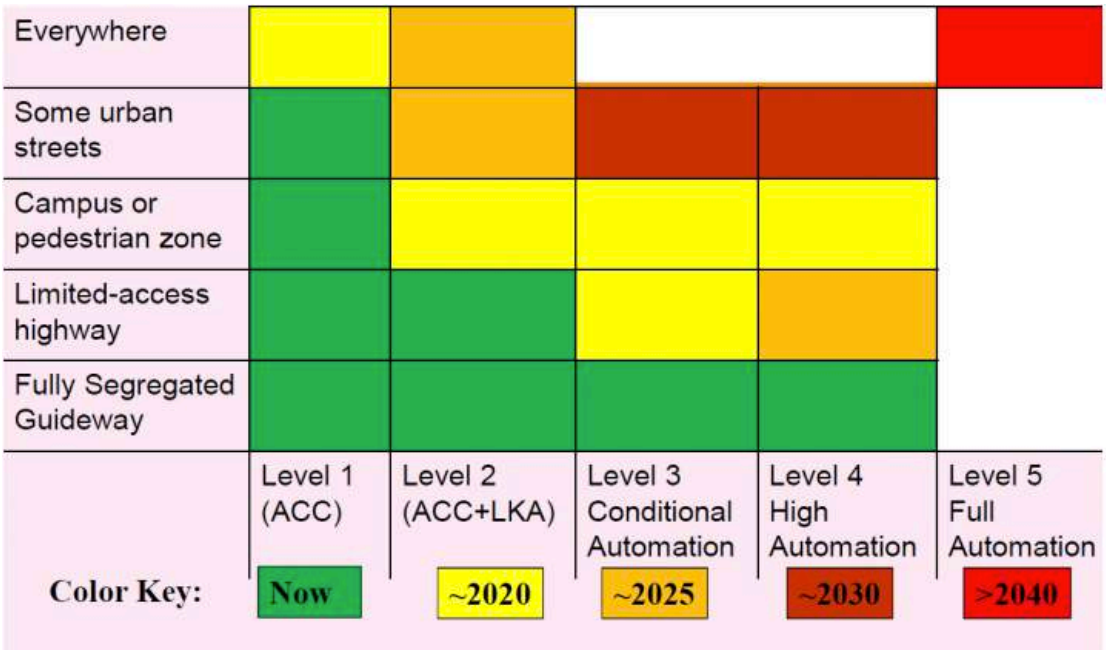

Figure 16 Estimates of first deployment times, divided in spatial areas. Source: (Shladover, 2015a)

Other estimates on market introduction were done by IHS automotive in a multi-client research (Juliussen & Carlson, 2014). The companies in their research consist of major OEMs like Audi and Ford, important tier-1 and tier-2 providers like HERE and branch organizations like IEEE and SAE. Figure 17 shows the availability of ADASs among Audi, BMW, Ford, GM, Nissan, Mercedes, Honda, Toyota, Volvo, Tesla and Google. All the major OEMs claim to have operational systems with level 0 and level

1 capabilities. Furthermore the majority claims to have up to level 3 vehicle automation systems installed in some of their models by 2017 – 2020.

ADAS availability and expected future systems

OEM	L0	L1	L2	L3	L4	Enabling systems
Audi – Volkswagen	Yes	Yes	Yes	2020		ACC & LKA; TJA; 2016
BMW	Yes	Yes	2014	2020		TJA 2014; AutoPA 2014
Ford	Yes	Yes	2014+	2017		AutoPA 2014; TJA 2017
General Motors	Yes	Yes	2016+			ACC & LKA 2016+
Nissan – Infiniti	Yes	Yes	2014+	2020		ACC & LKA 2014
Mercedes-Benz	Yes	Yes	Yes	2020		ACC & LKA; TJA
Honda – Acura	Yes	Yes	Yes			ACC & LKA
Toyota – Lexus	Yes	Yes	Yes			ACC & LKA
Volvo	Yes	Yes	2014+			TJA 2014; AutoPA 2016+
Tesla	Yes	Yes	2014+	2016+		Auto-Pilot for 90% of miles
Google	No	No	No	2017+	2017+	Likely to license self-driving software

Source: IHS © 2014 IHS

Figure 17 ADAS availability and expected future systems among OEMs and Google. Source (Juliussen, 2014)

In general IHS estimates the market introduction of level 3 before 2025. Level 5 is expected to be deployed on the market by 2030. IHS expects that by 2035 around 9% of all sales is a level 5 vehicle, accounting for 11.8M cars. In 2055 level 5 ought to replace around 90% of all cars in use.

In section 2.2.4 a research method called prediction market theory has been discussed. It was claimed that for predictions on the occurrence of a specific event you could use the average of predictions by a large group of people. As shown in the same Chapter the use of experts does not necessarily improve the accuracy of the prediction. For this reason a survey conducted by Kyriakidis (2014) among 4886 respondents can be useful. These respondents were no experts, but the number of respondents is large enough to gain a reliable average from. The study showed that people expect most of the vehicles to be driving fully automated on public roads around 2030. De Winter et al. (2014) asked the same question to 1,517 respondents and found the same average of 2030.

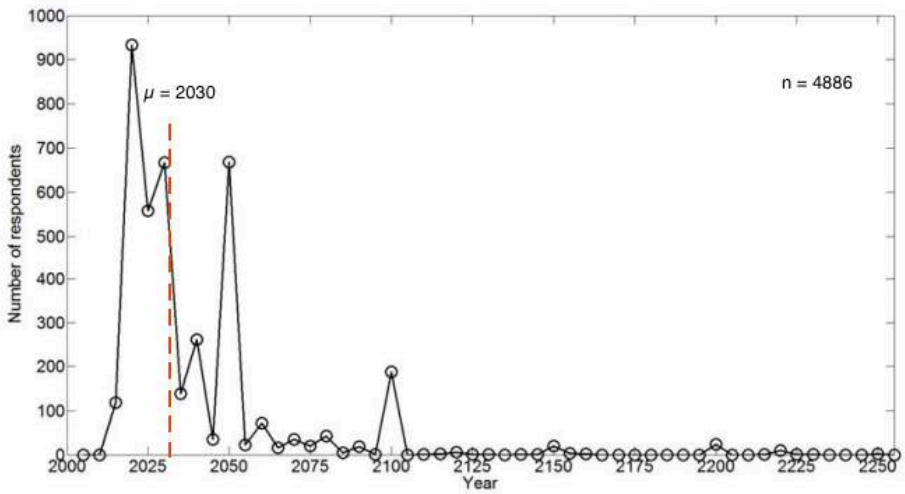

Figure 18 Number of respondents for the question: "In which year do you think that most cars will be able to drive fully automatically on the roads". Source: (Kyriakidis, 2014).

4.4.3 Overview

There is a vast amount of literature available that studies the adoption rate of vehicle automation. Table 5 shows an overview of the estimates on the market penetration

and market introduction that have been found in literature. Most of these studies present numbers about the market introduction and market penetration and not so much about the adoption rate. As said the terminology in literature various a lot, although most times the same phenomena are described. This makes it sometimes hard to compare studies with each other. The methodology that is used in literature also varies a lot. When adoption rates of the past are studied, researchers can use data from the market. When future adoption rates are studied, researchers lack a set of data. This lack of data makes the studies less reliable in a sense. The methodologies that have been seen are historical analogies, expert interviews, panel consensus, trend projections and scenario development.

Variable	Range	Source
Market penetration Level 1	0% - 10% in 2000 10% - 20% in 2015	(Shladover, 1995), (Kyriakidis et al., 2015)
Market penetration level 2	0% - 5% in 2015	(Kyriakidis et al., 2015)
Market penetration level 3	Introduction in 2017 – 2020 70% in 2020	(Rangarajan & Dunoyer, 2014; Underwood, 2014), (Juliussen & Carlson, 2014)
Market penetration level 4	Introduction in 2018 – 2024 Highway and some urban streets before 2030.	(Underwood, 2014), (Shladover, 2015)
Market penetration level 5	Market introduction in 2025 – 2045 (Milakis) Market introduction 2027 – 2030 (Underwood) 25% in 2035 50% in 2035 - 2050 75% in 2045 – 2060 90% in 2055	(Underwood, 2014), (Rangarajan & Dunoyer, 2014), Bierstedt et al., 2014), (Litman, 2015), (Juliussen & Carlson, 2014), (Milakis, Snelder, et al., 2015)

Table 5 Overview of market penetration estimations in literature

In the reviewed literature the market introduction of vehicle automation was seen as a discrete event with certain moments in time. That is in contrast with this research in which the diffusion is seen as a continuous feedback loop among all the vehicle automation levels. The market that is being analyzed is the market of level 0 up till level 5. This means that in this research at any given moment in time the sum of the market penetration of levels 0 up to 5 is 100%.

4.5 Carsharing

In this part the literature and available data on carsharing will be looked at. Specifically the effect of vehicle automation on the market growth of car sharing and the relation between car ownership and carsharing will be taken into account. Carsharing is defined by Shaheen (1999) as “a system that involves a small to medium fleet of vehicles to be used by a relatively large group of members”. In this sense carsharing should not be confused with ride sharing which involves a number of people, either known or not known to each other, sharing the same ride in the same vehicle.

Car ownership seems to face a possible significant reduction in the upcoming decades due to vehicle automation. The most heard explanation of his possible reduction is the growth of carsharing possibilities. In the current application of carsharing a car has to be parked at a certain drop-off location and any users of this shared car will have to travel towards this drop-off location to pick up the car. With vehicle automation functionalities a car doesn’t have to be parked at a drop-off location anymore. The car can drive itself to any user that has the need to use the car. This ought to have a positive impact on car sharing as a market.

4.5.1.1 *Growth of car sharing*

Car sharing has been growing significantly since 2000 when around 100.000 individuals used carsharing services worldwide. In 2006 there were approximately 348.000 individuals who shared nearly 11,700 vehicles as part of an organized carsharing service (Shaheen & Cohen, 2007). Statistics by Frost and Sullivan (2014) show that in 2014 the worldwide number of carsharing users was 4.940.000, using a total of 92,200 vehicles. The user to vehicle ratio is around 50:1. Europe represents about 60% of this market. The market penetration of carsharing in Europe is about 0,5% in 2014. The growth is shown in Figure 19.

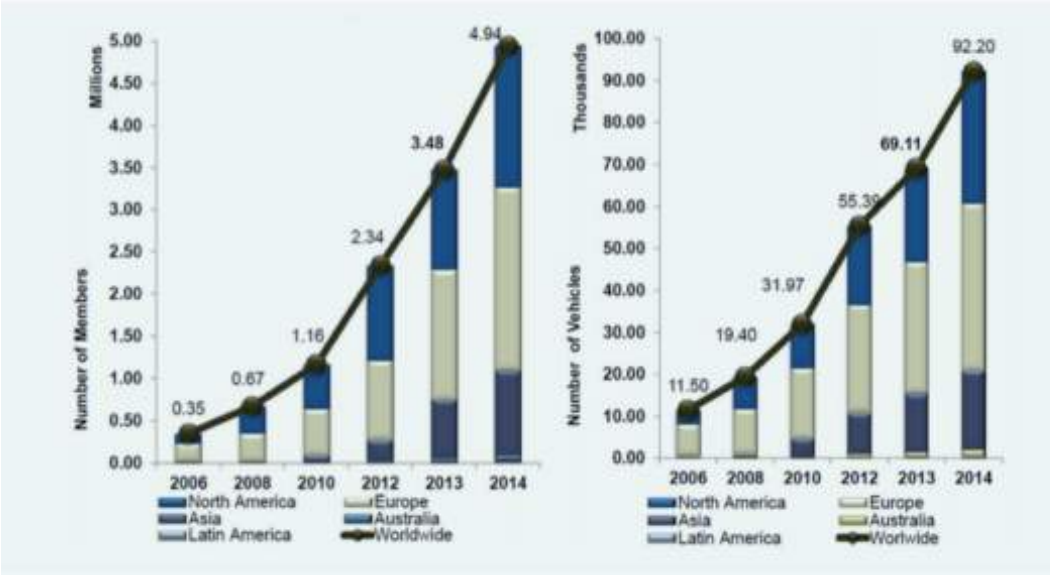

Figure 19 Growth of carsharing users worldwide. Source (Frost and Sullivan, 2014)

According to Tal (2009) car sharing could become part of around 10% of all households at the end of this decade (~2020). With 211.043.000 households in Europe, and 60% of the market-share, this would equal about 35 million members worldwide. More than a 700% increase compared to 2014. Baydere (2014) estimates that the global car-sharing revenue will grow from $1 billion in 2013 to $6.2 billion in 2020. More than 600% increase in 7 years.

4.5.1.2 *Impact on car use*

According to the Federal Highway Administration (FHA, 2013) the average annual miles travelled per vehicle in the USA is 11.244 miles (approximately 18.100 km). In Europe this average is much lower, at 13.000 km (ADAC, 2015). Schoettle (2015) states that vehicle automation can have a dramatic effect on car use. The car does not have to be parked when unused, but can be used by other people. Currently a car stands idle for an average of 90% of the time (Jorge & Correia, 2013). According to Schoettle's (2015) analytical model car usage could grow with 75% from 18.000 km to 33.000 km per year in the USA due to vehicle automation. He estimates this as an upper boundary. Milakis et al. (2015) present studies that indicate a lower estimation of an increased vehicle kilometers traveled (VKT) due to vehicle automation. These estimates are around 10% increased VKT (Fagnant & Kockelman, 2014) and 4% - 8% by Gucwa (2014).

4.5.1.3 *Impact on car ownership*

Center for Automotive Research (CAR, 2011) reports an average of 2 vehicles per household in the USA. In their predictions this number will steadily grow towards 2,1 vehicles per household in the period between 2010 and 2025. In a recent study by

Schoettle et al. (2015) the potential impact of automated vehicles on household vehicle demand is estimated. In his analytical study of NHTSA data, vehicle automation could lead to a reduction in car ownership. In the most extreme hypothetical scenario this could reduce average ownership rates by 43% (from 2.1 to 1.2 vehicles per household). The reason that is stated by Schoettle (2015) is that with in one household, one car could be sufficient if it has the ability to drive itself to different pick-up locations of different household members. Without vehicle automation two or more vehicles would be needed in this same household situation.

A study by Martin et al. (2010) states that carsharing could cause a drop on the average vehicles per household. In their study a group of early adopters of carsharing owned 0,47 vehicles per household before becoming a carsharing member. This dropped to 0,24 vehicles per household after being member for one year. Schure et al. (2012) shows a drop from 1,22 to 0,48 vehicles per household due to carsharing. The big difference in the number of vehicles per household between the two studies is hard to explain. One of the reasons could be that the study by Martin uses national data of the USA while Schure observes users in the region near San Francisco, California.

According to a study by Rydén (2005) one car sharing vehicle has the ability to replace up to 4 - 10 owned vehicles in Europe. Results from the same study, which observed user behavior of a car sharing service in Bremen and Belgium, show that of all the users 21% - 34% sold their car actually due to carsharing. Cervero (2003) shows that 26,6% of all carsharing users sold their car. 2,5% of all the users even sold two or more cars. Shaheen (2007) shows older European studies from between 1994 and 1996 that show a high influence of car-sharing on car ownership. These studies expect a drop of 15% - 30% of car ownership due to carsharing. The study by Martin shows that about 23% of the carsharing users abandoning their car. 25% of the users indicated that they did not purchase a new car due to carsharing.

In a press release carsharing service Zipcar (2015) indicates that 20% of its business members has sold their car due to carsharing. Other studies conclude a number between 10% and 43% of users that sold their car and a number between 14% and 63% of users that decided not to purchase a new car due to carsharing (Millard-Ball, 2005), (Lane, 2005), (Cervero & Tsai, 2003), (Katzev, 1999), (Krietemeyer, 2003), (Lane, 2005), (Holm, Birger, & Eberstein, 2002), (Robert, 2000), (Jensen, 2001) and (Cooper, Howe, & Mye, 2000). These same studies state that between 83% and 59% of all the people owned no car before joining a carsharing service as a member. The other people owned 1 or more cars, which they either kept, or abandoned after joining. The figures seem biased though as the people mentioned in these studies can all be considered early adopters of carsharing. The average car ownership among these early adopters of 14% - 41% seems very low compared with the car ownership of 60% - 70% of the general population (CBS Statline, 2015), (CBS, 2010). A study by Robert (2000) seems to be more in line with these statistics as he reports an average of 63% of the people owning a car before their carsharing membership.

Cervero et al. (Cervero, Golub, & Nee, 2007) have constructed a linear regression model to estimate car ownership, based on a membership status of carsharing services. They conclude that the “the odds of a person abandoning its car jumps from 5.4 percent if the person is a non-member to 18.8 percent if he or she is a member”.

An overview of the available data is shown in the 0 in Table 24. This overview has been made by collecting studies in the works of Jorge (2013), Shaheen (2007) and Millard-Ball (2005), who have made elaborate literature reviews on this subject. A visualization of the average values given by the various studies is shown in Figure 20.

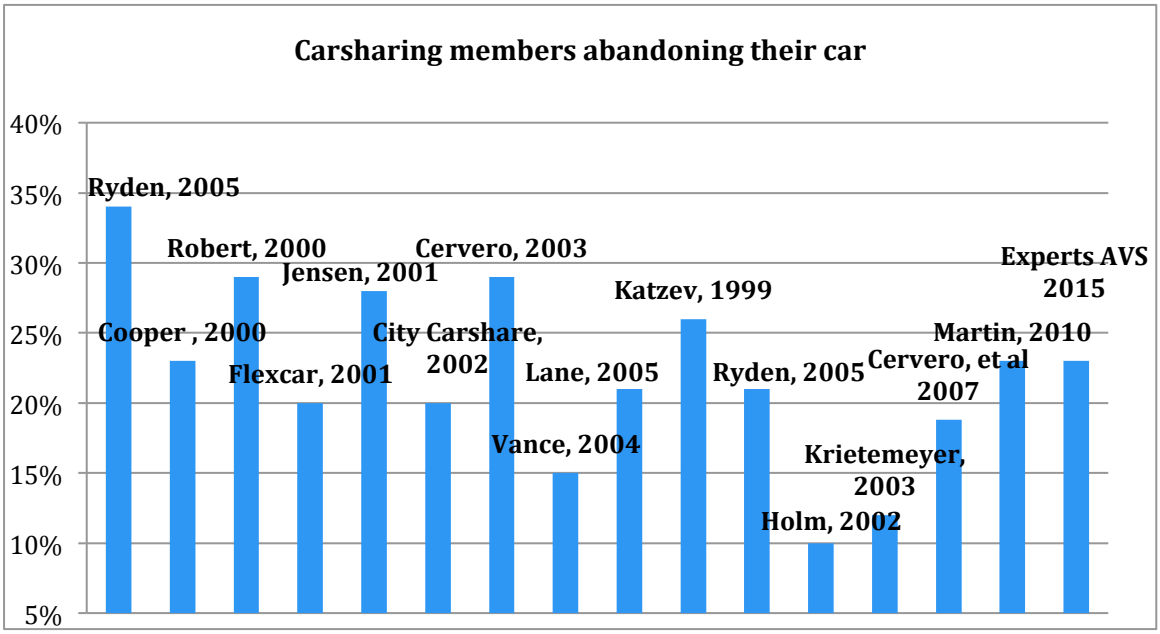

Figure 20 Percentage of people abandoning their car due to carsharing. Source of the idea (Tal, 2009)

An overview of data that has been found about carsharing and ownership is presented with their source of literature in Table 6.

Variable	Data	Region	Unit	Source
Average vehicle lifetime	9,7 10,4	EU USA	Year	(ACEA, 2015) (CAR, 2011)
Sales	12.6M in 2013 387K in 2014	EU NL	Car/Year	(ACEA, 2015)
Vehicles per person	0,564	EU	Car/person	(ACEA, 2015)
Vehicles per household	2 in 2010 2,1 in 2025 Drop of 49% - 61% in 1 year due to carsharing	USA	Car/household	(CAR, 2011), (Martin et al., 2010), (Schure et al., 2012), (Schoettle & Sivak, 2015)
Household size	2,2 in 2015 2,4 in 2015	NL EU	Person/household	(Eurostat, 2015),
Effect of car sharing on ownership	23%	EU & USA	Dmnl	Average of literature represented in Figure 20.
Growth car-sharing market	90% 2006 - 2014 85% 2013 - 2020	Global	1/year	(Baydere et al., 2014), (Tal, 2009)
Effect of vehicle automation on car-sharing	No data	-	1/year	
Ownership of car before joining carsharing	63% 1 or more cars 37% none	EU & USA	Dmnl	Averaged value from various source.
Initial carsharing user base	273 in 2000 6500 in 2006 93174 in 2014	NL	Person	Assuming a 90% growth rate from 2000 to 2006 and a 0,04% (2006) & 0,5% (2014) market

	penetration.

Table 6 Overview of available literature on parameters involving car ownership and carsharing.

4.6 Knowledge gaps

When assessing the availability of data on the system components in this research a few knowledge gaps become visible. In order to fill these knowledge gaps a set of interviews have been conducted with experts in the field of vehicle automation.

For the semi-structured interviews a selection of expects was asked to comment on the questions in the questionnaire. The interviews were approximately 20 minutes long and were held at the Automated Vehicle Symposium in Ann Arbor from July 21 until July 24 2015. This location and symposium was chosen as this is regarded as a very prestigious conference where a lot of top experts are present. This density of top experts made it very time efficient to conduct the interviews

The experts are a mix of people from both Europe and the USA. All experts represent the vehicle automation industry and knowledge institutes. Researchers from various knowledge institutes that were interviewed were either expert in transportation, human factors and/or vehicle automation. Experts from the industry are all highly influential people with a broad overview in their sector like the head of R&D continental, member of executive board of directors Porsche Holding and director Google car. All experts are depicted in Table 7.

Name	Country	Function	Description
David Agnew	Michigan, USA	Head of R&D Continental Automotive	Industry leader with knowledge on technology development and R&D expenditure within large corporations.
Adriano Alessandrini	Italy	Project lead City2Mobil	Mr. Alessandrini has experience with the deployment of various automated urban transit projects in Italy and other countries.
Richard Bishop	Maryland, USA	Bishop Consulting	Highly recognized expert of vehicle automation and chair of a TRB subcommittee
Tallis Blalack	California, USA	Tech-to-Market Advisor	Mr. Blalack is an expert in the process of bringing technology to market.
Bob Denaro	California, USA	Former Vice President Motorola and Nokia/Navteq	Private Consultant in Intelligent Transportation Systems technology and strategy. Mr. Denaro is currently chair of the TRB Joint Subcommittee on Vehicle Automation.
Maxime Flament	Belgium	Head of Sector Safe Mobility - Ertico / ITS Europe	Manager ITS Europe and experience in the policy implementation of automated vehicle and ITS related projects.
Chris Gerdes	California, USA	Assistant Professor Stanford University	Expert on the field of ethics in automated vehicles. Has been closely involved with the test track of Stanford University that is used for test drives of automated vehicles.
Philipp von Hagen	Germany	Member of executive board Porsche SE	Philipp von Hagen is responsible for investment management of Porsche. Porsche Holding owns 50.7% of the shares of Volkswagen Holding, which holds brands like Seat, Audi, VW, Skoda, Bugatti, Lamborghini, Scania and MAN. Philipp von Hagen is also director at INRIX, a data storage

			platform for connected cars.
Larry Head	Arizona, USA	Professor University of Arizona	Professor of transportation with experience in system engineering methodology
Alain Kornhauser	New Jersey, USA	Professor Princeton University	Expert with a long track record in the field of vehicle automation
Miltos Kyriakidis	Greece	Assistant Professor Delft University of Technology	Research expert in human factors related to automated driving
John Maddox	Michigan, USA	Director collaborative programs UMTRI	Started a program of $100M in Michigan to improve vehicle automation through testing facilities.
Glenn Mercer	Cleveland, USA	President at GM Automotive	Mr. Mercer is an expert in private investments in the vehicle automation domain.
Brian Park	South Korea	Associate professor University of Virginia	Research expert in transportation safety and connected vehicle applications.
Nick Reed	United Kingdom	Academy Director TRL (Transportation Research Lab)	In charge of the GATEway (Greenwich Automated Transport Environment) project – a flagship UK Government project to investigate the implications of the introduction of automated vehicles in the urban environment.
Constantine Samaras	Pennsylvania	Assistant Professor Carnegie Mellon University	One of the co-authors of the RAND report
Steven Shladover	California, USA	Director PATH	Dr. Shladover's work is widely recognized internationally, and he has held many leadership positions in transportation related organizations. He chairs the TRB Committee on Vehicle-Highway Automation
Chris Urmson	California, USA	Director automated car Google	Head of the automated vehicle program of Google with over 100 people working in his team on R&D
Joop Veenis	The Netherlands	Rijkswaterstaat	Expert on knowledge transfer and innovation management within the field of ICT and transportation
Mohammed Yousuf	Washington, USA	Transportation specialist U.S. Federal Highway Administration	Did a research for the US DOT on enabling technologies of vehicle automation.

Table 7 Overview of experts that have been interviewed at the AVS 2015

4.6.1 Utility

A clear value or ratio for the comfort of each of the individual levels of vehicle automation cannot be found in the literature. For this reason 15 experts were asked to rate the usefulness of time in a vehicle, shortly translated as comfort, according to the different levels of automation by SAE on a scale from 0 to 10. The experts rated the comfort of levels 0 up to level 5 with an average value of respectively 0,5; 1,5; 2,8; 4,8; 7,7 and 9,5. The median values that were estimated by the experts are respectively 0, 1, 2, 5, 8, and 10. A visualization of the results can be seen in the boxplot of Figure 21.

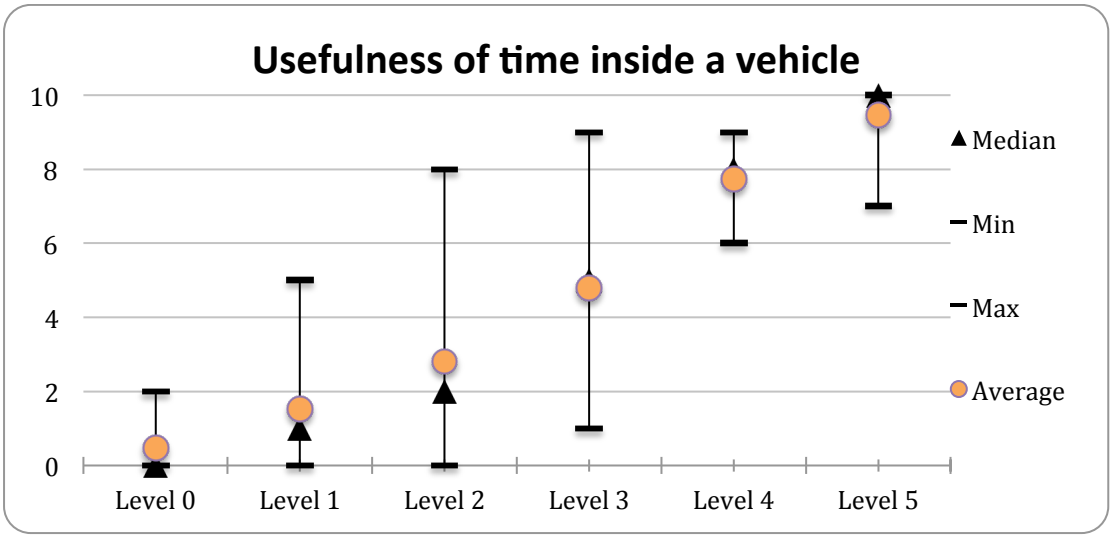

Figure 21 Median, average, min and max of comfort for all SAE levels

	Median	Min	Max	Average
Level 0	0	0	2	0,5
Level 1	1	0	5	1,5
Level 2	2	0	8	2,8
Level 3	5	1	9	4,8
Level 4	8	6	9	7,7
Level 5	10	7	10	9,5

Table 8 Results of comfort rating by experts for all SAE levels

Glenn Mercer expects that for the level of comfort the main benefit will be on highway driving. This highway automation starts at level 3. Chris Gerdes on the other hand states that as long as drivers are expected to monitor the system in some way, there will be little room for any comfort inside that car. In level 3 drivers still have to monitor the system in some way. He therefore rated up to level 3 with a '1' for comfort. Miltos Kyriakidis agrees with this as he states: "As long as the driver will be expected to monitor and supervise the system I can see no benefits. For level 4 and level 5 the rating assumes that those AVs have been tested and are safe."

Level 4 has a median of 8 and an average value of 7,7. There seems to be more consensus on the comfort in level 4 as the minimum and maximum are within a range of 3 points with respectively 6 and 9. The same consensus seems to be there on the level of comfort for level 5 automation. The range is 3 points with a minimum of 7 and a maximum of 10. The majority, about 73%, of the experts rated the comfort with a 10. This gives a median of 10 and an average value of 9,5.

4.6.2 R&D expenditure on vehicle automation

To get some feeling for the amounts that are spend on R&D, an estimate was asked to industry experts. Total R&D expenditure in the automotive industry is estimated at approximately 5% - 10% of the annual revenue. This total R&D budget is used for all sorts of research and development like the drive train, energy source, safety systems and vehicle automation technologies. The last few years an increasing amount is allocated for the development of vehicle automation and communication between vehicles and infrastructure.

Bob Denaro, former VP telematics Motorola and VP Navteq, estimated that "today about 10% of all R&D budget is allocated for vehicle automation. Within a few years this percentage will increase to approximately 50%". David Agnew could confirm this increasing focus on vehicle automation within R&D, although David Agnew was cautious to say any exact percentages. Also Chris Gerdes, professor mechanical engineering at Stanford University, recognizes the increasing focus on automated vehicles in R&D. "Especially the last 2 years this shift has been dramatic" says Chris Gerdes. Glenn Mercer, president GM automotive, says about 7% of all revenue is spent on R&D. Today 50% is spent on development on the drive train, 25% safety systems including ADAS and 25% is spent on material development and other related things. In 2025 Glenn Mercer expects at least 50% to be spent on automated vehicle related technologies. According to Philipp von Hagen, member of the executive board of Porsche SE, the average expenditure on R&D in the automotive market is 5 – 10% of the annual revenue. The total R&D expenditure in the German market is €30B per year. Philipp von Hagen expects the R&D expenditure on vehicle automation to become around €17B per year in 2018. The numbers are summarized in Table 9. What strikes the attention is that Germany alone already accounts for more than 35% of the global R&D expenditure.

Variable	Data	Year	Source
Percentage of annual revenue to R&D	5% - 10%	Constant	Expert estimations: Chris Gerdes, Glenn Mercer, Bob Denaro, and Philipp von Hagen.
R&D expenditure on vehicle automation	<1% of total R&D	2000	
	€17B in Germany (60% of total R&D)	~2018	
	€15B - €45B worldwide (20% - 50% of total R&D)	2025	(Von Hagen, 2015)
Total R&D expenditure automotive	€30B in Germany €41B in Europe €77B Worldwide	2013	(Von Hagen, 2015), (ACEA, 2015)
Annual revenue	€315B in Europe €400B - €800B	2013	(ICCT, 2014), (ACEA, 2015)

Table 9 Estimates on R&D expenditure by industry experts

4.6.3 Market penetration

To get higher validity on the available data about future market penetration and to get a better alignment of the data with the worldview of this research it has been chosen to use expert estimations on top of the already available data in literature.

In these interviews the experts were asked to draw trajectories of the market penetration of the various automation levels in a graph, which represented the Total market [0% -100%] on the y-axis and Time [Year] on the x-axis. Furthermore they reflected on the question what a likely adoption scenario for automated vehicles could be.

Overall the trend was quite optimistic about the market adoption of automated vehicles. In general the experts see a stepwise introduction of level 1, 2 and 3. Followed by an introduction of level 5. In general level 4 was a level of automation that people gave little chance to gain massive market adoption. Two pathways could be identified.

4.6.3.1 Private luxury

The pathway of private luxury consists mainly of luxurious vehicle equipped with vehicle automation features and safety systems. These features could be either considered as level 3 or as level 4 of 5. This private luxury does contain an ownership model. Many experts consider private luxury as an option for early

adoption. OEMs could equip existing vehicles with new automation features and existing vehicles on the road could also be equipped through the retrofit market. In the long future not many experts think that this option will be the dominant option as they predict that level 3 would have about 0 – 25% market share in the period 2075 – 2100.

4.6.3.2 Mobility as a service

The pathway of mobility as a service assumes a service-based usership model. Level 5 automation could play a big role in this model according to many experts. The vehicles in this model would mainly operate in densely populated areas with a low speed. Chris Gerdes says: "From an introduction strategy you could start to see fully automated level 5 vehicles, but very slow. Maybe on a campus, in some closed areas or cities with dedicated infrastructure. And then you will start to see some technologies added to conventional vehicles on highways. You will have these two paths, with the existing vehicles becoming more automated and the full autonomous vehicles starting out slow and then getting more capabilities. Both pathways will either merge if the public still has desire for one and the other. But probably one of the pathways will hit the tipping point before the other.

4.6.3.3 Level 5 automation

A majority of the experts expect that the diffusion of level 5 automation will occur in an s-shaped curve. The expected year for market introduction of level 5 automation varies between 2020 and 2040. One outlier can be found in 2075 as Steven Shladover is not so optimistic about level 5 automation. He expects big problems in the validation phase of the software of level 5. Nevertheless Steven Shladover expects that level 3 and 4 will likely hit the market around 2030.

Rapid increase in market penetration from 25% till 75% will happen between 2035 and 2060. The same majority of experts expect level 5 to gain market saturation before 2100. A minority of the experts expects that level 5 will not gain the full market penetration, as this market will be shared with either level 3 and/or level 4 vehicles.

Table 10 and Figure 22 show the years that the experts expect a market penetration of 10%, 25% 50% and eventually 75% and 100%. It should be mentioned that the experts were not asked to estimate the diffusion by giving percentages, but by drawing trajectories on a graph.

Automation level	Market penetration	Average [Year]	Min [Year]	Max [Year]
Level 5	Market introduction	2033	2020	2075
	10%	2048	2030	2100
	25%	2067	2035	2100
	50%	2075	2040	2100
	75%	2083	2045	2100
	100%	2096	2072	2100

Table 10 Expert estimates of market penetration Level 5 automation

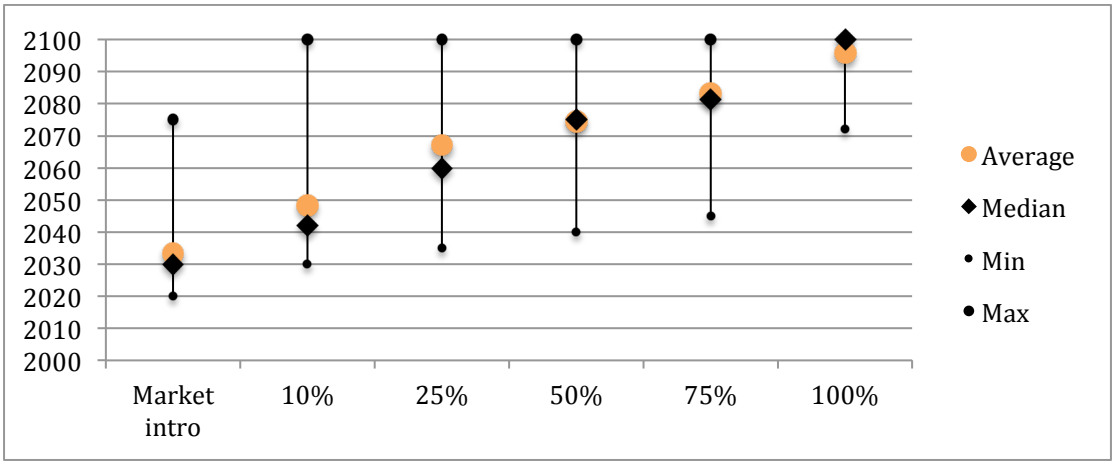

Figure 22 Overview of average, min and max expected years of market adoption

It can be seen that the estimated market penetration by the experts are a little less optimistic then the estimations that the literature shows. For example a 50% market penetration of level 5 is estimated in literature to happen between 2035 and 2050, while experts estimate it to happen in 2075.

4.6.4 Carsharing growth

A knowledge gap that is identified is the impact of vehicle automation on the growth of the carsharing market. Various prominent researchers refer to this impact (Alain Kornhauser, Emilio Frazzoli and Scott Le Vine (2014)), but none can give clear indications of the height of this impact. Although the effort, no reliable data has been found that indicates the impact of vehicle automation on the carsharing market.

Almost all experts expect a very high impact, more than 20% extra annual growth, of vehicle automation on the car sharing market. Alain Kornhauser states that: “the great thing about automated vehicles is not the moment that you are in the car. It is like a taxi that will get to you when you need it, and will go away without you whenever you want. That is the amazing thing of automated vehicles and we can only reach that at level 5.” In his opinion this will hugely benefit the car sharing market.

4.6.5 Carsharing vs. car ownership

Lots of literature is found on the effect of carsharing on car ownership. However little consensus with reliable empirical evidence is found in the literature. For this reasons this effect was included in the expert interviews. Most of the experts are agreeing on the fact that car sharing will have an effect on car ownership. About forty percent of the experts expect that car sharing will have a low probability (less or equal than 15%) that people will abandon their car. About half of the experts expect that car sharing will have a high probability (between 15% and 50%) that people will abandon their car over time. One person, Richard Bishop, expects a very high impact, (more than 50%) of car sharing on a decrease in vehicle fleetsize. He states: “carsharing will have a very high impact on the fleetsize as it is a huge societal change. It could either go fast, or it could get into a snowball effect and go very fast.”

5. Building the simulation model

In the previous chapters the system of vehicle automation has been compared with a Technology Specific Innovation System and the system components within this boundary has been identified. For each of the components the literature has been reviewed to find causalities between the components and look at the available of data for the system components. In this chapter the system components will be specified that have been used for the construction of a stock & flow simulation model. Furthermore the model settings for the simulation runs will be specified.

5.1 Specification of the simulation run

The model was implemented in VensimPro 6.3. The simulation is run between an initial time 2000 and the final time 2100. The unit for time is in 'Years'. VensimPro gives a limited number of options for the time step during the simulation. The four smallest possible time steps inside this software package are 0,0625; 0,0313; 0,0156 and 0,0078. The time step is set to 0,0156, representing about 6 days or almost a week. A smaller time step was tested, but made no difference in the outcome of the simulation run. The integration type was set to Euler.

The system components are specified separately in the model for each of the individual levels of automation. This means that level 1 has it's own purchase price, technology maturity and fleetsize, which is different than those of e.g. level 3. The levels are depicted with a $j = \{0, \ldots, 5\}$.

The endogenous variables in the equations in this report are all time dependent. For simplicity reasons it has been chosen not to write this time dependence with every variable. So for example the purchase price, p_j (t), is depicted as p_j. Variables that are depicted with a capital Latin letter are stocks, such as the Maturity, *M*. Endogenous variables are depicted with a lowercase Latin letter, such as market penetration, d_j. Constant parameters are either depicted with a lowercase Greek letter, such as the learning factor μ or with a Latin lowercase letter, such as the effectiveness of knowledge transfer, *ef*. If a constant parameter is depicted with a lowercase Latin letter it is indicated explicitly that it is a constant to prevent confusion with endogenous variables.

To improve the readability of the equations it has been chosen to notate some of the variables with a combination of letters, such as the learning-by-doing effect, *lbd,* and the exogenous growth rate, *eg.* This combination of letters should not be seen as a multiplication between various variables, but just as one variable. In case of a multiplication a star symbol ($*$) is used. In some equations the initial value of a stock is used. The initial value is indicated with the notation of the stock combined with a subscript 0. For example M_j (0) = $M_{j,0}$.

5.2 Specification of model structure

5.2.1 Technology maturity

R&D expenditure is traditionally a few percentages of the total revenue of a market. In the model the annual revenue of the market is specified as the product of the annual sales and the average purchase price of a vehicle. The technology development of the six levels of automation is all modeled as a separate module, *j*, within the model. The resources that are put in the technology development are coming from the annual sales of the respective markets of the six levels of

automation individually. The technology development of i.e. level 3 automation is therefore very much dependent on the sales of level 3. The technology development of level 5 is dependent on the sales of level 5 vehicles. This way of conceptualization is supported by the fact that different kinds of firms are focusing on the development of different levels of automation. Traditional OEMs are focusing more on level 3 vehicle automation, public transport authorities are focusing on the development of level 4 vehicles and other new players might focus more on level 5 automation. Different players on the technology development of different levels therefore spend the resources gained from the revenues of these activities.

To simulate the concept of learning and forgetting it has been chosen to configure a knowledge stock. In this stock the knowledge accumulates that is gathered through R&D. It is gathered in the form of new concepts, theories or formulas and stored in books, papers and other means of communication. This is wide ranged and very intangible, therefore is represented in a monetary way, by euros. The unit represents all the money and labor that went into the process of gathering the knowledge. Knowledge can be forgotten or depreciated if it is not being supported enough by institutions that set up rules and guidelines how to use the knowledge (Johnson, 2010).

The annual R&D expenditure, rd_j, determines the rate at which new knowledge is added to the knowledge stock, K_j. A certain percentage, ∂, of the knowledge stock depreciates, or is forgotten, every year.

$$\frac{dK_j}{dt} = \mathrm{rd}_j - (\mathrm{K_j} * \partial)$$

Equation 1 Knowledge stock

The knowledge stock has to be translated into the maturity of the technology, M_j, to represent the real world phenomenon of knowledge transfer from R&D towards product innovation. The maturity is a relative variable with a range from 0 to 1. The knowledge stock will therefore have to be normalized. In order to do so a variable is added that illustrates the 'total amount that is needed', an_j, for a fully matured technology. This variable is imaginary and does not really exist in real life. One might only determine this value ex post. Nevertheless this variable is needed to normalize the knowledge stock, nK_j. It is believed that this value can somewhat be estimated ex ante, for example by looking at the potential market size or looking at earlier investment amounts to fully mature a technology in the automotive sector.

$$nK_j = \frac{K_j}{MAX\ (K_j, an_j)}$$

Equation 2 Normalized knowledge of level *j*

The maturity of the technology is specified as a stock, M_j, with an inflow rate and no outflow rate. The maturity of a product can therefore only grow. The inflow rate is representing the development of maturity. A gap is specified as the inverse of the maturity, $(gap_j = 1 - M_j)$. The sum of the maturity and the gap will therefore always be 1. The normalized knowledge is multiplied by a gap to ensure the maturity stock, M_j, will not grow larger than 1. The inflow rate of the maturity is the product of the normalized knowledge, the gap and the effectiveness of the knowledge transfer, *ef*.

$$\frac{dM_j}{dt} = +\ (nK_j * gap_j * ef)$$

Equation 3 Maturity stock

It has been chosen to represent the maturity with a stock and an inflow rate and not

link the maturity directly to the knowledge stock. This way a delay is build in between the gathering of knowledge and the growth of maturity. This also causes that maturity is less sensitive for fluctuations or depreciation in the knowledge stock. The last reason is that in order to represent the maturity in a valid way, an s-shaped curve is needed. This s-shaped curve represents the marginal costs that increase when the technology gets more mature. At the end it takes a lot of knowledge to increase the maturity by a little bit. These increasing marginal costs are taken into account when modeling the maturity as a stock with a gap that needs to be filled.

The initial knowledge, M_{0j}, is specified as the product of the initial maturity, the maximum knowledge needed for full maturity and a depreciation factor of past knowledge, *df*. The depreciation factor symbolizes the knowledge that has been depreciated over the past years before the start of the simulation run time.

$$K_{0j} = nK_j * M_{0j} * df$$

Equation 4 Initial knowledge stock

5.2.2 Purchase price

The purchase price, p_j, is the sum of the baseline price, bp_j, and the retrofit price, rp_j.

$$p_j = bp_j + rp_j$$

Equation 5 Purchase price as a product of baseline price and retrofit price

Both the baseline price and the retrofit price are affected by a learning curve. The baseline price is influenced by learning-by-doing effect, which is caused by an accumulation of experience. The retrofit price is influenced by learning-by-searching effect, which is caused by an accumulation of maturity. The specification of the learning curves is adopted from Sterman's Business Dynamics (2000, p. 337). The learning curve of learning-by-doing, *lcd,* represents the effect in which costs fall by a fraction *x* for each increase of experience in the order of magnitude *ω*. The learning curve of learning-by-searching, *lcs,* represents the effect in which costs fall by a fraction *μ* for each doubling of maturity in the order of magnitude *Ω*.

$$lcd = \log_{\omega}(1 - x)$$

Equation 6 Learning-by-doing curve

$$lcs = \log_{\Omega}(1 - \mu)$$

Equation 7 Learning-by-searching curve

5.2.2.1 Baseline price

The baseline price represents the purchase price of a vehicle without any of the automation technology onboard. The baseline of a vehicle of automation level *j* thus represents a vehicle from a specific price class that is able to be equipped with automation features. Early in the development phase the type of vehicles that are suitable for vehicle automation are still from a premium price class. The expectation is that due to learning effects the costs of production will drop. This enables vehicles of a lower price range to get on the market of a level of automation *j.* The cumulative experience, E_j, is measured through an accumulation of sales over the time.

$$\frac{dEj}{dt} = \sum_{i=0}^{(j-1)} s_{ij}$$

Equation 8 Accumulation of experience

Instead of a direct relation between the learning-by-doing curve and the baseline price an artificial variable will be specified in-between. This variable, called learning-

by-doing *(lbd),* will represent the learning by doing effect and has a range of *0 ≤ lbd ≥ 1*. The learning-by-doing variable is specified as follows:

$$lbd_j = (1 - \left(\frac{E_j}{E_{0j}}\right)^{lcd})$$

Equation 9 Learning-by-doing variable

The baseline price, BP_j, will be specified as a stock. The stock has an initial value and will decrease by a rate: 'Decrease of price', dc_j.

$$\frac{dBP_j}{dt} = -\, dc_j$$

Equation 10 Baseline price stock

A desired baseline price, *dbp*, will be specified that represents the asymptote that the baseline price will reach. This desired baseline price is a constant. A 'price gap' variable, $pricegap_j$, will be specified as the baseline price minus the desired price.

$$pricegap = BP_j - \, dbp$$

Equation 11 Specification of the pricegap

The decrease of price is a product of the learning-by-doing variable, the price gap and a learning effect delay factor. This function represents the real world phenomenon that the baseline price of a vehicle decreases when the industry recognizes a certain market for a product. To make this product more attractive for this market the price should decrease. However if the production costs are still too high, the price cannot be decreased too much. If this market is growing the costs will decrease through process innovation, which leads to learning by doing effects. The cumulative experience that is build up has a direct effect on the learning by doing. This effect however is never so direct in the real system. In the real system there are information delays and delays in the gradual increase of process innovation. This delay is represented in the function of dc_j as well. This 'learning effect delay', *led*, has a dimension of: 1 / delay [in years]. This learning effect delay is a constant.

$$dc_j = pricegap_j * \, lbd_j \, * led$$

Equation 12 Decrease of price for level *j*

The total specification of the baseline price is depicted in Figure 23.

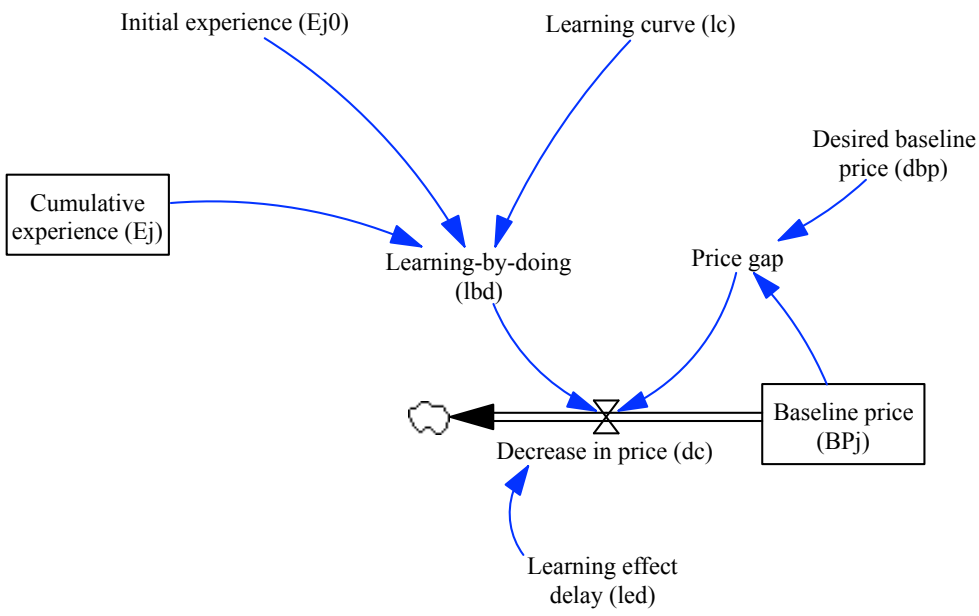

Figure 23 Structure of the new specification of Baseline price

5.2.2.2 Retrofit price through Learning by searching

The retrofit price represents the market price of all the electronics, sensors, actuators and software that enable a vehicle of level *j* to be automated. This equipment could either be installed into the vehicle within the manufacturing/assembling process, or retrofitted in the aftermarket. This distinction is left out of the scope of the model.

The retrofit equipment price decrease is very much dependent on the maturity of the technology and the R&D process and decreases in price through learning-by-searching. With every multiplication Ω of the maturity of a technology the retrofit price decreases with a fraction *μ.*

$$rp_j = rp_{j0}\left(\frac{M_j}{M_{j0}}\right)^{lcs}$$

Equation 13 Retrofit price

5.2.3 Utility

The utility of a specific level of automation, *j*, is the sum of the attractiveness, a_j, and the normalized price, np_j, both multiplied by a weight.

$$U_j = \left(np_j * ß_1\right) + \left(a_j * ß_2\right)$$

Equation 14 Utility function

The utility represents a value between 0 and 1. For this reason the purchase price has to be normalized, np_j. To normalize the purchase price it is divided by the highest price of all the levels of automation at a specific time instant.

$$np_j = p_j/(MAX(p_n)\ with\ n = \{0, \dots, 5\}$$

Equation 15 Normalized price

The attractiveness is the sum of the comfort, cf_j, the safety, sf_j, and the familiarity, pc_j, each multiplied by their weight. Comfort, cf_j, and safety, sf_j, are constants in the model.

$$A_j = (sf_j * ß_3) + (cf_j * ß_4) + (pc_j * ß_5)$$
Equation 16 Attractiveness

The ß parameters that can be found in Equation 14 and Equation 16 represent a weight value. These parameters indicate the weight that customer put on a specific attribute of the utility function. The weight factors are constants in the simulation model.

The familiarity, pc_j, consists of the current market penetration, d_j, of automation level *j*. This is the ratio of the fleetsize of *j* compared with the total fleetsize. This illustrates the word of mouth principle, which states that people will get more familiar with the automation level *j* if they see *j* more around them in comparison to the other levels of automation. This familiarity increases their familiarity and the attractiveness of *j*.

$$d_j = \frac{V_j}{V}$$
Equation 17 Market penetration

$$V = \sum_{n=0}^{5} V_n$$
Equation 18 Total fleetsize

5.2.4 Fleetsize

The fleetsize is the total number of vehicles of each level of automation *j = {0, …, 5}*, V_j. Each fleetsize starts with an initial value. This variable accumulates all the change of vehicles from i to j, c_{ij}, with *i = {0, …, j-1}*. All the changes of vehicles from j to the other levels of automation k, c_{jk} with *k = {j+1, …, 5},* are subtracted from the stock. Each fleetsize is also growing by an exogenous growth rate, eg_j.

$$\frac{dVj}{dt} = \sum_{i=0}^{(j-1)} c_{ij} + eg_j - \sum_{k=(j+1)}^{5} c_{jk}$$
Equation 19 Fleetsize stock

The exogenous growth rate, eg_j, is the product of the total fleetsize, the change in fleetsize and the market penetration of level *j*. The change in fleetsize, *cV,* will be explained further on in this chapter.

$$eg_j = V * cV * (\frac{V_j}{V})$$
Equation 20 Exogenous growth rate of the vehicle fleetsize

The variable c_{ij} represents the number of vehicles that are being changed from automation level *i* to automation level *j.* It is assumed that vehicles can only be changed towards a higher automation level. So *i < j.* It is possible to change a vehicle from any lower level of automation to any higher level of automation. So *i = {0, …, j-1}*. This specification assumes a continuous flow of the fleetsize among the different automation levels, depending on a customer choice. This is an essential part of the model, as it will represent the adoption rate of vehicles of automation level *j* in a later stage.

The change of vehicles from level *i* to level *j* depends on the fleetsize of *i* and on the average lifetime of a vehicle, *α*. Furthermore this is determined by the maturity of *j.* The choice that customers make for a specific level of automation *j* over *i* is

represented by the last part of the function (Equation 21) in which the utility of *j* is divided by the utility of *i* and *j* combined.

$$c_{ij} = V_i * \left({}^{1}/_{\alpha}\right) * M_j * \frac{U_j}{U_i + U_j}$$

Equation 21 Change of vehicles from level *i* to level *j*

If the maturity, M_j, is low, the change of vehicles to level *j* will also be lower. When the maturity grows, people will gain more confidence in the reliability and performance of a vehicle and will be more likely to change the type of their vehicle from *i* to *j*. The same goes for the utility of *j*, U_j. If this utility grows in respect to *i*, the likelihood increases that people will favor level *j* above level *i*. An illustration of this structure of this change of vehicles between the levels is depicted in Figure 24. For this illustration only the levels 1, 2 and 3 are depicted. In the whole model also level 0, level 4 and level 5 are included, but for reasons of simplicity and readability only 3 levels are shown in this illustration.

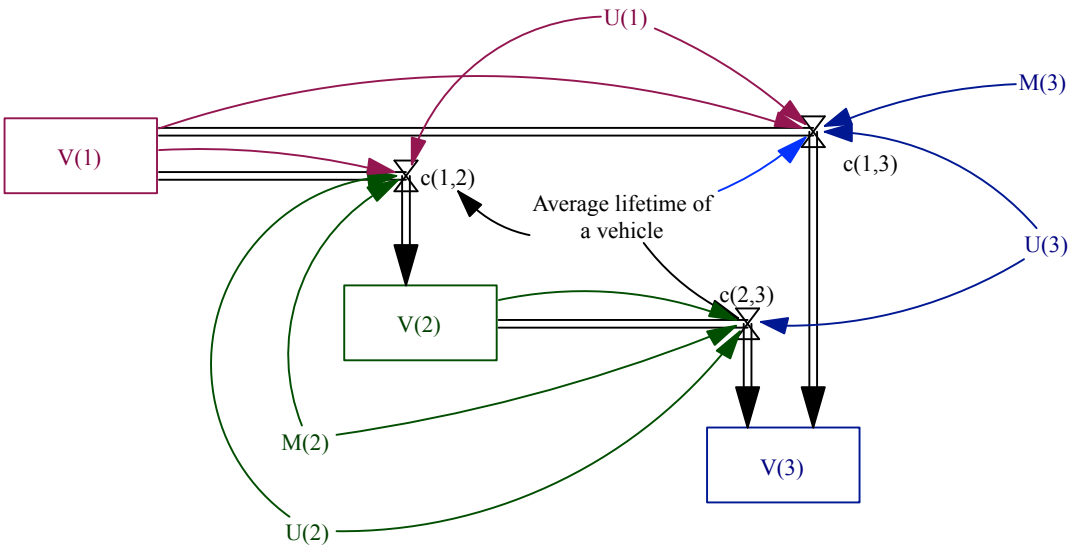

Figure 24 Illustration of change of vehicles between the levels in VensimPro.

The likelihood of people to change to level *j* will always be in respect to each of the individual levels *i* < *j*, but not to sum of all the levels together. This is in contrast to a normal logit function as described in Train (2007) and McFadden (1974). This function represents the probability that *j* is chosen over all the other alternatives.

$$P_j = \frac{e^{U_j}}{\sum_{j=0}^{5} e^{U_j}}$$

Equation 22 Logit function

The normal logit function will not be used in this model because it is specifically important to know the difference in utility between levels *i* and *j* for the change of vehicles between levels *i* and *j* and not just the advantage of level *j* over all the levels. For example in the change from level 1 to 3 ($c_{1,3}$) and from level 2 to 3 ($c_{2,3}$), it is important to know the utility of level 3 in respect to level 1, which is different than the utility of level 3 in respect to level 2.

The model assumes that in order to go from level *i* to level *j* this requires a change of vehicle, meaning that the owner of the vehicle will have to sell vehicle *i* and buy a new vehicle *j.* For this reason the average lifetime of the vehicle is incorporated in the function. However Tesla has recently (IEEE, 2015) shown that they are able to 'upgrade' a car from level *i* to level *j* just by an internet connected software update in their whole vehicle fleet, because all the hardware sensors were already onboard. It is possible to represent this in the model but adjusting the average lifetime of a vehicle.

5.2.5 Carsharing

To conceptualize the market of carsharing a stock is specified with the number of users *A* of car sharing. The number of people that haven't adopted carsharing yet are specified as the potential adopters, *PA.* The potential adopters are specified by the total population, *N,* minus the number of adopters. It is assumed for simplicity reasons that the potential adopter group is equal to the total population minus the people that have already adopted carsharing.

$$PA = N - A$$

Equation 23 Potential adopters

The population is a stock with an inflow representing both birth- and death rate. The carsharing users, with unit person, are split in users with a car, A_c, and a group without a car, A_{wc}.

$$A = A_c + A_{wc}$$

Equation 24 Number of carsharing users

The carsharing user stocks, with and without car, both increase through the same construction. The stock is the integral of the adoption rate of carsharing, ar_{cs}, multiplied with the fraction of users with a car, f_c, over time. The flow from people with a car towards people without a car is represented by the abandoning rate of cars, *abr,* which will be specified later in this paragraph and is shown in Equation 31.

$$\frac{dA_c}{dt} = (\mathrm{ar_{cs}} * f_c) - abr$$

Equation 25 Carsharing users with a car

$$\frac{dA_{wc}}{dt} = (\mathrm{ar_{cs}} * f_{wc}) + abr$$

Equation 26 Carsharing users without a car

The fraction of users with a car is dynamically determined by dividing the total number of vehicles in the fleetsize, *V,* with the total population.

$$f_c = \frac{V}{N}$$

Equation 27 Fraction of users with a car

The adoption rate of carsharing is the product of a growth rate, *g*, the potential adopters and the user stock divided by the total population. This equation is adopted from Sterman (2000). This way the potential users are reached through word-of-mouth in the beginning, but the growth is slowed down through a low number of actual users, which is divided among the total population. As the number of users rise, this slowing factor reduces. This results in a phase of massive adoption. As the potential adopters group decreases, the 'word-to-mouth' growth rate loses some of

its strength, resulting in a slowdown in the adoption rate. The adoption rate therefore results in an s-shaped curve over time. The adoption rate of carsharing has a dimension of 'person/year'. It should be noted that this is contrast with the adoption rate of vehicle automation, which is in '%/year'. The difference between the two adoption rates is that the adoption rate of carsharing is absolute and the adoption rate of vehicle automation is relative. The adoption rate of carsharing car easily be translated into '%/year' if needed.

$$ar_{cs} = g * PA * \frac{A}{N}$$

Equation 28 Adoption rate carsharing users

The growth rate *g* consists of the sum of a normal market growth rate, g_m, and a growth rate through vehicle automation, g_{va}.

$$g = g_m + g_{va}$$

Equation 29 Growth rate of carsharing

The growth rate through vehicle automation is specified as an IF THEN ELSE function of the maturity of vehicle automation level 5 and a technology multiplier, *tm*, which represents the added effect of vehicle automation on the growth of carsharing. Only the maturity of level 5 is chosen, because this level of automation enables the vehicles to drive without a human inside. This is an aspect of vehicle automation that is considered a very important enabler of carsharing. A level 5 vehicle is like a robot taxi as it can drop off a passenger and drive to a new passenger on a different location without having a human driver onboard.

In the real system a product would not become available on the market until the technology has reached a specific threshold maturity, lets say 40-60%. Until this threshold the manufacturers are not sure enough about the reliability and performances of the product. The first 10% of maturity could be defined as a phase of 'product development'. A phase of 'testing and validation' of the technology happens at a maturity of 10% - 40%. The deployment wouldn't happen until 40% maturity. The above-mentioned threshold values are estimated through expert conversations.

The added effect of vehicle automation on the growth of carsharing is only active after the maturity of level 5 has reached the threshold value of 40%.

$$g_{va} = IF\ THEN\ ELSE\ (M_j > 0.4\ , tm\ , 0\ )$$

Equation 30 Growth rate carsharing through vehicle automation level 5

Literature tells us that there is a high rate of car shedding among carsharing users, meaning that people abandon their private car. This abandoning rate, *abr*, is the product of the number of carsharing users with a car, A_c, and a percentage of car shedding among carsharing users, *sr*. The abandoning rate is specified as a flow of users from A_c to A_{cw}.

$$abr = A_c * sr$$

Equation 31 Abandoning rate of cars due to carsharing

The abandoning rate, *abr,* represents a flow of people. Each of those people abandons their car, so this leads to an annual change, *cV,* in the total vehicle fleetsize *V*. The abandoning rate (in *[person/year]*) is translated into a yearly number of shedded cars (in *[car/year]*), through a multiplication with the fraction of users with a car, f_c (in *[car/person]*). The number of shedded cars is divided by the total vehicle

fleetsize to create an annual percentage of shedded cars.

$$cV = \frac{abr * f_c}{V}$$

Equation 32 Change in vehicle fleetsize

The total vehicle fleetsize is changed through an exogenous growth rate, *eg,* at each of the levels of automation as described earlier in this Chapter and shown in Equation 19. This exogenous growth rate is the product of the change in fleetsize, portion of total fleetsize for *j* and the total fleetsize as can be seen in Equation 20.

5.2.6 Indicators

Various endogenous indicators are produced in the model, which have no influence on the dynamics of the model. These indicators are variables with a high availability of data in the literature, as such that they can be used in the validation process of the model.

The adoption rate of vehicle automation is the speed of growth of a new level of vehicle automation. The adoption rate of automation level *j* is specified as the total sales of *j* divided by the total vehicle fleetsize.

$$ar_{va,j} = \frac{\sum_{s=0}^{j-1} s_{ij}}{V}$$

Equation 33 Adoption rate of vehicle automation

The market penetration of vehicle automation, d_j, is the fraction of all the vehicles being automation level *j.*

The number of households, *hh*, is a quotient of the total population and the average household size, *shh*. The number of cars per household, *chh*, divides the total vehicle fleetsize by this total number of households.

$$chh = \frac{V}{N/shh}$$

Equation 34 Number of cars per household

The distance traveled per car, *tc*, is another indicator. It represents the quotient of the total travel demand, *td*, and the total vehicle fleetsize. The travel demand is the product of the travel demand per person, *ptd*, and the total population.

$$tc = \frac{ptd * N}{V}$$

Equation 35 Distance traveled per car

An overview of the equations of the stocks and the endogenous variables can be found in Appendix B.

5.3 Specification of parameters

The previous section shows all the equations of the system structure that are used to build the model. Some of the equations use static parameters. These parameters form the input for the model. A set of parameter values is chosen for a base run of the simulation model. This base run can be used to validate the behavior of the model in Chapter 6. By estimating the initial values it has to be taken into account that the simulation model uses a start time of the year 2000.

5.3.1 Fleetsize

It is assumed that the fleetsize in the year 2000 was totally dominated by traditional automobiles without automation features. Statistics by CBS Statline (CBS Statline, 2015) show that in 2000 around 6,4 million passenger vehicles were in use in the Netherlands. In this study it is assumed that a very small number of vehicles were level 1 in 2000. The initial value of level 2, 3, 4 and 5 has been set on 2 vehicles. This value can be neglected. These parameters won't be set on 0, because in one of the equations in the model a variable has to be divided by the initial value for the fleetsize. For this reason the initial values cannot be set on 0. The average lifetime of a car is estimated on 10,4 years, based on a report by the European Automobile Manufacturers Association (ACEA, 2015).

Name	Notation	(Initial) Value	Unit	Source
Initial fleetsize Level 0	$V_{0,0}$	6.390.000	Car	(CBS Statline, 2015)
Initial fleetsize Level 1	$V_{0,1}$	1000	Car	Own assumption
Initial fleetsize Level 2	$V_{0,2}$	2	Car	Own assumption
Initial fleetsize Level 3	$V_{0,3}$	2	Car	Own assumption
Initial fleetsize Level 4	$V_{0,4}$	2	Car	Own assumption
Initial fleetsize Level 5	$V_{0,5}$	2	Car	Own assumption
Average lifetime of a car	α	10,4	Year	(ACEA, 2015)

Table 11: Parameter values for the system component: Fleetsize.

5.3.2 Purchase price

The purchase price is the sum of the baseline price and the retrofit price.

5.3.2.1 Initial values baseline and retrofit price

Level 4 and level 5 are not yet on the market. No reliable purchase prices can therefore be found on these levels. This study has to rely on estimation of the experts. Among the experts there is still little consensus on the difference between the SAE levels. Some of the experts state that up until level 3 vehicles are already on the market for sale. Other experts state that level 3 vehicles are a long time from being in mass production and estimate an average price of $200.000 for the vehicle. The consensus among the experts is that the price of level 4 and level 5 is still very high. The results from the expert estimations of the purchase prices of all levels of automations in 2015 are shown in Table 12.

	Level 1	Level 2	Level 3	Level 4	Level 5
Average	$27.444	$43.200	$74.625	$107.167	$314.000
Max	$50.000	$80.000	$200.000	$200.000	$1.000.000

Table 12 Expert estimations of the purchase price in 2015.

It has to be taken in mind that the values represented in the table above are estimations of the price in 2015. Based on these expert estimates and the data found in Paragraph 4.2 the initial values for the baseline price and the retrofit price in 2000 has been estimated. The price of a mid-class vehicle of 40.000 euro has been chosen as the initial baseline price for level 2. 5000 euro will be added as the initial value for the retrofit price for level 2. The estimated price of a lidar system has been chosen as the initial value of the retrofit price of level 3. The price of a premium-class vehicle has been chosen as the initial baseline price of level 3. The initial value for the total purchase price of level 4 is set to 400.000 euro. The initial value of level 5 is set to 1.000.000 euro.

5.3.2.2 *Learning effects*

Both the baseline price and the retrofit price decrease through learning effects. The learning effects, both learning by doing and learning by searching, in the model are each dependent on two specific parameters. These are the parameters that determine the steepness of the learning curve.

The baseline price decreases through learning-by-doing effects. The parameters for this learning curve are the logarithmic scale ω and the factor x, which represents the effect on the price by an increase ω in the experience. Kamp (2002) describes a normal learning curve of 5-10% decrease for every accumulative doubling. For the logarithmic scale ω a value of 2 has been chosen. The factor x has a value of 0,05. This represents the effect of a 5% decrease in price when the cumulative experience doubles.

The retrofit price decreases through learning-by-searching effects. The parameters for this learning curve are the logarithmic scale Ω and the factor μ. For the logarithmic scale Ω a value of 10 has been chosen. The factor μ has a value of 0,7. This represents the effect of a 70% decrease in price when the cumulative experience is multiplied by a factor 10. These values have been tested through an iterative process. A few experiments have been set up where the learning curve parameters Ω and μ have been adjusted. The experiment have been set up for $\Omega = \{2, 5, 10\}$ and $\mu = \{0,1; 0,5; 0,6; 0,7; 0,8\}$. The curve of the retrofit prices of level 5 over all these experiments is depicted in Figure 25. From all the curves, the one with Ω=10 and μ=70% seems to be most realistic. In this curve the retrofit price (of level 5) starts at 500.000 euro in 2000, has a value of 105.000 euro in 2015 and eventually drops to an asymptote of approximately 5000 euro. These values seem realistic. Due to these tests it is proposed to set the parameter values at Ω=10 and μ=70%.

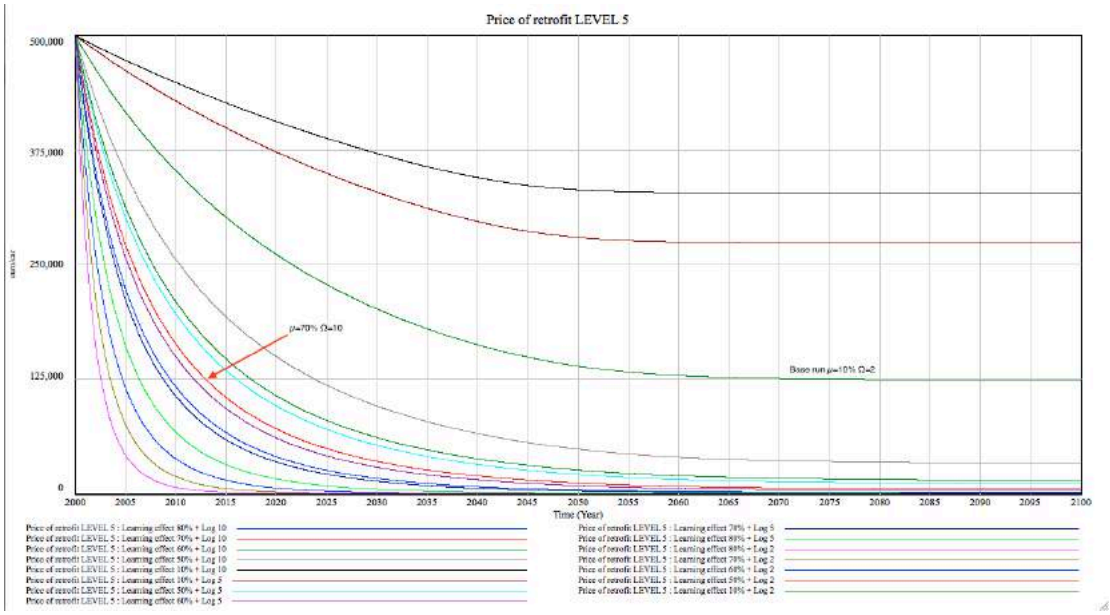

Figure 25 Retrofit price level 5 curves over a variation of learning curve parameter settings.

An overview of all the parameter settings that have been discussed in this paragraph can be found Table 13.

Name	Notation	(Initial) Value	Unit	Source
Initial Baseline price Level 0	$bp_{0,0}$	20.000	Euro/Car	(CAR, 2011)
Initial Baseline price Level 1	$bp_{0,1}$	30.000	Euro/Car	Own assumption

Initial Baseline price Level 2	$bp_{0,2}$	40.000	Euro/Car	Own assumption
Initial Baseline price Level 3	$bp_{0,3}$	80.000	Euro/Car	Expert estimations
Initial Baseline price Level 4	$bp_{0,4}$	200.000	Euro/Car	Expert estimations
Initial Baseline price Level 5	$bp_{0,5}$	500.000	Euro/Car	Expert estimations
Initial price of retrofit Level 0	$rp_{0,0}$	0	Euro/Car	Own assumption
Initial price of retrofit Level 1	$rp_{0,1}$	1000	Euro/Car	(Fagnant & Kockelman, 2013)
Initial price of retrofit Level 2	$rp_{0,2}$	5000	Euro/Car	(Fagnant & Kockelman, 2013)
Initial price of retrofit Level 3	$rp_{0,3}$	70.000	Euro/Car	(KPMG, 2012)
Initial price of retrofit Level 4	$rp_{0,4}$	200.000	Euro/Car	Expert estimations
Initial price of retrofit Level 5	$rp_{0,5}$	500.000	Euro/Car	Expert estimations
Logarithmic scale for learning-by-searching	Ω	10	Dmnl	Own assumption
Logarithmic scale for learning-by-doing	ω	2	Dmnl	(Kamp, 2002)
Effect of increase in experience	μ	0,7	Dmnl	Own assumption
Effect of increase in maturity	x	0,05	Dmnl	(Kamp, 2002)

Table 13: Parameter values for the system component: Purchase price.

5.3.3 Utility

The utility consists of the sum of attractiveness and price. The attractiveness is a combination of the comfort, safety and familiarity. Each level of automation has got an own utility assigned. The price and familiarity are dynamic variables in the model. Comfort and safety are exogenous parameters to the model. Their values are static and therefore have to be estimated before the simulation run. Each of the attributes of the utility function has a weight factor that determines the importance of an attribute in the utility function. An overview of the parameter settings of the utility system component can be found in Table 14.

5.3.3.1 Weights

It has to be taken into account that ß1 + ß2 = 1 and that ß3 + ß4 + ß5 = 1. For the values in the trade-off between price (ß1) and attractiveness (ß2) it is chosen to put a high value, 0,5. This is for the reason that Rogers states that price and economic effects “may even be the most important single predictor for the rate of adoption” (Rogers, 2003). The weight of comfort is chosen to be 3 times higher, with 0,6, than the weight for the familiarity, 0,2, and safety, also 0,2. The reason for this is that comfort and productivity effects of automated vehicles are seen as the most important value proposition for automated vehicles in the future. The familiarity and word-of-mouth effects will have an effect, but it is believed that these will not be the main decisive factor in the decision making process of the end consumer. It is expected that the safety attribute of vehicle automation will be perceived more a threshold. Like nowadays, vehicles will have to endure a safety test like the EURO NCAP. Vehicles with a high NCAP score do not get sold a lot more than vehicles with a slightly lower NCAP score. Car manufacturers do not always use the NCAP score in their advertisement, unless it is very high. However vehicles that score a very low

NCAP and are beneath the threshold are not allowed to be sold at all. This emphasizes the fact that safety is important, but just to a certain threshold value.

5.3.3.2 Comfort

As mentioned in Paragraph 4.3 a clear value or ratio for the comfort of each of the individual levels of vehicle automation cannot be found in the literature. For this reason 15 experts were asked to rate the usefulness of time in a vehicle. It has been chosen to use the median value estimated by the experts for the input parameters, as this is more robust on eliminating outliers than the average value. The median values that were estimated by the experts are respectively 0, 1, 2, 5, 8, and 10.

5.3.3.3 Safety

A clear distinction of the safety between the levels of automation is hard to make. A lot of complex factors constitute to the safety of a vehicle. The safety of a vehicle is among others dependent on the surrounding environment and the usage of the vehicle itself. A distinction in safety can be made between objective safety and perceived safety. This is an important distinction in the discussion of human factors. When a vehicle is perceived very safe, the driver might start behaving very unsafe which decreases the objective safety of a vehicle. An example of this is often mentioned with vehicle automation where the driver is still very much 'in the loop' of the operations of the vehicle, like level 2 and level 3. Because of the support that the automation gives in the operation of the vehicle, the driver could perceive a situation as very dangerous. Unsafe situations could occur when the driver starts increasing the speed of the vehicle because of this perceived safety. Another unsafe situation could occur when a driver over-relates on the automated system and starts doing other things while driving. If a situation then occurs where the driver has to take over full control of the vehicle, a lack of full situational awareness may lead to unsafe situations. These aspects are taken into account when the parameter values of the safety of automated vehicles are assessed. Kyriakidis (2015) shows in his study an elaborate overview of the added safety aspect of ADASs. However a clear advantage of level 2 over level 1 in terms of safety cannot easily be found. For this reason both level 1 and level 2 are assessed the same in terms of safety but are rated much higher safety than level 0. In level 3 vehicles the driver might experience a high level of perceived safety. Studies show that this perceived safety might not be justified in terms of objective safety. For this reason the safety of level 3 is rated slightly less than level 1 and level 2. Level 4 is rated a much higher safety. The vehicles will operate only on dedicated lanes or on highly suitable terrains. The driver will be mainly out of the loop. In a case the driver has to get back to control the operations of the vehicle, it will be notified way before, giving the driver time to gain situational awareness. Level 5 is rated with the highest score on safety because this contains vehicle automation without any human interaction involved. Due to the high number of sensors and the high computation speed of the control algorithms and its full control on all the actuators of the vehicle this is consider much safer than any human driver can gain with its limited brain capacity and one pair of eyes, legs and arms.

Name	Notation	(Initial) Value	Unit	Source
ß1 Weight Price	$ß_1$	0,5	Dmnl	Own assumption
ß2 Weight Attractiveness	$ß_2$	0,5	Dmnl	Own assumption
ß3 Weight Familiarity	$ß_3$	0,2	Dmnl	Own assumption
ß4 Weight Comfort	$ß_4$	0,6	Dmnl	Own assumption
ß5 Weight Safety	$ß_5$	0,2	Dmnl	Own assumption
Comfort Level 0	cf_0	0	Dmnl	Median from 15

				expert estimations
Comfort Level 1	cf_1	0,1	Dmnl	Median from 15 expert estimations
Comfort Level 2	cf_2	0,2	Dmnl	Median from 15 expert estimations
Comfort Level 3	cf_3	0,5	Dmnl	Median from 15 expert estimations
Comfort Level 4	cf_4	0,8	Dmnl	Median from 15 expert estimations
Comfort Level 5	cf_5	1	Dmnl	Median from 15 expert estimations
Safety Level 0	sf_0	0,01	Dmnl	Own assumption
Safety Level 1	sf_1	0,4	Dmnl	Own assumption
Safety Level 2	sf_2	0,4	Dmnl	Own assumption
Safety Level 3	sf_3	0,3	Dmnl	Own assumption
Safety Level 4	sf_4	0,7	Dmnl	Own assumption
Safety Level 5	sf_5	1	Dmnl	Own assumption

Table 14: Parameter values for the system component: Utility.

5.3.4 Technology maturity

The parameters that influence the dynamics of the system component technology maturity are:

- Initial value maturity, M_{j0};
- Amount needed for full maturity, an_j;
- R&D expenditure on vehicle automation, *frd;*
- Annual knowledge stock depreciation rate, *∂;*
- Depreciation factor of past knowledge, *df;*
- Effectiveness of knowledge transfer, *ef;*

5.3.4.1 Initial maturity

The maturity of vehicle automation is a variable that is not reflected by a counterpart in the real world. It therefore is difficult to get a good grip on the values that should be used for the levels of automation of which the technology development is in full progress. Furthermore it has to be taken into account that the initial value of the maturity represents the real-world counterpart back in 2000. There is not a lot of information available in that reflects in retrospect on the situation of the technology maturity in 2000. In order to find parameters for 2000 that can be used in the model, the level of maturity among the different levels of automation is first evaluated for 2015. For this evaluation of maturity among the different levels a breakdown has been made of the availability on the market; the maturity of its enabling technologies on which it relies for full operation and whether there are already field tests ongoing for this level of automation. This breakdown can be reviewed in Table 15.

Level of automation	Maturity	Argumentation
Level 0	Full (100%)	Traditional automobile that is on the market for over 100 years.

Level 1	High (50% - 80%)	On the market in some operational systems already. Mostly in the premium price segment, which tells us, the costs are relatively high.
Level 2	Medium (25% - 50%)	On the market in very low quantities. Traditional OEMs like Volvo, Ford and Daimler have invested huge amounts of R&D expenditure at systems of level 2 automation, mainly defined as ADASs or safety systems.
Level 3	Low (1%-15%)	Not available on the market. Is being tested with a lot by among others Google. Chris Urmson, director of Google Car project, states that the company has been driving more than 2 million test kilometers on highway automation pilot already (Urmson, 2015). Tier-1 supplier Delphi has driven a vehicle 9000 km from San Francisco to New York 99% on highway automation pilot.
Level 4	Low (<1%-3%)	Technology is in operation on very few locations like Rivium, Rotterdam (Netherlands), Oristano (Italy) and La Rochelle (France) by City2Mobil. The system needs a dedicated and closed environment and adapted infrastructure to be able to operate safely. On various places in the world numerous test sites are being developed currently to be demonstrate or deploy level 4 automation vehicles.
Level 5	Very low (<1%)	Not on the market and not being test yet. This level of automation is ought to operate always and everywhere. Under bad road- (bad lane markings) and weather (snow, heavy rain) conditions this level of automation still is not able to operate.

Table 15 Breakdown of maturity among the different levels of automation

Level 0 reflects a traditional automobile, which is already in use for more than a century. It can therefore be assumed that level 0 had 100% maturity back in 2000.

This is different however with the levels 1 and 2. A lot of OEMs, Tier-1 and -2 suppliers and other organizations are heavily investing in the development of the technology of these two levels. These levels are the first once that will be available on the market and thus will bring in new revenues. This has given a boost on the speed of development that these technologies have been going through. Some of the systems of level 1 and level 2 can already be found on the market as operational systems nowadays in 2015. Sources however suggest that the technology is still very expensive and hasn't reached its full potential performance. It is assumed that the maturity of level 1 and level 2 in 2000 were both 20%.

The maturity of level 3 has been developed rapidly the last few years. For example Google states that it has been driving more than 2 million test kilometers with an automated vehicle that represents level 3. However Google does not publish what the results of these tests are. The results of these tests would tell us more about the maturity than just the test kilometers that are being driven. The same goes for Delphi, who drove coast to coast from San Francisco to New York with a level 3 automated vehicle. From these tests it can be concluded that the technology is somewhat maturing, but there can't be concluded anything about the performance and reliability of the systems. The fact that none of the technologies are close to a market introduction yet tells us that the maturity is still in a very low state nowadays. In 2000

Google did not even launch it automated car project (as it barely existed back then). This gives us enough certainty to set a very low maturity for level 3 as its initial value.

The maturity of level 4 and 5 are still very low nowadays. It has therefore been chosen to set a very low initial value for the maturity of level 4 and level 5 in the model.

5.3.4.2 R&D and knowledge transfer parameters

The model in this research focuses its scope on data in the Netherlands. It sees the market in the Netherlands as the total market and thus all the knowledge building, R&D expenditure, technology development and knowledge transfer is coming from this single market.

The values of these variables are very hard to estimate. The first reason for this is that, beside the R&D expenditure, it are all artificial parameters that are build into the model to symbolize real world phenomena, but do not have a real world counterpart. The second reason is the fact that the values of the amount needed for full maturity are very much dependent on the eventual market size in the model. If the model were to simulate the technology development globally, the market size and thus the R&D expenditure would be significantly higher than when the model would model this same phenomenon with data from the Netherlands.

The annual revenue in this model all comes from vehicle automation. In the industry about 7,5% of the total revenue is spend on R&D. This value will also be used for the parameter settings and is an average of the estimates from the experts.

It is assumed that for each of the levels of automation it takes about twice as much knowledge to grow towards full maturity. For these reasons the amount needed for full maturity from level 1 to level 5 has been set on respectively 6B, 10B, 25B, 50B and 100B euros. The effectiveness of the knowledge transfer is set on 50%. It is assumed that 10% of the knowledge depreciates every year. To determine the initial value for the knowledge a depreciation factor for past knowledge has to be determined. For this parameter a value of 50% has been chosen. An overview of all the parameters can be found in Table 16.

Name	Notation	(Initial) Value	Unit	Source
Initial Maturity Level 0	$M_{0,0}$	1	Dmnl	Own assumption
Initial Maturity Level 1	$M_{0,1}$	0,2	Dmnl	Own assumption
Initial Maturity Level 2	$M_{0,2}$	0,2	Dmnl	Own assumption
Initial Maturity Level 3	$M_{0,3}$	0,01	Dmnl	Own assumption
Initial Maturity Level 4	$M_{0,4}$	0,0001	Dmnl	Own assumption
Initial Maturity Level 5	$M_{0,5}$	0,0001	Dmnl	Own assumption
R&D percentage of annual earnings	*frd*	0,075	1/year	Average of expert estimates
Annual knowledge stock depreciation rate	∂	0,1	1/year	Own assumption
Depreciation factor of past knowledge	*df*	0,5	Dmnl	Own assumption
Effectiveness of knowledge transfer	*ef*	0,5	1/year	Own assumption
Amount needed for full maturity Level 1	an_1	6 Billion	Euro	Own assumption
Amount needed for full maturity Level 2	an_1	10 Billion	Euro	Own assumption

Amount needed for full maturity Level 3	an_1	25 Billion	Euro	Own assumption
Amount needed for full maturity Level 4	an_1	50 Billion	Euro	Own assumption
Amount needed for full maturity Level 5	an_1	100 Billion	Euro	Own assumption

Table 16: Parameter values for the system component: Technology maturity

5.3.5 Carsharing

Because of a lack of reliable data, the growth of the carsharing market due to vehicle automation will be estimated on 20%. This number is based on the expert estimations that are mentioned in section 4.6.4. The annual growth will also be estimated at 20%. For the model in this research the effect of carsharing on vehicle ownership will be estimated at 23%. This is the average value of the data that has been reviewed in literature. An overview of these parameters can be found in Table 17.

Name	Notation	(Initial) Value	Unit	Source
Initial car-share users	A_0	273	Person	Estimated, based on (Frost and Sullivan, 2014)
Growth of car-sharing market	g_{cs}	0,2	1/year	(Frost and Sullivan, 2014)
Technology multiplier	*tm*	0,2	1/Year	Expert estimation
Percentage of car shedding among car share users	*sh*	0,23	Car/person	Average of literature, which can be found in Table 24.

Table 17: Parameter values for the system component: Carsharing.

5.3.6 Indicators

The population of the Netherlands was 15,9 million people in 2000. The population is considered as an exogenous variable in the model, modeled as a stock that has a slightly reducing population growth from 0,6% population growth in 2000 to 0,3% in 2015 and 0,02% in 2060 (CBS Bevolkingstrends, 2014). Dutch people travel an average of 15,57 km per day by car (CBS, 2014). The household size of 2,2 people per household has been found in statistics by the European Commission (Eurostat, 2015). An overview of these parameters can be found in Table 18.

Name	Notation	(Initial) Value	Unit	Source
Initial population	N_0	15.900.000	Person	(CBS Bevolkingstrends, 2014)
Average household size	*shh*	2,2	Person /household	(Eurostat, 2015)
Daily travel demand per person	*ptd*	15,57	Km/day/person	(Transport for London, 2011) (CBS, 2014)

Table 18: Parameter values for the system component: travel behavior.

6. Testing the model

This chapter aims to explore the validity and capabilities of the model. When testing the model the behavior of the model and its possible applications will become clearer. Testing of the model will be done in 7 steps, following the guidelines that Sterman describes in his work Business Dynamics (Sterman, 2000).

At first the boundaries of the model will be explored. This will reveal what aspects of the system scope described in Chapter 3 are included and excluded in this model. The dimensions and units in the model will be aligned and checked on consistency. This validates whether all the parameters in the model are representing a real life counterpart. By using a structure assessment the equations and dependencies of the variables will be tested. Existing theory will be sought to explore whether there are other ways to represent the behavior of the variables in the model. It will then be explained why the current way of specification of the structure has been chosen. As a fourth step the parameters will be checked. In order to support the model building data has been selected, as described in Chapter 4, to set the values for the input parameters. A full list of all the parameters can be found in the 0. The data of these parameters will be ranked upon their uncertainty. All these steps so far can be considered static, as the model doesn't have to be simulated over time to execute these steps.

The following steps are considered dynamic and the model has to be simulated in order to execute these steps. To assess the behavior of the model, in relation to the various tests and validation steps, a set of performance indicators are selected. In a sensitivity analysis the sensitivity of the model to minor changes in the input parameters is being tested. The behavior of the model to individual positive and negative changes of 10% in all the input parameter is being described. In the behavioral test the behavior of the important variables in the model will be tested. The last step is the uncertainty analysis. In this step the values of the uncertain parameters, which were identified in the parameter check, will be varied upon their uncertainty range. The behavior of the performance indicators according to these changes will be analyzed.

6.1 Static testing of the model

6.1.1 Boundaries adequacy

In this step it will be checked whether the problem described for this research is endogenously captured in the model. The main purpose of the model is to simulate the interactions between the technology development, the price dynamics and the diffusion of vehicle automation. These elements are all endogenous to the model. An important factor in the diffusion of vehicle automation is the value proposition that vehicle automation will bring to the end consumer. This value is specified exogenously in the model through a specification of comfort and safety for each level of automation. The price however is modeled endogenously in the model and is also part of this value proposition. In order to simulate the choice of the individual the model has a first-person perspective. As shown by Milakis et al. (2015), vehicle automation can have big impacts on travel behavior of people, safety, traffic and congestion, economics and even urban development. These effects however are left out of the stock and flow model. The effects discussed by Milakis are more on a macroscopic level and focus on the impact of the system, rather than on the individual. These effects can therefore be seen more on a third-person perspective.

The model simulates the ownership of vehicles and the growth of the carsharing user base, but doesn't incorporate the travel behavior of the individual. However travel behavior is an important factor related to vehicle ownership and carsharing. The costs involved with cars are partially due to the purchase of a vehicle and partially due to the usage of the vehicle. Furthermore various studies relate carsharing to a decrease of distance traveled by an individual. Travel behavior and car usage is left out of the scope of the model, because it does not serve the primary focus of the model to model the technology development and the diffusion of vehicle automation. Travel demand is modeled as an exogenous constant in the model.

Automated vehicles are often mentioned as the combination of cooperativeness and automation. However as mentioned earlier both game changers are different movements with different technologies. Furthermore cooperativeness is very much dependent on a certain threshold market penetration to function properly. Autonomous automated vehicle on the other side can already function properly without any market penetration needed. System dynamics did not seem as the appropriate modeling technique to model this threshold penetration that is needed for cooperativeness. Although vehicle automation and cooperativeness are supportive to each other, the development and deployment of vehicle automation is not dependent on cooperativeness. To make the model not unnecessary complex the development and deployment of cooperative vehicles is left out of the scope of the model.

The model stretches over a time period of 100 years. In this long time-period various big changes in the population, demographics and economy could occur. The model is however not designed to explore these changes. The economic growth and demography is therefore left out of the scope of the model and kept stable.

6.1.2 Dimension check

All the units in the model are checked on consistency and on existence of the dimension in the real world.

The majority of the variables that are used in the model do have a real world counterpart with dimensions that are consistent with this counterpart. However another large part of the variables is dimensionless. This has to do with the fact that the model is illustrating soft variables like technology development, perceived comfort and safety by people and utility. These variables are present as a counterpart in the real world, but are not represented with a clear dimension in the real world. Another set of variables is not represented by a real-world counterpart. These variables are the technology maturity and the amount of investment needed for full maturity. These artificial variables however are a spin-off from real world phenomena and are well represented in literature on innovation diffusion.

Using the unit checking tool in VensimPro one dimension error is identified and one warning is given about the use of a lookup function. The error that is identified involves the fraction coefficient f_c of carsharing users with a car and the adoption rate of carsharing. The equation of the carsharing users stock is $\frac{dA}{dt} = (\mathrm{ar_{cs}} * f_c)$. The carsharing stock, *A,* is measured in the unit 'person'. The adoption rate, ar_{cs}, that forms the inflow of this carsharing stock therefore is in 'person/year'. To make the units within the equation correctly aligned the fraction coefficient f_c should be dimensionless. The fraction coefficient however is part of a function that divides the vehicle fleetsize by the total population in order to represent the number of cars per carsharing user. Therefore this fraction coefficient has a unit 'car/person'. This coefficient is therefore not an exogenous parameter but part of the dynamics of the model. This makes the coefficient more realistic. However a dimension error occurs due to this construction. It is believed that the dimension error doesn't influence the

overall structure of the model nor does it influence the behavior of the model. It is therefore believed that the error doesn't harm the validity of the model.

6.1.3 Structure assessment

This test will check whether the dependencies of the components in the system are built according to the right structure and whether this structure is built according to the literature about technology diffusion, innovation systems and choice behavior.

When looking at the specification of the dependencies between the various components as described in Chapter 5, it can be concluded that these are defined well according to literature. The adoption of carsharing is modeled according to dynamics described by Sterman (2000, p. 333). So were the learning effects that influence the purchase price as Sterman describes them on page 338. The utility is a function of the price and the attractiveness of a product, as described by Rogers (2003). The specification of the knowledge stock is supported by the way Bjorn Johnson is describing institutional learning in (Johnson, 2010). Furthermore the structure of the model represents the distinction of process and product innovation through learning by doing and the leaning by searching effects. This phenomena is taken from work by Utterback in his study Mastering the Dynamics of Innovation (Utterback, 1996). All these studies are highly regarded works and well cited. It can therefore be said that the structure of the above-mentioned components is tested positively. The structure of the fleetsize adoption, the effect of carsharing on ownership, customer choice, the purchase price and the technology maturity will be discussed more elaborately further on.

6.1.3.1 Technology maturity

The exact way that the system component of technology maturity is specified cannot be found in literature this way. Johnson (2010) introduces a conceptual model in which he shows the relationship between learning by searching, R&D, a stock of knowledge and the birth of innovative ideas and projects that lead to innovation. Johnson doesn't specify his conceptual model into equations. In the simulation model this conceptual model of Johnson is the basis for the technology development and the growing stock of technology maturity. The structure as it is represented in the model is validated with expert David Agnew, head of R&D at Continental, though. His full interview can be found in the Appendix on page 152. He confirms that the industry is dividing the R&D investments among the various levels of automation and that the technology development is also split among these levels. There are parts of the technology that are common for all the levels of automation, but each of the levels also do have their own challenges in order to become mature. Another point that he confirms is the fact that the main driver of the technology maturity is the market growth and customer demand. This structure is represented in the model.

There are also other ways that technology maturity is specified in literature. The next paragraph will review some of the literature that has been found and will argue why it is chosen to specify the technology maturity in this model otherwise.

6.1.3.2 Other theories to model technology maturity

Beside the mentioned specification of maturity in Chapter 5 on page 55, an attempt has been done to specify the technology in another structure using different theories. Wiesenthal (2012) and Lassen (2005) introduce the Two Factor Learning Curve, or 2FLC, in addition to the traditional learning curve. The most frequently used learning curve looks like:

$$SPC = A * E^{-c}$$

Equation 36 Traditional learning curve

Here SPC is the investment cost of a technology per unit. A is the initial unit costs. E is the installed base, or cumulative experience in this case, and c is the learning effect. One of the shortcomings in this traditional learning curve, as Klaassen states, is that the R&D process is not taken into account. The traditional learning curve depends solely on the installed base, and thus on learning by doing. Therefore the 2FLC is introduced to incorporate learning by searching effects in the learning curve. The 2FLC is specified as follows:

$$SPC = A * (\frac{E}{E_0})^{-\alpha} * (\frac{K}{K_0})^{-ß}$$

Equation 37 Two-factor learning curve

Here K is the knowledge stock and K_o the initial knowledge stock. Alpha is the effect of learning by doing. ß is the effect of learning by searching. The function of the 2FLC seems to be representative of the dynamics of technology maturity. Most of the components of the 2FLC can be found in this model of this research. Nevertheless it was found that the 2FLC was not suitable to be used in this model for the following reasons.

The 2FLC used by Klaassen is designed to represent the technology development in the wind turbine industry. It therefore represents the specific costs per unit (SPC) for an increasing generated capacity of wind energy. The model is not looking for a specific cost per unit, but for a relative maturity of a technology with a range between 0 and 1. To make the translation between costs (SPC) and maturity a sort of 'budget' variable would be needed. This budget could be leveraged against the decreasing costs, leading to an increasing maturity over time. The budget for technology development would be coming from R&D. However, R&D was already taken into account in the 2FLC by the knowledge stock and learning by searching effect. When R&D would be taken into account two times in the same dynamics, this would put too much weight on the importance of R&D. As a solution R&D could be taken out of the 2FLC. What remains however looks a lot like the traditional learning curve.

$$SPC = A * (\frac{E}{E_0})^{-\alpha}$$

Equation 38 Adapted two-factor learning curve without R&D

If this traditional learning curve is used to calculate the costs (SPC) and leverage this with the R&D expenditure to generate the maturity, it would still be very hard to estimate a good balance between the R&D, the costs per unit and its initial costs. This lack of data would increase the uncertainty associated with the learning curve.

Vimmerstedt (2015) seems to have solved this part. She has replaced the SPC in the traditional learning curve for maturity, M, and specified it as follows.

$$M = \begin{cases} 1 - (1 - M)\left(\frac{L^*}{E}\right)^{\log_2(1-x)} & for\ E\ \geq L^* \\ M_0 & otherwise \end{cases}$$

$$L^* = max\{L, E_0\}$$

Equation 39 Adapted traditional learning curve with maturity (Vimmerstedt, 2015).

Vimmerstedt introduces a threshold value, L*, after which the maturity starts to grow in respect to its initial value. However this function seems very volatile to any learning effects. For any doubling in experience the maturity is increased with a fraction (x).

As doublings in experience happen more often in the beginning than in a later phase, this results in an inverse exponential curve for the maturity right after the threshold value is reached. As an alternative to solve this volatility the fraction is decreased. Decreasing the fraction results in a somewhat smoother inversed exponential curve. However by decreasing the fraction, the asymptote of the curve is also decreasing, meaning that the technology will not be able to reach a full maturity of 1 anymore.

As a conclusion it seems that both the 2FLC and the adapted learning curve by Vimmerstedt are not suitable to illustrate the maturity in this model. For a model that illustrates a process innovation in an industry with clear costs, the 2FLC seems most suitable. However this model illustrates a combination of product- and process innovation in a new assembling industry. For a model with a lower range between the initial experience and the maximum experience, the adapted learning curve seems suitable. However, this model has an extremely high range between the initial cumulative experience, which is almost zero cars, and the maximum number of cars that could get sold over time.

6.1.3.3 Effect of carsharing on ownership

Literature describes a few effects of carsharing on car ownership. People that have just become member and own a car could make a decision to sell this car. These people however could own 1 or more cars. If they would own multiple cars, they would still own a car when they sell 1 car. People that do not own a car could make a decision to buy one. However literature describes a phenomenon that members of carsharing often make a decision not to buy that new car because of the benefits that carsharing brings them. The members of carsharing services are often not mentioned as individuals, but as households. In the model this structure is simplified though. The carsharing users are seen as individual people. These people could either one none or one car. Multiple cars per person are not taken into account in the model. The decision of carsharing users whether to sell their car is assumed to be made every year. Every year a percentage of the carsharing user with a car stock therefore is flowing to the stock of carsharing users without a car. This flow is directly representing all the people that abandoned their car in a given year. This number of people is translated to a number of cars, which is assumed to be a 1:1 relationship as mentioned. This number of cars is directly subtracted from the total vehicle fleet in that respective year. It is realized that this structure is a somewhat simplified representation of the real world phenomenon of the effect of carsharing on car ownership. One of its shortcomings is the fact that people without a car cannot go back to own a car anymore in this model. This is due to that fact that there is simply not enough data that supports this phenomenon. Furthermore the fact that the decisions whether to sell a car is made every year by the 'carsharing users with a car' is also not very representative. Both facts make the model a little biased towards the assumption that carsharing users will sell their car and that this will have an effect on the ownership rate. The purposed of the model however was not to explore whether this assumption is true or not. The purpose of the model is more directed towards showing the potential effect that this assumption could have on the ownership rate and gaining more understanding about the role that vehicle automation plays in this phenomenon. The structure as currently specified is therefore assumed to be valid for the real world effect of carsharing on the ownership rate.

6.1.3.4 Fleetsize adoption

The way that the adoption of vehicle automation among the various levels is modeled takes on a functional approach. As mentioned earlier there are two main pathways mentioned in literature, one being the functional approach and the other being the spatial approach. Both pathways are non-exclusive to the other, meaning that both could happen together over time. If it had been chosen to model the spatial pathways,

the structure of the model would have been different. The categorization of the different levels of automation would have been left out. One or multiple stock(s) would be needed that represent(s) the area(s) that automated vehicles are able to drive in, like dedicated lanes, campuses, highways and suburban roads. A variable representing the operational speed of the vehicle would gradually increase along with the time. This approach however is much more representative for a scenario where one or multiple organizations own and operate the whole fleet, and the individual end consumer is seen as a user of this fleet of automated vehicles. The adoption rate of automated vehicles would then be dependent both on the decisions made by the fleet owner and by the travel demand of the individual end consumer. The fleet owner would make the purchasing decisions, so the role of price of the technology would be less significant in this business-to-business market. The decision making process of the end-consumer would be more dependent on its travel demand and on the level of service that the fleet owner is able to bring with automated vehicles. This service is partially dependent on the technology of automated vehicles and on its type of business model. The dynamics of the model in this case would be a relation between supply and demand of vehicles, a combination of technology and business models and the advancing capabilities of automated vehicles in different spatial terrains. This however is not the purpose of the model. It is also believed that not system dynamics but rather agent based modeling would be the most suitable modeling technique for simulating the spatial approach.

The current structure resembles the functional pathway and illustrates an evolutionary growth of vehicle automation among the levels with an emphasis on the value proposition of the individual levels of automation towards the end consumer. This structure is not supported by all literature as it gives a very clear distinction between the levels of automation, which in the real world can't always be made so distinctively. However the distinction serves its purpose as it gives a good view on the different dynamics around each of the individual levels and therefore could better help policy makers and industry leaders in their decision making process.

6.1.3.5 Baseline price

Different ways have been tried to specify the baseline price. In the current model the baseline price is specified through a learning-by-doing variable that causes the baseline price to decrease due to an increase in cumulative experience. It has also been tried out to connect the baseline price directly to the cumulative experience powered by a learning curve. This relation is shown in Equation 40.

$$bp = bp_0 * \left(\frac{E}{E_0}\right)^{lc}$$

Equation 40 Baseline price directly connected to cumulative experience.

The function of the learning curve, *lc,* was specified as follows

$$lc = log_{\omega}(1 - x)$$

Equation 41 Learning curve

This equation is used more often in literature and depicts a traditional learning curve. A problem however is that the model is very sensitive to this type of specification of the baseline price. Because of the fact that the initial vehicle fleetsize of the levels 1 up to 5 is very low, any slight increase of this fleetsize easily causes a doubling of the fleetsize. This means that in the beginning of the simulation run, the cumulative experience doubles many times in a very short timespan, causing the costs of the baseline price also to drop rapidly in this short timespan. This decreasing baseline

price has an increasing effect on the utility, which cause the sales to increase even more. This causes a very sensitive feedback loop in the model. This feedback loop is depicted in a simplified way in Figure 26. When a certain volume of experience is reached, it becomes harder to double. This causes the baseline price to stop decreasing rapidly and reaching an asymptote.

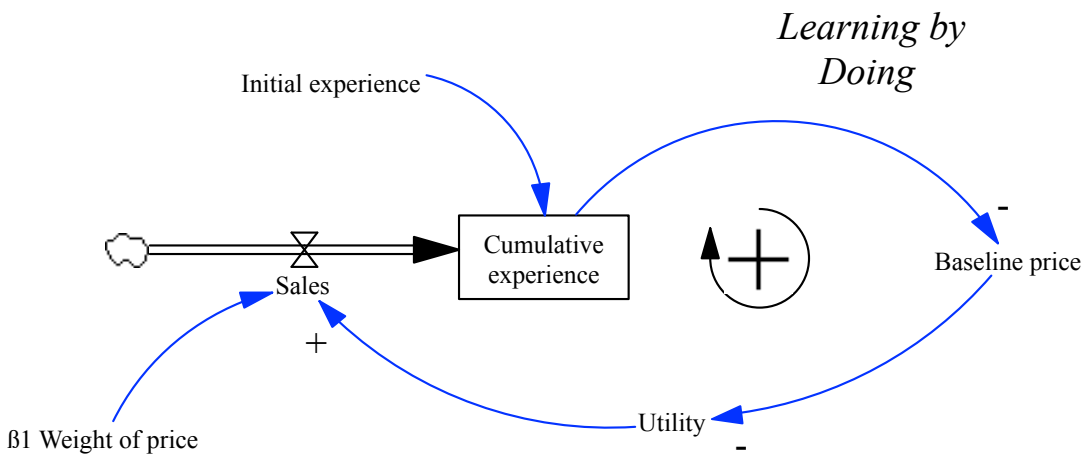

Figure 26 Simplified illustration feedback loop of learning by doing

Note that the fleetsize doesn't have to increase dramatically or unrealistically in order to cause this sudden drop in the baseline price. Simulation results shows for example that the sales of level 2 in the first year is 44.000 vehicles. This seems as a realistic sales figure in a year. This increases the cumulative experience however in one year from 2 vehicles up to 44.000 vehicles: a doubling of about 14 times. This means that due to the learning curve the initial baseline price has decreased 14 times in one year with 5%, which is an overall decrease of almost 50%.

Above-mentioned effect is not shown in the learning by searching curve, which has an effect on the retrofit price. This is because this learning by searching curve is not dependent on the experience but on the maturity. The maturity doesn't increase rapidly, which means that it doesn't double many times in a short timespan.

It has been tried by experimentation to slow down the effect that the rapid doublings of experience have on the baseline price by increasing the ω or decreasing the x parameters. This however doesn't stop the baseline price to drop dramatically in the beginning; it just increases the level of the asymptote. Evidence of this is shown in Figure 27.

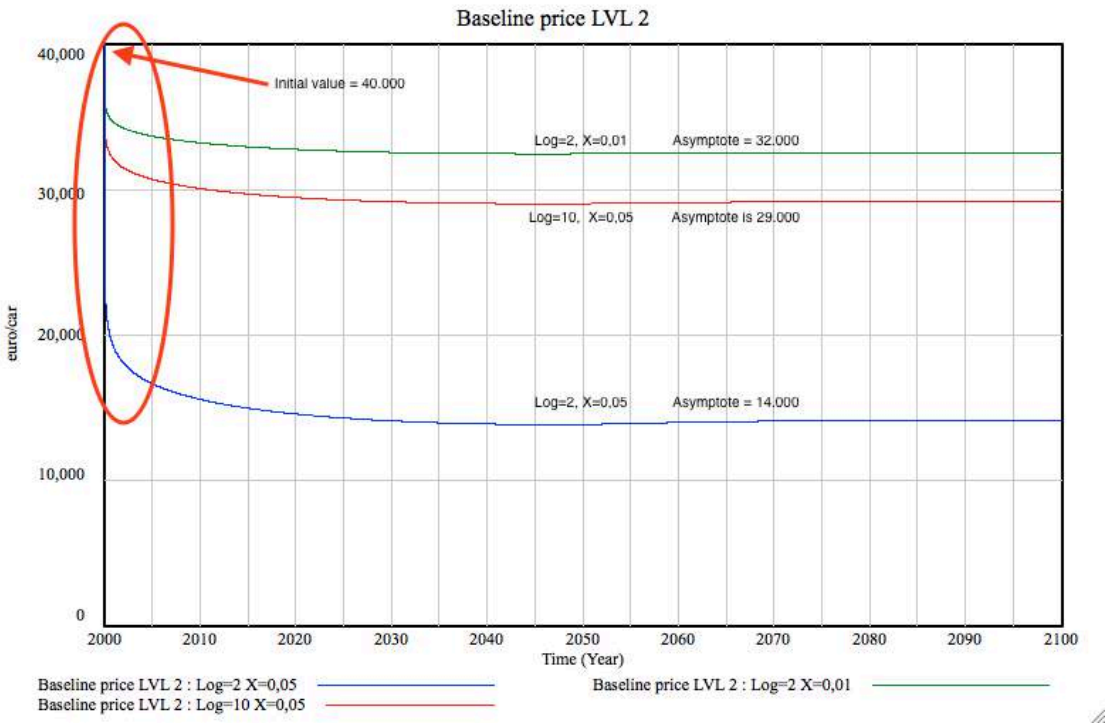

Figure 27 Evidence of learning effects of indicator: Baseline price Level 2

The behavior that is shown in Figure 27 is not found realistic. It has therefore been chosen to model the baseline price not with a traditional learning curve but with a learning-by-doing variable between the cumulative experience and the baseline price. This specification has been explained earlier in Paragraph 5.2.2.1.

6.1.3.6 Normalized price

The last point worth mentioning is the specification of the normalized price, np_j, in the model. In an earlier stage of the model building process, this normalized price was specified through a quotient of the price *j* by the average price of all modes. This however had a result that some of the prices were >1 and the other half would be <1. The purpose however was to normalize the price in a range so that $0 \leq np_j \geq 1$. It was therefore chosen to take the highest price at a time instant and divide the prices over this highest price to get a normalized price. The effect of this was that the highest price would always be normalized to a value of 1 and the other lower normalized prices get higher as the price of this highest price decreased through learning effects. The effect of the learning could therefore not be notified directly in the curve of the normalized highest price, but could be noted indirectly in the reversed learning curve of the other normalized prices.

6.1.4 Parameter check

The parameter settings have been introduced in Paragraph 5.3. The values have been based on the literature review conducted in Chapter 4. An overview of all the parameters can be found in the 0. In this parameter check the input values will be validated with the literature. All the parameters are ranked based on the uncertainty of their value. Uncertainty is defined as a non-existence of data in literature or as a very large range of values in literature. Uncertainty is categorized in the following way:

- **Low uncertainty**: High availability literature available, high availability of historical data and a high level of consensus on the range of data.

- **Medium uncertainty**: A few studies available on the topic and some consensus on the range of the data
- **High uncertainty**: Some to no studies available and/or no consensus on the range of the data.

All the parameters with a high uncertainty are depicted in Table 19. The range and assumed value of these parameters are reviewed in this paragraph. The variables with a low uncertainty are not mentioned in this paragraph as they are well elaborated on in Chapter 4. These parameters are assumed to be valid as there is enough available data that supports their existence and their value. Some parameters with a medium uncertainty are shortly mentioned later in this paragraph.

Name	Value	Range	Unit	Reason
Comfort level 0	0	0 - 1	Dmnl	Represents a very 'soft' variable. Technology is not in use currently; so revealed preference research is not yet possible on a large scale.
Comfort level 1	0,1			
Comfort level 2	0,2			
Comfort level 3	0,5			
Comfort level 4	0,8			
Comfort level 5	1			
Safety level 0	0,01	0 – 1	Dmnl	A factor that is dependent on a lot of factors.
Safety level 1	0,4			
Safety level 2	0,4			
Safety level 3	0,3			
Safety level 4	0,7			
Safety level 5	1			
ß1 Weight Price	0,5	0 – 1	Dmnl	The weight that people put on a specific attribute of a product can only with certainty be determined ex post, for example with revealed preference research. As vehicle automation is not yet fully on the market, this kind of research cannot be conducted yet and this causes an unavailability of data.
ß2 Weight Attractiveness	0,5	0 – 1	Dmnl	
ß3 Weight Familiarity	0,2	0 – 1	Dmnl	
ß4 Weight Comfort	0,6	0 – 1	Dmnl	
ß5 Weight Safety	0,2	0 – 1	Dmnl	
Initial maturity level 1 and 2	0,2	0 – 1	Dmnl	An intangible variable that is not represented by a real world counterpart. For this reason there is no viable data available in literature.
	0,2	0 – 0,5		
Amount needed for full maturity (level 1 - 5)	6B	2B – 10B	Euro	No real world counterpart.
	10B	4B – 12B		
	25B	10B – 30B		
	50B	25B – 75B		
	100B	50B – 200B		
R&D percentage of annual earnings	7,5%	1% - 20%	1/Year	
Annual knowledge stock depreciation rate	10%	0 – 20%	1/Year	
Depreciation factor of past knowledge	50%	20% - 80%	Dmnl	
Effectiveness of knowledge transfer	50%	20% - 80%	1/Year	
Initial price level 4 and 5	400K	100K – 500K	Euro	Level 4 and 5 are not on the market yet. So no reliable price

	1M	300K - 1M		can be estimated.
Growth of car-sharing market	20%	0% - 70%	1/Year	Carsharing is a young market that only seized to exist around 2006 with large volumes of users. will have to extrapolate the rapid growth that the market has gone through in these 9 years towards a long horizon.
Technology multiplier	20%	0% - 50%	1/Year	Vehicle automation level 5 is not on the market, so this phenomenon can only be speculated upon ex ante, but no ex post data is available yet.
Percentage of car shedding among car share users	23%	0% - 43%	Dmnl	Lots of studies both ex ante and ex post describe this phenomenon. The range of estimations of the effect however is very large. This makes the data uncertain, especially into the future as the market will get bigger.

Table 19 Parameters with a high uncertainty

6.1.4.1 Comfort, Safety and Weights

The perceived comfort and safety of vehicle automation is still uncertain. The vehicles are not yet available on the market so these values are hard to estimate. 15 experts from the field of vehicle automation were asked about the parameter value of comfort. This builds confidence in the values that are used for the parameter settings in the base run simulation. The values for safety were not asked to the experts but were estimated based on literature. Both parameters can be ranked as highly uncertain. Their uncertainty range is therefore specified over the full range from 0 (no comfort or safety) – 1 (very high level of comfort or safety). The weight that people put on a specific attribute of a product can only with certainty be determined ex post, for example with revealed preference research. As vehicle automation is not yet fully on the market, this kind of research cannot be conducted yet and this causes an unavailability of data. The values of these parameters also touch upon the point of the value proposition that vehicle automation will bring to the market. If people for example put a high weight on the safety of vehicles, then the vehicles with the highest safety will, in economic theory, bring the most utility to the customer and have the highest demand.

To put a value on each of the weight cannot be done without a lot of certainty. The uncertainty range for the weights of each of the attributes is therefore chosen to be from 'very unimportant' (0) to 'very important '(1).

6.1.4.2 Initial maturity

The maturity of level 0 is not uncertain, as the technology has been in use for 100 years already. The technology of level 4 and 5 are also assumed to have a low uncertainty. The technology is still very much in an early phase and a lot of issues and challenges are still unsolved. It can therefore be assumed with much confidence that the maturity of the level 4 and 5 are still very low nowadays and were even lower in 2000.

The maturity of level 3 is assumed to be of medium uncertainty. The reason for this is that there are a lot of speculations around this level of automation, but not so much viable data has been found. The R&D process of these technologies all happen

behind closed doors. It is therefore very hard to estimate the real state of maturity of these technologies both in 2000 and 2015. As it is assumed that the technology of level 1 and level 2 have made the most progress over the last 15 years, it is most uncertain what the maturity of level 1 and level 2 was in 2000. The uncertainty of level 1 is over the full range from 0 to 100%. The uncertainty of level 2 is limited from 0 to 50% as it can be assumed that level 2 was certainly not fully matured in 2000.

6.1.4.3 R&D and knowledge transfer parameters

The values of the parameters that involve the technology maturity are considered highly uncertain. The reason for this is that they are all artificial parameters that are build into the model to symbolize real world phenomena, but do not have a real world counterpart.

6.1.4.4 Initial prices level 4 and 5

There is no data available about the initial price of level 4 and level 5 back in 2000. The expert estimated a purchase price in 2015 of level 4 on $105.000 and of level 5 on $315.000. An initial value of level 4 of 400.000 euro in 2000 seems therefore reasonable. This is more than four times the value of the estimated price by the experts (taking into account the conversion of dollar to euro). The uncertainty of this prices ranges from 100.000 to 500.000 euro. The lower boundary of this uncertainty range is determined by the fact that the price in 2000 could never have been lower than the average estimated price in 2015. The initial value of level 5 is set to 1.000.000 euro. This is more than three times higher than the estimated price in 2015 by the experts. The uncertainty of this prices ranges from 300.000 to 1.000.000 euro.

6.1.4.5 Growth of carsharing market

A global car-sharing growth of revenue of more than 600% in 7 years is estimated. These figures estimate on the growth of the carsharing market ranging from 70% - 85% per year. This could be the case in terms of revenue. In terms of users the growth rate has been dropping from 70% in 2010 to 40% in 2014 as the user base became bigger. It has to be noted that carsharing services often are introduced in densely populated areas as the supply and demand of vehicles have to balance in this peer to peer model of carsharing. Therefore the user base that has been build up can be mainly found in large cities. The growth rate is expected to decrease a little bit as carsharing now has to expend to other metropolitans, the urban ring and more separately located areas. Furthermore it is uncertain whether the current users are just the early adopters, as Everett Rogers refers to them, or whether they are all the potential adopters. If the current users are the early adopters then the biggest growth rate will still have to come yet as the majority of the population will still adopt the carsharing service. However if the current users are all the potential adopters, than this pool of potential adopters might be getting dry, meaning that the growth rate will gradually drop. The estimated of 70% seems too large for the model. The growth for carsharing in the model of this research is therefore assumed to be 20%.

6.1.4.6 Effect of level 5 automation on car sharing market

This parameter is highly uncertain. No literature can be found that quantitatively describes this effect. The range of uncertainty is from no effect (0%) to a major effect of 50%.

6.1.4.7 Effect of car sharing on car ownership

Despite the huge amount of forecasting studies about the impact of carsharing on travel behavior, the data is still presented in a very high range. This increases the uncertainty about the impact of carsharing on the ownership rate. As presented in Chapter 4 an overview has been made of the available literature that show effects of

carsharing on ownership. The range of these estimations is very wide. This makes the parameter uncertain. The average, 23%, of all the estimations has been taken as a parameter value for the base simulation runs. Within the range of the uncertainty stretches the lower boundary is chosen to be 0% as this represents no effect of carsharing on ownership. The upper boundary is chosen as 43% as this is the maximum estimated effect in literature and is also defined by Schoettle (2015) as a upper boundary.

6.1.4.8 Lifetime of a car

The average lifetime of a car has a very low uncertainty, however it is worth mentioning the variable here. The data in literature show a lot of consistency on the number. Historical data shows that over the years the lifetime of a car has been relatively steady. However this data is taken from a paradigm with traditional cars that has been in play for the past 100 years. In this paradigm the incumbent regime has been a very strong automotive sector. The business model of this automotive sector has had a strong focus on private individual who bought a new car every so many years. Vehicle automation however might be a big transition that might change this paradigm. New players might overthrow the incumbent players and business models might change radically. There is a lot of uncertainty about what this will do with the ownership rate of vehicles and thus with the average lifetime of a car. An argument for this is the combination of hardware and software in a car. Software has a much more rapid updating cycle than hardware. With technology accelerating it might get harder for installed hardware in a vehicle to keep up with the constantly being updated software. You can already see this with pre-installed navigation systems hardware in vehicles of 5-8 years of age. The vehicle itself might work fine, but the navigation system will look very old and is not according to the speed and performance of what people are used to around them any more. This is a problem that requires new business models and this might affect the average lifetime of a car in a big way.

6.2 Dynamic testing of the model

6.2.1 Performance indicators

Performance indicators have to be in line with the purpose of a model and should give clear insights in the dynamics of the system. A performance indicator should therefore have a clear counterpart in the real life system in order to relate the results of the model with the real world data. Stocks are often being used as performance indicators. Furthermore variables with a high number of incoming relations are often chosen as indicators as these variables often have a high dependency on the variables around them.

The performance indicators that are chosen for this model are the total fleetsize, market penetration and adoption rate of automated vehicles, purchase price and the number of carsharing users (both with and without a car). Further insight in the dynamics of the system can be gained by looking at the indicators 'cars per household' and the distance traveled per car.

6.2.2 Sensitivity analysis

In this step it will be checked how sensitive the model is for changes in the input parameters. The value of all the input parameters in the model will be changed by -10% and +10%. The effect of these changes will be checked with appropriate performance indicators. With these indicators the numerical and behavioral sensitivity can be monitored. When the indicators do not change by altering a specific input parameter, the sensitivity of the model on these input parameters is low. When a numerical change is noticed, the sensitivity is medium. When a behavioral change

in the indicators is noticed, the sensitivity of the model for this specific input parameter is high.

Overall the model seems not very sensitive to 10% changes in the parameter values. The model has a low sensitivity to most of the parameters.

6.2.2.1 Effect of car-sharing on vehicle ownership

Remarkable is the low sensitivity to the parameter "effect of car-sharing on vehicle ownership", indicated from here on as the 'car-shedding factor". Remember, this parameter seemed very uncertain and the value for the base run was set to 23%. There is a lot of debate about this effect in the literature, claiming that this factor will lead to a decrease in the total fleetsize. The model indeed shows this behavior. However when the parameter value is changed with 10 percent the model showed no sensitivity. Even when an experiment is executed by changing the parameter value to its maximum boundary (43%) in the uncertainty range, the model showed little change. Interesting though is the effect on the model when the parameter is changed to a low value (5%) and a very low value (1%). With these last two experiments both the 'total fleetsize', V, and the 'carsharing user stock without a car', A_{wc}, showed a behavioral change. The curves of both indicators are shown in Figure 28 and

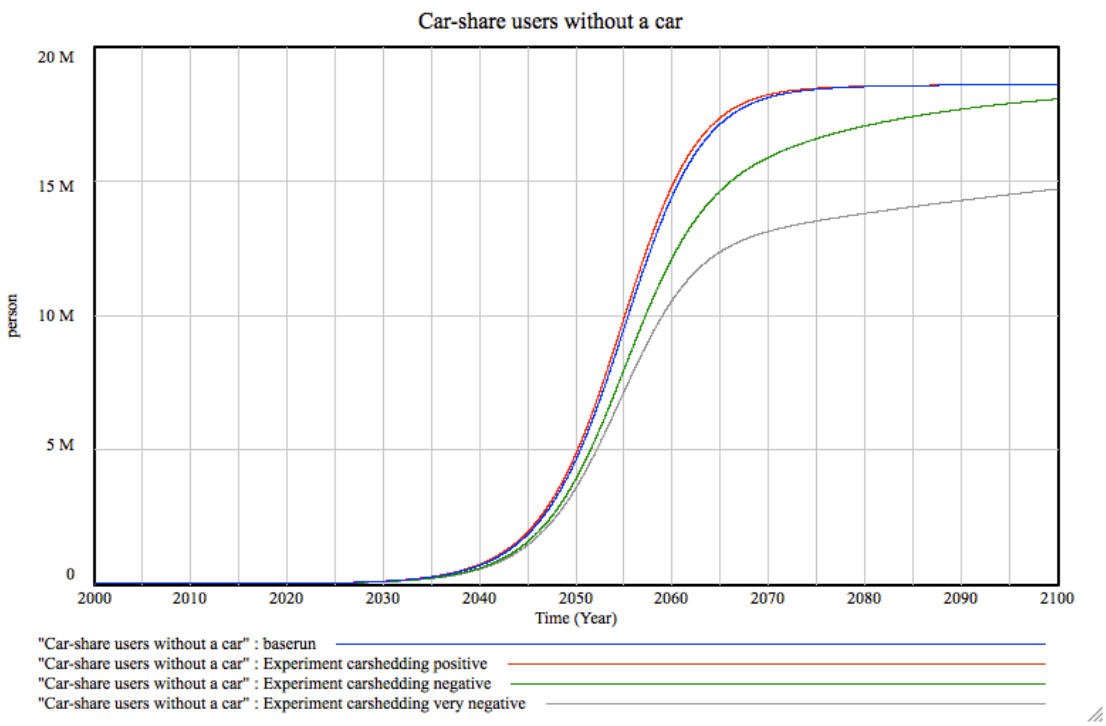

Figure 29.

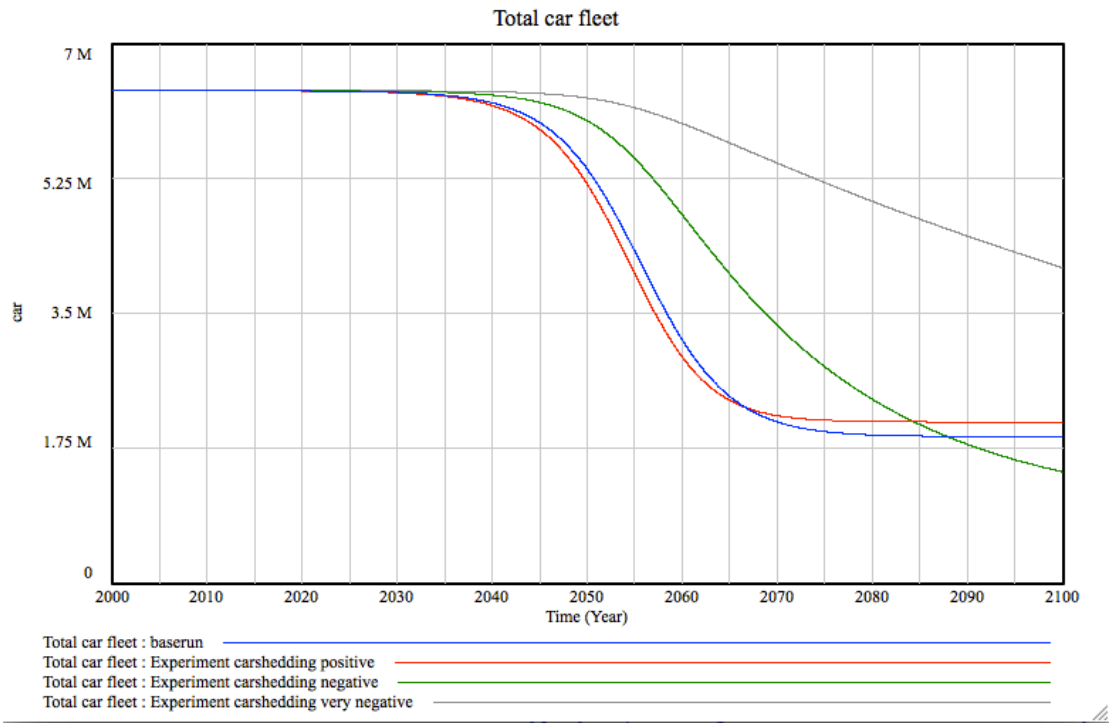

Figure 28 Graph of total fleetsize, V, with sensitivity analysis to car shedding factor.

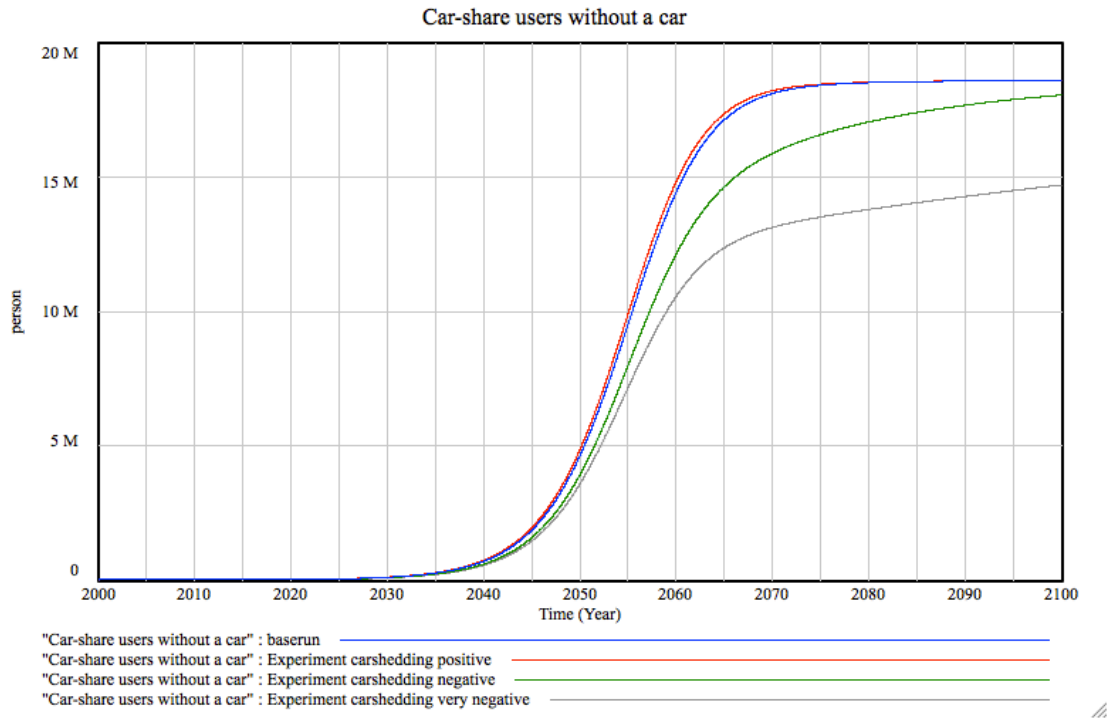

Figure 29 Graph of carsharing users without a car, A_{wc}, with sensitivity analysis to car shedding factor.

What seems to be the case is that there is a certain threshold value for the car-shedding factor. If this threshold is reached, further increase of the factor has no big impact on the fleetsize anymore. Below this threshold, any change in the value does have an effect on the fleetsize.

What seems to be very important in relation to the height of this car shedding is the actual growth of the carsharing market itself. If the percentage of people abandoning their car is very low, but the actual market is very big, than this will still have a major impact on fleetsize and the ownership rate. The same goes for the other way around. If the car-shedding factor is very big, but the growth of the carsharing market is low, than this will only have a minor impact on the fleetsize and the ownership rate. To use a phrase much heard: “A small piece of a very big pie is still a lot, while a big piece of a small pie might be much less.”

This brings us right into another important lesson from the sensitivity analysis: the sensitivity of the ‘growth rate of the carsharing market’.

6.2.2.2 Growth rate carsharing market

The model showed sensitivity to a 10% change in the value of this parameter. Remember that this parameter value was set to 0,2 (20% annual growth) for the base runs. To explore this effect further, a 50% change to the parameter value has been conducted, both negative and positive. The effect that can be seen is a big numerical change in the indicators ‘total fleetsize’ and ‘carsharing users’. The behavior stays the same but is shifted in time. A change in the growth rate causes the total fleetsize to decrease earlier and later. However the total fleetsize finds the same asymptote in all cases, as can be seen in

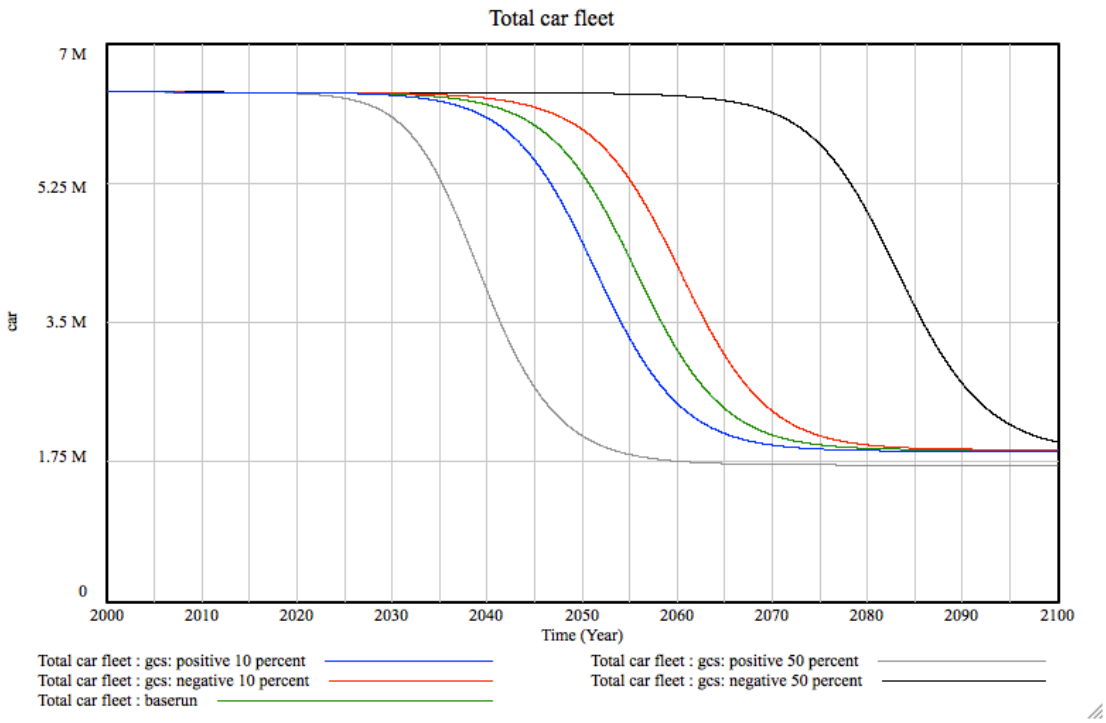

Figure 30. Changing the growth factor with 50% has an effect that the peek of the carsharing user stock shifts about 2 decades in respect to the base run. This

behavior can be seen in

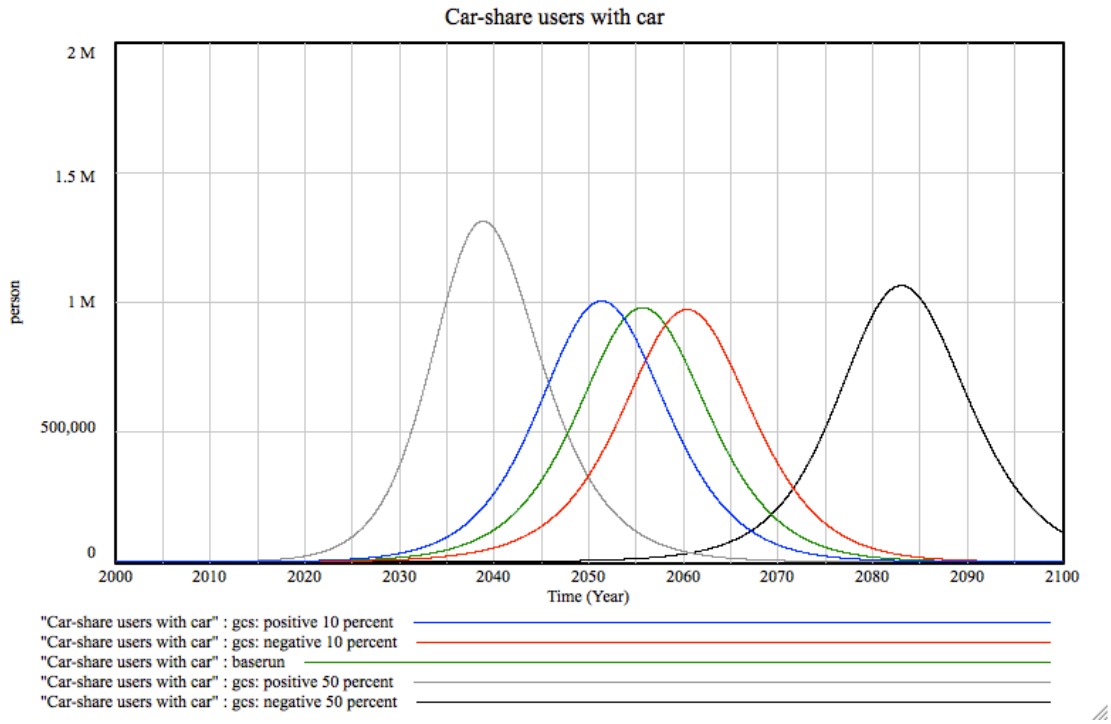

Figure 31.

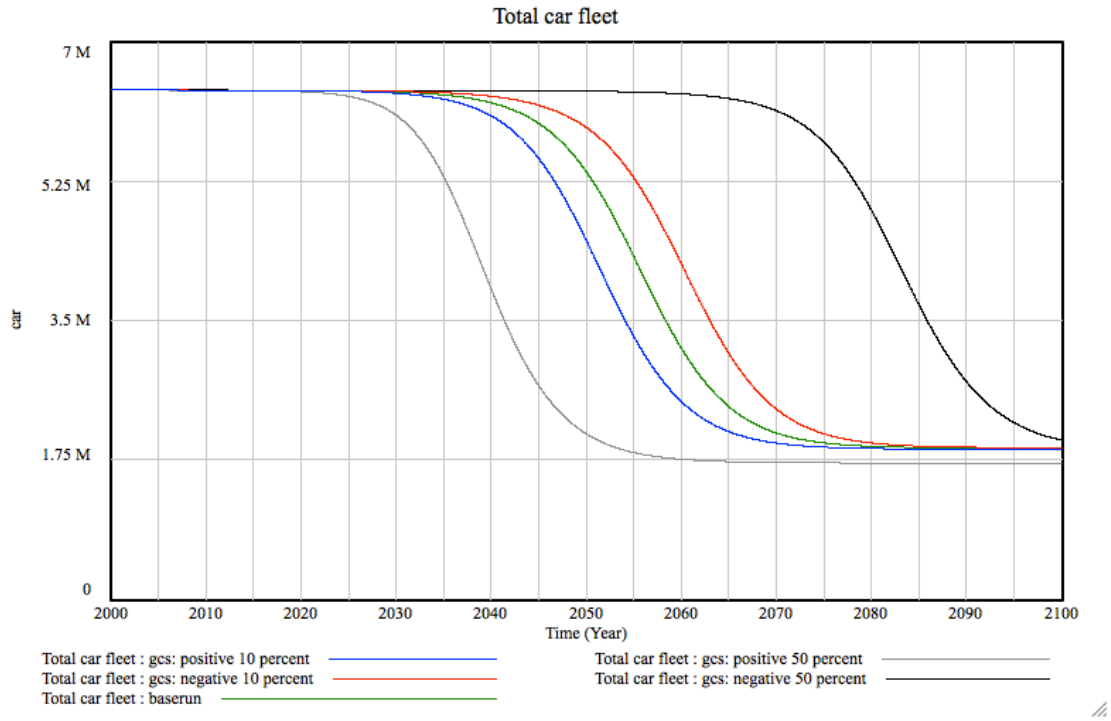

Figure 30 Graph of total fleetsize, V, with sensitivity analysis to growth rate of carsharing.

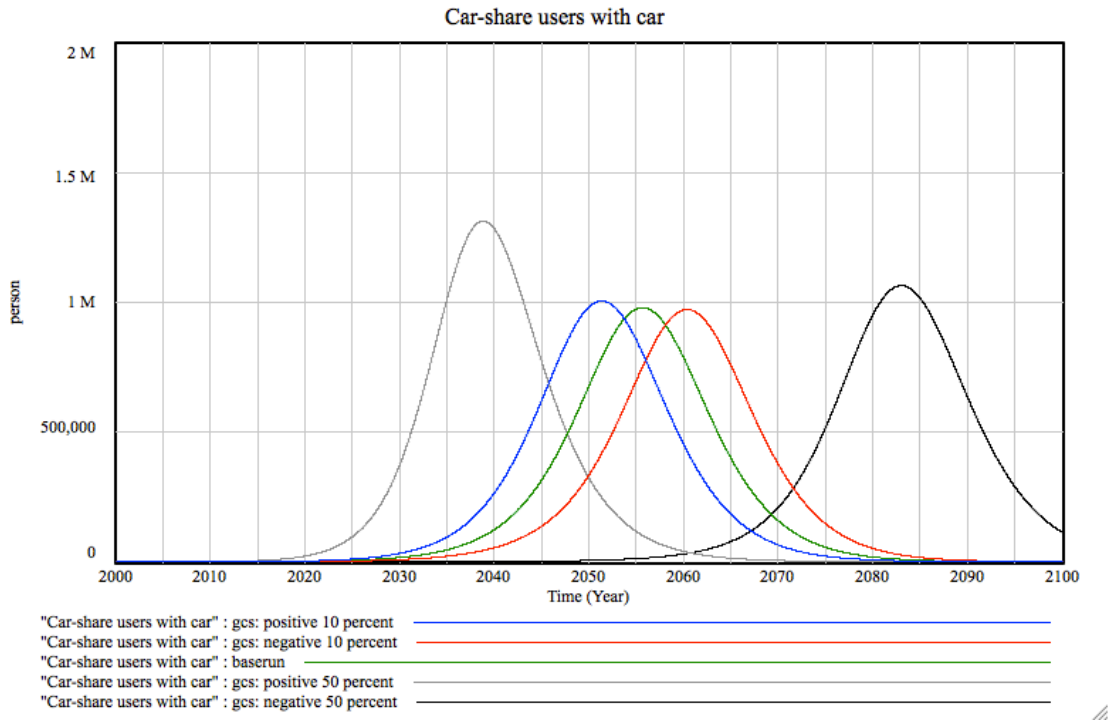

Figure 31 Graph of carsharing users, Ac, with sensitivity analysis to growth rate of carsharing.

6.2.2.3 Lifetime of a car

Remarkable is the sensitivity to the lifetime of a car. This factor is very much related to the adoption of vehicle automation. Remember this value to be set on 10,4 years for the base run. Upon changing the parameter values with 10% for the sensitivity test, the values have also been changed with 50% to see the extended sensitivity of the model to this parameter. As an indicator it is chosen to look at the adoption rate of level 4 and 5 as these show the most clear change in behavior. The graphs of these indicators are shown in Figure 32 and Figure 33.

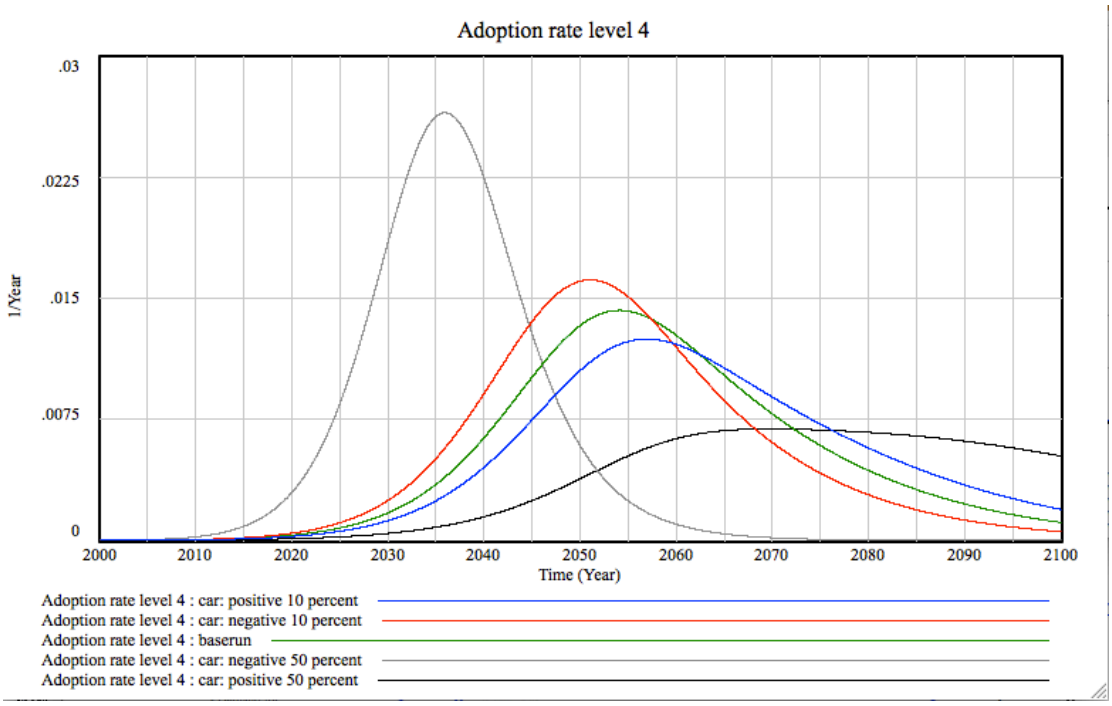

Figure 32 Graph of adoption rate level 4, with sensitivity analysis to lifetime of a car

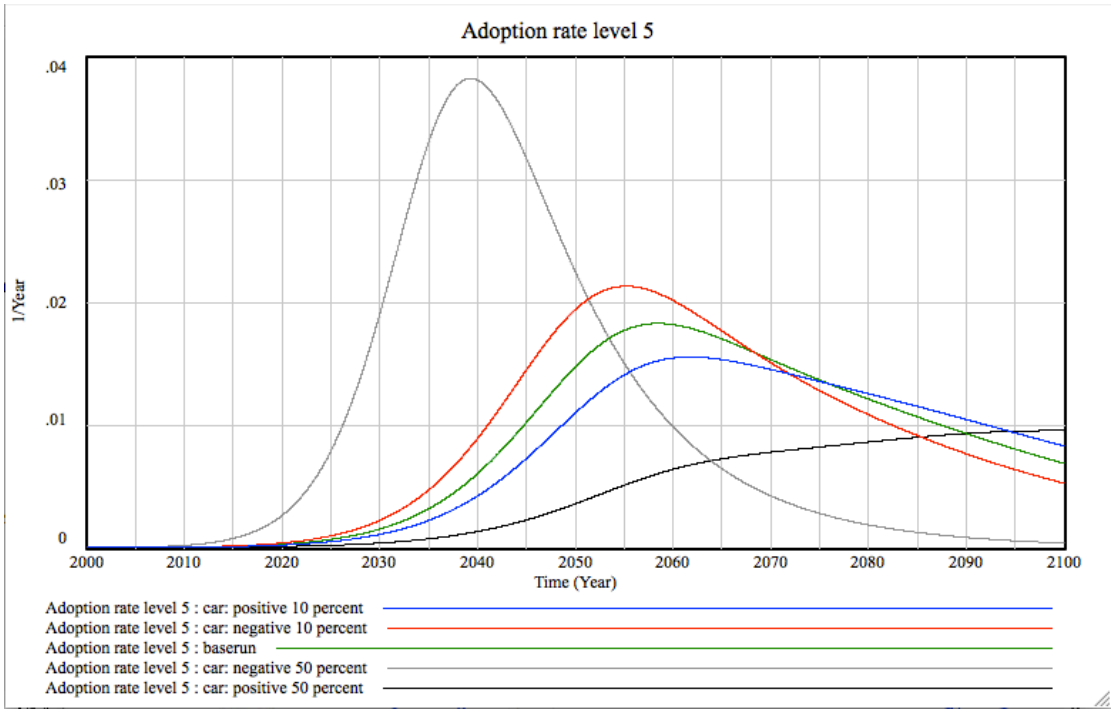

Figure 33 Graph of adoption rate level 5, with sensitivity analysis to lifetime of a car

The indicators show both numerical and behavioral changes. This leads to the conclusion that the parameter is highly sensitive. When the lifetime of a car is extended to 15,6 years (+50%) the adoption rate of level 4 and 5 is increasing slowly. When the lifetime of a vehicle is decreased to 5,2 years (-50%), both adoption rates show a high peek and than rapidly fades out. This is caused by the fact that through the short lifetime of a car, all levels are converted very rapidly to any level that is more beneficial. As there is only a limited amount of potential adopters of a new level of automation, when the lifetime of a vehicle get shorter, the decrease of the adoption rate also get more rapidly.

6.2.2.4 R&D parameters

Of all the parameters that involve the technology development and R&D aspect of the model, there are two parameters that seem to be most sensitive to change. These parameters are the 'percentage of R&D expenditure' and 'effectiveness of knowledge transfer'. The model shows very low sensitivity to the depreciation rate of knowledge.

6.2.2.5 Learning effects

The sensitivity of the parameters in the learning curves are medium, meaning that changes in the values cause a numerical change in the indicator 'purchase price', but doesn't cause the indicator to change its behavior.

6.2.3 Uncertainty analysis

Parameters that are both sensitive and uncertain are likely to have a high impact on the behavior of the model. These parameters are shown in Table 20 and are selected for an uncertainty analysis.

As it is unknown how these parameters will behave in the future an uncertainty range is defined. A Monte Carlo simulation will be done in which multiple simulation runs will be executed, each with another sampled starting value of the selected parameters. The starting values of each individual run will be drawn uniformly from

the defined range. The Monte Carlo simulation will simulate 1000 runs and uses Latin Hypercube sampling.

Name	(Initial) Value	Range	Unit	Uncertainty	Sensitivity
ß1 Weight Price	0,5	0 – 1	Dmnl	High	Medium
R&D percentage of annual earnings	7,5%	1% – 20%	1/Year	Medium	Medium
Effectiveness of knowledge transfer	50%	20% - 80%	1/Year	High	Medium
Average lifetime of a car	10,4	2 – 11	Year	High	High
Growth of car-sharing market	20%	0% - 70%	1/Year	High	High
Technology multiplier	20%	0% - 50%	1/Year	High	Medium

Table 20 Selected parameters for uncertainty analysis

6.2.3.1 Effect of the selected parameters

It is interesting to see that with this uncertainty analysis, when the selected parameters are varied over their uncertainty range, the maturity still develops in an s-shaped curve. However this maturity growth goes either very slow or it goes very rapidly. It is especially interesting to look at the maturity of level 3, 4 and 5, as there is a lot of debate around the development of technologies of these levels.

Within 50% likelihood, the maturity of level 3 grows to at least 95% within 2020 and 2050. In 25% of the most negative scenarios however, the maturity does not grow further than 30%. Within 50% likelihood level 4 will either reach 100% maturity around 2050, or does not reach higher than 50% maturity at all. Almost the same behavior goes for level 5. In a negative scenario for both 4 and 5, their maturity will not grow higher than 5% - 20%. These negative scenarios are likely to consist of parameter settings with a low R&D percentage and a low effectiveness of knowledge transfer.

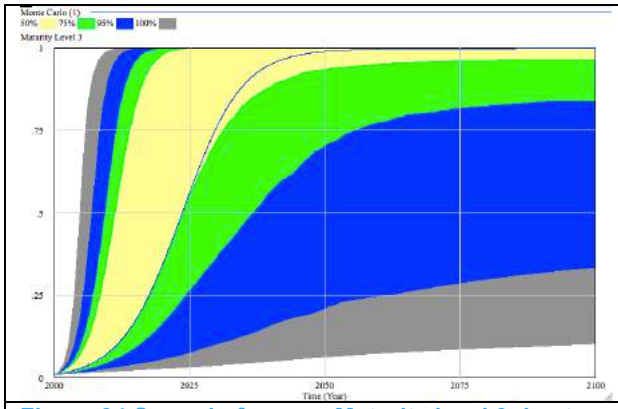

Figure 34 Spread of curves Maturity level 3 due to uncertainty analysis

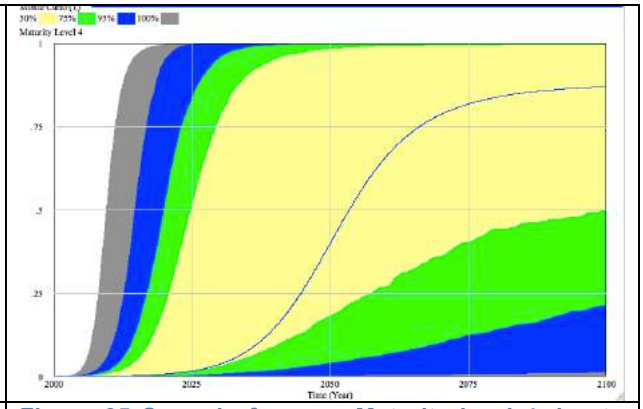

Figure 35 Spread of curves Maturity level 4 due to uncertainty analysis

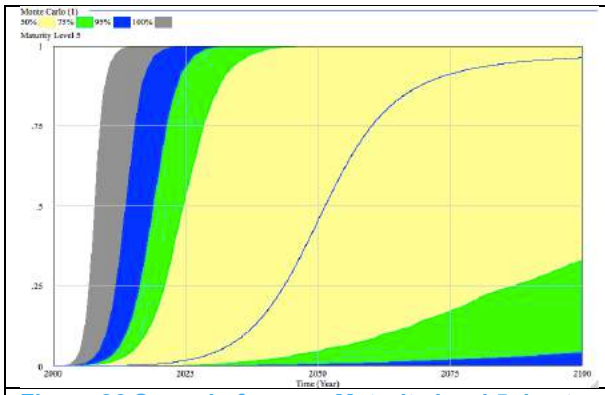

Figure 36 Spread of curves Maturity level 5 due to uncertainty analysis

The model shows a big range of possible scenarios in the fleetsize due to variations in the selected parameters. The adoption rate and fleetsize are likely to change due to a wide range of parameter values of average lifetime of a car. Due to the wide range of scenarios it is difficult to pick one specific conclusion on this part of the uncertainty analysis. What can be said from these results though is that the level 0 fleetsize (Figure 37) is very likely to decrease rapidly once vehicle automation gains momentum. Over the whole range of uncertainty the stock of level 0 vehicles decreases in rapid pace. Level 1 (Figure 38) seems to be growing fast in the first years that vehicle automation gains momentum. The uncertainty with level 1 lies in the moment of which the fleetsize of level 1 will start decreasing. Within 50% of all the runs the stock of level 1 decreases quite soon after it gained a prominent share of the market. However there are scenarios in this uncertainty range that level 1 will stay the prominent type of vehicles for a very long time. The fleetsize of level 2 (Figure 39) shows the same behavior as level 1, however there is a numerical difference, as level 2 is about double the number of vehicles of level 1. The fleetsize of level 3 (Figure 40) is growing rapidly in 50% of the simulation runs over the uncertainty range, but fading out rather slowly. In less than 5% of the simulation runs the fleetsize of level 3 grows very quickly and keeps on being the dominant type of vehicle on the market. In 50% of the simulation runs the fleetsize of level 4 (Figure 41) and level 5 (Figure 42) are rather low. This seems to be the case due to a combination of a high carsharing market growth and a high lifetime of the car. The high carsharing market growth causes the amount of vehicles to drop. The high lifetime of a car causes to stagnate adoption of vehicle automation. The other way around is the case with a low market growth and a low lifetime of the car. This causes the level 4 and 5 vehicles to rapidly be adopted and stay dominant at respectively 3,5 – 6 million (level 4) and 6 million (level 5) vehicles until the end of the simulation time in year 2100.

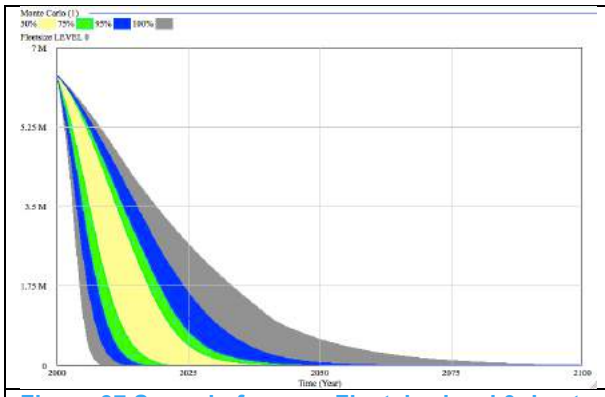

Figure 37 Spread of curves Fleetsize level 0 due to

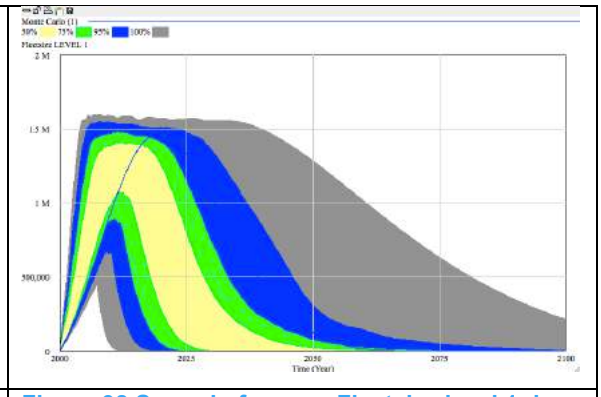

Figure 38 Spread of curves Fleetsize level 1 due

uncertainty analysis

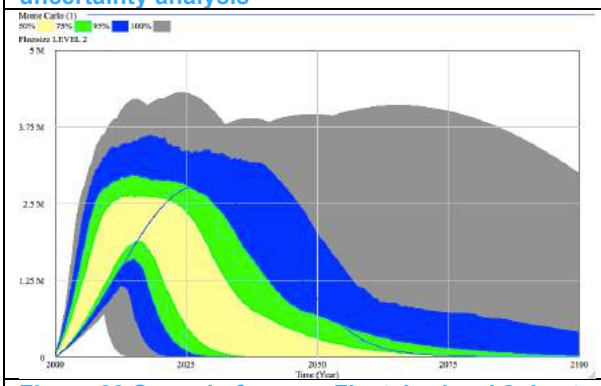

Figure 39 Spread of curves Fleetsize level 2 due to uncertainty analysis

to uncertainty analysis

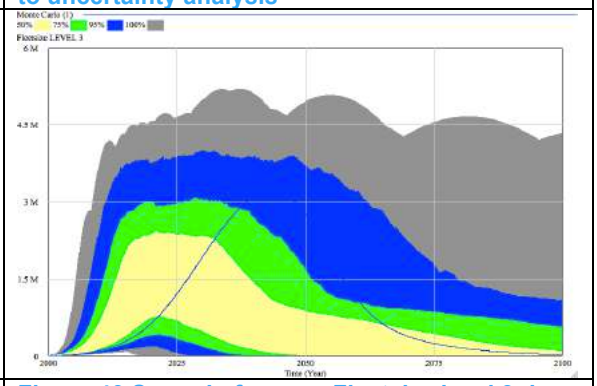

Figure 40 Spread of curves Fleetsize level 3 due to uncertainty analysis

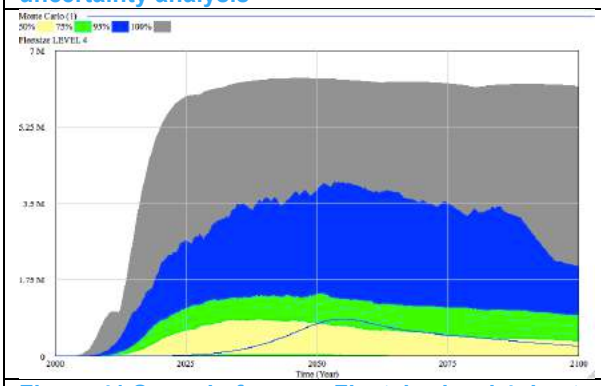

Figure 41 Spread of curves Fleetsize level 4 due to uncertainty analysis

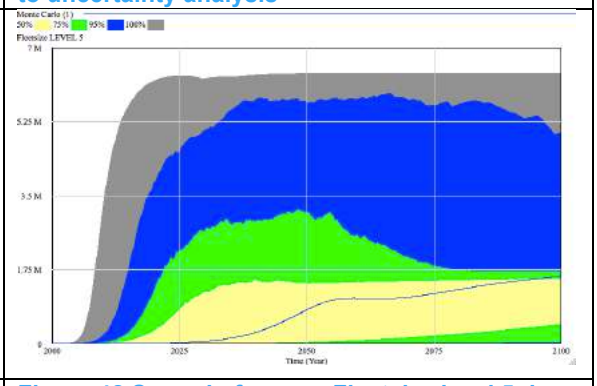

Figure 42 Spread of curves Fleetsize level 5 due to uncertainty analysis

The stocks with carsharing users with and without car; A_c (Figure 43) and A_{wc} (Figure 44), also show changes due to the variation in the uncertainty range. A_c however shows much more behavioral changes, while A_{wc} only shows numerical changes. The range of A_c that includes 50% of the simulation runs over the uncertainty range is remarkably small. The peek of the number of users within this 50% likelihood lies at 1,5 million users. The stock of carsharing users without a car always grows to an asymptote of 20 million users in 100% of the runs. The speed of this growth varies though over the uncertainty range.

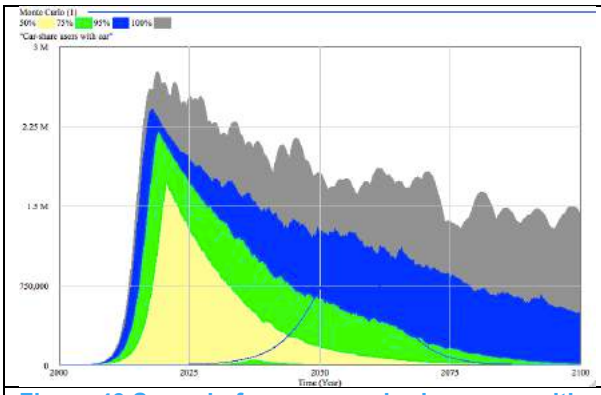

Figure 43 Spread of curves carsharing users with a car due to uncertainty analysis

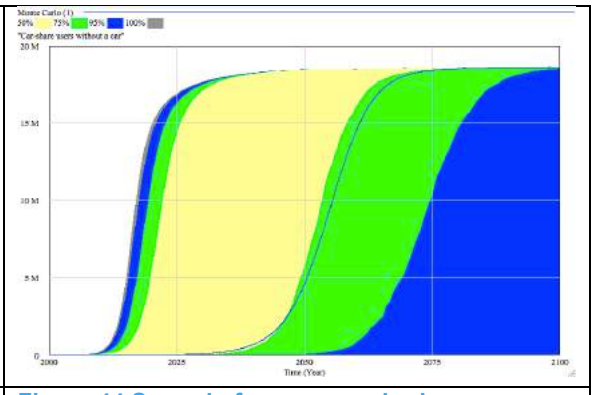

Figure 44 Spread of curves carsharing users without a car due to uncertainty analysis

A separate Monte Carlo simulation will be done on the parameters ‘comfort’ and ‘safety’. These parameters have been found to have a low sensitivity. However the uncertainty about the parameters is very high. This makes it insightful to see what

the effect on the model is when a Monte Carlo simulation is executed over the full range of 0-1 of comfort and safety on all the levels. In some cases this makes it unrealistic, as it can happen that through random sampling a value of 1 is assigned to the comfort of level 0 and a value of 0,1 is assigned to the comfort of level 5. Although these parameter values are not expected to occur in the real world, it is interesting to see how the model behaves on these settings.

Name	**(Initial) Value**	**Range**	**Unit**
ß4 Weight Comfort	0,6	0 – 0,8	Dmnl
Comfort Level 0	0	0 - 1	Dmnl
Comfort Level 1	0,1	0 - 1	Dmnl
Comfort Level 2	0,2	0 - 1	Dmnl
Comfort Level 3	0,5	0 - 1	Dmnl
Comfort Level 4	0,8	0 - 1	Dmnl
Comfort Level 5	1	0 - 1	Dmnl
ß5 Weight Safety	0,2	0 – 0,8	Dmnl
Safety Level 0	0,01	0 - 1	Dmnl
Safety Level 1	0,4	0 - 1	Dmnl
Safety Level 2	0,4	0 - 1	Dmnl
Safety Level 3	0,3	0 - 1	Dmnl
Safety Level 4	0,7	0 - 1	Dmnl
Safety Level 5	1	0 - 1	Dmnl

Table 21 Values and uncertainty range for the safety and comfort parameters

As an indicator we will specifically look at the behavior of fleetsize of level 3, 4 and 5 because the behavior of these levels seems most dominant throughout the simulation runs and most sensitive to changes in the parameter values of comfort and safety over the uncertainty range.

The sensitivity of the model to changes in the 'safety' of each mode over the full uncertainty range, *sf = {0, …, 1},* is very low. The fleetsize of level 3 (Figure **69**) and level 4 (Figure **71**) are a good example of this low sensitivity. The 100% likelihood range is very low. Within this 100% likelihood the fleetsize of level 4 in 2100 is between a range of 250.000 and 500.000 vehicles. The results of the Monte Carlo simulation show a much higher sensitivity of the model towards changes in 'comfort' than towards changes in 'safety' over the full uncertainty range *cf = {0, ... , 1}*. The curve of the fleetsize of level 3 (Figure 68) doesn't show this sensitivity so much yet. But when comparing the curves of the fleetsize of level 4 (Figure 72) and 5 (Figure 76) in the uncertainty analysis of 'comfort' with the uncertainty analysis of 'safety', this difference becomes very clear. Within a 100% likelihood the fleetsize of level 4 in 2100 is between a range of 250.000 and 1.750.000 vehicles. A numerical difference of 600% can be seen between the uncertainty analysis of 'comfort' and 'safety' at the fleetsize of level 4. The same numerical difference goes for level 5.

The reason for this difference might be explained by the higher weight *that* has been put on the comfort over safety in the utility function of the model. The weight for comfort, $ß_4$, has given a value of 0,6, while the weight of safety, $ß_5$, has been given a value of 0,2. This difference might amplify the sensitivity of the model for the parameter 'comfort' over its uncertainty range.

To check this assumption the same Monte Carlo simulation has been run, including the weight parameters for 'comfort' and 'safety'. The weight parameter of 'price' has also been included in this Monte Carlo simulation run, because comfort and safety (and familiarity) together define the 'attractiveness' in the utility function and this utility function is a trade-off between 'attractiveness' and 'price'. The results of these runs show that the weight factor indeed plays a significant role in the sensitivity of the model to the parameters 'comfort' and 'safety'. When the weight of an attribute is low, the sensitivity of the model is also very low. And when this weight gets bigger, the sensitivity to the attribute parameters grows with it. The model shows not clear distinction in sensitivity between the attribute parameters 'comfort' and 'safety' when the weight parameters are included in the Monte Carlo simulation. This can be seen when comparing the two runs with each other through the indicators of level 3 (Figure 70 & Figure **71**), level 4 (Figure 74 & Figure **75**) and level 5 (Figure 78 & Figure **79**).

The uncertainty over the values of the attributes in the utility function is very big in literature. However the model shows a very low sensitivity over this full uncertainty range. What is shown to be much more important is the weight that people put on these attributes in their utility function.

6.2.4 Behavioral testing

In this paragraph the behavior of the model will be tested. This test looks both at the shapes of the curves and the numerical results from the model. As system dynamics shows a continuous process it is hard to show all numerical results. Therefore the numerical results that are shown are chosen from indicators on time instants that theses variables show interesting behavior. The results come from a base run that uses parameter input values that have been found in literature, specified and tested earlier in this Chapter. The full overview of the parameter values that have been used in the base run can be found in Table 27 in the 0.

Part of the model runs from 2000 – 2015. At the time that this report is written this time span can be considered as the past and could be compared with historical data, if available. The simulation run time from 2015 – 2100 is considered as the future and thus its behavior in the real world is still unknown. To get a sense of what this behavior might look like, experts have been asked to reflect on this behavior from their point of view. The expert forecasts teach a lot about the potential behavior and dynamics that might be expected in the system. For this reason the expert forecasts are useful to use in this behavioral analysis.

6.2.4.1 Technology development

The maturity has an s-shaped curve. This shape of a curve that represents technology development is confirmed in work of both Mahajan (1985) and Sterman (2000). Of all the experts asked about the shape of this curve, more than 90% confirmed the curve to be s-shaped.

Figure 45 shows the maturity curve of all the 5 levels of automation. If the results are analyzed of the maturity in 2015 it can be seen that both level 1 and level 2 are for 75% matured. Within respectively 7 and 12 years both levels will reach 90% maturity. Level 3 lacks behind with a maturity of about 17%. 2015 seems to be a tipping point for level 3, because in about 10 years it grows from 17% to 55%. Level 4 and 5 still

have a very low maturity of less than 1% in 2015. Looking at all the challenges that developers of these levels of automation have to deal with, this seems very reasonable. The maturity of level 4 and 5 won't reach 25% before 2044. The slope of the curve of level 4 and 5 is less steep than the slope of level 3. The maturity of both level 4 and 5 seems to converge to an asymptote before it reaches a maturity of 100%. This asymptote is around respectively 70% and 80%. Above described behavior seems reliable and representative for the behavior that will occur in the real system.

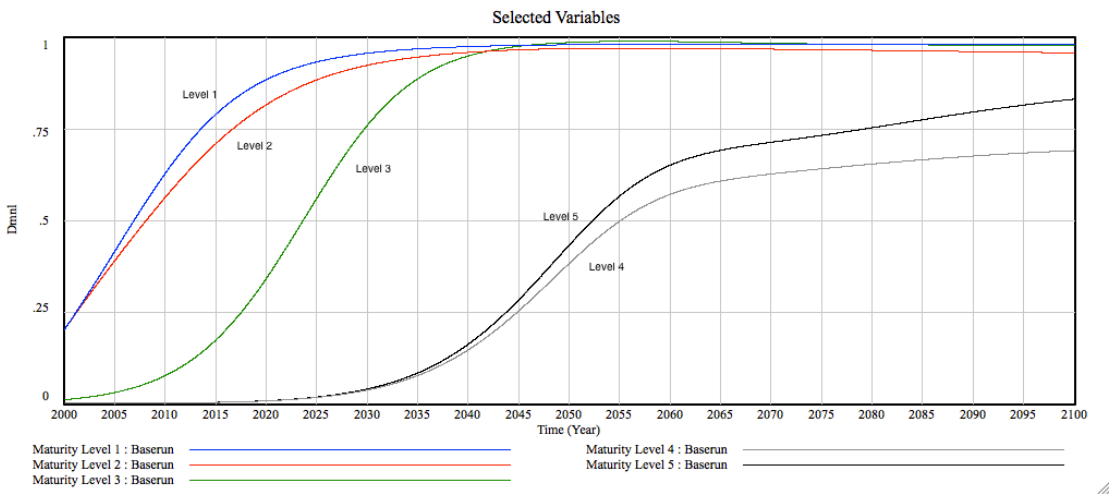

Figure 45 Maturity curve of level 1 - 5

6.2.4.2 Purchase price

The purchasing price is the sum of the retrofit price and the baseline price. From literature and expert interviews it has been identified that a normal purchasing price of a vehicle is around €20.000 - €30.000. A typical purchase price of a premium vehicle is €40.000 - €80.000, but these vehicles have a smaller customer base.

The behavior of the learning-by-doing variable and the baseline price is shown in Figure 46 and Figure 47. It can be recognized that the learning-by-doing does have a sudden jump in the beginning of the simulation run due to the increase in cumulative experience. The baseline price however doesn't drop dramatically and seems less sensitive to this effect. The behavior of the baseline shows a gradual decreasing slope and reaches an asymptote of the desired price. Figure 47 shows the behavior of the baseline price while testing different settings for the learning effect delay, *led* = *{10%, 20%, 40%}*.

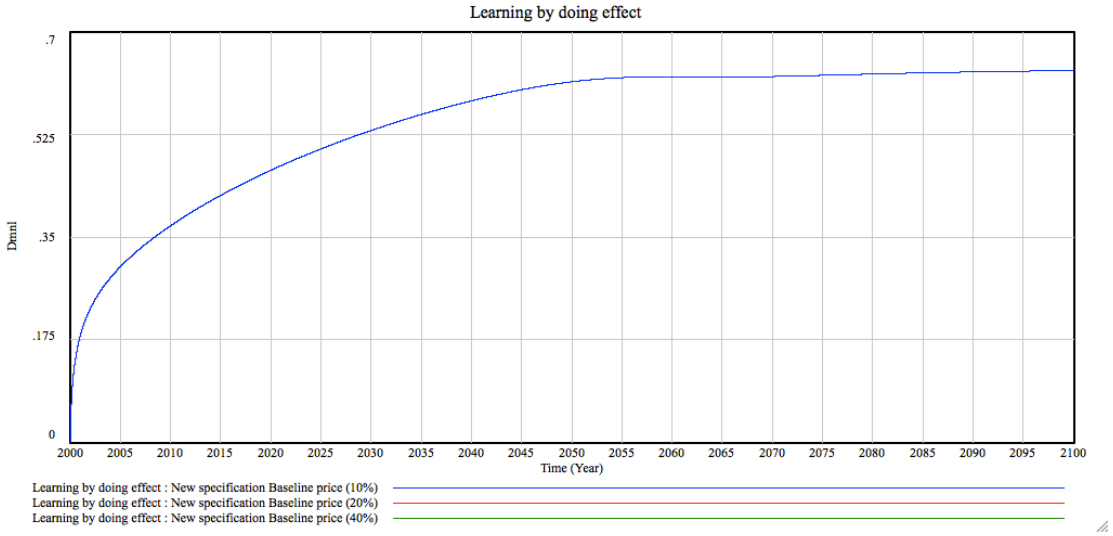

Figure 46 Learning by doing effect of level 5

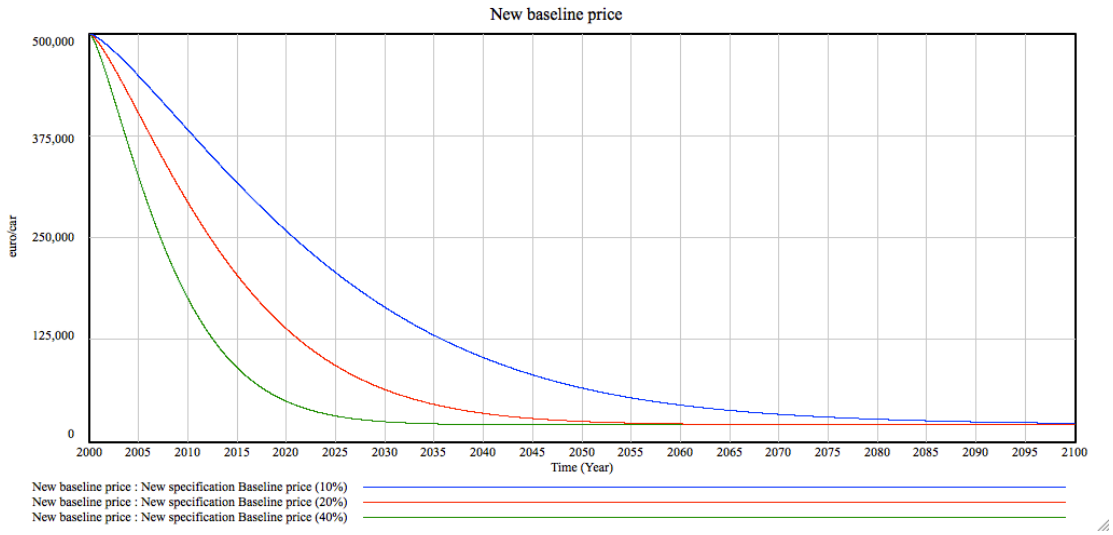

Figure 47 Behavior of re-defined baseline price level 5

These graphs give confidence in the behavior of the purchase price in this model. In the base run the purchase price of level 4 in 2015 is 129.000 euro and the asymptote is 24.000 euro. In the base run the purchase price of level 5 is in 2015 307.000 euro and the asymptote is 34.000 euro. In the base run the purchase price of level 1, 2 and 3 are in 2015 respectively 23.700 euro, 25.670 euro and 72.200 euro. The asymptotes of these levels are respectively 20.400 euro, 22.160 euro and 26.540 euro. These prices in the base run seem representative for the behavior in the real system.

6.2.4.3 Carsharing and travel behavior

The adoption of carsharing by its users is worth looking at, as the stock of carsharing users has an influence on the number of cars that will get abandoned due to carsharing. The number of carsharing users both 'with a car' and 'without a car' increase steadily with an s-shaped curve. This gives confidence in the behavior of the stock, because Sterman also mentions this kind of behavior. The carsharing users do eventually all end up owning no car. Furthermore it can be seen that as the population grows over the years from 15,9 million to 20 million, this whole population starts being a carsharing user. One might argue whether this is realistic. However the

behavior is according to Sterman's description in Business Dynamics (2000) who suggests that the full potential adopters-stock will be used. If carsharing will be seen in the future as a replacement for public transport and cars will be able to drive themselves, than it might be possible that the whole population starts using 'carsharing'.

Two indicators that are often mentioned in literature when talking about carsharing are: Vehicle Kilometers Traveled (VKT) (Figure 48) and Number of Cars per Household (Figure 49). In the simulation run the VKT increases from 11.000 km/vehicle/year to 43.000 km/vehicle/year. This is a result of a constant travel demand, but a growing number of people and a shrinking number of vehicles. This increase is consistent with studies of Schoettle (2015), Fagnant et al. (Fagnant & Kockelman, 2014) and Gucwa (2014). The number of cars per household shrinks from around 0.92 cars per household to 0.23 cars per household, a decrease of 75%. This is due to a growing number of households (growing population with a constant household size) and a decrease number of vehicles. This decrease in vehicles per household is consistent with studies from Martin (2010), Schure (2012) and Shaheen (2012). An increase of kilometers traveled per car could lead in reality to a shorter average lifetime of vehicles. The average lifetime of vehicles in this model is seen as a constant and the causal relation with VKT is not taken into account, because the relation seems rather small and there is no clear empirical evidence.

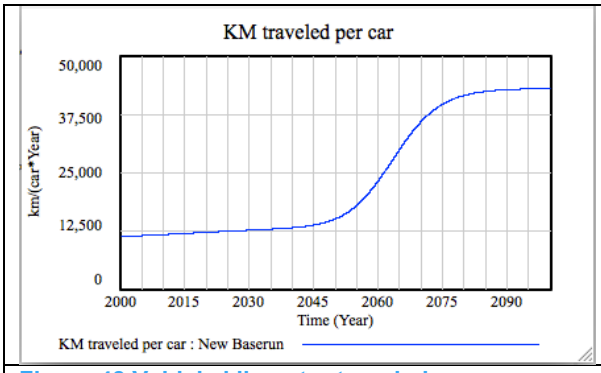

Figure 48 Vehicle kilometer traveled per year

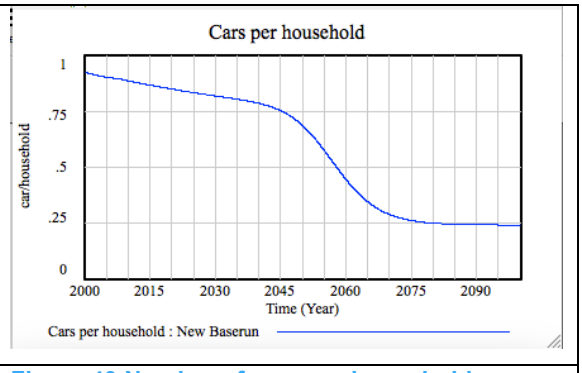

Figure 49 Number of cars per household.

6.2.4.4 Utility

The utility of the various levels is a normalized result of the attractiveness and the normalized price. The attractiveness is a sum of 'comfort', 'safety' and 'familiarity'. Comfort and safety are static exogenous parameters; familiarity and price are dynamic endogenous variables. These last two variables are thus the only ones that can change the utility of a vehicle automation level. The utility therefore is dynamic variable. As depicted in Figure 50 in 2000 the utility of level 0 is the highest. When the price starts decreasing and the fleetsize starts increasing of the other levels the utility of level 2 is the highest from 2007 until 2035. From 2035 until 2100 level 4 has the highest utility. Level 5 has an almost straight utility the whole time span of the simulation run. This is due to the fact that the price is normalized in a way that it is divided by the highest price at a moment. Level 5 has the highest price throughout the whole run, so the normalized price keeps being 1. However the price of level 5 does decrease quite a lot in comparison to the other levels. Although the normalized price of level 5 keeps being 1, the normalized price of the other levels increases from 0,04 to 0,63 (level 2) from 0,15 to 0,76 (level 3) and from 0,4 to 0,71 (level 4). This causes the effect that the utility of level 1, 2 and 3 are higher than level 5 in the beginning of the simulation run, but are lower at the end of the simulation run, while level 5 stays relatively constant.

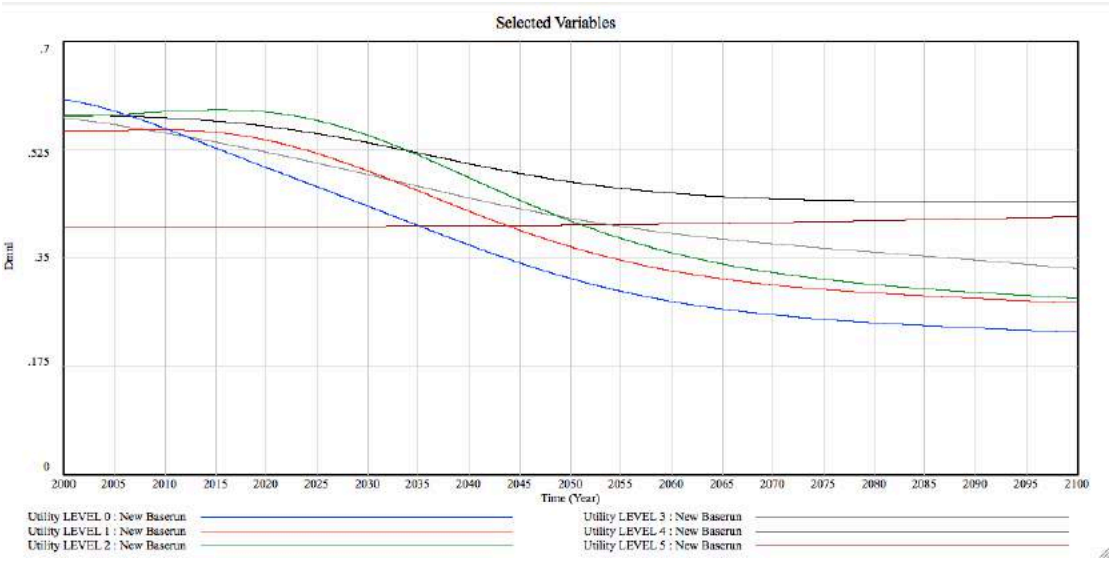

Figure 50 Utility of all levels of automation from 2000 - 2100

6.2.4.5 Fleetsize and adoption rate

The first thing that can be noticed with the curves of the fleetsize of all the levels as shown in Figure 51 is that the fleetsize of level 0 starts declining right from the start of the simulation run. The fleetsize of level 1 and level 2 starts increasing from this point. This results in a fleetsize in 2015 of level 0, 1, 2 and 3 of respectively 2,8M (level 0); 1,3M (level 1); 1,9M (level 2) and 235K (level 3) vehicles. The fleetsize of level 4 and 5 are still very low at this point at respectively 3345 and 2795 vehicles. The overall fleetsize stays constant at this moment in time. What is remarkable is the high number of automated vehicles of various levels that are already on the market, determining a high portion of the total fleetsize. Compared to data in the real world this is not very representative. Currently in 2015 there are not so many automated vehicles on the road. Certainly level 3, 4 and 5 are not yet available on the market and a realistic number for their fleetsize would be 0 vehicles. The fleetsize of level 1 and 2 is less certain. However it is not as high as depicted by the results of the simulation run. Are these results a problem though?

The problem that is faced here is caused by the fact that the model is biased. The model is intended to produce a change in fleetsize among the different vehicle automation levels. These levels are sort of competing among each other in terms number of vehicles. The level with the highest maturity and utility will gain most increase in its fleetsize stock. Even if the maturity and the utility of a specific level of automation are very low, than still a slight growth in its fleetsize can be observed. This is due to the fact that the model is continuous and is build this way. The fleetsize cannot simply be stopped from growing for a certain moment in time to make it more realistic. As the simulation start time is set to 2000, the model starts running from this date. All the dynamics that are involved in the model start working from this time onwards, which causes a direct increase in number of vehicles in the fleetsize of both level 1 and level 2. This behavior is inevitable and this would have also happened if the starting time had been set to 1980, 2015 or 2030. In the real system a product would not become available on the market until the technology has reached a specific threshold maturity. As everything is interrelated in this dynamic model a threshold value for the maturity cannot simply be defined. If this threshold value would be defined then no sales would occur of a specific automation level until this level reached threshold maturity. However the maturity is grown from R&D expenditure that come directly from the sales. If the sales is zero, than this R&D expenditure is zero and so the technology development is zero, which brings the

whole dynamics to a standstill. For this reason we will accept the overestimation of the fleetsize of the various levels in this study and will take into account to look more at the shape and behavior of the curves than at the exact numerical values at a time instant.

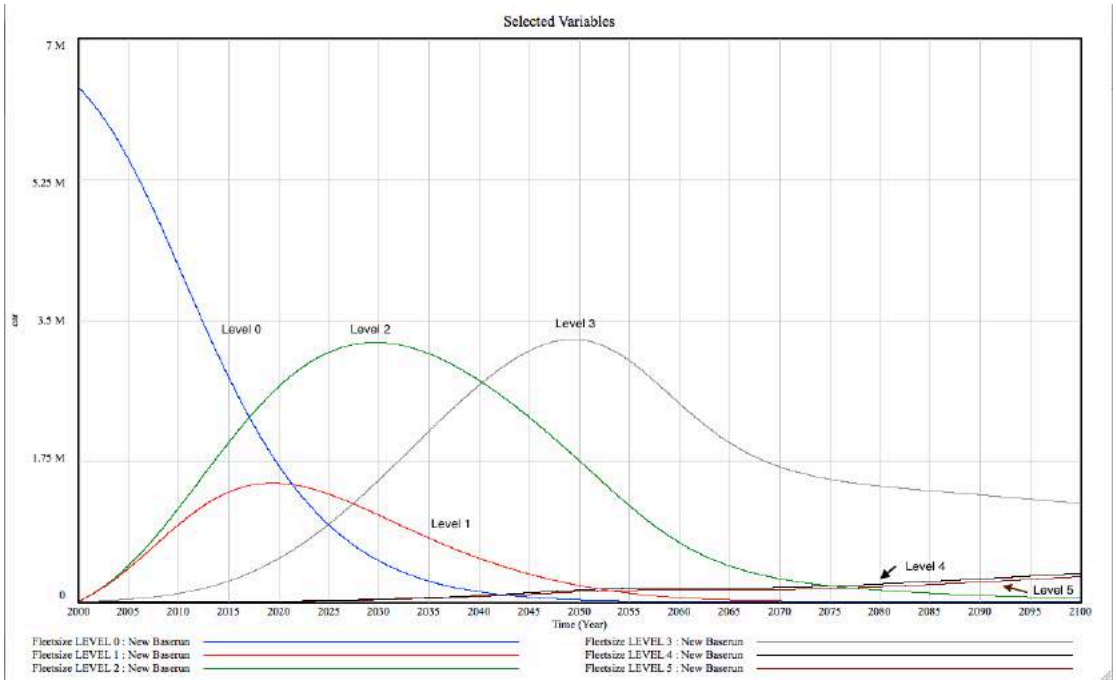

Figure 51 Fleetsize of all levels of automation

Another thing that can be noticed is the low fleetsize throughout the whole simulation run of level 4 and level 5. Around 2100 the fleetsize of these levels are respectively 335K and 293K vehicles. The fleetsize of level 3 reaches a peak at 2050 of approximately 3,3M vehicles. After this peak it starts to decrease however towards 1,2M vehicles in 2100. The reason for this is that the total fleetsize of vehicles also decrease heavily due to the rise of carsharing. Around 2050 the adoption of carsharing (Figure 52) is on a maximum of 900.000 new users per year. This causes that each year 220.000 new carsharing users abandon their car around this time (Figure 53). This causes the total fleetsize to drop from approximately 6,4M to 1,9M vehicles (Figure 54).

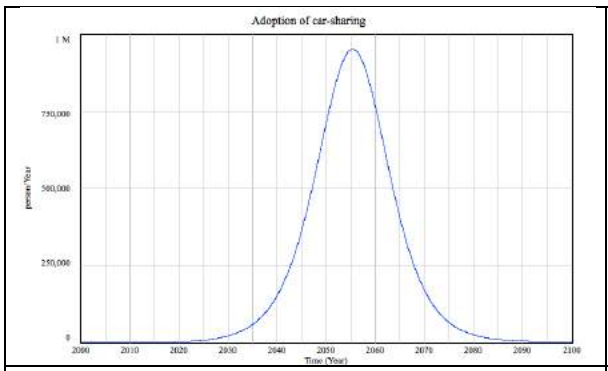

Figure 52 Adoption rate of carsharing

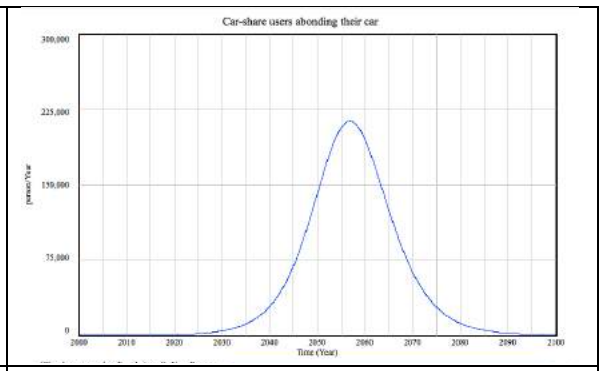

Figure 53 Number of people abandoning their car

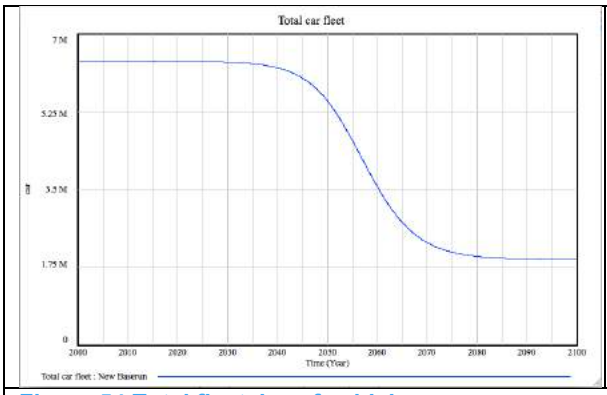

Figure 54 Total fleetsize of vehicles

Given this high drop in total fleetsize it is best to look at the normalized fleetsize of the automation levels. The curves of the normalized fleetsize are depicted in Figure 55.

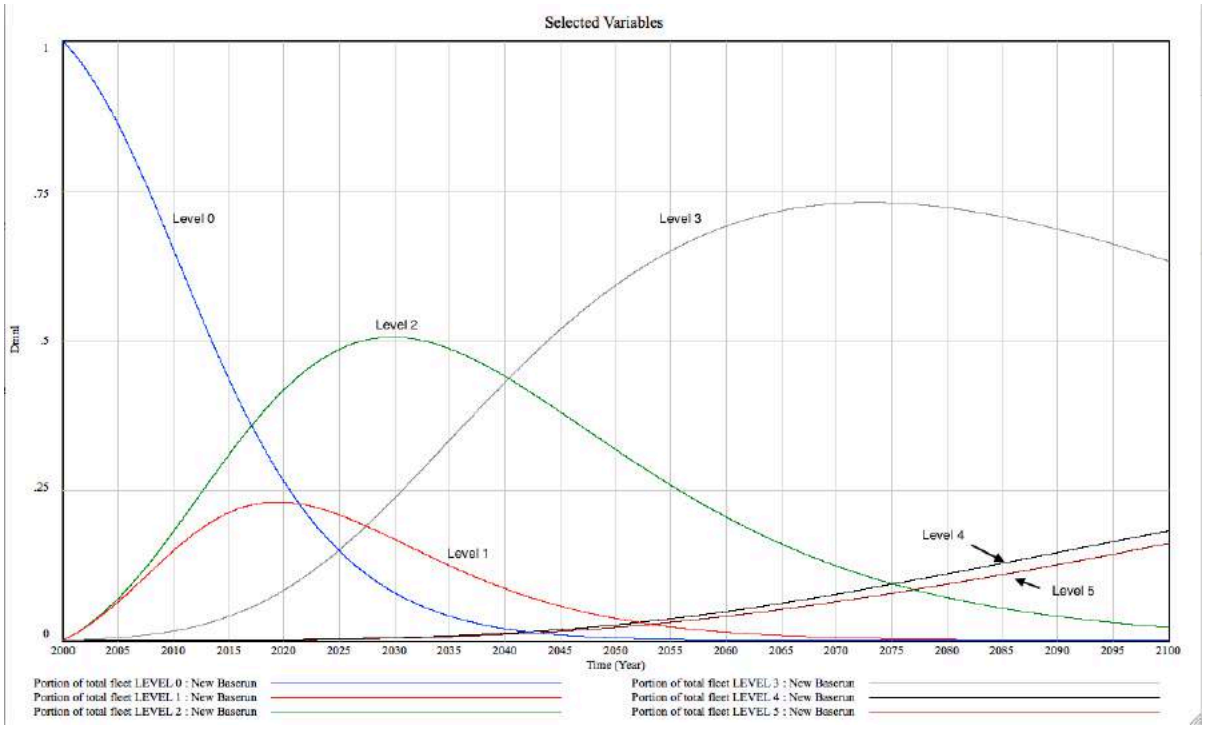

Figure 55 Normalized fleetsize of all levels of automation

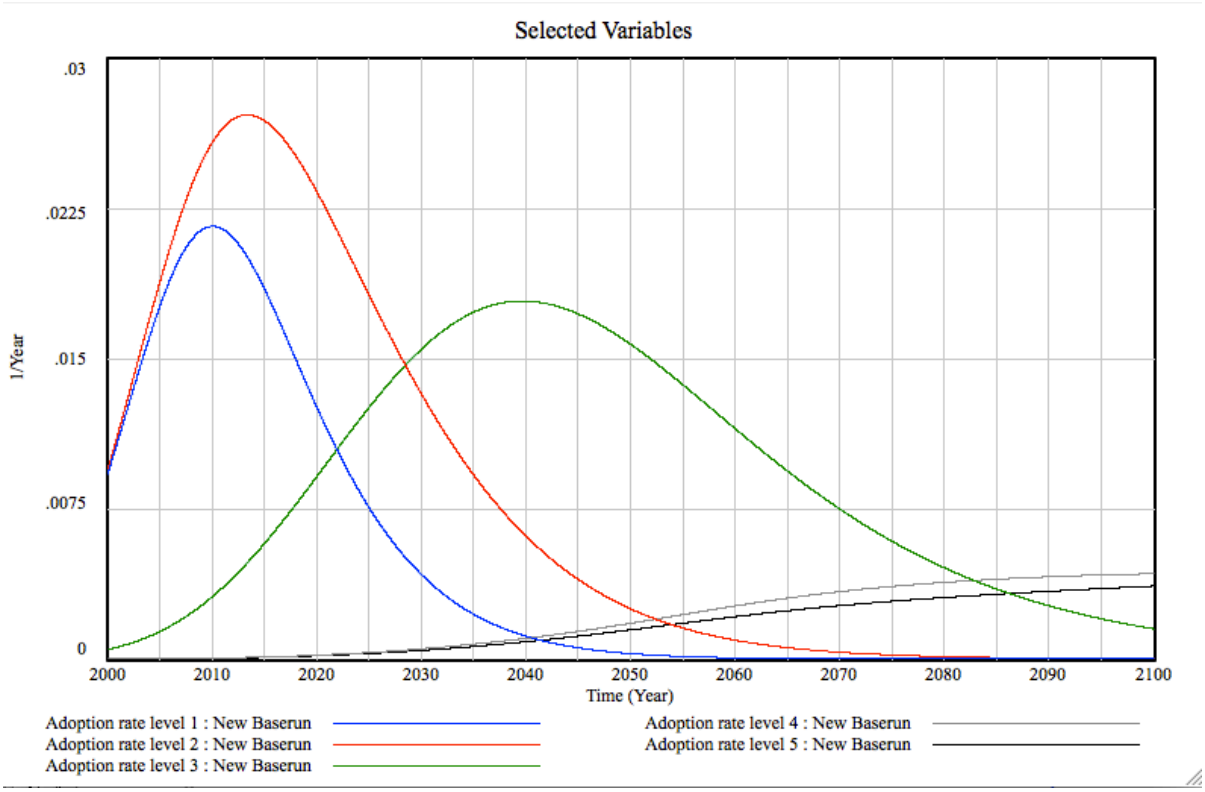

Figure 56 Adoption of vehicle automation

What can be seen is that during 2017 – 2040 level 2 is the most dominant level of automation. The adoption rate of level 3 vehicles is largest around 2040, as can be seen in Figure 56. Between 2040 and 2100 level 3 is the most dominant level of automation. At its peak, almost 75% of all vehicles are level 3. Level 4 and 5 slowly grow to a share of approximately 20% both in 2100. The simulation results show that it won't take until 2055 until every vehicle is automated.

These results can be compared with the estimations that the experts gave at the Automated Vehicle Symposium. The estimations of the experts were very diverse and cannot be generalized in any way. An overview of these estimations can be found on page 168. Two common estimations were: a dominant share of level 3 around 2030 – 2070 and a dominant share of level 5 in the period 2050 – 2100. The simulation results show a growing adoption rate of level 5. However this adoption rate is still to low for level 5 to gain a dominant share within the simulation run time of 100 years. However it has been shown that the input parameters are uncertain. With different parameter settings within the utility functions and different settings of the lifetime of a vehicle, level 5 could gain a dominant share of the fleetsize within the simulation run time. In that case the behavior of the fleetsize of level 5 would be according to the estimations made by the experts. The other common estimation of the experts was a dominant share of level 3. The current simulation results seem to show this kind of behavior.

7. Using the model

A system dynamics study won't show some clear results in a few numbers. It won't give a straight answer on a well-defined question. What a system dynamics study does produce is a playground in which you can explore the behavior of a system. It shows you how the system works, what possible directions it is going and how it can be influenced.

In Chapters 4 we have defined the system that the model will represent. Through a thorough literature review we have found what is already known and what is unknown about this system and turned this into a solid dataset. After building the model in Chapter 6 we have defined a list of parameters that have been filled with a dataset. After this we have tested the model, which gave us more confidence on the structure of the model and on the uncertainty and sensitivity of the input parameters that have been used. We also have looked at the behavior of the base run simulation and validated this behavior with the data and the expert estimations that we have gathered. During this behavioral analysis we have made some slight changes to the model to make it better represent the actual system.

In this chapter we will use the model. By using the model we will learn more about the applicability of the model itself and about the dynamics of the system of automated vehicles. In order to use the model we will ask four questions about the system that we can explore through different settings of the simulation model.

1. How can we change the direction and the speed of the adoption rate of automated vehicles?
2. How can we increase the speed of technology development?
3. What is the influence of high economic growth on the model?
4. What is the influence of a supportive AV policy and a High technological development?

7.1 How can we change the direction and the speed of the adoption of automated vehicles?

Various studies have shown the positive impact that automated vehicles can have on society. For this reason it might be beneficial to know for policymakers how they can change the direction and speed of the adoption of automated vehicles with the tools they have at hand. The speed of adoption is defined by the adoption rate curve. The direction of adoption is defined as in stimulating the adoption of a specific level of vehicle automation while not stimulating other levels.

A common tool that policymakers can use to change the adoption rate of an innovation is giving subsidy or doing a tax reduction to lower the costs of a specific innovation. Another instrument that policymakers could use is encouraging people to faster replace their old car with a new one. This can be done with special programs or putting tax benefits on new vehicles. With this instrument the average lifetime of a vehicle will be shorted.

7.1.1 Price reductions through tax reduction or subsidy program

To symbolize a tax reduction or subsidy in the simulation model we will artificially adjust the purchase price with an exogenous variable. This variable subtracts a pre-defined amount from the purchase price of a vehicle. However this subtraction is not executed until the maturity of a vehicle automation level is above 40%. This way we

will see a step in the purchase price at the moment that the maturity reaches 40%. The price reduction is depicted in the following graphs.

$$p_j = (bp_j + rp_j) - Subsidy_j$$

Equation 42 Purchase price with a subsidy subtracted from it

$$Subsidy_j = IF\ THEN\ ELSE(M_j > 0.4\ , 5000, 0)$$

Equation 43 Subsidy function

A price reduction of €5000 seems like a realistic number. The specification of the subsidy is executed in a right way by the model as we can observe a step from 0 to 5000 in 2030 when the maturity of level 3 reaches 40%. This causes the purchase price of level 3 to decrease from 2030 onwards with 5000 euro. We can also observe a sudden step in the utility of level 3. The subsidy is meant for stimulation of vehicle automation. In this sense level 1 is not considered to be part of the subsidy program. The subsidy is only put on levels 2, 3, 4 and 5.

Although the utility of level 2 and 3 make a sudden step, there can be seen little to no effect in the adoption rate. Even with a weight of 50% on the price, the model seems to be non-sensitive for a sudden drop in price. As the adoption rate is not affected, we can also observe little effect in a change of the fleetsize of level 2 and 3. The subsidy has no effect on 4 and 5 as these levels never reach a maturity of 40% within the simulation run time.

7.1.2 Adjusting the average lifetime of a vehicle

The current average lifetime of a vehicle is 10,4 years. Shortening this average lifetime in the real-world system requires a huge effort as it concerns about 6 million vehicles. Lowering this lifetime to 9 years would make a change in the adoption rate as can be seen in Figure 57. For level 2 the adoption rate shifts from a peak of 0,027% in 2014 to a peak of 0,03% in 2012. For level 3 the adoption rate shifts from a peak of 0,017% in 2040 to a peak of 0,02% in 2035. What can be seen is that the peak of the adoption rate gets higher, but also shifts backward in time. The peak of the adoption rate of level 3 was even realized 5 years earlier, by lowering the lifetime of a vehicle from 10,4 to 9 years. When the average lifetime of a vehicle is set to 8 years, the peak of the adoption rate of level 3 is realized another 2,5 years earlier. Also its maximum increases.

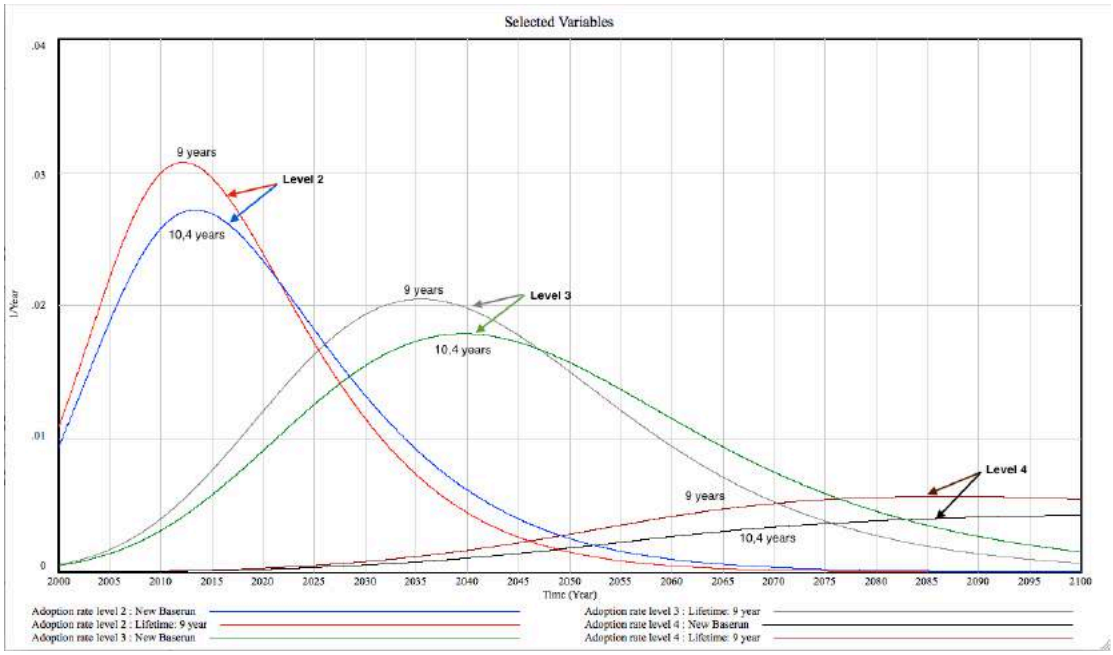

Figure 57 Adoption rate curves of average lifetime of a car with 10,4 years and 9 years

Another point that should be recognized is the fact that the adoption rate increases faster when shortening the lifetime of a vehicle, but also decreases faster after reaching its peak. This is caused by the fact that while a vehicle of a specific level of automation might be bought faster due to a short lifetime, the vehicle is also sold faster again when people give the preference over a more advanced level of automation.

When policymakers prefer one specific level of automation to all the other levels of automation, these policymakers might also want to steer the system into this direction. Lets assume that policymakers have invested heavily in new infrastructure and dedicated lanes for level 4 vehicle automation and they now want people to start adopting these level 4 vehicles. What they might do in this case is; encouraging people that own a vehicle of a different level of automation to sell this car and buy a level 4 vehicle. We will test this policy by adjusting the lifetime of a vehicle that is used in the flow from level 0, 1, 2 and 3 towards level 4. The average lifetime of a vehicle will stay the same in the rest of the model. When adjusting this average lifetime of a vehicle from 10,4 to 8 years we can already see a big shift in adoption rate of level 4. The adoption rate reaches a maximum in 2080 of 0,009% where it used to have a maximum of 0,0045%. This is a doubling in adoption rate. The fleetsize is also doubled from 168.000 to 411.000 vehicles in 2060 due to this change of average lifetime. When the policy turns out to be effective and it is even pushed harder it might be possible to get the average lifetime, of vehicles that change from level 0, 1, 2 or 3 to level 4, back to 6 years. It turns out that this change from 8 to 6 years has an even greater effect on the system than the change from 10,4 to 8 years. Both the adoption rate and the fleetsize more than double due to this change. Another effect is that the adoption happens earlier, as the peak of the adoption rate with a lifetime of 6 years is in 2065: a 15-year difference with the parameter settings of 8 years.

7.1.3 Conclusion

The policy instrument of adjusting the lifetime of a vehicle seems much more effective than price policies. However adjusting the average lifetime of a vehicle nation-wide by just 1 year seems as a difficult task form a policy perspective. This policy instrument therefore might be more effective than a subsidy program, it is also

much harder to execute. The effect also seems fairly modest compared to that effort that it takes. One of the problems with trying to change the adoption rate is that the policymakers are still very much dependent on the state and maturity of the technology. This technology development is mainly executed by the private sector. In the next paragraph we will see how this technology development can be influenced and speeded up both by policymakers as by the industry.

7.2 How can we increase the speed of technology development?

The development of technology can be speeded up in various ways. As an indicator the maturity will be used to observe the effect of the various instruments on technology development. In specific the maturity of level 4 will be used. Looking at all the levels doesn't have an added value and would make it unnecessarily more complex.

7.2.1 Knowledge transfer

One way of speeding up the development of technology is to create a supportive environment for field tests, validation practices and deployment strategies. An example of this is how the Dutch Minister of Infrastructure and Environment has stated that The Netherlands will be very supportive to speed up the approval procedure of field tests of automated vehicles (Dutch Ministry of Infrastructure and Environment, 2014). A way to simulate this behavior would be to increase the 'effectiveness of knowledge transfer' in the model.

For the base run the 'effectiveness of knowledge transfer', *ef*, was set on 50%. This parameter is specified in such a way that of all the knowledge that is created and normalized, 50% is used to improve the maturity of the technology. For this experiment *ef* was adjusted to 75% and 95% effectiveness. The results are shown in Figure 58. In the base run the maturity of level 4 reached a maximum of 11%. With *ef* = 75% a maturity of 33% was reached in 2100. With *ef* = 95% a maturity of 51% was reached in 2100. To reach the barrier of 40% maturity, an *ef* of at least 85% is necessary. 40% maturity was reached with *ef* = 95% around 2068. In comparison, in 2068 the maturity of *ef* = 75% was 22% and of the base run was 7%. This is an increase of almost 600% when increasing the effectiveness of knowledge transfer from 50% to 95%.

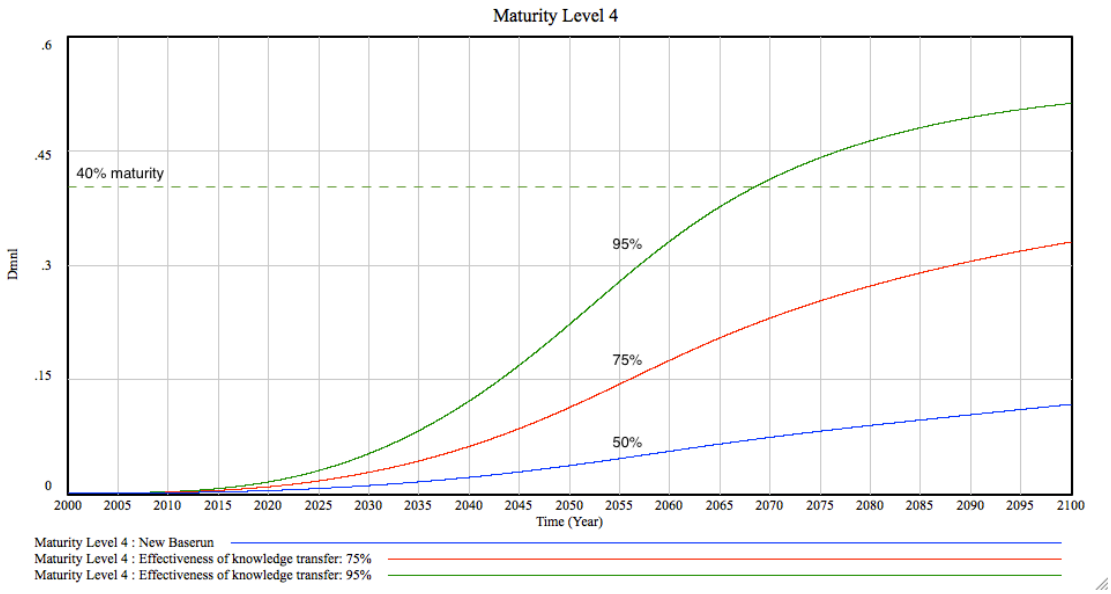

Figure 58 Maturity curves of level 4 with ef =50%, 75%, 95%

7.2.2 Knowledge depreciation

Knowledge is a very important driver for technology development. Knowledge is created and accumulated both by the public and private sector. Universities, applied science institutions and governmental research institutions represent the public sector. The private sector has its own R&D departments within organizations and consultancy firms to gain knowledge on a topic. This knowledge is not always openly available, especially not in the private sector. This way it happens a lot that knowledge on the same topic is gained by multiple organizations at the same time. This is a waste of the resources that have been put into the knowledge creation. Furthermore it might happen that knowledge, which is created by player A, might not be useful for player A, but very useful for player B. When this knowledge is not distributed from player A to player B this knowledge might get lost, which is not beneficial for the technology development as a whole. There are various ways to prevent this depreciation of knowledge. One way is to better exchange knowledge between private- and public sector players through network organizations with round table meetings. Governmental organizations might start a public research agenda and identify topics that still need the attention from research. To prevent industry players to do research on the same topic, organizations with the same objectives might work together in collaborative projects. Another tool is to stimulate open databases from the public sector. Also the private sector can stimulate this by opening up their source code, databases and improving their Application Program Interface (API) to stimulate open innovation.

To see the effect of these instruments on the system the parameter 'depreciation rate of knowledge', ∂, will be adjusted in the model. Its value was set on 10% per year in the base run. This value is already quit low, so it cannot be improved very much upon any more. Nevertheless the values of 5% and 1% will be tested. It isn't reasonable to test a parameter setting were 0% of the knowledge will be depreciated.

It is remarkable to see in the results that a little change in this depreciation factor already has a big effect on the maturity of the technology. The results are depicted in Figure 59. As said before the maturity of level 4 don't grow further than 11% in the base run. With ∂ = 5%, this 11% is already reached in 2058. With ∂ = 1%, this 11% maturity is reached in 2046. The maturity in the simulation run with ∂ = 5% reaches a maximum of 30% maturity in 2100. The maturity in the simulation run with ∂ = 1% reaches this 30% in 2063 and reaches a maximum of almost 70% in 2100. The barrier of 40% is reached with a ∂ = 1% around 2071. In comparison to the previous experiment with *ef = 95%* the maturity was reached around the same period. The maturity curve with *ef* = 95% however flattened out at the end, where the maturity curve of ∂ = 1% goes on upwards after 2070.

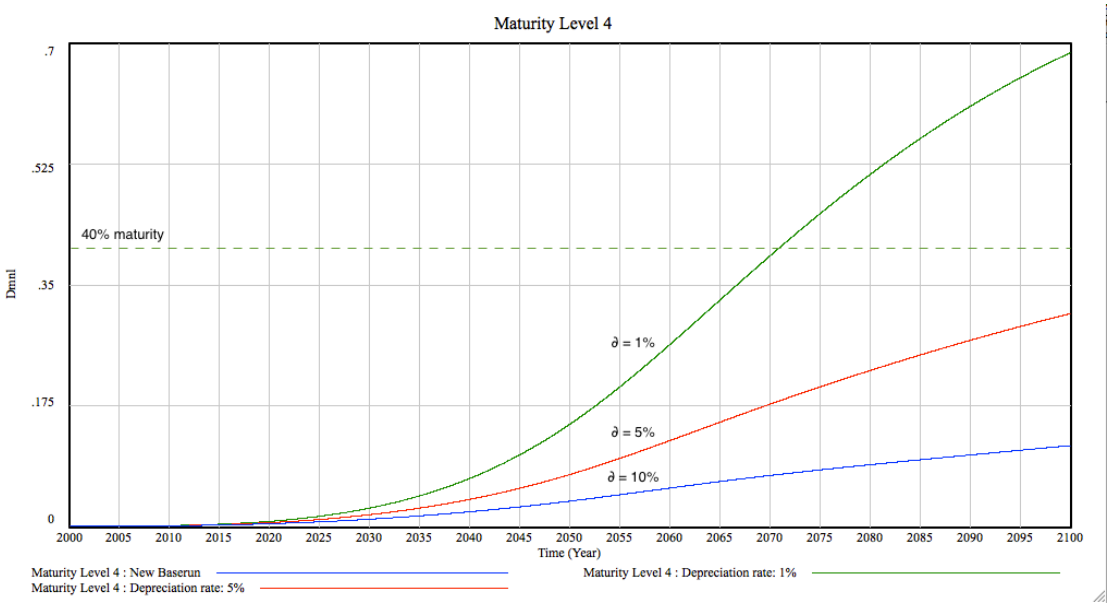

Figure 59 Maturity curves of level 4 with ∂ =10%, 5%, 1%

7.2.3 R&D budget

In terms of money external funds can be created both by the public and the private sector. The public sector might create monetary funds to supply research and applied knowledge institutions with more resources. The Horizon 2020 fund of the European Commission is a good example of this. The industry might create private investment funds to encourage entrepreneurial activities of new start-up companies around a technology.

This external R&D fund is specified in the model as a stock, *F*. The stock is increased by a periodical allocation of resources. The stock is decreased by an outflow of resources towards the research activities. This outflow is specified as a certain percentage of the total fund. The outflow of resources is added annual R&D expenditure.

$$\frac{dF_j}{dt} = \text{Periodical allocation of resources} - (\mathrm{F_j} * \%)$$

Equation 44 External monetary research fund

The periodical allocation of resources is defined as a step function over the period 2015 – 2020.

$$Periodical\ allocation\ of\ resources = \mathrm{STEP}(\mathrm{x}, 2015) - STEP(x, 2020)$$

Equation 45 Periodical allocation of resources that fills the fund

The amount that is being allocated to the fund is hard to estimate. For this experiment we have defined a total allocation of 400 million euros over 5 years and an allocation of 1 billion euros over 10 years. These two scenarios are defined as *pa*=400M and *pa*=1B.

The effect on the knowledge stock is big, as can be seen in Figure 60. This stock increases with 250% (*pa*=400M) and 400% (*pa*=1B). However the 'knowledge depreciation factor' and the 'knowledge transfer effectiveness' are not beneficial in these scenarios. This leads to the fact that not all of this knowledge will be translated into a growing maturity, meaning that a lot of the resources of the funds will be

wasted. The maturity of level 4 is growing to 26% with the 400M fund and to 37% with the 1B fund.

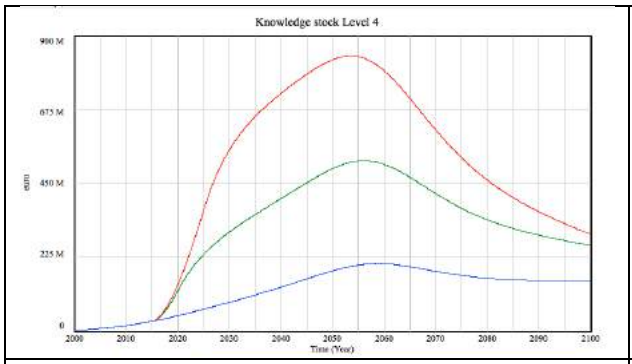

Figure 60 Knowledge stock level 4 for pa=400M (green) and pa=1B (red)

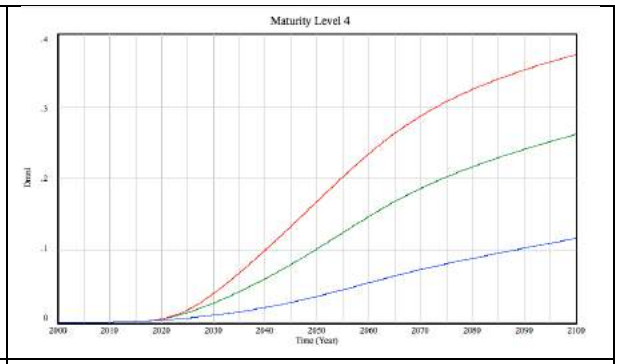

Figure 61 Maturity level 4 f for pa=400M (green) and pa=1B (red)

7.2.4 Combination of instruments

As can be seen above, all three instruments can lead to an increase in the technology development speed. Of the three instruments a decrease of the knowledge depreciation stock seems to be the most influential. The allocation of extra resources seems to be the least influential, but could have a big effect on the system once combined with the other instruments. The simulation will therefore be run with two scenarios where all the three instruments are combined.

The first scenario is named: "Scenario 1" and has the following parameter settings: *∂* = 5%, *ef* = 75% and *pa* = 400M. The second scenario is named: "Scenario 2" and has the following parameter settings: *∂* = 1%, *ef* = 95% and *pa* =1B. The results of both scenarios are shown by the maturity curves of level 4 in Figure 62. Both scenarios seem to be very effective in terms of technology development. Scenario 1 reaches a maturity of more than 75% at the end of the simulation run. In the period between 2045 and 2070 the development goes fastest with an average increase of maturity of 1% per year. Scenario 2 reaches a full maturity of 100% around 2075. The curve is -shaped with a steep phase in the period 2025 – 2050. In this period of 25 years the maturity increases from 10% to 80%.

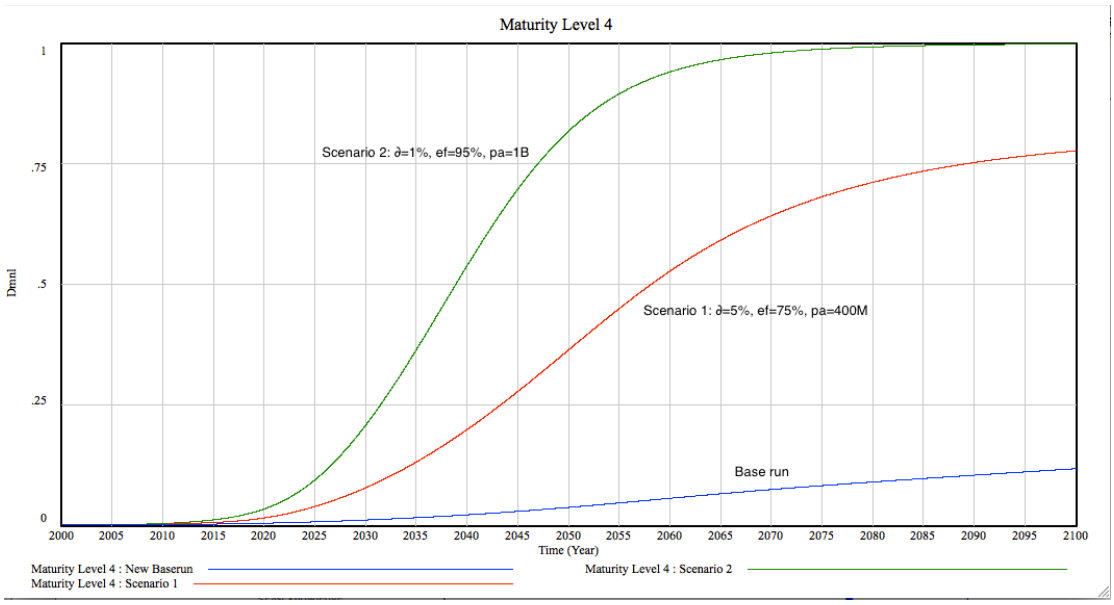

Figure 62 Maturity of level 4 for scenario 1 and scenario 2.

The focus on technology development also seems very beneficial for the adoption rate of an innovation. With Scenario 1 the adoption rate of level 4 rose with 400% in respect to the base run. The fleetsize of level 4 also increased with 400% due to a focus on technology development. Scenario 2 increased the adoption rate and fleetsize of level 4 with about 600% and made the adoption occur much earlier, with a peak around 2035.

To conclude we can say that, while taking the boundaries and possible limitations of the model into account, it might be more beneficial for policymakers and the industry to focus on developing the technology towards a mature state rather than focusing on pushing the customers towards a faster adoption. If the technology gets more mature, the customers will see the benefit and the adoption will follow. The way to speed up the technology development seems to be a combination of the three described instruments. However if one has limited resources and has to choose, the best option might be to stop the knowledge depreciation by: creating a common research agenda, getting people together, opening up databases and sharing knowledge.

7.3 What is the influence of high economic growth on the model?

The current base run of the simulation model takes little to none of the possible demographic and economical changes into account. However it is interesting to know what the effects of these exogenous factors might be on the system. In this paragraph a scenario will be created that represents a high economic future growth. This economical growth will be represented in the model by adjusting current parameter settings. First of all 'change in fleetsize' will be adjusted to a 3% of all vehicles increase per year. The 'weight on price', ß1, will be decreased as people will be less worried about the price of a product with high economic prosperity. The average lifetime of vehicles will be decreased as people will buy a new vehicle and adopt new technologies sooner when the economic growth is high. The population growth will be set to a constant growth of 1% due to increased immigration and a longer lifetime of people (which results in a lower death rate). The last parameter value that will be changed is the percentage of their total revenue that the industry allocates for R&D. With a high economic growth organizations tend to focus more on innovation than in hard economic times. The parameter settings can be viewed in Table 22.

Parameter	Base run	Economic growth
Annual change in vehicles	0%	+3%
ß1 Weight on price	0,5	0,2
Lifetime of a vehicle	10,4 year	7,4
Percentage to R&D	7,5%	10%
Population growth	Decreasing 0,7% - 0%	Constant 1%

Table 22 Parameter settings for base run and economic growth scenario

Due to this economic growth the technology development takes a rapid increase. The technology maturity of level 5 reaches a maturity of more than 80% around 2050. Due to this rapid development and due to the fact that level 5 has the most attractive attributes in the utility function the adoption rate of level 5 also takes a rapid incline. In this beneficial economic climate the adoption rate of level 5 is around 3% in the period 2035 – 2045. This results that around year 2020 – 2025 level 5 will start hitting the market and a 10% market penetration will be reached around 2027. After this period the diffusion of level 5 into the market goes very rapidly and around 2040 – 2045 a 50% market penetration is reached. In this economically beneficial scenario level 5 will reach a total market penetration around 2075. Figure 63 shows the market penetration of all the levels of automation.

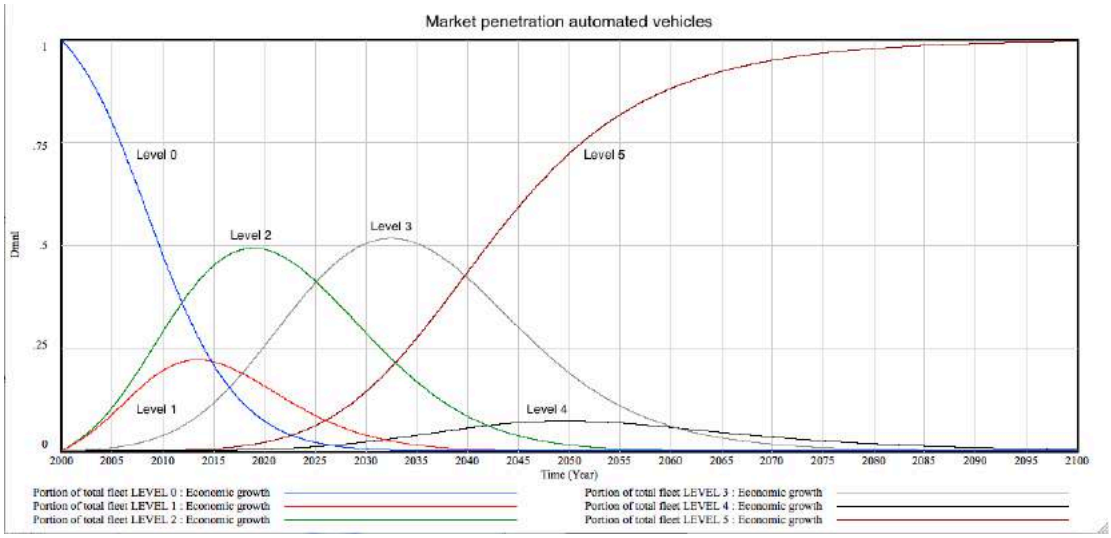

Figure 63 Market penetration automated vehicles in economic growth scenario

7.4 What is the influence of a supportive policy and a high technological development?

The last scenarios that will be explored have been described in a study by Milakis et al. (2015). In this study Milakis describes the system of automated vehicles as a dynamic relation between the components: economical factors, customer attitudes, technology development and policy. These components can also be found in the model. Milakis specifies a scenario called 'AV in bloom' in which the customer attitude is positive, economic growth is strong, the technology development is high and the policy is supportive. This scenario will be quantified and tested in this paragraph.

In this scenario we will have a extra focus on positive policy stimuli towards level 4 and 5 as these two levels are likely to be most beneficial in a policy perspective. The scenario will explore the time span between 2015 and 2100. As we start the simulation run in 2015 instead of 2000 some parameter settings will be changed to account for different initial values in 2015. All the parameter settings for this scenario run can be found in Table 28 in the Appendix D on page 140. Beside the initial values some other parameter values had to be changed to specify the scenario in the simulation model. To illustrate a positive customer attitude the weight for attractiveness will be increased (and thus the weight for price will be decreased), The economic growth will be illustrated by an annual increase in the total number of vehicles. The high technology development will be illustrated by an increased effectiveness of knowledge transfer, a higher percentage to R&D and a decreased depreciation rate. A subsidy on the purchase price of level 4 and level 5 vehicles will account for the supportive policy. Furthermore we will create an artificial fund in the simulation model that has to boost the technology development of level 4 and level 5. The parameter settings for the AV in bloom will be specified both conservatively and progressively. These settings are shown in Table 23.

Parameter	Base run	AV in bloom – conservative	AV in bloom – progressive
ß1 Weight for price	0,5	0,4	0,2
Annual change in vehicles	0%	1%	3%
Effectiveness of knowledge transfer	50%	75%	95%
Percentage to R&D	7,5%	8,5%	10%

Knowledge depreciation rate	10%	5%	1%
Subsidy on vehicle automation.	0 euro	2500 euro	5000 euro
External resource fund	0 euro	1B over 10 years	2B over 10 years

Table 23 Parameter settings for base run and AV in bloom scenario

The adoption rate and market penetration of the conservative scenario are shown in Figure 64 and Figure 65. In 2025 level 3 has the highest adoption rate of nearly 3% per year. Between 2035 and 2040 level 3 has the highest market penetration of 50%. The adoption rate of level 4 and 5 start increasing rapidly after 2020. In 2043 this adoption rate makes a sudden step, this is due to a subsidy that is put on the price during this period. It can be seen that this subsidy leads to a sudden increase of 0,1% adoption rate. After 2050 level 5 has the most dominant market penetration, which will increase towards 90% in 2100.

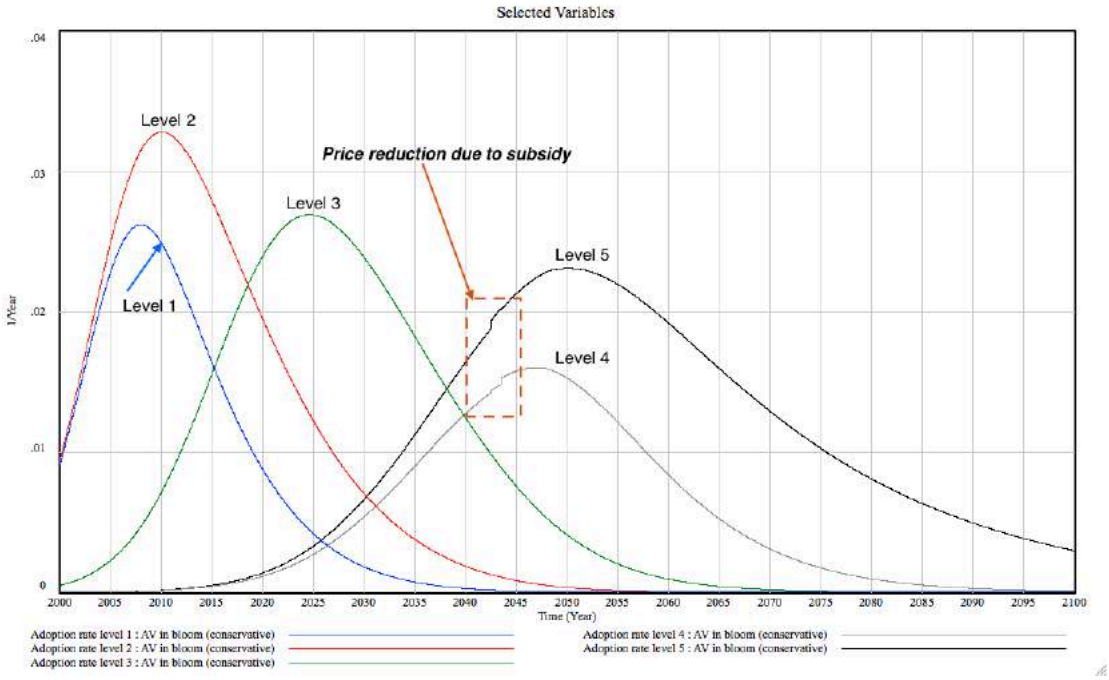

Figure 64 Adoption rate of AV in bloom conservative scenario

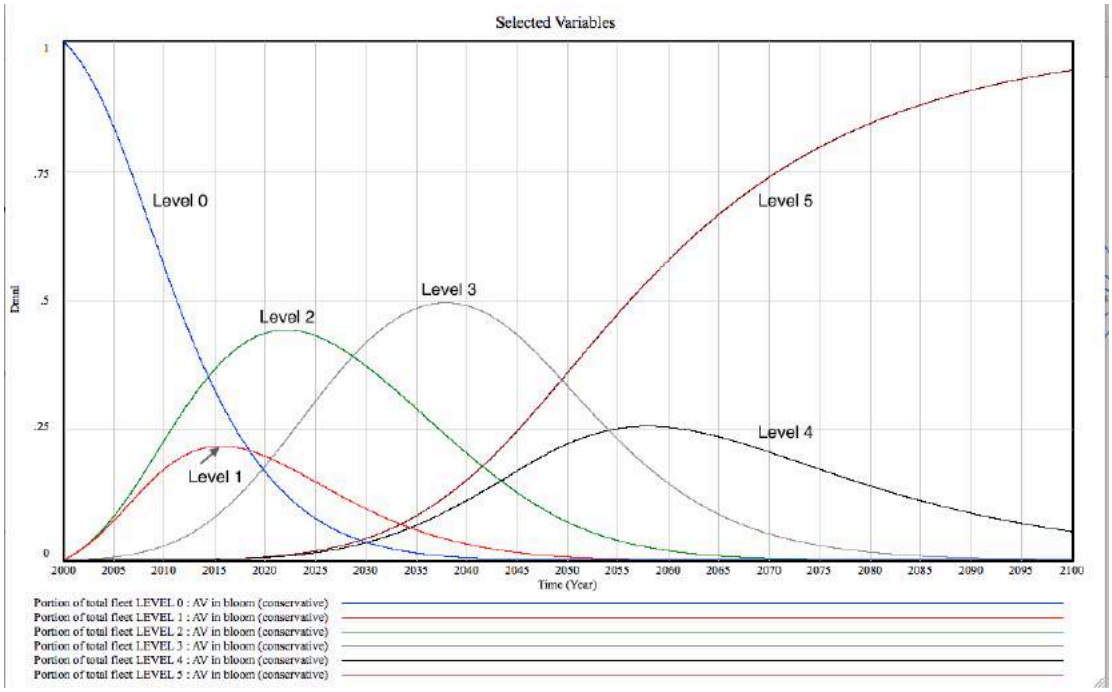

Figure 65 Market penetration of AV in bloom conservative scenario

The adoption rate and market penetration of the progressive scenario are shown in Figure 66 and Figure 67. It can be recognized that the adoption rate of the progressive scenario is much steeper and higher with all the levels of automation in comparison to the conservative scenario. Another remarkable point is that all the levels of automation reach a peak of their adoption rate before 2040. This causes a dominant market penetration for level 5 already between 2035 and 2040. In both scenarios the market penetration of level 0 drops very rapidly after 2015.

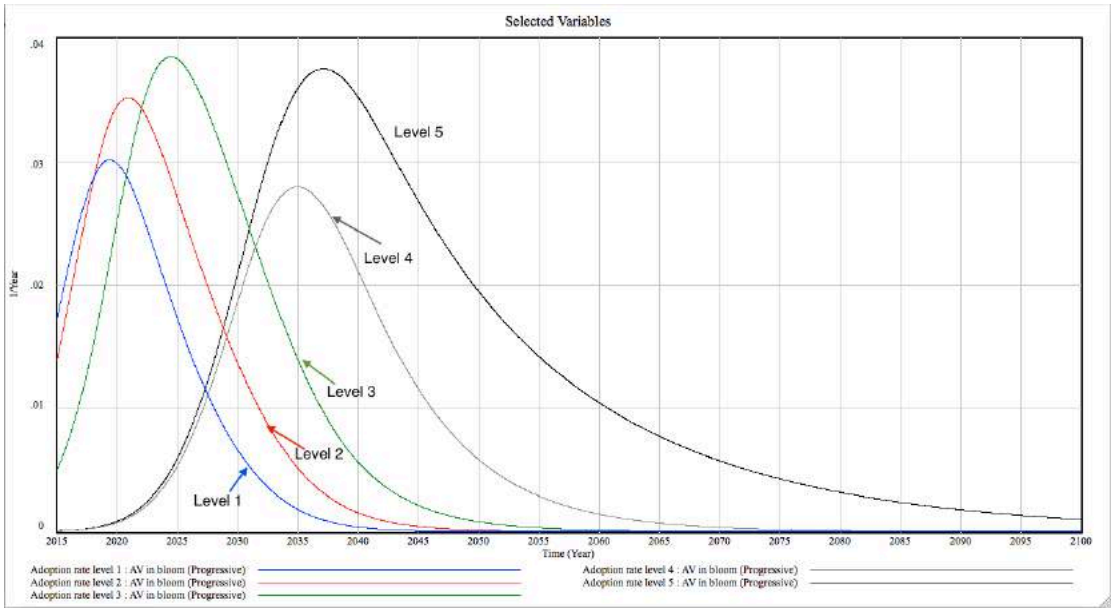

Figure 66 Adoption rate of AV in bloom conservative scenario

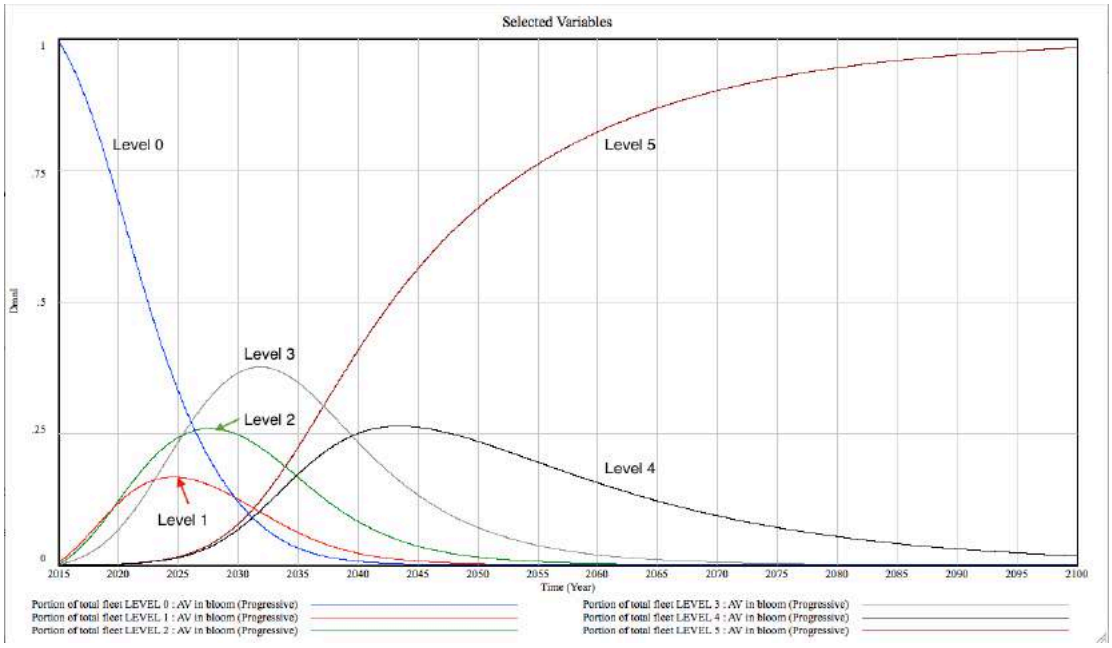

Figure 67 Market penetration of AV in bloom progressive scenario

7.4.1 Monte Carlo

The scenarios have been run in a Monte Carlo simulation of 1000 runs, with a Latin Hypercube sampling. The conservative scenario was used as the lower boundary and the progressive scenario formed the upper boundary of the parameters. The results can be found in Appendix D.

The technology development in the AV in bloom scenario goes fast as expected. The conditional and partially automated vehicles (level 2 and 3) will reach a full maturity of 100% within 10 and 15 years. Highly and fully automated vehicles (level 4 and 5) will reach a maturity of 40% somewhere between 2035 and 2040. This means that these types of vehicles will than be available for mass adoption by the public. Fully automated vehicles will reach a maturity of 100% around 2050 - 2070.

Partially automated vehicles (level 2) will be available on the market for mass adoption within the upcoming 5 – 10 years. This will lead to a market penetration of 10% around 2022. Around 2030 partially automated vehicles have reached their peak market penetration of nearly 30%. After 2030 this will drop. Conditionally automated vehicles (level 3) will reach an adoption rate of >3% within 10 years. Level 3 will reach a market penetration of 10% around 2022 as well. A peak in the market penetration of level 3 is at 40% and will be around 2035. After this the market penetration drops quite rapidly, towards nearly 0% around 2080. This is because of the rise of the fully automated vehicles.

Highly and fully automated vehicles (level 4 and level 5) will start being available on the market for early adopters around 2030, when they reach a 1% adoption rate per year. The purchase price of these vehicles will then still be somewhere between 55.000 and 65.000 euros. This is the price without subtraction of the subsidy (between 2500 and 5000 euro). Massive adoption, meaning a rate >3% per year, will not occur before 2035 – 2045. Highly automated vehicles will reach a market penetration of 30% in 2050. After this peak the market penetration will start dropping. Fully automated vehicles have a market penetration of 30% around 2045. After this it will grow towards a 75% in 2065 and a 95% market share in the period between 2080 and 2100.

Traditional vehicles (level 0) will start decreasing rapidly after 2015. In 2015 level 0 has a market penetration of nearly 95%. In 2023 this is only 50% and in 2035 this will be around just 5%. A few vehicles with no automation will be still around for a long time though. This might be as an old timer, a racecar or some other classic vehicle. The last vehicles of these types seem to get of the market around 2060.

In the year 2030 there will be mainly partially and conditionally automated vehicles on the market. Level 2 and 3 will have about 60% market penetration. The market penetration of highly and fully automated vehicles is around 12% in this time period. In 2045 – 2050 this has been changed however and fully automated vehicles dominate the market. Partially and conditionally automated vehicles will have a 20% market penetration together. Level 4 and 5 will have around 75% market penetration.

In the AV in bloom scenario the number of vehicles per household will drop slightly around 2060. This is the period that the adoption rate of carsharing is on its peak. There is a big uncertainty range after 2060 what the number of vehicles per household will do. Due to the economic growth in the model there is a likelihood that the number of vehicles per household will grow. The distance traveled per vehicle will likely increase around 2060 from 9.000 km per vehicle to 13.000 km per vehicle.

8. Conclusion

In this research a novel quantitative model is constructed that can be used to learn more about the dynamic and complex nature of the system of automated vehicles. The feedback loops between the model components form a dynamic behavior that influences the diffusion of automated vehicles. The model takes the approach of the functional pathway of vehicle automation. In this approach vehicle automation is represented in 6 different levels varying from no automation to full automation. Each level has its own technology maturity. This maturity is developed through funding that is created by the sales of this level. When the technology grows more mature, the purchase price decreases through learning effects. Together with the comfort, the safety and the familiarity of a level this purchase price forms the utility of an automation level. In the model it is assumed that the end users make a constant trade-off between the vehicle with a level of automation that they currently own and a higher level of automation. This trade-off is made within the average lifetime of a vehicle, based on the maturity of the higher level of automation and a comparison between the utility of their current level of automation and the higher level of automation. Because of these changes of vehicles by the end-users the fleetsize of the levels of automation gradually shifts over time. This effect causes the diffusion of vehicle automation into society.

What have to be taken into account is that the model is just a mere representation of the real-world system. Although the structure and input values have been carefully tested and validated the model still is biased and has its constraints. The model can be used for the objective to gain more knowledge about the factors that influence the diffusion of automated vehicles and to better understand the interaction of complex policies and their potential effects on the diffusion of automated vehicles. The model is not designed or intended to *predict* future behavior of the system and so it can't be used with this objective. The model represents a whole-world perspective in a developed country.

For a base run of this model a dataset with socio-economical characteristics from the Netherlands has been collected. Given the boundaries and possible constraints of the model and the parameter values that have been set for the base run we can conclude the following about the adoption rate and market penetration of vehicle automation. Level 1 and 2 seem to make a market introduction around the same time period. After this market introduction the adoption rate of level 2 will be slightly higher than the adoption rate of level 1. This results in a 25% market penetration of level 1 around 2020 and a 50% market penetration of level 2 around 2030. The adoption rate of level 3 will be higher than 1% per year after 2020. In the period from 2017 until 2040 level 2 is expected to be the most dominant level of automation in the market. After 2040 level 3 will be the most dominant level and will gain market penetration until its peak of 75% in 2070. Level 4 and level 5 will make a market introduction around 2040 and will grow slowly after that. The adoption rate won't be more than 0,5% per year before 2100. At the end of the simulation run in 2100 level 3 has a dominant market penetration of around 60%. Level 4 and level 5 both have a market penetration of 20%. The reason for this domination of level 3 and this slow growth of level 4 and 5 seems to be the high technology maturity of level 3 in comparison with level 4 and 5.

The diffusion of vehicle automation is seen from the perspective of the end user and is thus dependent on the maturity of the technology, the purchase price and the utility that it offers to the end user. The technology development has the biggest influence

on the adoption rate of vehicle automation in this model. The low adoption rate of highly and fully automated vehicles seem problematic from a policy perspective as these type of automated vehicles will have the most impactful societal benefits. In order to speed up the diffusion of highly and fully automated vehicles it might be most effective to focus on the technology development. This technology development can be influenced through multiple policy implementations. The speed of the technology development seems to be most affected by a combination of knowledge sharing and collaborative projects between industry players. This way less knowledge is depreciated over time and the effectiveness of the knowledge transfer into maturity increases. Another very effective way to speed up the technology development could be to create a fund that can be used for internal R&D projects and startup capital.

It has been shown in the model that the diffusion of vehicle automation can be speeded up through a high economic growth, a supportive policy towards vehicle automation and a high technological development. In this so-called 'AV in bloom' scenario highly and fully automated vehicles (level 4 and level 5) will start being available on the market for early adopters around 2030. Until that time there will be mainly partially and conditionally automated vehicles on the market. Level 2 and 3 will have about 60% market penetration. The market penetration of highly and fully automated vehicles is around 12% in this time period. In 2045 – 2050 this has been changed however and fully automated vehicles dominate the market. Partially and conditionally automated vehicles will have a 20% market penetration together. Level 4 and 5 will have around 75% market penetration.

Overall two different transition pathways to a future with vehicle automation can be recognized. The first pathway is illustrated by the base run of the simulation model and shows a dominant market penetration of level 3 vehicles. Most of the automation is found on highways and the vehicles are likely to still being owned. If however industry succeeds in reaching a significant technology maturity of level 4 and level 5 in the near future another pathway is likely to occur. This other pathway illustrates a high market penetration of level 5 vehicles early on. Studies have shown that a high market penetration of level 5 automation is likely to have the most significant positive impact on society. Policymakers can make this work through extra focus and funding for the development of the technology.

9. Reflection

In this Chapter we will take a step back and reflect on this study. The main purpose of this study was to create a new method for modeling the diffusion of vehicle automation in a quantitative way. In order to test and use this method a case study in the Netherlands done. A point of reflection can be put on the fact that the data that has been used for this case study is from a combination of different regions including USA, EU and specifically the Netherlands. This negatively impacts the consistency of the model outcome. Furthermore various assumptions have been made in the dataset to fill some of the gaps of scarcely available empirical data. This causes that some of the outcomes of the case study can be argued upon. It is strongly encouraged that the model is enriched with new data in the future or being used with completely new datasets, because through experimentation and usage of the model we can learn more about the dynamics that are behind the diffusion of automated vehicles.

By looking at the approach in this study we have to admit that the way we look at the system of vehicle automation is very technocratic and deterministic. It is believed in this worldview that technology is the main factor that determines the future of automated vehicles. If we put enough money in the development of the technology it is believed that this technology will get more mature as a continuous process and will get ready for actual deployment. In reality this technology maturity, as it is referred to in this research, is much more complex and complicated. The process isn't as continuous as portrayed in this study. Vehicle automation won't be ready for deployment before the technology has gone through a very long and intense testing- and validation process. In this process it could encounter legal or social constraints that make it harder for the actual deployment of vehicle automation. This could mean that although the technology is ready and mature enough for deployment, for example the public perception is so negative that there is no demand for automated vehicles. In the worldview of this study these legal and social constraints are not taken into account.

In this study we conclude that two possible transition pathways of vehicle automation seem likely. Others sometimes refer to the first pathway with a dominant market penetration of level 3 as the 'private luxury' scenario. The second pathway with a dominant market penetration of level 5 is often referred to as the 'mobility as a service' scenario. The first scenario focuses most dominantly on the ownership of automated vehicles, where in the second scenario the primary focus is on the usage of automated vehicles. The model is built in 2015. This means that the model also shares the common worldview of 2015. In this worldview the OEMs are the dominant players in the automobile industry and the dominant business model in this industry is based on private ownership of cars. For this reason the simulation is best applicable for simulating the implications of the first scenario, which is also based on ownership. The simulation model has a very long time horizon up until 2100. It is likely that in the next few decades new players, new sectors and new possibilities arise that are not possible to see nowadays. An interesting topic for future research might be to incorporate the transition pathway of mobility as a service into the system dynamics model that is created in this study.

In the private luxury scenario it is most likely that the OEMs will be the most dominant market players. In this scenario most of the vehicles will likely still being owned by individuals. The market players might have to slightly change their business model and find a good value proposition for these new models to work, but

the change won't be as radical as the second scenario. Level 5 automation is a radical innovation that could change more than just one sector. It might be very hard for traditional car manufacturers to come up with radical new designs that find a high demand in the market. A parallel can be seen here with how Christensen and Overdorf (2000) describe the difference between sustaining and disrupting innovations. A transition pathway of private luxury can be categorized as a sustaining innovation, because it likely serves the same needs of the customers as the product that it replaces. A transition pathway like mobility as a service with a low priced level 5 can be categorized as a disruptive innovation, because it will likely serve the needs of new customers. Traditional car manufacturers have a solid base of customers. All the production processes are standardized in a way that aligns with the proven customer needs. To adjust these designs and come up with something radically new, which might align with new future customers, is in contrast with the needs of the current customers. This experimentation phase has been proven to be very hard for traditional players and only few traditional OEMs might therefore survive this second scenario. It might be for this reason that the traditional OEMs are still skeptical about the technological feasibility of level 5 automation and are much more keen in investing in the technology development of level 1, 2 and 3.

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Appendix

A quantitative method to model the diffusion of automated vehicles with system dynamics

TU Delft

Appendix A. Literature overview carsharing

Literature	Region	Year	Cars replaced	% of members		Ownership of car before membership	
				Sold their car	Forgone buying a car	None	1 or more
(Rydén & Morin, 2005)	Bremen, EU	2005	6,5	34%	17%		
(Cooper et al., 2000)	USA	2000		23%	25%		
(Robert, 2000)	USA	2000	4,7	29%	56%	38%	63%
Flexcar, 2001	USA	2001	3,0	20%			
(Jensen, 2001)	USA	2001	5,0	28%	57%	86%	14%
City Carshare, 2002	USA	2002	5,0	20%	63%	65%	35%
(Cervero & Tsai, 2003)	USA	2003	6,0	29%	4%	67%	33%
Vance, 2004	USA	2004		15%	40%		
(Lane, 2005)	USA	2005	4,7	21%	44%		
(Katzev, 1999)	USA	1999	3,5	26%	53%	59%	41%
(Rydén & Morin, 2005)	Belgium, EU	2005	3,8	21%	14%		
(Holm et al., 2002)	Germany, EU	2002	3,5	10%	21%		
(Krietemeyer, 2003)	Germany, EU	2003		12%	35%		
(Cervero et al., 2007)	USA	2007		19%			
(Martin et al., 2010)	USA	2010	6,0	23%	25%	62%	38%
(Zipcar, 2015)	USA	2015		20%	20%		
(Schoettle & Sivak, 2015)	USA	2015		43%			
Expert panel AVS 2015	USA	2015		23%			

Table 24 Overview of available data on impact of carsharing. Adapted from Millard-Ball (2005).

Appendix B. Specification

Specification stocks

Name	Notation	Equation	Unit
Fleetsize	V_j	$\frac{dVj}{dt} = \sum_{i=0}^{(j-1)} s_{ij} + g_j - \sum_{k=(j+1)}^{5} c_{jk}$	Car
Maturity	M_j	$\frac{dM_j}{dt} = +\,(nK_j * gap_j * ef)$	Dmnl
Knowledge	K_j	$\frac{dK_j}{dt} = \mathrm{rd}_j - (\mathrm{K_j} * \partial)$	Euro
Cumulative experience	E_j	$\frac{dEj}{dt} = \sum_{i=0}^{(j-1)} s_{ij}$	Car
Carsharing users with car	A_c	$\frac{dA_c}{dt} = (\mathrm{ar_{cs}} * f_c) - abr$	Person
Carsharing users without car	A_{wc}	$\frac{dA_{wc}}{dt} = (\mathrm{ar_{cs}} * f_{wc}) + abr$	Person
Population	N	$\frac{dN}{dt} = \text{birth rate} - \text{death rate}$	Person

Table 25 Specification of the stocks

Specification endogenous variables

Name	Notation	Equation	Unit
Sales	c_{ij}	$s_{ij} = V_i * \left(1/\alpha\right) * M_j * \frac{U_j}{U_i + U_j}$	Car/year
Annual R&D expenditure	rd_j	$\mathrm{rd}_j = s_j * p_j * frd$	Euro/year
Purchase price	p_j	$p_j = bp_j + rp_j$	Euro/car
Baseline price	bp_j	$bp_j = bp_{0j}\left(\frac{E_j}{E_{0j}}\right)^{lc}$	Euro/car
Retrofit price	rp_j	$rp_j = rp_{0j}\left(\frac{M_j}{M_{0j}}\right)^{lc}$	Euro/car
Learning curve	lc	$lc = \log_2(1-x)$	Dmnl
Utility	U_j	$U_j = \left(nP_j * ß_1\right) + \left(A_j * ß_2\right)$	Dmnl
Normalized price	np_j	$np_j = p_j \,/\, ((MAX(p_n)$ $with\ n = \{0, \ldots, 5\})$	Dmnl
Attractiveness	a_j	$a_j = \left(sf_j * ß_3\right) + \left(cf_j * ß_4\right) + \left(pc_j * ß_5\right)$	Dmnl
Market penetration	d_j	$d_j = \frac{V_j}{V}$	Dmnl
Total fleetsize	V	$V = \sum_{n=0}^{5} V_n$	Car
Normalized knowledge	nK_j	$nK_j = \frac{K_j}{MAX\ (K_j, an_j)}$	Dmnl

Initial Knowledge stock	K_{0j}	$K_{0j} = nK_j * M_{0j} * df$	Euro
Maturity gap	gap_j	$gap_j = 1 - M_j$	Dmnl
Potential adopters	PA	$PA = N - A$	Person
Total number of carsharing users	A	$A = A_c + A_{wc}$	Person
Fraction of cars per person	f_c	$f_c = \frac{V}{N}$	Car/person
Adoption rate carsharing	ar_{cs}	$ar_{cs} = g * PA * \frac{A}{N}$	Person/year
Adoption rate vehicle automation	$ar_{va,j}$	$ar_{va,j} = \frac{\sum_{s=0}^{j-1} s_{ij}}{V}$	1/year
Growth rate carsharing	g	$g = g_m + g_{va}$	1/year
Growth rate carsharing through vehicle automation	g_{va}	$g_{va} = IF\ THEN\ ELSE (M_j > 0.4, tm, 0)$	1/year
Change in vehicle fleetsize	cV	$cV = \frac{abr * f_c}{V}$	1/year
Cars per household		$chh = \frac{V}{hh}$	Car/household
Number of households	hh	$hh = \frac{N}{shh}$	Household
Total travel demand	td	$td = ptd * N$	Km/year
Distance traveled per car	tc	$tc = \frac{td}{V}$	Km/car/year

Table 26 Specification of the rates and auxiliaries

Overview parameters

Name	Notation	(Initial) Value	Unit	Uncertainty	Sensitivity
Initial Maturity Level 0	$M_{0,0}$	1	Dmnl	Low	Low
Initial Maturity Level 1	$M_{0,1}$	0,2	Dmnl	High	Low
Initial Maturity Level 2	$M_{0,2}$	0,2	Dmnl	High	Low
Initial Maturity Level 3	$M_{0,3}$	0,01	Dmnl	Medium	Low
Initial Maturity Level 4	$M_{0,4}$	0,0001	Dmnl	Low	Low
Initial Maturity Level 5	$M_{0,5}$	0,0001	Dmnl	Low	Low
Initial fleetsize Level 0	$V_{0,0}$	6.390.000	Car	Low	Low
Initial fleetsize Level 1	$V_{0,1}$	1000	Car	Medium	Low
Initial fleetsize Level 2	$V_{0,2}$	2	Car	Medium	Low
Initial fleetsize Level 3	$V_{0,3}$	2	Car	Low	Low
Initial fleetsize Level 4	$V_{0,4}$	2	Car	Low	Low
Initial fleetsize Level 5	$V_{0,5}$	2	Car	Low	Low
Initial Baseline price Level 0	$bp_{0,0}$	20.000	Euro/Car	Low	Low
Initial Baseline price Level 1	$bp_{0,1}$	30.000	Euro/Car	Low	Low
Initial Baseline price Level 2	$bp_{0,2}$	40.000	Euro/Car	Medium	Low
Initial Baseline price Level 3	$bp_{0,3}$	80.000	Euro/Car	Medium	Low
Initial Baseline price Level 4	$bp_{0,4}$	200.000	Euro/Car	High	Low
Initial Baseline price Level 5	$bp_{0,5}$	500.000	Euro/Car	High	Low
Initial price of retrofit Level 0	$rp_{0,0}$	0	Euro/Car	Low	Low
Initial price of retrofit Level 1	$rp_{0,1}$	1000	Euro/Car	Low	Low
Initial price of retrofit Level 2	$rp_{0,2}$	5000	Euro/Car	Medium	Low
Initial price of retrofit Level 3	$rp_{0,3}$	70.000	Euro/Car	Medium	Low
Initial price of retrofit Level 4	$rp_{0,4}$	200.000	Euro/Car	High	Low
Initial price of retrofit Level 5	$rp_{0,5}$	500.000	Euro/Car	High	Low
Initial car-share users	A_0	273	Person	Medium	Low
Initial population	N_0	15.900.000	Person	Low	Low
ß1 Weight Price	$ß_1$	0,5	Dmnl	High	Medium
ß2 Weight Attractiveness	$ß_2$	0,5	Dmnl	High	Medium
ß3 Weight Familiarity	$ß_3$	0,2	Dmnl	High	Low
ß4 Weight Comfort	$ß_4$	0,6	Dmnl	High	Low

ß5 Weight Safety	$ß_5$	0,2	Dmnl	High	Low
Comfort Level 0	cf_0	0	Dmnl	High	Low
Comfort Level 1	cf_1	0,1	Dmnl	High	Low
Comfort Level 2	cf_2	0,2	Dmnl	High	Low
Comfort Level 3	cf_3	0,5	Dmnl	High	Low
Comfort Level 4	cf_4	0,8	Dmnl	High	Low
Comfort Level 5	cf_5	1	Dmnl	High	Low
Safety Level 0	sf_0	0,01	Dmnl	High	Low
Safety Level 1	sf_1	0,4	Dmnl	High	Low
Safety Level 2	sf_2	0,4	Dmnl	High	Low
Safety Level 3	sf_3	0,3	Dmnl	High	Low
Safety Level 4	sf_4	0,7	Dmnl	High	Low
Safety Level 5	sf_5	1	Dmnl	High	Low
R&D percentage of annual earnings	*frd*	0,075	1/year	Medium	Medium
Annual knowledge stock depreciation rate	∂	0,1	1/year	High	Medium/Low
Depreciation factor of past knowledge	*df*	0,5	Dmnl	High	Low
Effectiveness of knowledge transfer	*ef*	0,5	1/year	High	Medium
Amount needed for full maturity Level 1	an_1	6 Billion	Euro	High	Low
Amount needed for full maturity Level 2	an_1	10 Billion	Euro	High	Low
Amount needed for full maturity Level 3	an_1	25 Billion	Euro	High	Low
Amount needed for full maturity Level 4	an_1	50 Billion	Euro	High	Low/Medium
Amount needed for full maturity Level 5	an_1	100 Billion	Euro	High	Low/Medium
Average lifetime of a car	α	10,4	Year	High	High
Logarithmic scale for learning-by-searching	Ω	10	Dmnl	Low	Medium
Logarithmic scale for learning-by-doing	ω	2	Dmnl	Low	Medium

Effect of increase in experience	*x*	0,05	Dmnl	Low	Medium
Effect of increase in maturity	*μ*	0,7	Dmnl	Low	Medium
Average household size	*shh*	2,2	Person/household	Low	Low
Daily travel demand per person	*ptd*	15,57	Km/day/person	Low	Low
Growth of car-sharing market	g_{cs}	0,2	1/Year	High	High
Technology multiplier	*tm*	0,2	1/Year	High	Medium
Percentage of car shedding among car share users	*sh*	0,23	Car/person	High	Low

Table 27 Full overview of parameters with input values for the Base Run

Appendix C. Results uncertainty analysis

Fleetsize level 3 over uncertainty range Comfort (left column) and Safety (right column)

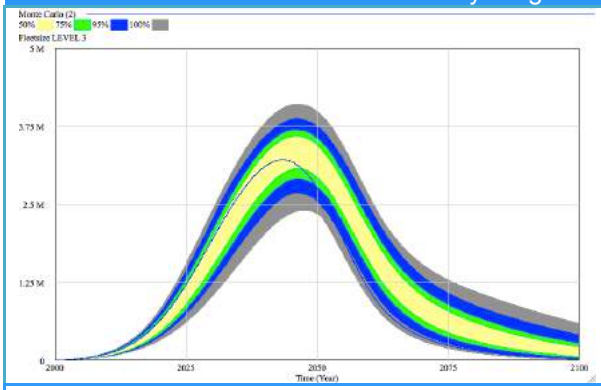


Figure 68 Fleetsize level 3 over uncertainty range parameter: 'Comfort'

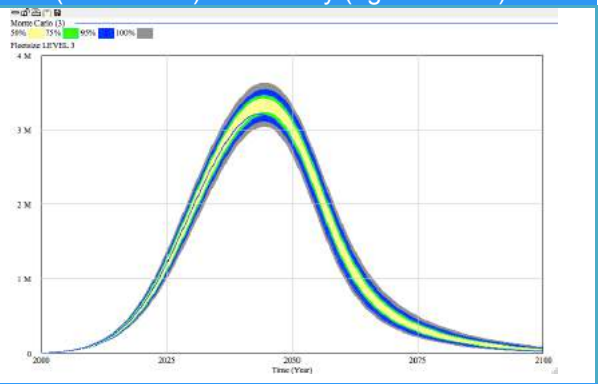


Figure 69 Fleetsize level 3 over uncertainty range parameter: 'Safety'

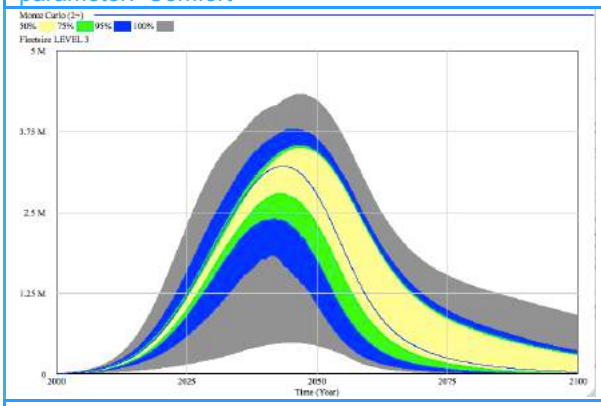


Figure 70 Fleetsize level 3 over uncertainty range parameter: 'Comfort' + 'Weight Price' + 'Weight Comfort'

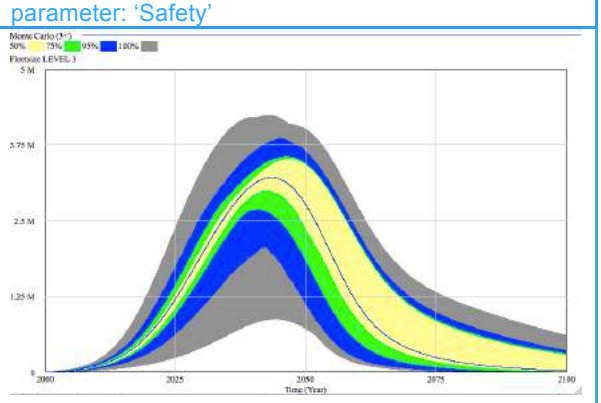


Figure 71 Fleetsize level 3 over uncertainty range parameter: 'Safety' + 'Weight Price' + 'Weight Comfort'

Fleetsize level 4 over uncertainty range Comfort (left column) and Safety (right column)

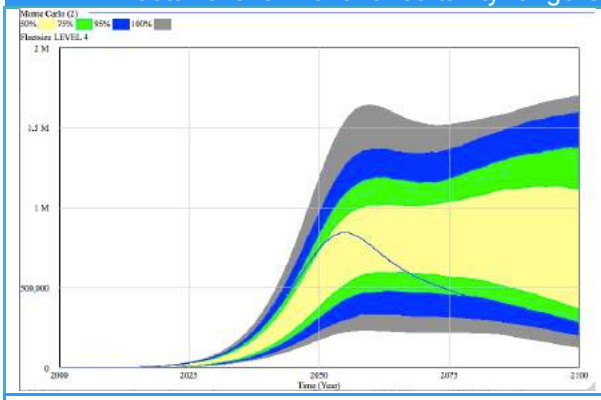


Figure 72 Fleetsize level 4 over uncertainty range parameter: 'Comfort'

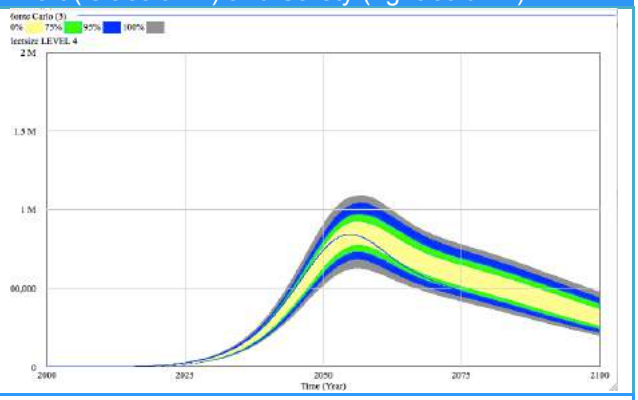


Figure 73 Fleetsize level 4 over uncertainty range parameter: 'Safety'

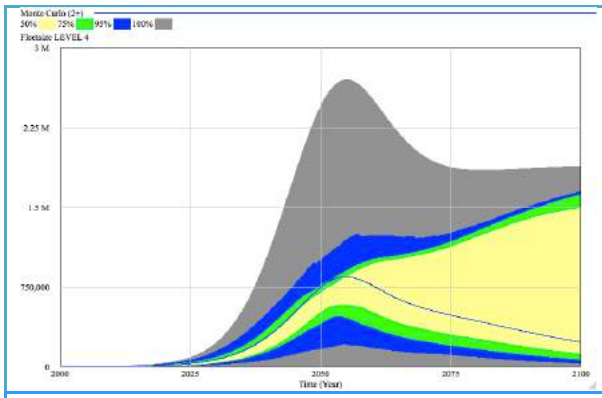


Figure 74 Fleetsize level 4 over uncertainty range parameter: 'Comfort' + 'Weight Price' + 'Weight Comfort'

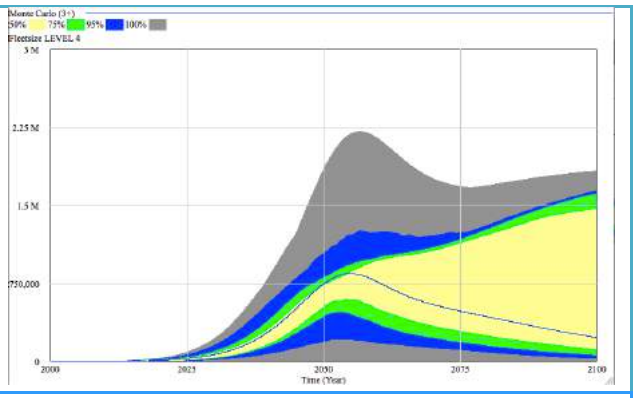


Figure 75 Fleetsize level 4 over uncertainty range parameter: 'Safety' + 'Weight Price' + 'Weight Comfort'

Fleetsize level 5 over uncertainty range Comfort (left column) and Safety (right column)

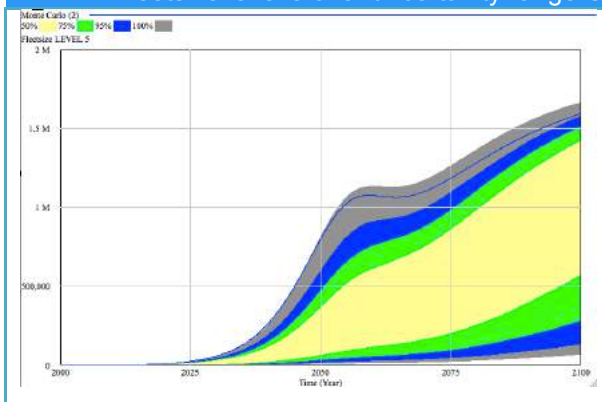


Figure 76 Fleetsize level 5 over uncertainty range parameter: 'Comfort'

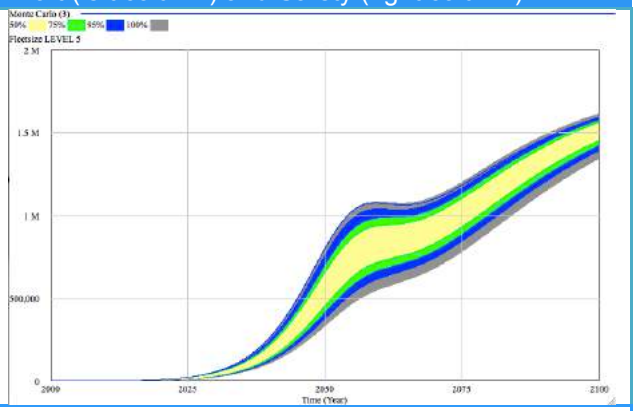


Figure 77 Fleetsize level 5 over uncertainty range parameter: 'Safety'

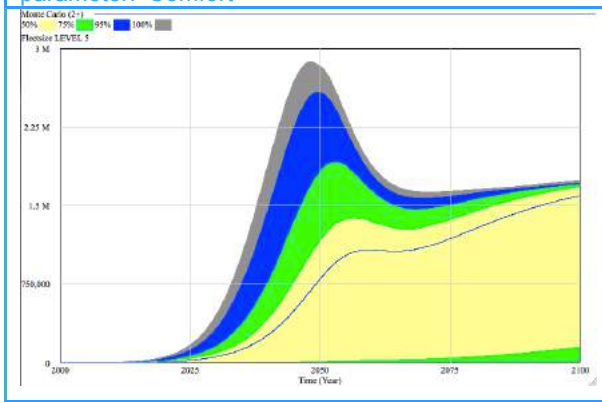


Figure 78 Fleetsize level 5 over uncertainty range parameter: 'Comfort' + 'Weight Price' + 'Weight Comfort'

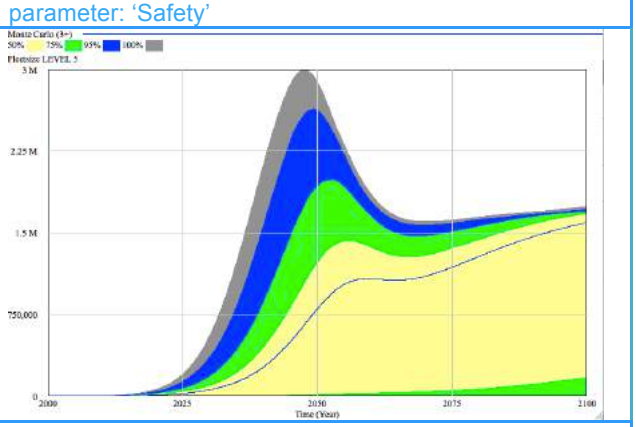


Figure 79 Fleetsize level 5 over uncertainty range parameter: 'Safety' + 'Weight Price' + 'Weight Comfort'

Appendix D. Scenario AV in Bloom

Parameters

Name	Notation	Original value	Changed value in scenario run	Unit
Initial Maturity Level 0	$M_{0,0}$	1		Dmnl
Initial Maturity Level 1	$M_{0,1}$	0,2	0,4	Dmnl
Initial Maturity Level 2	$M_{0,2}$	0,2	0,3	Dmnl
Initial Maturity Level 3	$M_{0,3}$	0,01	0,1	Dmnl
Initial Maturity Level 4	$M_{0,4}$	0,0001	0,001	Dmnl
Initial Maturity Level 5	$M_{0,5}$	0,0001	0,001	Dmnl
Initial fleetsize Level 0	$V_{0,0}$	6.390.000	7.902.290	Car
Initial fleetsize Level 1	$V_{0,1}$	1000	30000	Car
Initial fleetsize Level 2	$V_{0,2}$	2	1000	Car
Initial fleetsize Level 3	$V_{0,3}$	2		Car
Initial fleetsize Level 4	$V_{0,4}$	2		Car
Initial fleetsize Level 5	$V_{0,5}$	2		Car
Initial Baseline price Level 0	$bp_{0,0}$	20.000		Euro/Car
Initial Baseline price Level 1	$bp_{0,1}$	30.000	25.000	Euro/Car
Initial Baseline price Level 2	$bp_{0,2}$	40.000	35.000	Euro/Car
Initial Baseline price Level 3	$bp_{0,3}$	80.000	50.000	Euro/Car
Initial Baseline price Level 4	$bp_{0,4}$	200.000	180.000	Euro/Car
Initial Baseline price Level 5	$bp_{0,5}$	500.000	300.000	Euro/Car
Initial price of retrofit Level 0	$rp_{0,0}$	0		Euro/Car
Initial price of retrofit Level 1	$rp_{0,1}$	1000		Euro/Car
Initial price of retrofit Level 2	$rp_{0,2}$	5000		Euro/Car
Initial price of retrofit Level 3	$rp_{0,3}$	70.000		Euro/Car
Initial price of retrofit Level 4	$rp_{0,4}$	200.000	100.000	Euro/Car
Initial price of retrofit Level 5	$rp_{0,5}$	500.000	300.000	Euro/Car
Initial car-share users	A_0	273	16.000	Person
Initial population	N_0	15.900.000	16.829.289	Person
ß1 Weight Price	$ß_1$	0,5		Dmnl
ß2 Weight Attractiveness	$ß_2$	0,5		Dmnl
ß3 Weight Familiarity	$ß_3$	0,2		Dmnl

ß4 Weight Comfort	$ß_4$	0,6	Dmnl
ß5 Weight Safety	$ß_5$	0,2	Dmnl
Comfort Level 0	cf_0	0	Dmnl
Comfort Level 1	cf_1	0,1	Dmnl
Comfort Level 2	cf_2	0,2	Dmnl
Comfort Level 3	cf_3	0,5	Dmnl
Comfort Level 4	cf_4	0,8	Dmnl
Comfort Level 5	cf_5	1	Dmnl
Safety Level 0	sf_0	0,01	Dmnl
Safety Level 1	sf_1	0,4	Dmnl
Safety Level 2	sf_2	0,4	Dmnl
Safety Level 3	sf_3	0,3	Dmnl
Safety Level 4	sf_4	0,7	Dmnl
Safety Level 5	sf_5	1	Dmnl
R&D percentage of annual earnings	*frd*	0,075	1/year
Annual knowledge stock depreciation rate	∂	0,1	1/year
Depreciation factor of past knowledge	*df*	0,5	Dmnl
Effectiveness of knowledge transfer	*ef*	0,5	1/year
Amount needed for full maturity Level 1	an_1	6 Billion	Euro
Amount needed for full maturity Level 2	an_1	10 Billion	Euro
Amount needed for full maturity Level 3	an_1	25 Billion	Euro
Amount needed for full maturity Level 4	an_1	50 Billion	Euro
Amount needed for full maturity Level 5	an_1	100 Billion	Euro
Average lifetime of a car	*a*	10,4	Year
Logarithmic scale for learning-by-searching	Ω	10	Dmnl
Logarithmic scale for learning-by-doing	ω	2	Dmnl
Effect of increase in experience	*x*	0,05	Dmnl
Effect of increase in maturity	μ	0,7	Dmnl
Average household size	*shh*	2,2	Person/household
Daily travel demand per person	*ptd*	15,57	Km/day/person
Growth of car-sharing market	g_{cs}	0,2	Dmnl
Technology multiplier	*tm*	0,2	1/Year
Percentage of car shedding among car share users	*sh*	0,23	Car/person

Table 28 Parameter settings for scenario AV in Bloom

Results

Maturity of automated vehicles in AV in bloom scenario

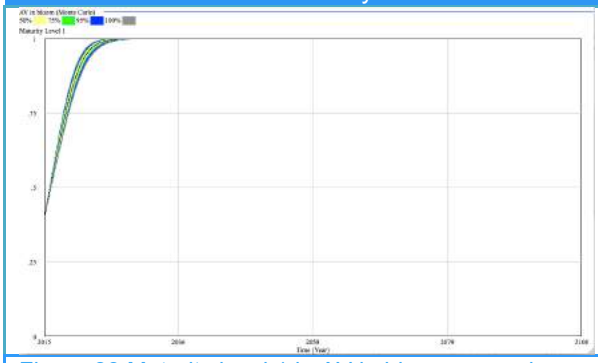


Figure 80 Maturity level 1 in AV in bloom scenario

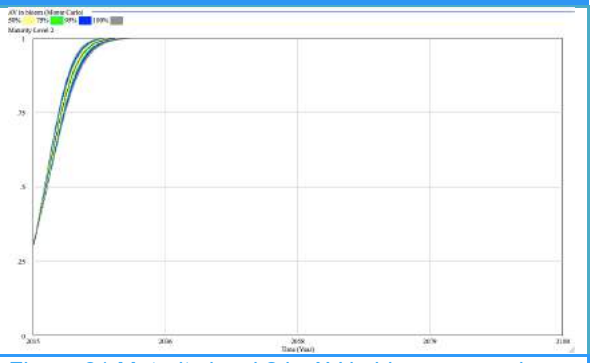


Figure 81 Maturity level 2 in AV in bloom scenario

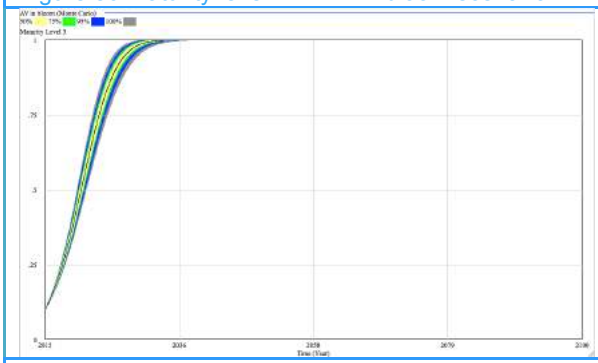


Figure 82 Maturity level 3 in AV in bloom scenario

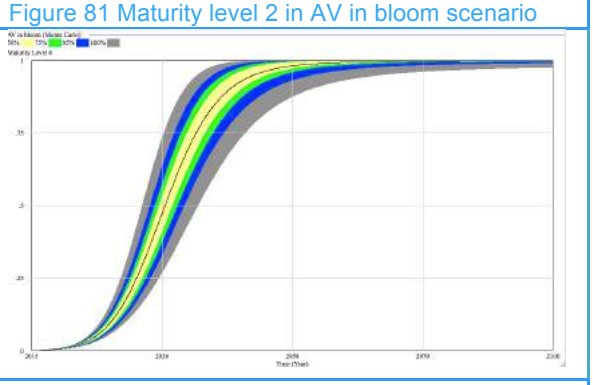


Figure 83 Maturity level 4 in AV in bloom scenario

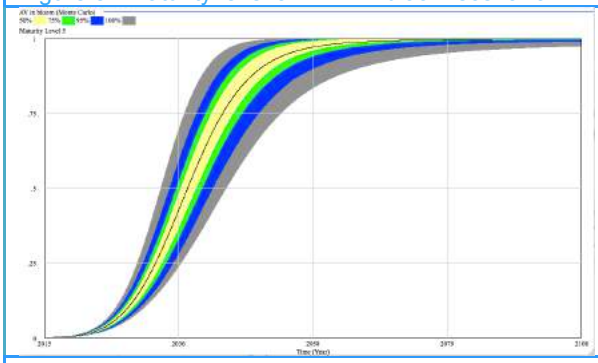


Figure 84 Maturity level 5 in AV in bloom scenario

Purchase price of automated vehicles in AV in bloom scenario

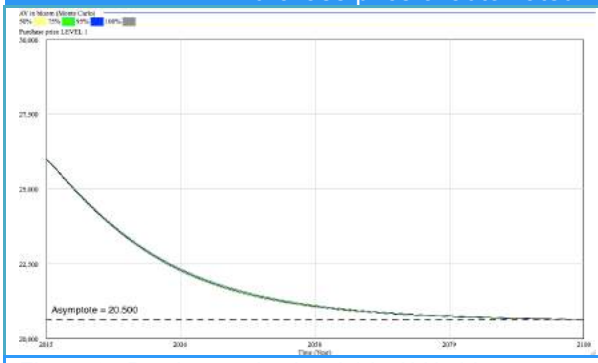


Figure 85 Purchase price level 1 in AV in bloom scenario

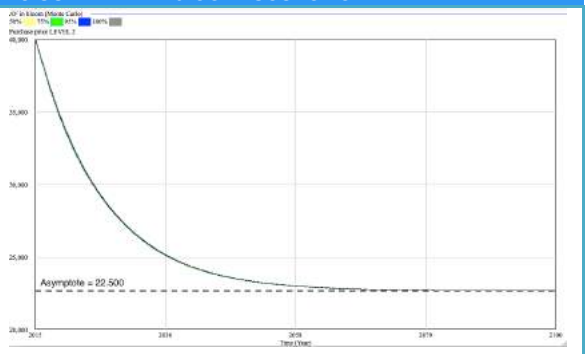


Figure 86 Purchase price level 2 in AV in bloom scenario

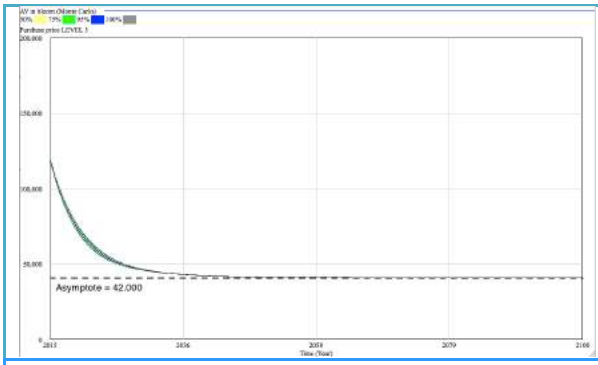


Figure 87 Purchase price level 3 in AV in bloom scenario

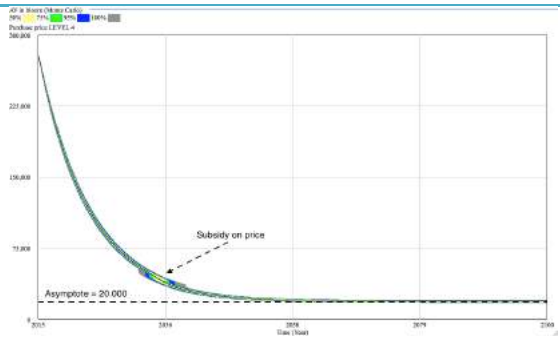


Figure 88 Purchase price level 4 in AV in bloom scenario

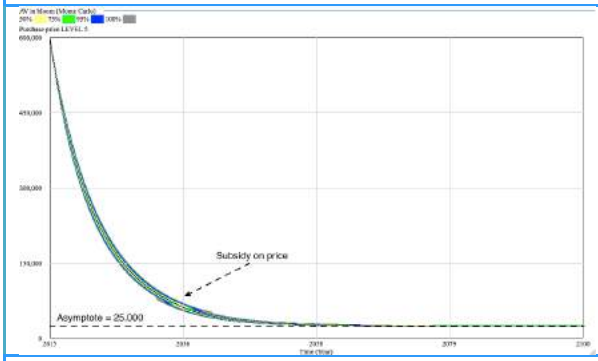


Figure 89 Purchase price level 5 in AV in bloom scenario

Adoption rate of automated vehicles in AV in bloom scenario

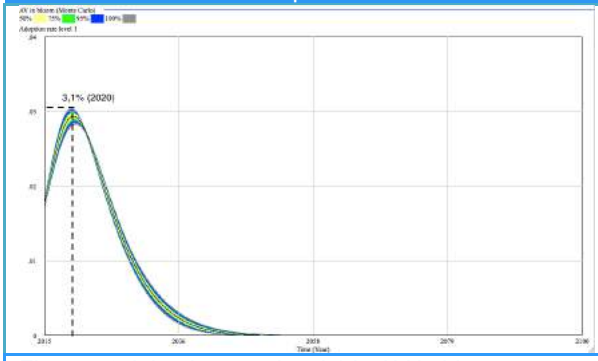


Figure 90 Adoption rate level 1 in AV in bloom scenario

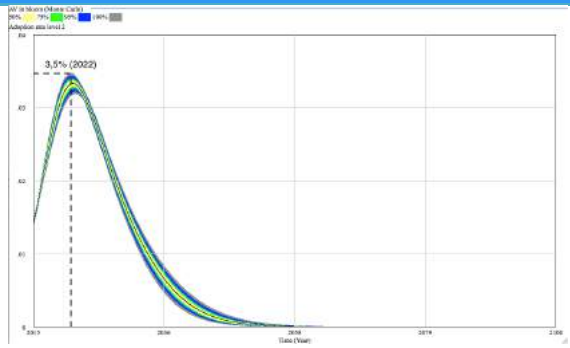


Figure 91 Adoption rate level 2 in AV in bloom scenario

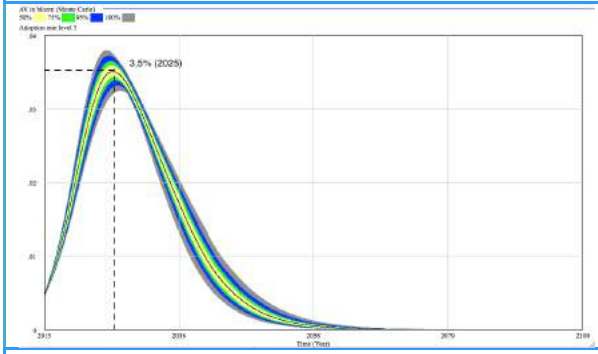


Figure 92 Adoption rate level 3 in AV in bloom scenario

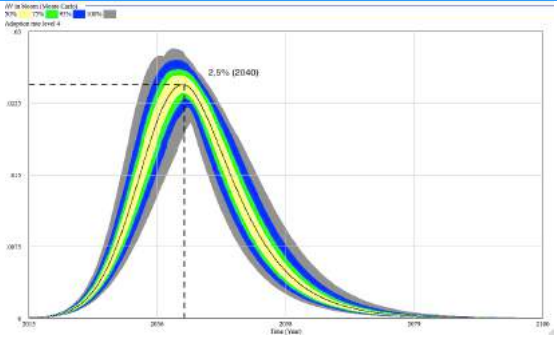


Figure 93 Adoption rate level 4 in AV in bloom scenario

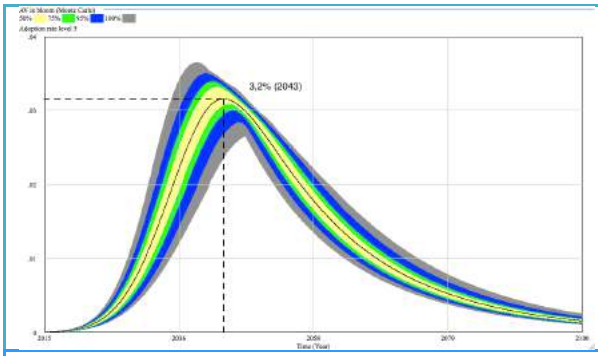


Figure 94 Adoption rate level 5 in AV in bloom scenario

Market penetration of automated vehicles in AV in bloom scenario

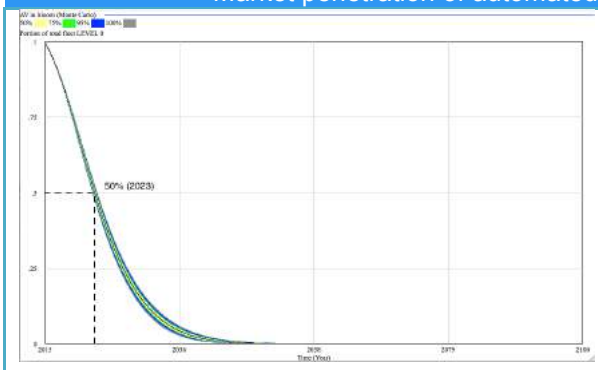


Figure 95 Market penetration level 0 in AV in bloom scenario

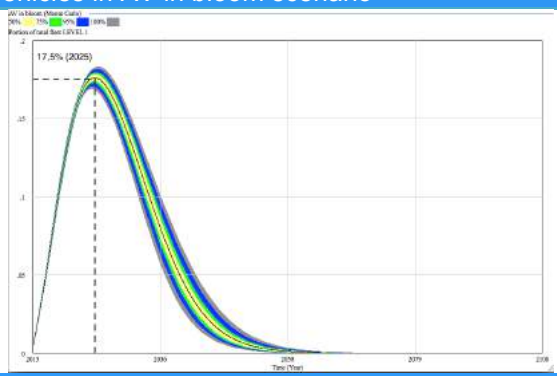


Figure 96 Market penetration level 1 in AV in bloom scenario

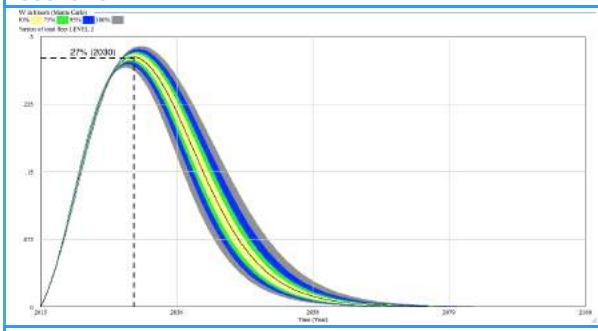


Figure 97 Market penetration level 2 in AV in bloom scenario

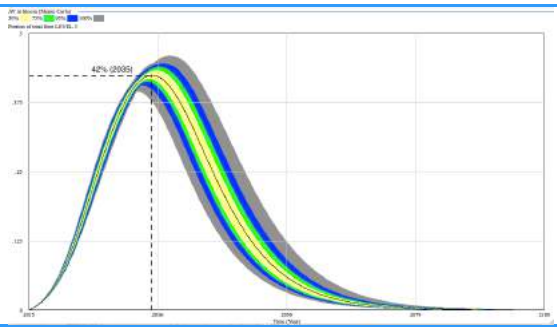


Figure 98 Market penetration level 3 in AV in bloom scenario

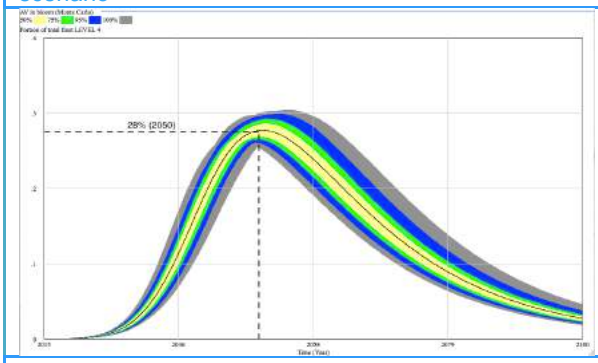


Figure 99 Market penetration level 4 in AV in bloom scenario

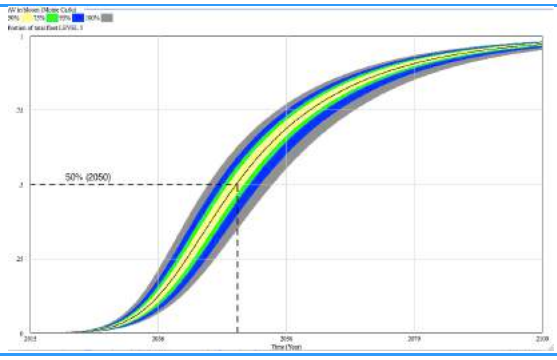


Figure 100 Market penetration level 5 in AV in bloom scenario

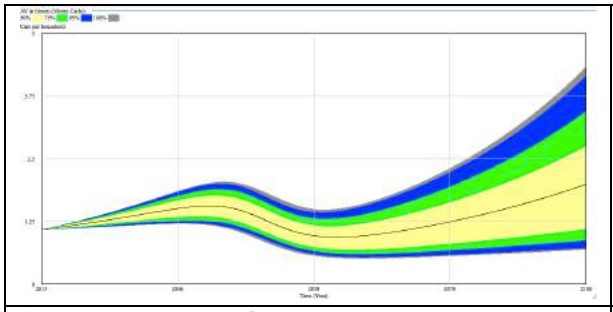


Figure 101 Number of cars per household in AV in bloom scenario

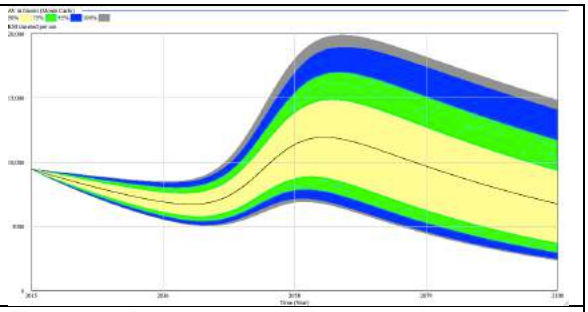


Figure 102 Distance traveled per vehicle in AV in bloom scenario

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
40% maturity	-	2015	2017	2020	2033	2036
95%-100% maturity	-	2025	2025	2030	2060	2060
1% adoption rate	-	<2015	<2015	2017	2030	2030
>3% adoption rate	-	2020	2020 - 2025	2020 - 2030	-	2040 – 2045
Maximum adoption rate	-	2020	2022	2025	2040	2043
10% market penetration (growing)	-	2020	2020	2023	2036	2033
30% market penetration (growing)	-	-	-	2028	-	2042
Maximum market penetration	2015	2025	2030	2035	2050	2100

Table 29 Milestones of vehicle automation in AV in bloom scenario

Appendix E. Questionnaire

The questionnaire was used as a guideline for a semi-structured interview with a selection of experts. The questionnaire had textual explanation, so it could be filled in individually. The questionnaire was designed to be filled in during a taped interview so that the interviewer could make notes on the comments that were placed during the answers.

The questionnaire is a combination of multiple choice, open numerical questions and questions to draw certain trajectories of graphs.

Q1 Fleetsize of cars

"Estimate the growth, steadiness or shrinkage of the total fleetsize (automation and no automation) of cars in the US over a vast period of time, from 2000 to 2100. The year 2000 has been used as an index. Since 2000 the fleetsize has been growing with 3% per year."

A. Steady growth of fleetsize
B. No change in fleetsize since 2015
C. Slight decreasing fleetsize
D. Strong decreasing fleetsize
E. Other. Draw your own estimation in the graph below.

This question can be used to validate the model behavior after simulation runs.

Q2 Effect of car sharing on car ownership

"Imagine car-owner "Rene" has just discovered car-sharing and is now a frequent user of car-sharing services. In your opinion, what is the likelihood that Rene will change his car-ownership in the next coming year?"

- Low probability of buying an extra car (0-15%)
- No change in car-ownership
- Low probability of abandoning his/her car (0-15%)
- High probability of abandoning his/her car (15-50%)
- Very high probability of abandoning his/her car (>50%)

This value can be used to estimate the model parameter value of the effect of car sharing on the ownership rate. The question was beforehand tested in a more generic way in which the interviewee was asked to estimate the effect of car sharing on ownership. This question was easily misunderstood and therefore the question was changed for the real interviews. The question that was used was framed in a personal sense towards 'car owner Rene' so that people could more easily relate to the question. The name Rene was chosen, as this could be either male or female. This excluded the aspect of gender from the question.

Q3 Purchase price automated vehicles

"In your observation, what are the current (2015) average purchase prices of vehicles according to SAE levels of automation."

- Level 0 $21.000
- Level 1 $.....
- Level 2 $.....
- Level 3 $.....
- Level 4 $.....

- Level 5 $.....

These values can be used to estimate the initial values of the purchase price within the model.

Q4 Purchase price automated vehicles (2000 – 2050)
"Please draw the trajectory of the purchase price of Level 5 you expect in the upcoming decades."

This question is related to the previous question. It shows the behavior of the price over time. The interest in this question is not so much to see the exact values over time, as it is more to see the chosen trajectories and the shape that expert give to graph of the price over time.

Q5 Price of Level 5 vehicle at market introduction
"What is an acceptable price of a level 5 vehicle during market introduction for mass adoption."

- <$20.000
- $20.000 - $30.000
- $30.000 - $40.000
- $40.000 - $60.000
- $60.000 - $80.000
- >$80.000

This question was chosen to use during validation of the model. The price during mass adoption in the simulation runs can be compared with the answers by the experts on this question.

Q6 Market penetration of automated vehicles over time (2000-2100)
"Please draw the trajectories of all the levels (0, 1, 2, 3, 4, 5) you expect in the upcoming decades."

On the y-axis a percentage of the total market was indicated. The x-axis showed the years 2000 – 2100. The graph already showed a line with the market adoption of level 0, level 1 and level 2 in the period 2000 – 2005. This market adoption line was assumed very roughly and was meant as a rough starting point and guideline for the interviewee. The interviewee was asked to fill in the lines for level 0, 1, 2, 3, 4 and 5. In total the lines of all levels at any given moment should add up to 100%. Nevertheless the shape of the curves is more important than the actual value as it is very hard for people to handle the sum of 6 dynamic lines over time to add up to 100%.

Q7 Effect of vehicle automation on carsharing
"In your opinion: What will be the impact on the car-sharing market, when the adoption rate of automated vehicle of SAE Level 5 ("Robot taxis") rises with 10%:"

- Car-sharing market drops with more than 10% (non-linear effect)
- Car-sharing market drops by 10% (linear effect)
- No effect
- Car-sharing market grows with 10% (linear effect)
- Car-sharing market grows with more than 10% (non-linear effect)

This value can be used to estimate the parameter of the effect of level 5 automation on the growth of the car-sharing market.

Q8 Usefulness of time inside a car

"Much has been said about the benefits of automated vehicles. The level of comfort and productivity that can be experienced while traveling in an automated vehicle is among one of those benefits. The time people spent in a car can be dedicated on useful things because people do not have to spent time watching the road or handling the steering wheel.

Indicate the scale of usefulness of time in a car compared, between the SAE levels of automation (from 0 - 10)"

Rating usefulness of time

	0	1	2	3	4	5	6	7	8	9	10
Level 0 - No automation	○	○	○	○	○	○	○	○	○	○	○
Level 1 - Driver assistance	○	○	○	○	○	○	○	○	○	○	○
Level 2 - Partial automation	○	○	○	○	○	○	○	○	○	○	○
Level 3 - Conditional automation	○	○	○	○	○	○	○	○	○	○	○
Level 4 - High automation	○	○	○	○	○	○	○	○	○	○	○
Level 5 - Full automation	○	○	○	○	○	○	○	○	○	○	○

This question can be used to estimate the parameters for comfort in the simulation model. At first hand the explanation of the question indicated a level of comfort. It was thereafter chosen not to communicate 'comfort' but to communicate 'usefulness of time' because comfort could also be associated with luxury, which was not the appropriate association for this question.

Q9 Annual revenue earnings of vehicle automation in total global market

"The vehicle automation global market is indicated as sales x market price of all ADAS systems, ITS applications, V2X communication technologies and autonomous vehicles worldwide. Please draw the trajectory you expect in the upcoming decades and indicate the values on the y-axis."

This question asked to draw the trajectory of the total market size over the period 2000 – 2050. The y-axis was kept blank to let the interviewee interpret the total market value himself.

Q10 Percentage to R&D

"What percentage of the total annual revenue is generally spent in the market on R&D of vehicle automation each year?"

This question was first meant in order to get to know the general R&D expenditure in the automotive market. Later on it was discovered that an additional question could be added of 'how much percentage of the total R&D expenditure was allocated to vehicle automation".

Technology maturity

"To indicate the development of the vehicle automation technology the term "technology maturity" is used.

"A mature technology is a technology that has been in use for long enough that most of its initial faults and inherent problems have been removed or reduced by further development. In some contexts, it may also refer to technology that has not seen widespread use, but whose scientific background is well understood"

In this research the technology maturity is indicated on a scale from 0 - 100%. A technology that touches 100% maturity is available for widespread commercial use.

Please indicate which (shape) trajectory of the technology maturity do you expect most likely to occur."

In this question the experts were asked to reflect on the appropriate shape of a maturity curve.

Appendix F. Experts

Overview of experts

For the semi-structured interviews a selection of expects was asked to comment on the questions in the questionnaire. The interviews were approximately 20 minutes long and were held at the Automated Vehicle Symposium in Ann Arbor from July 21 until July 24 2015. This location and symposium was chosen as this is regarded as a very prestigious conference where a lot of top experts are present. This density of top experts made it very time efficient to conduct the interviews. Due to time constraints of some people, not all people could answer all the questions.

All experts represent the vehicle automation industry and knowledge institutes. Researchers from various knowledge institutes that were interviewed were either expert in transportation, human factors and/or vehicle automation. Experts from the industry are all highly influential people with a broad overview in their sector like the head of R&D continental, member of executive board of directors Porsche Holding and director Google car.

Name	Country	Function	Description
David Agnew	Michigan, USA	Head of R&D Continental Automotive	Industry leader with knowledge on technology development and R&D expenditure within large corporations.
Adriano Alessandrini	Italy	Project lead City2Mobil	Mr. Alessandrini has experience with the deployment of various automated urban transit projects in Italy and other countries.
Richard Bishop	Maryland, USA	Bishop Consulting	Highly recognized expert of vehicle automation and chair of a TRB subcommittee
Tallis Blalack	California, USA	Tech-to-Market Advisor	Mr. Blalack is an expert in the process of bringing technology to market.
Bob Denaro	California, USA	Former Vice President Motorola and Nokia/Navteq	Private Consultant in Intelligent Transportation Systems technology and strategy. Mr. Denaro is currently chair of the TRB Joint Subcommittee on Vehicle Automation.
Maxime Flament	Belgium	Head of Sector Safe Mobility - Ertico / ITS Europe	Manager ITS Europe and experience in the policy implementation of automated vehicle and ITS related projects.
Chris Gerdes	California, USA	Assistant Professor Stanford University	Expert on the field of ethics in automated vehicles. Has been closely involved with the test track of Stanford University that is used for test drives of automated vehicles.
Philipp von Hagen	Germany	Member of executive board Porsche SE	Philipp von Hagen is responsible for investment management of Porsche. Porsche Holding owns 50.7% of the shares of Volkswagen Holding, which holds brands like Seat, Audi, VW, Skoda, Bugatti, Lamborghini, Scania and MAN. Philipp von Hagen is also director at INRIX, a data storage platform for connected cars.

Larry Head	Arizona, USA	Professor University of Arizona	Professor of transportation with experience in system engineering methodology
Alain Kornhauser	New Jersey, USA	Professor Princeton University	Expert with a long track record in the field of vehicle automation
Miltos Kyriakidis	Greece	Assistant Professor Delft University of Technology	Research expert in human factors related to automated driving
John Maddox	Michigan, USA	Director collaborative programs UMTRI	Started a program of $100M in Michigan to improve vehicle automation through testing facilities.
Glenn Mercer	Cleveland, USA	President at GM Automotive	Mr. Mercer is an expert in private investments in the vehicle automation domain.
Brian Park	South Korea	Associate professor University of Virginia	Research expert in transportation safety and connected vehicle applications.
Nick Reed	United Kingdom	Academy Director TRL (Transportation Research Lab)	In charge of the GATEway (Greenwich Automated Transport Environment) project – a flagship UK Government project to investigate the implications of the introduction of automated vehicles in the urban environment.
Constantine Samaras	Pennsylvania	Assistant Professor Carnegie Mellon University	One of the co-authors of the RAND report
Steven Shladover	California, USA	Director PATH	Dr. Shladover's work is widely recognized internationally, and he has held many leadership positions in transportation related organizations. He chairs the TRB Committee on Vehicle-Highway Automation
Chris Urmson	California, USA	Director automated car Google	Head of the automated vehicle program of Google with over 100 people working in his team on R&D
Joop Veenis	The Netherlands	Rijkswaterstaat	Expert on knowledge transfer and innovation management within the field of ICT and transportation
Mohammed Yousuf	Washington, USA	Transportation specialist U.S. Federal Highway Administration	Did a research for the US DOT on enabling technologies of vehicle automation.

Table 30 Overview of experts that have been interviewed at the AVS 2015

Additional comments

David Agnew

Technology development

You got your expenditure the money comes in, now you are ready to start developing. But the bottleneck is talent in certain areas. As the market is rising, the talent gets more scarcity. A bigger proportion of your money goes up to talent. The money is there, it is just harder to get the same results done with the same money. It is a rapidly changing area, the engineering that has to be done to get an automated vehicle on the road. There are a lot of areas that are very different, and it hasn't been done in the past. You have machine learning, artificial intelligence, the visual imaging, machine vision and so on. Some of these things have been done in the past for

robotics and other types of industry. But now we have to take these things up a few orders of magnitude higher in order to contextualize the surroundings for the vehicles on the road. A lot of these things are new and hasn't been taught on schools yet. So there is a lag of talent there, and the industry will have to cope with this.

Enabling technologies

How do you see all those enabling technologies like perception, localization, communication, processing come together in one vehicle? David Agnew thinks that connectivity will not have to be a key feature. As cyber security is a very risky bottleneck that is not being solved yet. So as long as cyber security remains to be a problem, the deployment of connected vehicle will not happen. So automated vehicles will have to rely on their own sensors instead of communication with other vehicles and infrastructure. Communication is not needed for autonomous. A key bottleneck is vision capabilities. The sensors are very strong, the processors are very strong and they are growing with the rate of Moore's law So within a few years, this hardware is not even an issue anymore. The issue is the engineering work that it takes, to build and teach clever algorithms that can process all this data into valuable information. The software will therefor be a huge bottleneck. Getting all these difficult methodologies that the brain uses into this software. MobilEye from Israel seems to be way ahead of everybody. The sensors are there, but the software, to utilize that data real-time is a bottleneck. It takes good software and time. Time to be on the road, get a lot of miles and build new tools and simulation tools. It is a slow process.

Budget allocated on levels

Would it make sense to split these enabling technologies into the different SAE levels? And does the industry also see these different levels and divide their budget among these different levels to develop the technologies? It appears to be in the traditional auto industry this seems to be the case. Going stepwise from ADAS, active safety systems towards more advanced automation. Google says this might be the wrong way to go, as you have to go right into level 5. You go right to it, develop your requirements and tools to go full autonomous and then go right after it. Everybody seems to be deciding on which level he or she wants to be working on. If you have enough budget you might even work on various levels. Most are focusing on the level that they are going after.

Industry decides upon their R&D expenditure based on the potential market of the level of automation that they are going after. That is the main driver for the industry.

Percentage of R&D

For every company there is a certain percentage of their sales or revenue that they put in R&D. In general that is about 5%-10%. But then of that budget the level that is going into autonomous vehicles and vehicle automation is definitely a larger number that it is 5 years ago. Even as it is hard to predict what the real moneymaker is going to be, still there is a huge awareness, even in the traditional auto industry, that the market is going to emerge, change and shift and maybe be misunderstood initially, but it is being recognized as so big that we going after it, in one form or another.

The way we see this market is safety. It is the number one cause of death, it is a huge amount and nobody talks about it. It is crazy. It is like a jumbo jet falling out of the sky every day. It is disperses and therefore we don't see it anymore. If we can come up with autonomous solutions that the customer wants, but also is going to increase safety while you go from point A to point B, that is what we are going after.

Value proposition

The safety has to be included. What we are selling is to get you from point A to point B, and when it comes to safety it has to be recognized that you get all these other

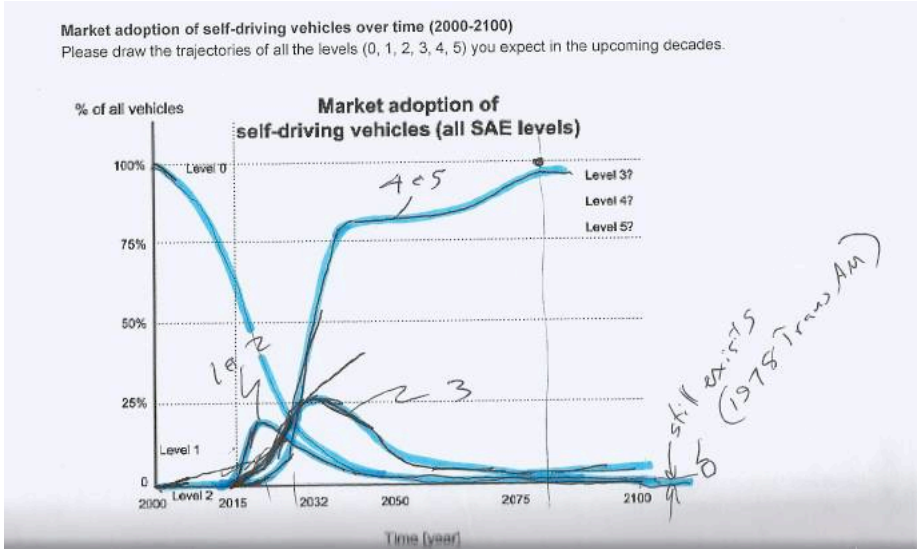
things with it. You get extra free time inside the car, it releases the stress in traffic and the costs decrease. So if you give people the safety and at the same time give them all the other benefits: that is the value proposition.

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	0	2	2	4	9	10

Table 31 Estimation of comfort by David Agnew

Market adoption of automated vehicles

Eventually you will have level 4 & 5 as the full market. Level 1 and 2 is coming earlier and having some adoption. That level 3 in 2015 is marginal and than will come up but will fall shortly at the end. Level 3 is for people that want to have some comfort, but want to drive themselves as well. But level 4 and 5 will drive you everywhere. Some people will still want to drive: for the sport of it or as a recreational thing. At the end we will still be having those level 0 old timer classics like the 1987 Trans Am, as my daughter we get my car and will keep it on the road.



Adriano Alessandrini

Adriano Alessandrini believes we need slow automated vehicles on dedicated roads. The infrastructure needs to be adapted if needed to secure safety for vulnerable traffic users.

Adriano Alessandrini sees two transition pathways. “Either we will have private cars taking over all transit, or we will have transit in all urban areas if this can be adopted fast enough. If automated transit services cannot be adopted fast enough, in his opinion people will be choosing for a private car with private ownership. This privately owned car should be less than €30.000 for mass adoption. “Currently these level 4 vehicles cost more than €120.000 and a minibus + driver costs even €200.000 as in the city2mobil project, so we still have a long way to go.” Adriano Alessandrini expects the current price to drop towards €30.000 within the upcoming 7 years.

The comfort experienced inside an automated vehicle is like airplane entertainment according to Adriano Alessandrini. If you still have the driver in the loop than the comfort will be very less, but once the drivers can put the car on highway automation pilot the comfort will be around 4 – 7 on a scale of 0 to 10.

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	0	1	1	5	9	10

Richard Bishop

Fleetsize
Vehicle automation will cause a decrease in the fleetsize but an increase in the miles travel per vehicle. The fleetsize will continue to increase, but then around 2070 it will drop dramatically due to automation and car sharing. Car sharing will have a very high impact on the fleetsize as it is a huge societal change. It could go fast, or it could get into a snowball effect and go very fast.

Car sharing
Automation will have an effect on car sharing as well. "People own cars on a just in case basis. They own very big vehicles just in case they have to carry 6 people around. Some own a SUV just in case they have to carry something big from the hardware store. If that trend could be shifted where you can order a vehicle just for 1 person if you need it, or a vehicle for 6 people if you need it, that will have a huge societal impact. Of course this ordering of vehicles is already possible, where you have somebody just delivering your vehicle if you order it. But that is just too expensive and vehicle automation will make this economically feasible. That is how automation will change the market of car sharing."

"Automation is like a Uber without the driver. It will change the cost profile of car-sharing and therefore change the business model."

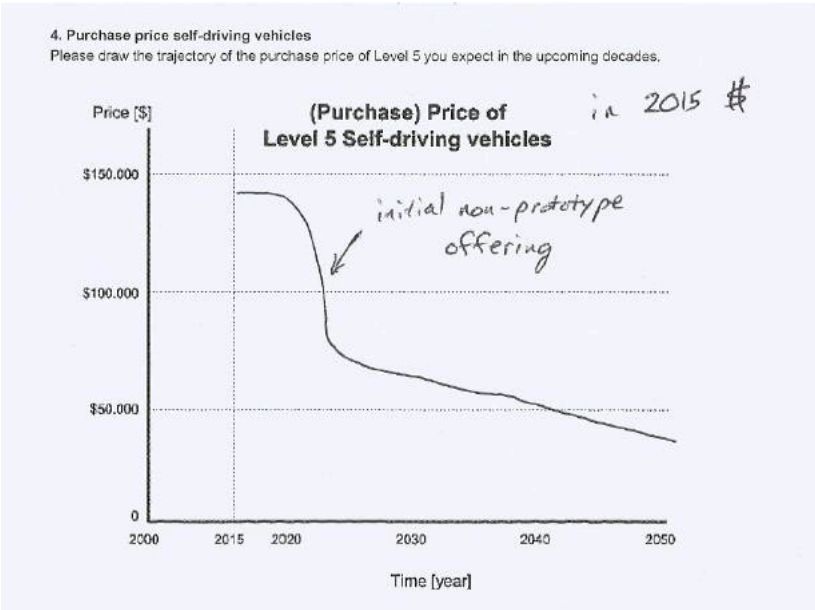
Market adoption
By 2050 all cars will be level 4 or level 5 according to Richard Bishop. Level 1 is out there on the road right now. There will be level 1 and 2 and 3 on the road simultaneously. The adoption rate is mimicking each other. "Level 4 and 5 will hit the market before 2030." Level 4 and 5 will be the main vehicles on the road. The type of ownership and mobility as a service will be a mix.

Value proposition
People will have time and money to spend on other things due to vehicle automation. There will be no time costs to live 2 hours from your work. People would be willing to buy the level 4 vehicles for roughly $60.000.

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	0	0	2	6	8	10

Tallis Blalack
Level 1 vehicles are currently priced around $21.000 as they are just regular cars with these ABS and CC features in them. Level 2 vehicles are currently about $40.000 as vehicles with ACC and Lane Keeping Assistance. The level 3, 4 and 5 vehicles you can't buy currently.

It won't take until 2030 when the first level 5 prototype will initially come on the market as is shown in Figure 103. The price will then decrease to $30.000 according to Tallis Blalack.



Tallis Blalack assumes that most vehicles that are on the market today are higher than level 0 as they are equipped with an anti-lick braking system (ABS) and electronic stability control (ESC). These vehicles are regarded as level 1. Tallis foresees a quick rise of level 2 vehicles with an 80% market share around 2035. Level 3, 4 and 5 will make their market introduction in about the same time frame between 2020 and 2030. Overall Tallis predicts that level 5 will gain most market share with 80%. The remaining 20% market share will be level 3 vehicles.

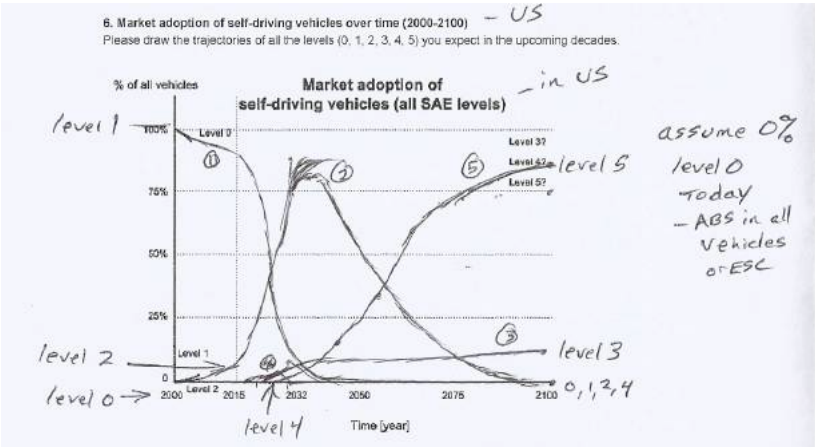


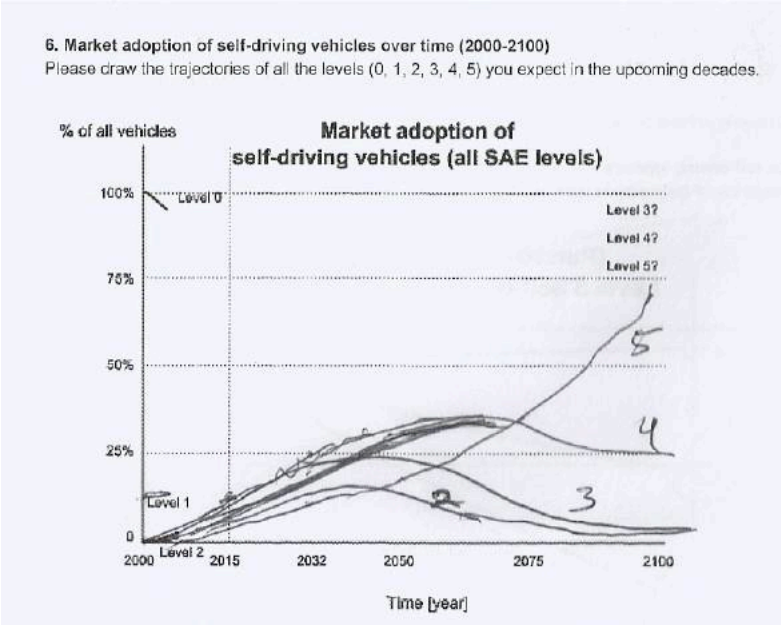
Figure 103 Development of the price of level 5 vehicles according to Tallis Blalack

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	2	2	3	4	6	7

Bob Denaro

Bob Denaro expects that for vehicle automation of level 1 – 3 'safety' will be the dominant value proposition for people. Vehicle automation of level 1 to 3 is mainly characterized by ADASs and safety features in more luxurious cars. For the levels 4 & 5 'Productivity' of 'Comfort' will be the main value proposition. This way Bob Denaro gives a clear distinction between levels 1 – 3 and levels 4 & 5. Bob Denaro expects that level 4 & 5 vehicles will not be like the private luxurious cars we see nowadays. He expects the purchase price to be much lower than level 1 – 3 and

expects the vehicles to be used more as shared transit people movers. This could mean that the vehicles are not bought and owned but used as a service. As a purchase price he estimates small level 5 vehicles to cost around $12.000 and large level 5 vehicles around $32.000.



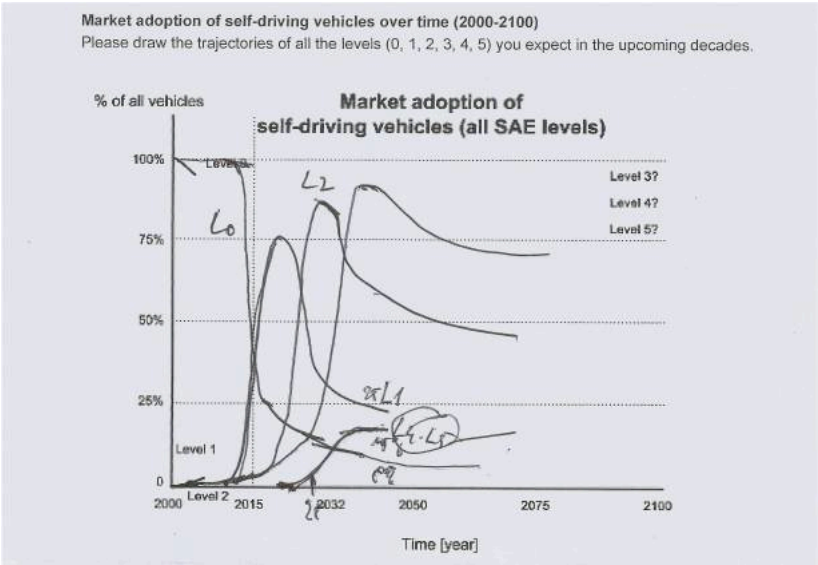
Bob Denaro estimated that "today about 10% of all R&D budget is allocated for vehicle automation. Within a few years this percentage will increase to approximately 50%".

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	0	1	2	3	7	10

Maxim Flament

Maxim Flament sees the innovation system not only as a technological challenge. The technology is getting more mature when the years go by. The processing power will start increasing. The hardware and software will get more mature. And the communication devices will get better. "The challenge is also in getting societal benefits from these systems. What do we want to do as a society with these systems? We will have a challenge as a society to direct the innovation system in such a way that it is a win-win for industry, society and policymakers. If we only focus on customers we will have a selfish system that will not reach it full societal benefits like safety, congestion release and cleaner emissions".

On the diffusion of automated vehicles Maxime Flament sees two types of pathways. The pathway of level 1 – 3 automated vehicles, being a product with an ownership model that you purchase for an average price of $24.000. And another pathway of level 4 and 5 automated vehicle, being a service with a 'usership' model that you do not purchase, but pay on a monthly basis.



The adoption rate of automated vehicles level 1, 2 and 3 all have a very rapid market introduction according to Maxim Flament's expectations. After this introduction the adoption rate drop again as the next level takes over the market dominance. Level 3 will remain to have a dominant market share as level 4 and 5 will gain a market share of about 20% together. This low market share of level 4 and 5 is due to the mobility as a service model, which needs fewer cars in the fleet in comparison to the ownership model.

Maxime Flament thinks the usefulness of your time inside a vehicle will gradually increase among the difference levels of automation. Level 1 to level 2 will have any advantages on usefulness of your time. The comfort and usefulness of time you experience in a level 5 vehicle can be compared to the comfort in an airplane, Maxime Flament concludes.

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	1	3	3	4	6	8

Chris Gerdes

Total fleetsize changes

There are big trends that Chris Gerdes is seeing. In big cities Uber is becoming very popular. So you see people not replacing their current vehicle by a new one. So Chris thinks that in New York and San Francisco and other bigger cities we will see a decrease in the fleetsize. Otherwise in the USA the fleetsize will stay relatively constant or a slight increase with the population. But in the urban areas we will see a decrease, one that could be accelerated by the technology that we will see.

This technology will therefore have an impact of 15% or higher on the car sharing market in the densely populated areas. In less densely populated areas this technology will have no impact on ride- and car sharing.

Value proposition

As a technology that is added to my personal vehicle, automation will bring comfort and free time as the biggest value for the end user. You could go on a long drive or a traffic jam and use the time for other purposes. Also not having to worry about parking is a huge benefit. People will pay about $5000 extra for this service in luxury vehicles. In the vehicles where the driver still has to monitor what the status of the

vehicle and the traffic is, Chris does not see the value of those systems yet. There has to be a change for the driver to really disengage in order to be a value in the systems.

Therefore there is no advantage for the first 3 levels of automation. Chris Gerdes does see value for having the time available for other purposes. This would be a really big step in comfort. You could indeed compare this by being in a plane.

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	0	1	1	1	8	10

Technology development

The s-shape is very appropriate for the technology development. You are going to have a slow initial phase, followed by a tipping point where it starts to go quickly. And Chris Gerdes can also see on this tail end certain applications where it just doesn't make much sense.

Adoption rate

From an introduction strategy you could start to see fully automated level 5 vehicles, but very slow. Maybe on a campus, in some closed areas or cities with dedicated infrastructure. And then you will start to see some technologies added to conventional vehicles on highways. You will have these two paths, with the existing vehicles becoming more automated and the full autonomous vehicles starting out slow and then getting more capabilities. Both pathways will either merge if the public still has desire for one and the other. But probably one of the pathways will hit the tipping point before the other. Chris Gerdes would place a bet on the level 5 vehicle to gain the total market share. This will probably gain a faster uptake than the gradual way the OEMs trying to introduce these automated vehicles.

Mobility as a service is a very likely scenario as people will really benefit from this and will see the added value for their lives. But now companies like Tesla have made a really wonderful ownership experience, so Chris thinks that people will still want to own cars in the future as companies can provide this great experience. But nobody should assume that people will buy a car, which is the way companies are build now.

Price

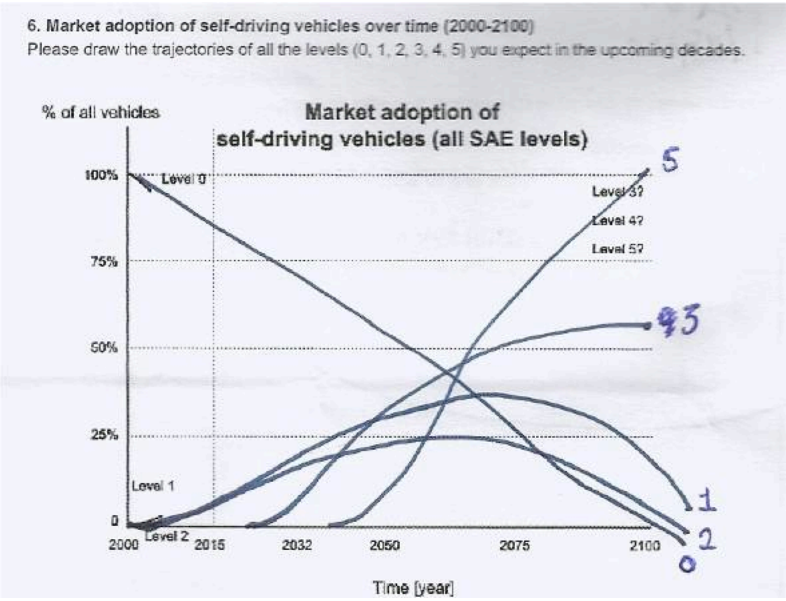
These slow vehicles of level 5 are most likely not attractive for people to own themselves. But if you can make it possible to make vehicles in a range from $50.000 - $70.000, you can probably make a very profitable business in the B2B market.

R&D

Chris Gerdes recognizes the increasing focus on automated vehicles in R&D. "The change is huge. I have been working with automated vehicles since 1992. Especially the last 2 years this shift has been dramatic. You can see this in the number of engineers working in this field and in R&D departments. For example Google has more than 100 people working in this field within their R&D department." says Chris Gerdes.

Larry Head

Level 1 and level 2 will first make their appearance and reach 25% market share in respectively 2030 and 2040. Professor Larry Head expects a market introduction of level 5 vehicles around 2040. 25% and 50% adoption rate will be achieved for level 5 by respectively 2055 and 2065. Level 3 will be the other dominant vehicle automation type next to level 5 in the future.



Larry Head estimates the usefulness of time inside the car as a stepwise increase by 2 points of comfort by every increase in automation level.

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	0	2	4	6	8	10

Alain Kornhauser

Alain Kornhauser reflects on the value that automated vehicles can bring to society: "the value proposition of automated vehicles is enormous! It consists of the added safety for the driver and the comfort it will gain from using these automated vehicles." People will not gain more comfort from level 4 and 5 compared to level 3. It is like you are in a bus or a train. What ever you want to do with you time, it is possible. The main benefit will be on the highway, as in urban areas you are more distracted.

The great thing about automated vehicles is not the moment that you are in the car though… It is like a taxi that will get to you when you need it, and will go away without you whenever you want. That is the amazing thing of automated vehicles and we can only reach that at level 5.

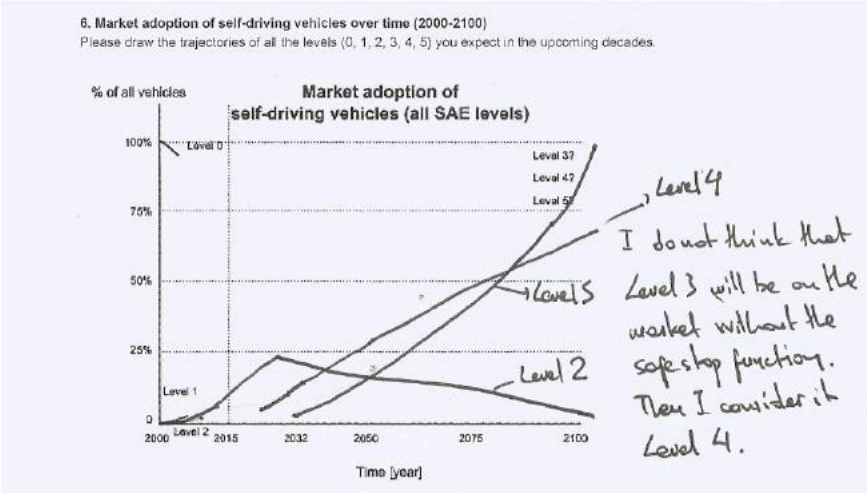
Alain therefore sees the ownership desire shrink if level 5 vehicles make their way into the market. "It is like a bottle and a drink. If you just want a drink, why would you get a whole bottle? If you just want mobility, why would you get a whole car which is idle for more than 90%?"

This is a huge moment where safety can finally sell. Safety will become a value proposition that will create a certain standard in the industry: a great business case for the insurance companies who will start demanding people to get safer cars.

Alain Kornhauser is skeptical about the technology development. None of the industry parties that is active in this field has ever tried to put an unmanned vehicle on the open road and just test with it. They do not dare to do this yet. Once we have some systems in place that can bring us autonomous features, there is a huge potential for the retrofit aftermarket. Look at turn-by-turn navigation systems. Nobody wanted that at first, but the aftermarket of these devices has grown very big.

Miltos Kyriakidis

Miltos Kyriakidis does not think that level 3 will be on the market without the safe-stop function, he then considers it level 4. Miltos Kyriakidis does not expect any level 5 vehicle before 2030. It will then hit the market at a price of $30.000 – $40.000 according to his expectations.



Miltos Kyriakidis expects that "As long as the driver will be expected to monitor and supervise the system I can see no benefits. For level 4 and level 5 the rating assumes that those AVs have been tested and are safe."

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	2	2	2	2	8	10

John Maddox

Fleetsize

The fleetsize will grow. The effect of car sharing will grow dramatically, but as vehicles will be in use much more than they are currently, the effect of car sharing will be neutral on sales and fleetsize. The ownership will probably still be for about 80% with private individuals, but the remaining 20% will shift to fleet owners. So if you have for example 10 million vehicles on the road. Car sharing will get to about 25% of all the vehicles of that, so the majority of the vehicles will still be owned by individuals. This will also hugely affect the miles traveled per vehicle.

Price

Probably the price of vehicles overall will start increasing. As fleet owners in a B2B market have different price elasticity this will affect the pricing of these automated vehicles. Level 5 wont be available before 2025.

Comfort

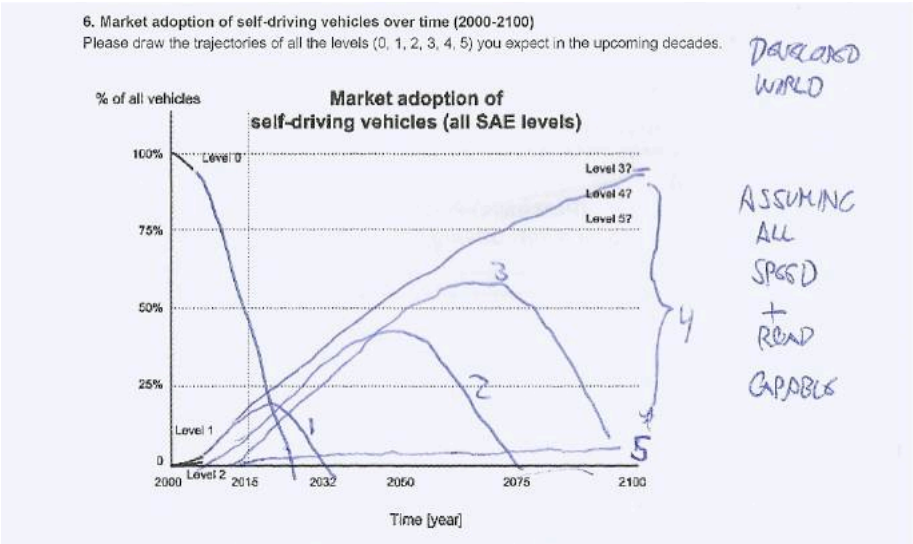
This does not necessarily mean you use your time effectively; you could basically just relax or sleep. John Maddox did a little expert survey on this.

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	2	2	3	6	8	10

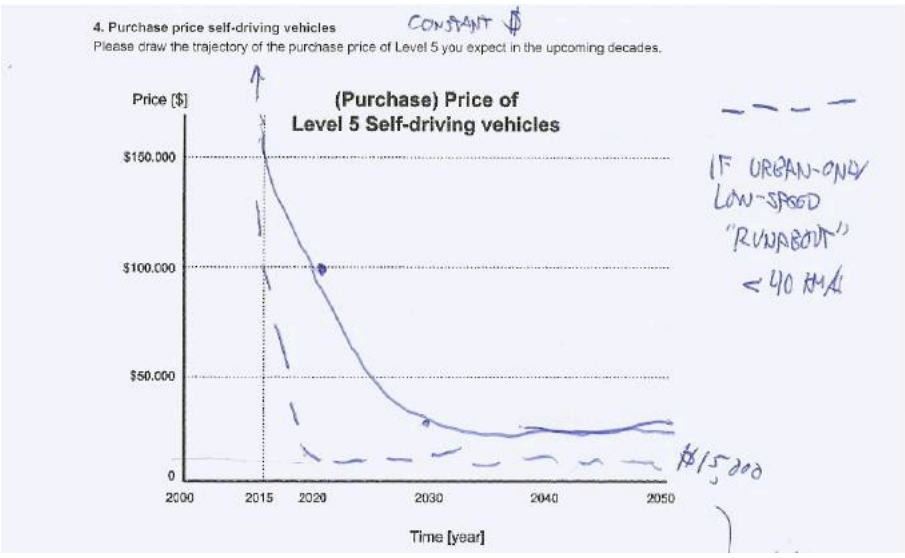
The market will probably gain a lot of value in 2025 when level 4 and 5 are coming on the market. A lot of new revenue opportunities will be possible then.

Glenn Mercer

Glenn Mercer expects the adoption to take place on a functional way with level 1, 2 and 3 each gaining market share after each other. Glenn Mercer thinks that eventually level 4 automation will have the dominant share. In Glenn Mercer's vision this is a vehicle on dedicated roads, with all possible speeds. He assumes that the road is capable of handling these types of vehicles.



The price of level 5 vehicles has to drop dramatically from the current purchase price to be adopted on a large scale by the general public says Glenn Mercer. A level 5 vehicle is not yet available and would cost about $1M. Glenn Mercer expects that two types of vehicles will emerge. A small low speed 'runabout' and a normal speed automated vehicle. The high-speed vehicle will be twice the price of the low speed vehicle during market introduction.



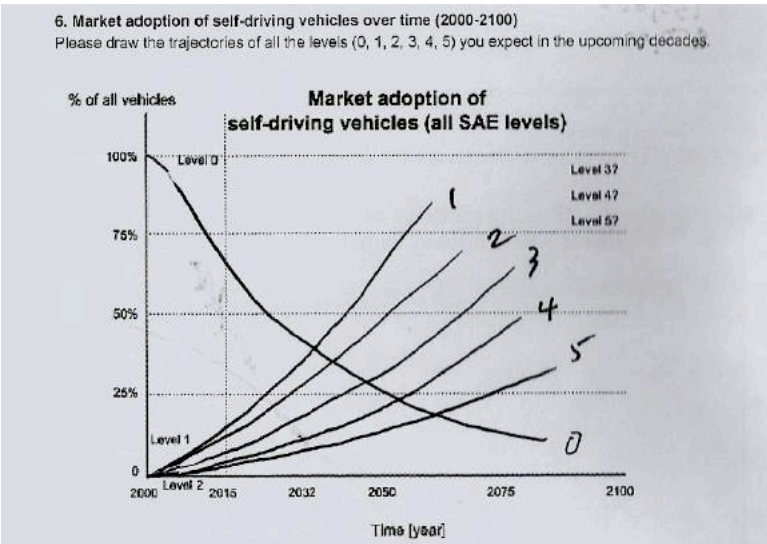
Glenn Mercer says about 7% of all revenue is spent on R&D. Today 50% is spent on development on the drive train, 25% safety systems including ADAS and 25% is spent on material development and other related things. In 2025 Glenn Mercer expects at least 50% to be spent on automated vehicle related technologies.

For the usefulness of time inside the car the benefit is mainly to be found at level 3, 4, and 5 as the benefit of comfort is especially on highways according to Glenn Mercer.

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	0	0	1	7	8	9

Brian Park

Brian Park expects the adoption of the various levels to happen gradually over time. Level 1 will reach 50% market adoption in 2040 according to Brian Park's expectations. Level 2, 3 and 4 will follow over time. Level 5 will reach a 25% market adoption in 2075.



Brian Park expects the comfort of your time inside a car to gradually increase if the levels of automation increase.

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	0	1	2	5	7	10

Table 32 Usefulness of time inside a car according to Brian Park

Nick Reed

Nick Reed did not answer all the questions of the questionnaire due to time constraints. In the short interview Nick Reed did have an opinion about the possible diffusion pathways of vehicle automation. He sees two transitions going on. "The first transition is the one of the OEMs who are gradually introducing more luxurious cars with more safety systems and ADASs on board. These systems can be considered level 2 and level 3 automation. On the other hand you have companies like Google and City2Mobil who introduce level 4 and 5 right away, but with a very low speed and on certain dedicated tracks.

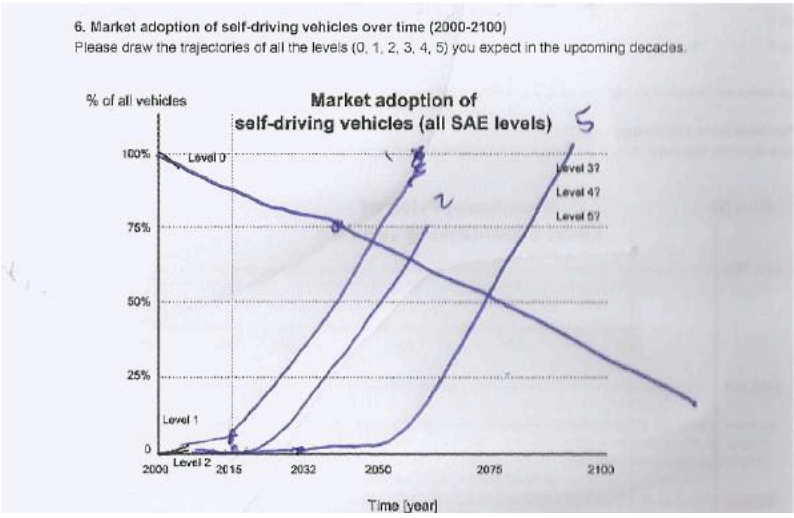
Nick Reed thinks the vehicle automation will have an enormous effect on the increase of the car-sharing market.

Constantine Samaras

Constantine Samaras expects a steadily growing fleetsize of cars due to demographic growth. The effect of car sharing will cause this growth of the fleetsize to be lower than it would be with only the demographic changes taken into account.

Car sharing will cause a 15 – 50% decrease of fleet ownership according to Constantine Samaras.

The adoption of vehicle automation will start around 2015 - 2020 with a steep increase in level 1 and 2 vehicles. Level 5 vehicles will hit the market in 2032 and will rapidly grow to 25% from 2050 – 2060 according to Constantine Samaras. Level 0 will slowly decrease as the other modes take over.



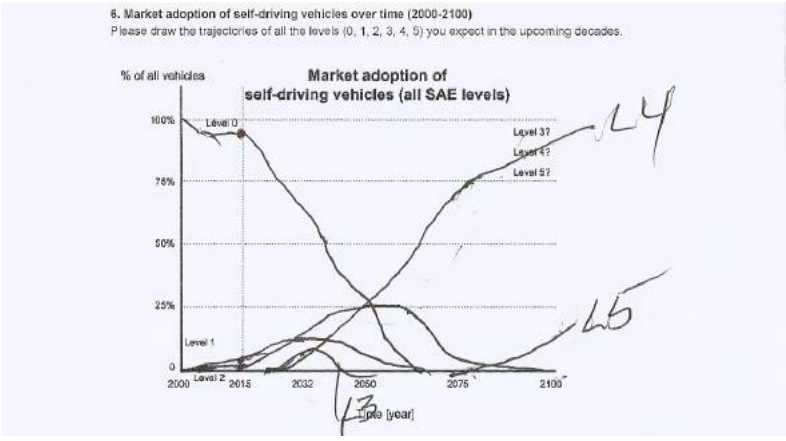
Constantine Samaras expects a sudden increase of comfort when some driver tasks are done automated. The comfort of level 5 automation is described by Constantine Samaras as “off the chart”.

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	0	5	8	9	9	10

Steven Shladover

According to Steven Shladover the current price of level 1 vehicles is $50.000 and of level 2 vehicles it is $80.000. Level 3, 4 and 5 are not on the market yet. Level 5 will not exist for a long time.

Level 1 will gain market share in the period 2015 – 2030 together with level 2. Level 3 and level 4 will hit the market in 2020. Level 3 will only gain about 10% market adoption until it drops to 0 again. Level 4 will gain the majority of the market share towards 2100. The extra development costs, extra redundancy and extra functionalities would make level 5 incredibly expensive that it would only be available for a minority of the population. Level 4 under certain conditions can do all of the driving, but to get the car out on the road under all conditions is much harder.



The rise of vehicle automation will have a major effect on car sharing according to Steven Shladover. Car sharing will on its turn have an effect on a decreasing fleetsize of vehicles.

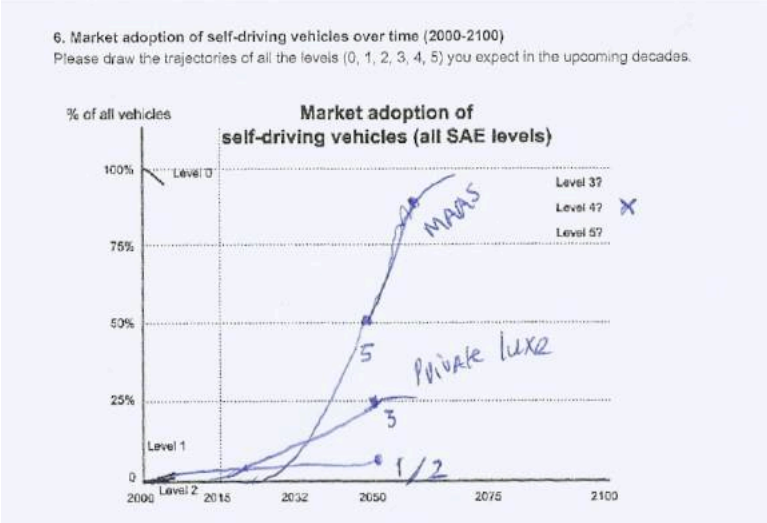
Level 0, 1 and 2 is all useless time. Level 3 will be a little more productive, but still you can't do very much. Level 4 and level 5 will be a mayor gain in comfort.

	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Comfort	0	0	0	2	7	10

A normal performance vs. time curve on product development is an s-shaped curve. It takes time to get up to speed with development. But then you get into a time with rapid improvement and then it saturates. The rapid improvement is caused buy the fact that you have resources to invest in the development. The tipping point is caused by the fact that you have overcome some hard barriers and some technological impediments. Software will likely be the most important technological impediments for level 5 automation. When you look at current software, this technology is far from fail-safe. The hard thing is to get software safety with good environmental perception with very false positive and the false negative. This takes a lot of time and is very important. Both false positive and false positive are unacceptable. Imagine you have to guarantee this safety and redundancy in a vehicle. How do you design these systems that can run for millions of hours without having a fault. It takes a lot of years of verification and validation of these software systems to get safe level 5 vehicles on the road.

Joop Veenis

Joop Veenis has not commented on the useful of time inside a car. The adoption rate of automated vehicles will happen in quite a rapid speed according to Joop Veenis. Joop expects to have two types of vehicles dominating the market in the future. The first is the private luxury level 3 vehicle with a steady 25% market share in 2075. The second type is a level 4 or 5 small people mover that operates as a transit service or by a construction as a mobility as a service.



Mohammed Yousuf

Mohammed Yousuf did not answer all the questions of the questionnaire due to limited knowledge on some of the subjects according to himself. Mohammed Yousuf has done research for the US Department of Transportation on the development of the enabling technologies of automated vehicles. In this research he recognized the s-shaped curve of the technology becoming more mature.

According to Mohammed Yousuf the transition from level 1 to level 4 or 5 will be sooner than the transition from level 1 to level 2, 3 and 4. He assumes the second transition to be more difficult because you have the human in the loop.

Appendix G. Interview results

Fleetsize

Q1 Shape of the fleetsize in upcoming years

There is not much consensus on the size of the vehicle fleet that we might expect the upcoming decades. About one third expect either a steady growth, no change or a slight decrease. What we might conclude is that the experts do not expect any extreme changes in the fleetsize.

	Count
Steady growth of fleetsize	4
No change in fleetsize since 2015	4
Slight decrease in fleetsize	5
Strong decrease in fleetsize	0
Other	1

Richard Bishop expects that "the fleetsize will continue to increase, but then around 2070 it will drop dramatically due to automation and car sharing."

Q2 Effect of carsharing on car ownership

Most experts are agreeing on the fact that car sharing will have an effect on the future size of the vehicle fleet. About 43% of the experts expect that car sharing will have a low probability that people will abandon their car. About 50% expect that car sharing will have a high probability that people will abandon their car over time. Richard Bishop expects a very high impact of car sharing on the vehicle fleetsize. "Car sharing will have a very high impact on the fleetsize as it is a huge societal change. It could go fast, or it could get into a snowball effect and go very fast."

Purchase price

Q3 Purchase price of all levels in 2015

There is still little consensus on the difference between the SAE levels. Some of the experts state that up until level 3 vehicles are already on the market for sale. Other experts state that level 3 vehicles are a long time from being in mass production and estimate an average price of $200.000 for the vehicle.

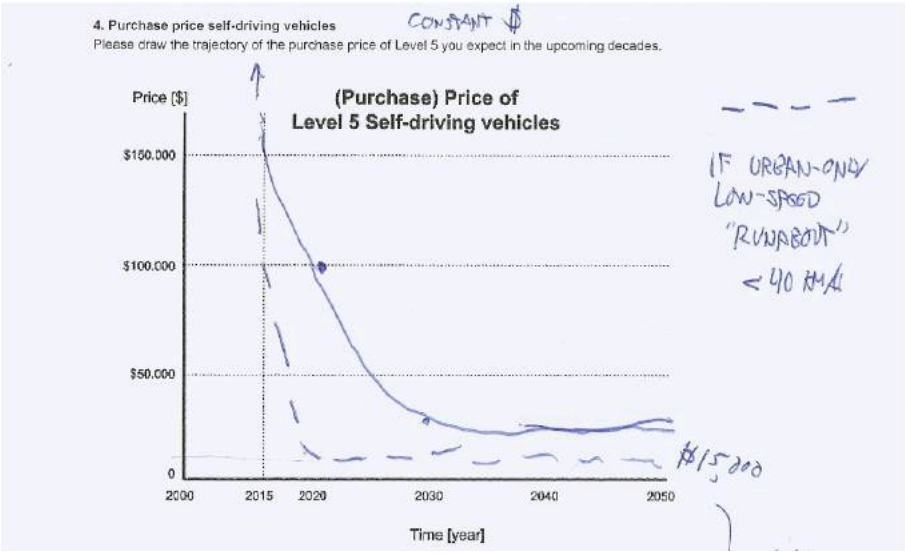
The minimum price for level 4 and level 5 was estimated as respectively $28.000 and $12.000. This price might be interpreted as the type of vehicles that are currently on the market driving on dedicated lanes with a very low speed.

	Level 1	Level 2	Level 3	Level 4	Level 5
Average	$27.444	$43.200	$74.625	$107.167	$314.000
Min	$21.000	$24.000	$24.000	$28.000	$12.000
Max	$50.000	$80.000	$200.000	$200.000	$1.000.000

Chris Gerdes has made some comments on the price that are interesting to share. "These slow vehicles of level 5 are most likely not attractive for people to own themselves. But if you can make it possible to make vehicles in a range from $50.000 - $70.000, you can probably make a very profitable business in the B2B market."

Q4 Purchase price level 5 over time (2000 – 2050)
Most experts found it hard to answer this question. The people that responded on this particular question showed a decrease of price over time. The drop in price correlated with most respondents with the market introduction that they predicted in question 6.

This is a comment made by Glenn Mercer: “The price of level 5 vehicles has to drop dramatically from the current purchase price to be adopted on a large scale by the general public says Glenn Mercer. A level 5 vehicle is not yet available and would cost about $1M. Glenn Mercer expects that two types of vehicles will emerge. A small low speed ‘runabout’ and a normal speed automated vehicle. The high speed vehicle will be twice the price of the low speed vehicle during market introduction.”



Q5 Acceptable purchase price for market introduction
Experts estimate an average purchase price of $32.000 for a level 5 vehicle to reach mass adoption. Chris Gerdes expects that “as a technology that is added to a personal vehicle, automation will bring comfort and free time as the biggest value for the end user. You could go on a long drive or a traffic jam and use the time for other purposes. Also not having to worry about parking is a huge benefit. People will pay about $5000 extra for this service in luxury vehicles.” This $5000 would get to a baseline price of $27.000, which seems like a reasonable amount for a luxurious vehicle.

About 30% of the experts think that a level 5 vehicle will only be ready for mass adoption if the price is $15.000 or lower. The reason for this is that these experts think that a level 5 vehicle will only be available on a low speed and people are less willing to pay money for these types of vehicles.

Market adoption

Q6 Market adoption of all levels
Eleven experts reflected on the question what a likely adoption scenario for automated vehicles could be. Overall the trend was quite optimistic about the market adoption of automated vehicles. In general people see a stepwise introduction of level 1, 2 and 3. Followed by an introduction of level 5. In general level 4 was a level of automation that people gave little chance to gain massive market adoption. Two pathways could be identified.

Private luxury

The pathway of private luxury consists mainly of luxurious vehicle equipped with vehicle automation features and safety systems. These features could be either considered as level 3 or as level 4 of 5. This private luxury does contain an ownership model. Many experts consider private luxury as an option for early adoption. OEMs could equip existing vehicles with new automation features and existing vehicles on the road could also be equipped through the retrofit market. In the long future not many experts think that this option will be the dominant option as they predict that level 3 would have about 0 – 25% market share in the period 2075 – 2100.

Mobility as a service

The pathway of mobility as a service assumes a service-based usership model. Level 5 automation could play a big role in this model according to many experts. The vehicles in this model would mainly operate in densely populated areas with a low speed. Chris Gerdes says: "From an introduction strategy you could start to see fully automated level 5 vehicles, but very slow. Maybe on a campus, in some closed areas or cities with dedicated infrastructure. And then you will start to see some technologies added to conventional vehicles on highways. You will have these two paths, with the existing vehicles becoming more automated and the full autonomous vehicles starting out slow and then getting more capabilities. Both pathways will either merge if the public still has desire for one and the other. But probably one of the pathways will hit the tipping point before the other.

Level 5 automation

The expected year for market introduction of level 5 automation varies between 2020 and 2040. One outlier can be found in 2075 as Steven Shladover is not so optimistic about level 5 automation. Nevertheless Steven Shladover expects that level 3 and 4 will likely hit the market around 2030.

Figure 104 shows the years that the experts expect the market adoption by 10%, 25% 50% and eventually 75% and 100%. Figure 105 show a visualization of all the charts of the eleven experts on the market adoption of level 5 combined.

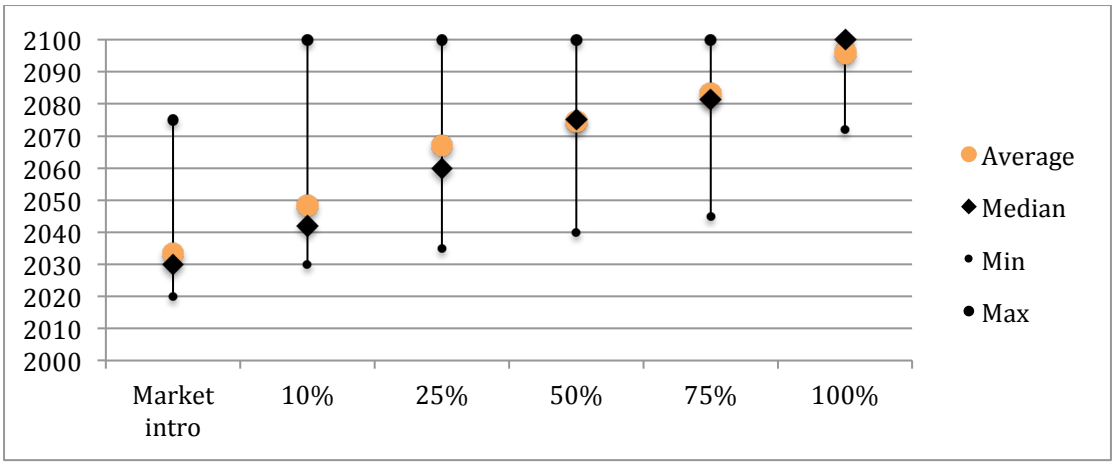


Figure 104 Overview of average, min and max expected years of market adoption

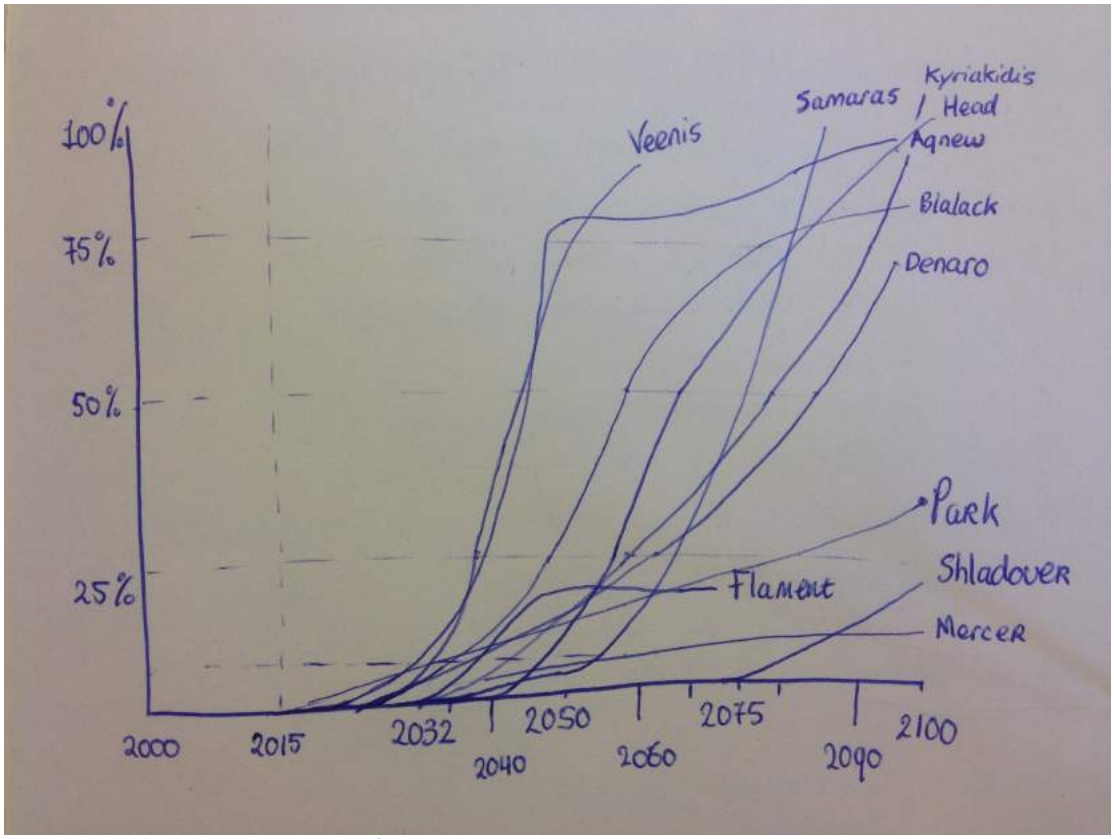


Figure 105 Market adoption rate for level 5 by eleven experts

From Figure 105 it can be seen that a majority of the experts expect the market to adopt level 5 automation in an s-shaped curve. The rapid adoption will happen between 2035 and 2060. This same majority expects level 5 to gain full market adoption. A minority of the experts expects that level 5 will not gain the full market share, as this market will be shared with either level 3 and/or level 4 vehicles.

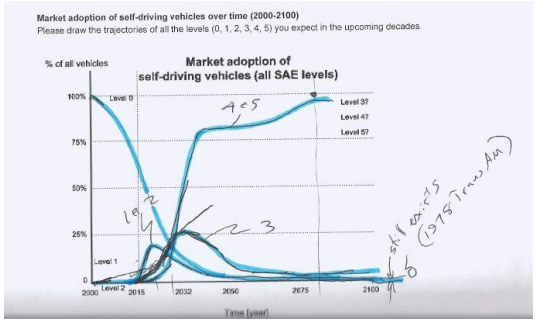


Figure 106 David Agnew

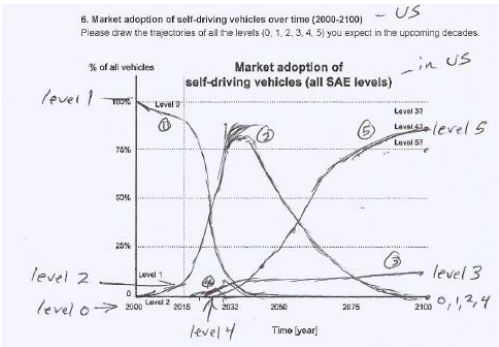


Figure 107 Tallis Blalack

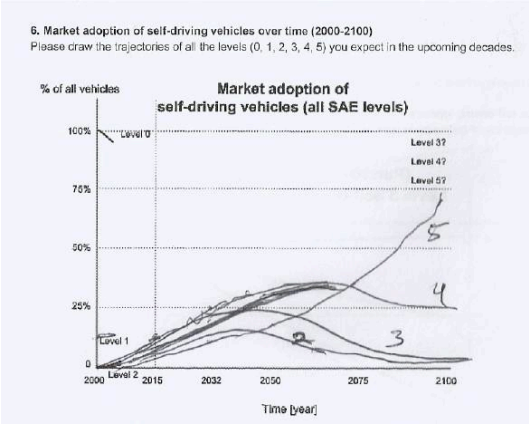


Figure 108 Bob Denaro

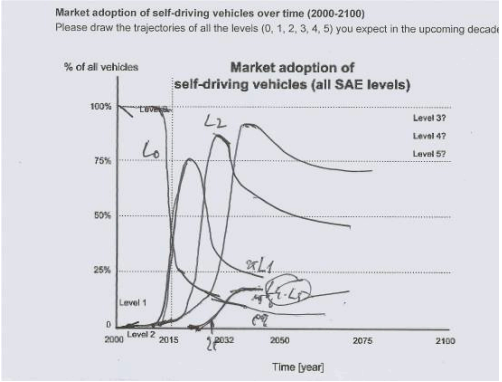


Figure 109 Maxime Flament

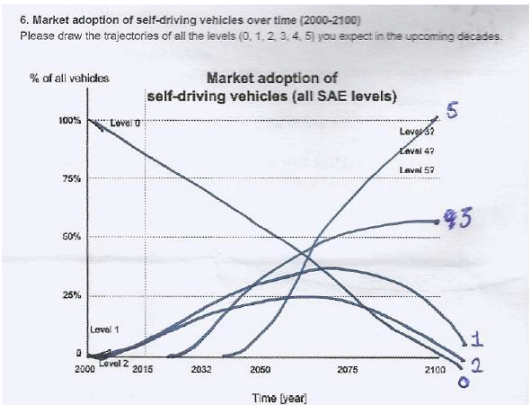


Figure 110 Larry Head

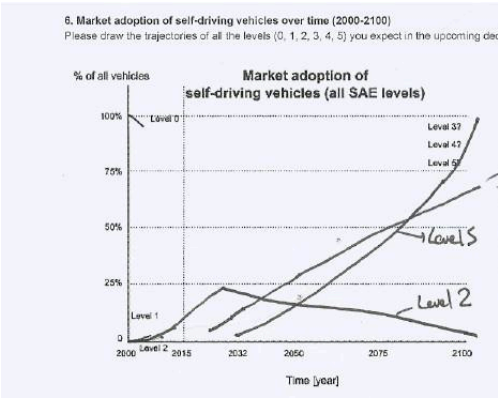


Figure 111 Miltos Kyriakidis

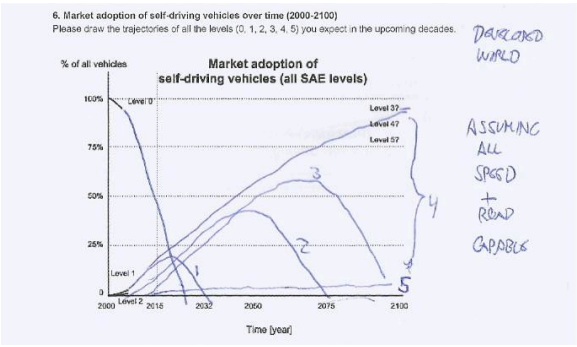


Figure 112 Glenn Mercer

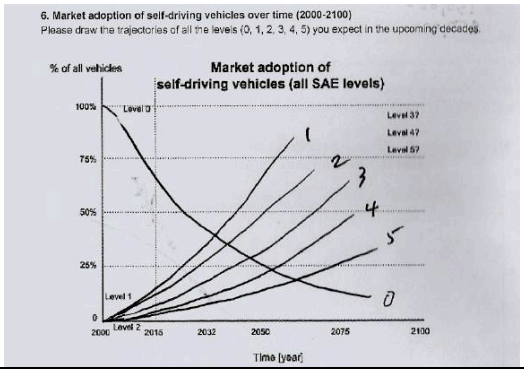


Figure 113 Brian Park

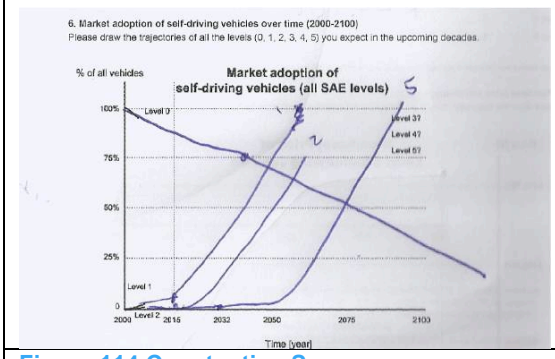


Figure 114 Constantine Samaras

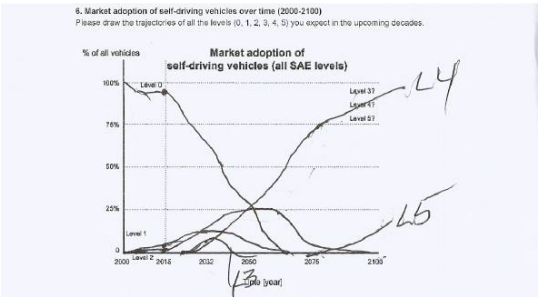


Figure 115 Steven Shladover

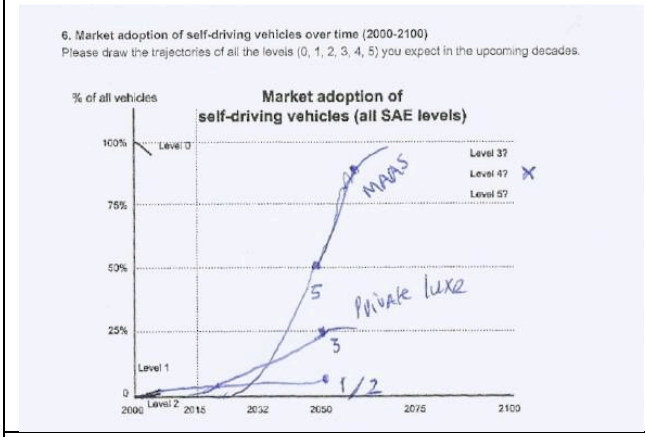


Figure 116 Joop Veenis

Q7 Effect of vehicle automation on car-sharing market

Almost all experts expect a very high impact of vehicle automation on the car sharing market. Alain Kornhauser states that: "the great thing about automated vehicles is not the moment that you are in the car. It is like a taxi that will get to you when you need it, and will go away without you whenever you want. That is the amazing thing of automated vehicles and we can only reach that at level 5." In his opinion this will hugely benefit the car sharing market.

Utility

Q8 Usefulness of time inside the car

15 experts were asked to rate the usefulness of time in a vehicle, shortly translated as comfort, according to the different levels of automation by SAE on a scale from 0 to 10. The results can be seen in Table 33 and a visualization can be seen in the boxplot of Figure 117.

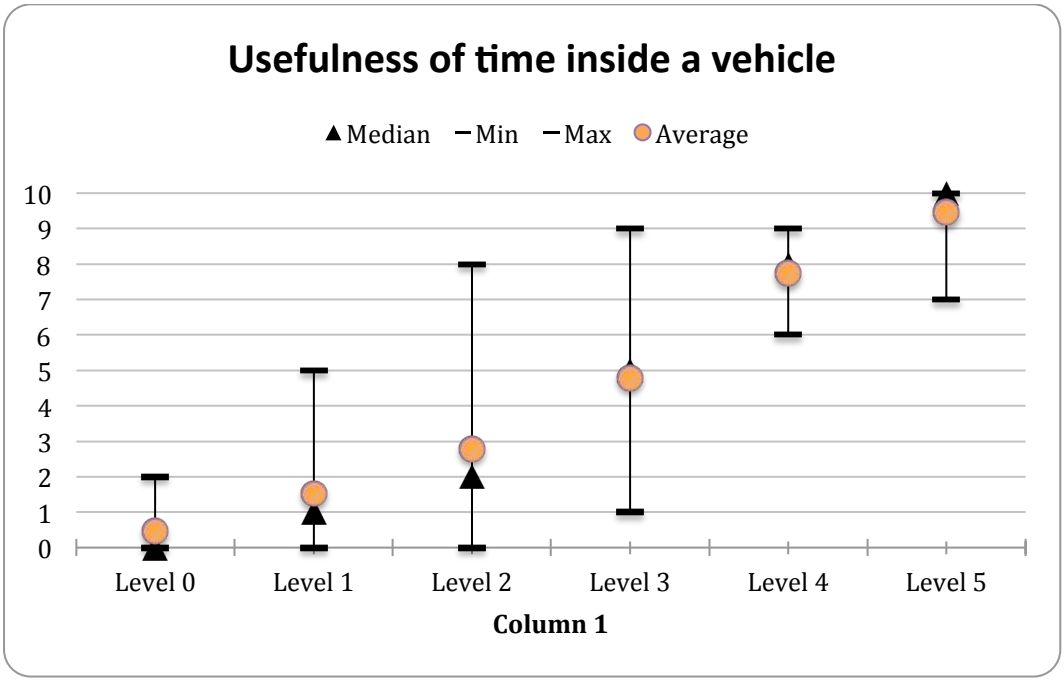


Figure 117 Median, average, min and max of comfort for all SAE levels

- Level 0 has a median value of 0, a max of 2 and an average value of 0,5.
- Level 1 has a median value of 1, a max of 5 and an average 1,5. Overall there was quite some consensus on the comfort of level 1 as the values were mostly in between 0 and 2. An outlier rated the comfort on 5 for level 1. Constantine Samaras has given this rating as he expects a sudden increase of comfort already when "some driver tasks are done automated".
- Level 2 has a very wide range with a minimum of 0 and a maximum of 8. Two experts specifically rated this value of '8'. Besides these two ratings of 8, the density of ratings was between 1 and 3. The median value of level 2 is a comfort of 2 and the average is 2,8.
- Level 3 has a median value of 5 and an average of 4,8. This median and average are close to each other. There was little consensus on the value of comfort for level 3. Experts used essentially the whole range of the scale as the minimum value is 1 and the maximum is 9. Glenn Mercer expects that for the level of comfort the main benefit will be on highway driving. This highway automation starts at level 3. Chris Gerdes on the other hand states that as long as drivers are expected to monitor the system in some way, there will be little room for any comfort inside that car. In level 3 drivers still have to monitor the system in some way. He therefore rated level 3 with a 1 for comfort. Miltos Kyriakidis agrees with this as he states: "As long as the driver will be expected to monitor and supervise the system I can see no benefits. For level 4 and level 5 the rating assumes that those AVs have been tested and are safe." Besides these minimum and maximum values the ratings are not all high and low as can be seen in the count of all ratings in Figure 118. The majority of the ratings are in between 5 and 7. To conclude this result for level 3 it seems that the comfort that is rated in level 3 depends very much on the definition and expectations that people have on level 3.
- Level 4 has a median of 8 and an average value of 7,7. There seems to be more consensus on the comfort in level 4 as the minimum and maximum are within a range of 3 points with respectively 6 and 9.
- The same consensus seems to be there on the level of comfort for level 5 automation. The range is 3 points with a minimum of 7 and a maximum of 10. The majority, about 73%, of the experts rated the comfort with a 10. This gives a median of 10 and an average value of 9,5.

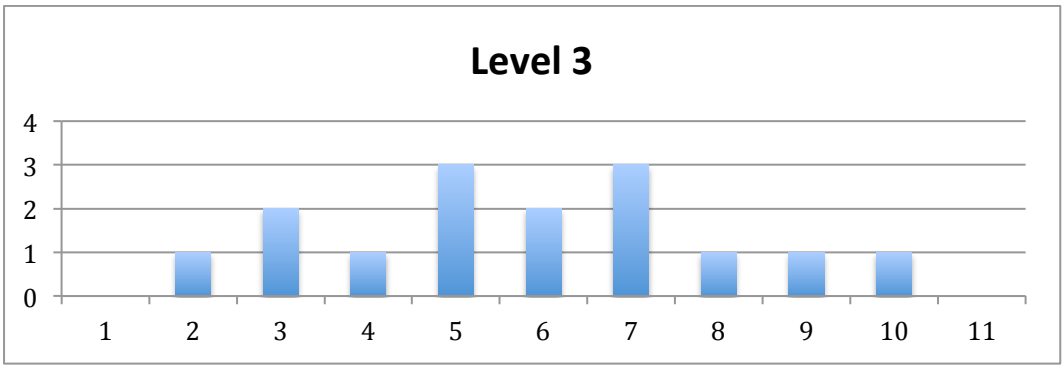


Figure 118 Count of ratings of comfort for Level 3

	Median	Min	Max	Average
Level 0	0	0	2	0,5
Level 1	1	0	5	1,5
Level 2	2	0	8	2,8
Level 3	5	1	9	4,8

Level 4	8	6	9	7,7
Level 5	10	7	10	9,5

Table 33 Results of comfort rating by experts for all SAE levels

R&D expenditure

Q9 Total market size

Most experts found it hard to answer this question. There was little consensus what was to be seen as the market for vehicle automation. Some argued this market was mainly the ADA systems and sensor market. Other experts argued that the vehicle price should definitely be included in the market size. A wide range of market value was therefore estimated. The range goes from $18 billion, $75 billion and $150 billion up to $800 billion and $2 trillion. Most see the market to reach it maximum value around the year 2030 – 2050 though. This correlates with the expected market introduction of level 4 and level 5 as most experts answer in question 6.

Q10 Percentage of R&D from annual revenue

Total R&D expenditure in the industry was estimated on approximately 5% - 10% of the annual revenue. This total R&D budget is used for all sorts of research and development like the drive train, energy source, safety systems and vehicle automation technologies. The last few years an increasing amount is allocated for the development of vehicle automation and communication between vehicles and infrastructure.

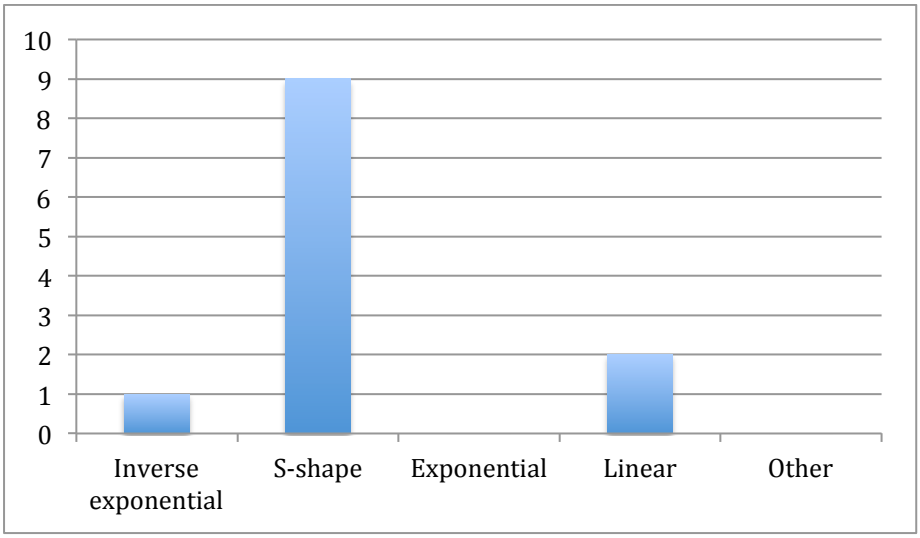
Bob Denaro estimated that “today about 10% of all R&D budget is allocated for vehicle automation. Within a few years this percentage will increase to approximately 50%”. David Agnew could confirm this increasing focus on vehicle automation within R&D, although David Agnew was cautious to say any exact percentages. Also Chris Gerdes recognizes the increasing focus on automated vehicles in R&D. “Especially the last 2 years this shift has been dramatic” says Chris Gerdes.

Glenn Mercer says about 7% of all revenue is spent on R&D. Today 50% is spent on development on the drive train, 25% safety systems including ADAS and 25% is spent on material development and other related things. In 2025 Glenn Mercer expects at least 50% to be spent on automated vehicle related technologies.

According to Philipp von Hagen, member of the executive board of Porsche SE, the average R&D expenditure in the automotive market is 5 – 10% of the annual revenue. The total R&D expenditure in the German market is €30B per year. Philipp von Hagen expects the R&D expenditure on vehicle automation to become around €17B per year in 2018.

Q10 Maturity curve

The majority of the experts think the s-shape is the most appropriate curve for the maturity of the technology over time.


10
9
8
7
6
5
4
3
2
1
0
Inverse exponential
S-shape
Exponential
Linear
Other

Appendix H. Full model

The full model can be explored and downloaded at Forio Simulate. To access this model use the url: https://forio.com/simulate/jurgen.nieuwenhuijsen/automated-vehicles-diffusion. The mathematical equations of the full model are depicted below.

```
"Adoption of car-sharing"=
  (("Growth of car-sharing market")*"Potential car-share users"*("Total car-share
users"
  /Total population))+("Growth of car-sharing through vehicle automation"*"Total car-
share users")

Adoption rate level 1=
  (Sales LEVEL 1-External change fleetsize LEVEL 1)/Total car fleet

Adoption rate level 2=
  (Sales LEVEL 2-External change fleetsize LEVEL 2)/Total car fleet

Adoption rate level 3=
  (Sales LEVEL 3-External change fleetsize LEVEL 3)/Total car fleet

Adoption rate level 4=
  (Sales LEVEL 4-External change fleetsize LEVEL 4)/Total car fleet

Adoption rate level 5=
  (Sales LEVEL 5-External change fleetsize LEVEL 5)/Total car fleet

Annual earnings Level 1=
  Purchase price LEVEL 1*(Sales LEVEL 1-External change fleetsize LEVEL 1)

Annual earnings Level 2=
  Purchase price LEVEL 2*(Sales LEVEL 2-External change fleetsize LEVEL 2)

Annual earnings Level 3=
  Purchase price LEVEL 3*(Sales LEVEL 3-External change fleetsize LEVEL 3)

Annual earnings Level 4=
  Purchase price LEVEL 4*(Sales LEVEL 4-External change fleetsize LEVEL 4)

Annual earnings Level 5=
  Purchase price LEVEL 5*(Sales LEVEL 5-External change fleetsize LEVEL 5)

Annual knowledge stock depreciation rate=
  0.1

"Annual R&D expenditure Level 1"=
  Annual earnings Level 1*"R&D percentage of annual earnings"

"Annual R&D expenditure Level 2"=
  Annual earnings Level 2*"R&D percentage of annual earnings"

"Annual R&D expenditure level 3"=
  Annual earnings Level 3*"R&D percentage of annual earnings"

"Annual R&D expenditure Level 4"=
  Annual earnings Level 4*"R&D percentage of annual earnings"

"Annual R&D expenditure Level 5"=
  ("R&D percentage of annual earnings"*Annual earnings Level 5)

Attractiveness LEVEL 0=
  (b4 Weight comfort*Comfort LEVEL 0)+(b3 Weight perception*Perception towards LEVEL 0
)+(b5 Weight safety*Safety LEVEL 0)

Attractiveness LEVEL 1=
  (b4 Weight comfort*Comfort LEVEL 1)+(b3 Weight perception*Perception towards LEVEL 1
 automation)+(b5 Weight safety*Safety LEVEL 1)

Attractiveness LEVEL2=
  (b4 Weight comfort*Comfort LEVEL 2)+(b3 Weight perception*Perception towards LEVEL 2
 automation)+(b5 Weight safety*Safety LEVEL 2)
```

```
Attractiveness LEVEL3=
  (b4 Weight comfort*Comfort LEVEL 3)+(b3 Weight perception*Perception towards LEVEL 3
 automation)+(b5 Weight safety*Safety LEVEL 3)

Attractiveness LEVEL4=
  (b4 Weight comfort*Comfort LEVEL 4)+(b3 Weight perception*Perception towards LEVEL 4
 automation)+(b5 Weight safety*Safety LEVEL 4)

Attractiveness LEVEL5=
  (b4 Weight comfort*Comfort LEVEL 5)+(b3 Weight perception*Perception towards LEVEL 5
 automation)+(b5 Weight safety*Safety LEVEL 5)

Average household size=
  2.3

Average lifetime of car=
  10.4

Average Purchase price=
  (Purchase price LEVEL 0+Purchase price LEVEL 1+Purchase price LEVEL 2+Purchase price
 LEVEL 3+Purchase price LEVEL 4+Purchase price LEVEL 5)/6

b1 Weight Price=
  0.5

b2 Weight Attractiveness=
  1-b1 Weight Price

b3 Weight perception=
  0.2

b4 Weight comfort=
  0.6

b5 Weight safety=
  0.8-b4 Weight comfort

Baseline price level 1= INTEG (
  -Decrease of price Level 1,
    Initial Baseline price LVL 1)

Baseline price level 2= INTEG (
  -Decrease of price Level 2,
    Initial Baseline price LVL 2)

Baseline price level 3= INTEG (
  -Decrease of price level 3,
    Initial Baseline price LVL 3)

Baseline price level 4= INTEG (
  -Decrease of price Level 4,
    Initial Baseline price LVL 4)

Baseline price Level 5= INTEG (
  -Decrease of price Level 5,
    Initial Baseline price LVL 5)

Car per person=
  Total car fleet/Total population

"Car-share users abonding their car"=
  "Car-share users with car"*Percentage of car shedding among car share users

"Car-share users with car"= INTEG (
  "Increase in car-share users"-"Car-share users abonding their car",
    "Initial car-share users")

"Car-share users without a car"= INTEG (
  "Car-share users abonding their car"+"Increase in car-share users without car",
    0)

Cars per household=
  Total car fleet/Number of households

Change in fleetsize=
  -Percentage of car shedding

Comfort LEVEL 0=
```

```
  0.05

Comfort LEVEL 1=
  0.1

Comfort LEVEL 2=
  0.2

Comfort LEVEL 3=
  0.4

Comfort LEVEL 4=
  0.7

Comfort LEVEL 5=
  1

Cumulative experience LEVEL 1= INTEG (
  Sales LEVEL 1,
    Initial fleetsize LEVEL 1)

Cumulative experience LEVEL 2= INTEG (
  Sales LEVEL 2,
    Initial fleetsize LEVEL 2)

Cumulative experience LEVEL 3= INTEG (
  Sales LEVEL 3,
    Initial fleetsize LEVEL 3)

Cumulative experience LEVEL 4= INTEG (
  Sales LEVEL 4,
    Initial fleetsize LEVEL 4)

Cumulative experience LEVEL 5= INTEG (
  Sales LEVEL 5,
    Initial fleetsize LEVEL 5)

Daily travel demand per person=
  14.5

Decrease of price Level 1=
  Learning by doing effect level 1*Learning effect delay*Price gap level 1

Decrease of price Level 2=
  Learning by doing effect level 2*Learning effect delay*Price gap level 2

Decrease of price level 3=
  Learning by doing effect level 3*Learning effect delay*Price gap level 3

Decrease of price Level 4=
  Learning by doing effect level 4*Learning effect delay*Price gap level 4

Decrease of price Level 5=
  Price gap level 5*Learning by doing effect level 5*Learning effect delay

Demand for LEVEL 1 from L0=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 0*
  (Utility LEVEL 1/(Utility LEVEL 0+Utility LEVEL 1))*Maturity Level 1
  )

Demand for LEVEL 2=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 1*
  (Utility LEVEL 2/(Utility LEVEL 1+Utility LEVEL 2))*Maturity Level 2
  )

Demand for LEVEL 2 from L0=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 0*
  (Utility LEVEL 2/(Utility LEVEL 0+Utility LEVEL 2))*Maturity Level 2
  )

Demand for LEVEL 3=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 1*
  (Utility LEVEL 3/(Utility LEVEL 1+Utility LEVEL 3))*Maturity Level 3
  )
```

```
Demand for LEVEL 3 from L0=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 0*
  (Utility LEVEL 3/(Utility LEVEL 0+Utility LEVEL 3))*Maturity Level 3
  )

Demand for LEVEL 3 from L2=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 2*
  (Utility LEVEL 3/(Utility LEVEL 2+Utility LEVEL 3))*Maturity Level 3
  )

Demand for LEVEL 4=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 1*
  (Utility LEVEL 4/(Utility LEVEL 1+Utility LEVEL 4))*Maturity Level 4
  )

Demand for LEVEL 4 from L0=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 0*
  (Utility LEVEL 4/(Utility LEVEL 0+Utility LEVEL 4))*Maturity Level 4
  )

Demand for LEVEL 4 from L3=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 3*
  (Utility LEVEL 4/(Utility LEVEL 3+Utility LEVEL 4))*Maturity Level 4
  )

Demand for LEVEL 5=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 1*
  (Utility LEVEL 5/(Utility LEVEL 1+Utility LEVEL 5))*Maturity Level 5
  )

Demand for LEVEL 5 from L0=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 0*
  (Utility LEVEL 5/(Utility LEVEL 0+Utility LEVEL 5))*Maturity Level 5
  )

Demand for LEVEL 5 from L3=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 3*
  (Utility LEVEL 5/(Utility LEVEL 3+Utility LEVEL 5))*Maturity Level 5
  )

Demand for LEVEL 5 from L4=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 4*
  (Utility LEVEL 5/(Utility LEVEL 4+Utility LEVEL 5))*Maturity Level 5
  )

Demand LEVEL 4 from L2=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 2*
  (Utility LEVEL 4/(Utility LEVEL 2+Utility LEVEL 4))*Maturity Level 4
  )

Demand Level 5 from L2=
  (
  (1/Average lifetime of car)*Fleetsize LEVEL 2*
  (Utility LEVEL 5/(Utility LEVEL 2+Utility LEVEL 5))*Maturity Level 5
  )

Depreciation of knowledge Level 1=
  MAX(Annual knowledge stock depreciation rate*Knowledge stock Level 1,0)

Depreciation of knowledge Level 2=
  MAX(0,Annual knowledge stock depreciation rate*Knowledge stock Level 2)

Depreciation of knowledge Level 3=
  Knowledge stock Level 3*Annual knowledge stock depreciation rate

Depreciation of knowledge Level 4=
  Annual knowledge stock depreciation rate*Knowledge stock Level 4

Depreciation of knowledge Level 5=
```

```
  Knowledge stock Level 5*Annual knowledge stock depreciation rate

Desired baseline price level 1=
  20000

Desired baseline price level 2=
  20000

Desired baseline price level 3=
  20000

Desired baseline price level 4=
  20000

Desired baseline price level 5=
  20000

Development of Maturity Level 1=
  Gap of maturity Level 1*Normalised knowledge Level 1*Effectiveness of knowledge tran
sfer

Development of Maturity Level 2=
  Normalised knowledge Level 2*Gap of maturity Level 2*Effectiveness of knowledge tran
sfer

Development of maturity Level 3=
  Gap of maturity Level 3*Normalised knowledge level 3*Effectiveness of knowledge tran
sfer

Development of maturity Level 4=
  Gap of maturity Level 4*Normalised knowledge Level 4*Effectiveness of knowledge tran
sfer

Development of maturity level 5=
  Gap of maturity Level 5*Normalised knowledge*Effectiveness of knowledge transfer

Effect by increase in experience=
  0.05

Effect of double maturity=
  0.7

Effect of learning on price=
  LN( 1-Effect by increase in experience )/LN( Logaritm scale )

Effect of tech development on price=
  LN( 1-Effect of double maturity )/LN( 10 )

Effectiveness of knowledge transfer=
  0.5

External change fleetsize LEVEL 0=
  Change in fleetsize*Total car fleet*Portion of total fleet LEVEL 0

External change fleetsize LEVEL 1=
  Change in fleetsize*Total car fleet*Portion of total fleet LEVEL 1

External change fleetsize LEVEL 2=
  Change in fleetsize*Total car fleet*Portion of total fleet LEVEL 2

External change fleetsize LEVEL 3=
  Change in fleetsize*Total car fleet*Portion of total fleet LEVEL 3

External change fleetsize LEVEL 4=
  Change in fleetsize*Total car fleet*Portion of total fleet LEVEL 4

External change fleetsize LEVEL 5=
  Change in fleetsize*Total car fleet*Portion of total fleet LEVEL 5

"External R&D funding"=
  Usage of fund

External resource fund= INTEG (
  Extra funding-Usage of fund,
    0)

Extra funding=
  Periodical fund input
```

```
FINAL TIME  = 2100

Fleetsize LEVEL 0= INTEG (
  External change fleetsize LEVEL 0-Demand for LEVEL 1 from L0-
Demand for LEVEL 2 from L0-Demand for LEVEL 3 from L0-Demand for LEVEL 4 from L0-
Demand for LEVEL 5 from L0,
    Initial fleetsize LEVEL 0)

Fleetsize LEVEL 1= INTEG (
  Demand for LEVEL 1 from L0+External change fleetsize LEVEL 1-Demand for LEVEL 2-
Demand for LEVEL 3-Demand for LEVEL 4-Demand for LEVEL 5,
    Initial fleetsize LEVEL 1)

Fleetsize LEVEL 2= INTEG (
  Demand for LEVEL 2+Demand for LEVEL 2 from L0+External change fleetsize LEVEL 2-
Demand for LEVEL 3 from L2-Demand LEVEL 4 from L2-Demand Level 5 from L2,
    Initial fleetsize LEVEL 2)

Fleetsize LEVEL 3= INTEG (
  Demand for LEVEL 3+Demand for LEVEL 3 from L0+Demand for LEVEL 3 from L2+External ch
ange fleetsize LEVEL 3-Demand for LEVEL 4 from L3-Demand for LEVEL 5 from L3,
    Initial fleetsize LEVEL 3)

Fleetsize LEVEL 4= INTEG (
  Demand for LEVEL 4+Demand for LEVEL 4 from L0+Demand for LEVEL 4 from L3+Demand LEVE
L 4 from L2+External change fleetsize LEVEL 4-Demand for LEVEL 5 from L4,
    Initial fleetsize LEVEL 4)

Fleetsize LEVEL 5= INTEG (
  Demand for LEVEL 5+Demand for LEVEL 5 from L0+Demand for LEVEL 5 from L3+Demand for
LEVEL 5 from L4+Demand Level 5 from L2+External change fleetsize LEVEL 5,
    Initial fleetsize LEVEL 5)

Fraction users with a car=
  Min(Car per person,1)

Fraction users without a car=
  1-Fraction users with a car

Gap of maturity Level 1=
  1-Maturity Level 1

Gap of maturity Level 2=
  1-Maturity Level 2

Gap of maturity Level 3=
  1-Maturity Level 3

Gap of maturity Level 4=
  1-Maturity Level 4

Gap of maturity Level 5=
  1-Maturity Level 5

"Growth of car-sharing market"=
  0.2

"Growth of car-sharing through vehicle automation"=
  IF THEN ELSE( Portion of total fleet LEVEL 5>0.4 , Technology multiplier , 0 )

Highest price at the moment=
  MAX( Purchase price LEVEL 0 , MAX( Purchase price LEVEL 1 , MAX( Purchase price LEVE
L 2 , MAX( Purchase price LEVEL 3 , MAX( Purchase price LEVEL 4 , Purchase price LEVEL
 5 ) ) ) ) )

"Increase in car-share users"=
  "Adoption of car-sharing"*Fraction users with a car

"Increase in car-share users without car"=
  "Adoption of car-sharing"*Fraction users without a car

Initial Baseline price LVL 1=
  30000

Initial Baseline price LVL 2=
  40000

Initial Baseline price LVL 3=
  80000
```

```
Initial Baseline price LVL 4=
  200000

Initial Baseline price LVL 5=
  500000

"Initial car-share users"=
  273

Initial fleetsize LEVEL 0=
  6.39e+06

Initial fleetsize LEVEL 1=
  1000

Initial fleetsize LEVEL 2=
  2

Initial fleetsize LEVEL 3=
  2

Initial fleetsize LEVEL 4=
  2

Initial fleetsize LEVEL 5=
  2

Initial knowledge stock Level 1=
  Initial Maturity LEVEL 1*Maximum Knowledge needed for Level 1*Past knowledge depreci
ation factor

Initial knowledge stock Level 2=
  Maximum Knowledge needed for Level 2*Initial Maturity LEVEL 2*Past knowledge depreci
ation factor

Initial knowledge stock Level 3=
  Initial Maturity LEVEL 3*Maximum Knowledge Needed for Level 3*Past knowledge depreci
ation factor

Initial knowledge stock Level 4=
  Past knowledge depreciation factor*Initial Maturity LEVEL 4*Maximum knowledge needed
 for Level 4

Initial knowledge stock Level 5=
  Initial Maturity LEVEL 5*Past knowledge depreciation factor*Maximum knowledge needed
 for level 5

Initial Maturity LEVEL 1=
  0.2

Initial Maturity LEVEL 2=
  0.2

Initial Maturity LEVEL 3=
  0.01

Initial Maturity LEVEL 4=
  0.0001

"Initial Maturity Level 4 (test)"=
  0.1

Initial Maturity LEVEL 5=
  0.0001

Initial price of retrofit LEVEL 1=
  1000

Initial price of retrofit LEVEL 2=
  5000

Initial price of retrofit LEVEL 3=
  70000

Initial price of retrofit LEVEL 4=
  200000

Initial price of retrofit LEVEL 5=
```

```
  500000

INITIAL TIME  = 2000

KM traveled per car=
  (Total travel demand/Total car fleet)

"Knowledge adding through R&D Level 1"=
  "Annual R&D expenditure Level 1"

"Knowledge adding through R&D Level 2"=
  "Annual R&D expenditure Level 2"

"Knowledge adding through R&D Level 3"=
  "Annual R&D expenditure level 3"

"Knowledge adding through R&D Level 4"=
  "Annual R&D expenditure Level 4"+((1-Ratio 5 over 4)*"External R&D funding")

"Knowledge adding through R&D Level 5"=
  "Annual R&D expenditure Level 5"+(Ratio 5 over 4*"External R&D funding")

Knowledge stock Level 1= INTEG (
  "Knowledge adding through R&D Level 1"-Depreciation of knowledge Level 1,
    Initial knowledge stock Level 1)

Knowledge stock Level 2= INTEG (
  "Knowledge adding through R&D Level 2"-Depreciation of knowledge Level 2,
    Initial knowledge stock Level 2)

Knowledge stock Level 3= INTEG (
  "Knowledge adding through R&D Level 3"-Depreciation of knowledge Level 3,
    Initial knowledge stock Level 3)

Knowledge stock Level 4= INTEG (
  "Knowledge adding through R&D Level 4"-Depreciation of knowledge Level 4,
    Initial knowledge stock Level 4)

Knowledge stock Level 5= INTEG (
  "Knowledge adding through R&D Level 5"-Depreciation of knowledge Level 5,
    Initial knowledge stock Level 5)

Learning by doing effect level 1=
  (1-
(Cumulative experience LEVEL 1/Initial fleetsize LEVEL 1)^Effect of learning on price)

Learning by doing effect level 2=
  (1-
(Cumulative experience LEVEL 2/Initial fleetsize LEVEL 2)^Effect of learning on price)

Learning by doing effect level 3=
  (1-
(Cumulative experience LEVEL 3/Initial fleetsize LEVEL 3)^Effect of learning on price)

Learning by doing effect level 4=
  (1-
(Cumulative experience LEVEL 4/Initial fleetsize LEVEL 4)^Effect of learning on price)

Learning by doing effect level 5=
  (1-
(Cumulative experience LEVEL 5/Initial fleetsize LEVEL 5)^Effect of learning on price)

Learning effect delay=
  0.2

Logaritm scale=
  2

"Market share car-sharing"=
  "Total car-share users"/Total population

Market size LEVEL 2=
  Fleetsize LEVEL 2*Purchase price LEVEL 2

Marketshare LEVEL 0=
  User market LEVEL 0/Total user market

Marketshare LEVEL 1=
  User market LEVEL 1/Total user market
```

```
Marketshare LEVEL 2=
  User market LEVEL 2/Total user market

Marketshare LEVEL 3=
  User market LEVEL 3/Total user market

Marketshare LEVEL 4=
  User market LEVEL 4/Total user market

Marketshare LEVEL 5=
  User market LEVEL 5/Total user market

Maturity LEVEL 0=
  1

Maturity Level 1= INTEG (
  Development of Maturity Level 1,
    Initial Maturity LEVEL 1)

Maturity Level 2= INTEG (
  Development of Maturity Level 2,
    Initial Maturity LEVEL 2)

Maturity Level 3= INTEG (
  Development of maturity Level 3,
    Initial Maturity LEVEL 3)

Maturity Level 4= INTEG (
  Development of maturity Level 4,
    Initial Maturity LEVEL 4)

Maturity Level 5= INTEG (
  Development of maturity level 5,
    Initial Maturity LEVEL 5)

Maximum Knowledge needed for Level 1=
  6e+09

Maximum Knowledge needed for Level 2=
  1e+10

Maximum Knowledge Needed for Level 3=
  2.5e+10

Maximum knowledge needed for Level 4=
  5e+10

Maximum knowledge needed for level 5=
  1e+11

Normalised knowledge=
  Knowledge stock Level 5/MAX(Maximum knowledge needed for level 5,Knowledge stock Lev
el 5)

Normalised knowledge Level 1=
  Knowledge stock Level 1/(MAX(Maximum Knowledge needed for Level 1,Knowledge stock Le
vel 1))

Normalised knowledge Level 2=
  Knowledge stock Level 2/(MAX(Maximum Knowledge needed for Level 2,Knowledge stock Le
vel 2))

Normalised knowledge level 3=
  Knowledge stock Level 3/MAX(Maximum Knowledge Needed for Level 3,Knowledge stock Lev
el 3)

Normalised knowledge Level 4=
  Knowledge stock Level 4/MAX(Maximum knowledge needed for Level 4, Knowledge stock Le
vel 4)

Normalised price LEVEL 0=
  Purchase price LEVEL 0/Highest price at the moment

Normalised price LEVEL 1=
  Purchase price LEVEL 1/Highest price at the moment

Normalised price LEVEL 2=
  Purchase price LEVEL 2/Highest price at the moment
```

```
Normalised price LEVEL 3=
  Purchase price LEVEL 3/Highest price at the moment

Normalised price LEVEL 4=
  Purchase price LEVEL 4/Highest price at the moment

Normalised price LEVEL 5=
  Purchase price LEVEL 5/Highest price at the moment

Number of households=
  Total population/Average household size

Number of shedded cars per person=
  1

Number of traveling days per year=
  (104*0.78)+(260*0.87)

Past knowledge depreciation factor=
  0.5

Percentage of car shedding=
  Yearly number of shedded cars/Total car fleet

Percentage of car shedding among car share users=
  0.23

Percentage of fund used=
  0.1

Perception towards LEVEL 0=
  Portion of total fleet LEVEL 0

Perception towards LEVEL 1 automation=
  Portion of total fleet LEVEL 1

Perception towards LEVEL 2 automation=
  Portion of total fleet LEVEL 2

Perception towards LEVEL 3 automation=
  Portion of total fleet LEVEL 3

Perception towards LEVEL 4 automation=
  Portion of total fleet LEVEL 4

Perception towards LEVEL 5 automation=
  Portion of total fleet LEVEL 5

Periodical fund input=
  0+STEP(Total fund size/Total fund period,Start date of fund)-
STEP(Total fund size/Total fund period,Start date of fund+Total fund period)

Population growth= WITH LOOKUP (
  Time,
    ([(2000,0)-
(2100,0.009)],(2000,0.0065),(2004,0.004),(2008,0.0028),(2009,0.0049),(2011,0.0048),(20
12,0.0044),(2015,0.004),(2020,0.004),(2030,0.0029),(2040,0.0013),(2050,0.00014),(2060,
0.00027),(2100,0.0001) ))

Population rate=
  Population growth*Total population

Portion of initial fleetsize LVL0=
  Initial fleetsize LEVEL 0/Total initial fleetsize

Portion of initial fleetsize LVL1=
  Initial fleetsize LEVEL 1/Total initial fleetsize

Portion of initial fleetsize LVL2=
  Initial fleetsize LEVEL 2/Total initial fleetsize

Portion of initial fleetsize LVL3=
  Initial fleetsize LEVEL 3/Total initial fleetsize

Portion of initial fleetsize LVL4=
  Initial fleetsize LEVEL 4/Total initial fleetsize

Portion of initial fleetsize LVL5=
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  Initial fleetsize LEVEL 5/Total initial fleetsize

Portion of total fleet LEVEL 0=
  Fleetsize LEVEL 0/(Total car fleet)

Portion of total fleet LEVEL 1=
  Fleetsize LEVEL 1/(Total car fleet)

Portion of total fleet LEVEL 2=
  Fleetsize LEVEL 2/(Total car fleet)

Portion of total fleet LEVEL 3=
  Fleetsize LEVEL 3/(Total car fleet)

Portion of total fleet LEVEL 4=
  Fleetsize LEVEL 4/(Total car fleet)

Portion of total fleet LEVEL 5=
  Fleetsize LEVEL 5/(Total car fleet)

"Potential car-share users"=
  Total population-"Total car-share users"

Price gap level 1=
  Baseline price level 1-Desired baseline price level 1

Price gap level 2=
  Baseline price level 2-Desired baseline price level 2

Price gap level 3=
  Baseline price level 3-Desired baseline price level 3

Price gap level 4=
  Baseline price level 4-Desired baseline price level 4

Price gap level 5=
  Baseline price Level 5-Desired baseline price level 5

Price of retrofit LEVEL 1=
  Initial price of retrofit LEVEL 1*(Maturity Level 1/Initial Maturity LEVEL 1)^Effect
 of tech development on price

Price of retrofit LEVEL 2=
  Initial price of retrofit LEVEL 2*(Maturity Level 2/Initial Maturity LEVEL 2)^Effect
 of tech development on price

Price of retrofit LEVEL 3=
  Initial price of retrofit LEVEL 3*(Maturity Level 3/Initial Maturity LEVEL 3)^Effect
 of tech development on price

Price of retrofit LEVEL 4=
  Initial price of retrofit LEVEL 4*(Maturity Level 4/Initial Maturity LEVEL 4)^Effect
 of tech development on price

Price of retrofit LEVEL 5=
  Initial price of retrofit LEVEL 5*(Maturity Level 5/Initial Maturity LEVEL 5)^Effect
 of tech development on price

Purchase price LEVEL 0=
  20000

Purchase price LEVEL 1=
  Baseline price level 1+Price of retrofit LEVEL 1

Purchase price LEVEL 2=
  (Baseline price level 2+Price of retrofit LEVEL 2)-Subsidy for level 2

Purchase price LEVEL 3=
  (Baseline price level 3+Price of retrofit LEVEL 3)-Subsidy for level 3

Purchase price LEVEL 4=
  (Baseline price level 4+Price of retrofit LEVEL 4)-Subsidy for level 4

Purchase price LEVEL 5=
  (Baseline price Level 5+Price of retrofit LEVEL 5)-Subsidy for level 5

"R&D percentage of annual earnings"=
  0.075
```

```
Ratio 5 over 4=
  Annual earnings Level 5/(Annual earnings Level 5+Annual earnings Level 4)

Relative adoption rate=
  "Adoption of car-sharing"/"Total car-share users"

Safety LEVEL 0=
  0.01

Safety LEVEL 1=
  0.4

Safety LEVEL 2=
  0.4

Safety LEVEL 3=
  0.3

Safety LEVEL 4=
  0.7

Safety LEVEL 5=
  1

Sales LEVEL 1=
  External change fleetsize LEVEL 1+Demand for LEVEL 1 from L0

Sales LEVEL 2=
  Demand for LEVEL 2+External change fleetsize LEVEL 2+Demand for LEVEL 2 from L0

Sales LEVEL 3=
  Demand for LEVEL 3+Demand for LEVEL 3 from L2+External change fleetsize LEVEL 3+Dema
nd for LEVEL 3 from L0

Sales LEVEL 4=
  Demand for LEVEL 4+Demand for LEVEL 4 from L3+Demand LEVEL 4 from L2+External change
 fleetsize LEVEL 4+Demand for LEVEL 4 from L0

Sales LEVEL 5=
  Demand for LEVEL 5+Demand Level 5 from L2+Demand for LEVEL 5 from L3+Demand for LEVE
L 5 from L4+External change fleetsize LEVEL 5+Demand for LEVEL 5 from L0

SAVEPER  =
        TIME STEP

Start date of fund=
  2015

Subsidy amount level 2 and 3=
  0

Subsidy amount level 4 and 5=
  0

Subsidy for level 2=
  IF THEN ELSE( Maturity Level 2>0.4 , Subsidy amount level 2 and 3 , 0 )

Subsidy for level 3=
  IF THEN ELSE( Maturity Level 3>0.4 , Subsidy amount level 2 and 3 , 0 )

Subsidy for level 4=
  IF THEN ELSE( Maturity Level 4>0.4 , Subsidy amount level 4 and 5 , 0 )

Subsidy for level 5=
  IF THEN ELSE( Maturity Level 5>0.4 , Subsidy amount level 4 and 5 , 0 )

Technology multiplier=
  0.2

TIME STEP  = 0.015625

Total car fleet=
  Fleetsize LEVEL 0+Fleetsize LEVEL 1+Fleetsize LEVEL 2+Fleetsize LEVEL 3+Fleetsize LE
VEL 4+Fleetsize LEVEL 5

"Total car-share users"=
  "Car-share users with car"+"Car-share users without a car"

Total fund period=
```

```
  10

Total fund size=
  0

Total initial fleetsize=
  (Initial fleetsize LEVEL 0+Initial fleetsize LEVEL 1+Initial fleetsize LEVEL 2+Initi
al fleetsize LEVEL 3+Initial fleetsize LEVEL 4
+Initial fleetsize LEVEL 5)/6

Total population= INTEG (
  Population rate,
    1.59e+07)

Total travel demand=
  Total population*Travel demand per person

Total user market=
  User market LEVEL 0+User market LEVEL 1+User market LEVEL 2+User market LEVEL 3+User
 market LEVEL 4+User market LEVEL 5

Travel demand per person=
  Daily travel demand per person*Number of traveling days per year

Usage of fund=
  External resource fund*Percentage of fund used

User market LEVEL 0=
  (Maturity LEVEL 0*Utility LEVEL 0)

User market LEVEL 1=
  (Maturity Level 1*Utility LEVEL 1)

User market LEVEL 2=
  (Maturity Level 2*Utility LEVEL 2)

User market LEVEL 3=
  (Maturity Level 3*Utility LEVEL 3)

User market LEVEL 4=
  (Maturity Level 4*Utility LEVEL 4)

User market LEVEL 5=
  (Maturity Level 5*Utility LEVEL 5)

Utility LEVEL 0=
  ((1-
Normalised price LEVEL 0)*b1 Weight Price)+(Attractiveness LEVEL 0*b2 Weight Attractiv
eness)

Utility LEVEL 1=
  ((1-
Normalised price LEVEL 1)*b1 Weight Price)+(Attractiveness LEVEL 1*b2 Weight Attractiv
eness)

Utility LEVEL 2=
  ((1-
Normalised price LEVEL 2)*b1 Weight Price)+(Attractiveness LEVEL2*b2 Weight Attractive
ness)

Utility LEVEL 3=
  ((1-
Normalised price LEVEL 3)*b1 Weight Price)+(Attractiveness LEVEL3*b2 Weight Attractive
ness)

Utility LEVEL 4=
  ((1-
Normalised price LEVEL 4)*b1 Weight Price)+(Attractiveness LEVEL4*b2 Weight Attractive
ness)

Utility LEVEL 5=
  ((1-
Normalised price LEVEL 5)*b1 Weight Price)+(Attractiveness LEVEL5*b2 Weight Attractive
ness)

Yearly number of shedded cars=
  Number of shedded cars per person*"Car-share users abonding their car"
```