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Towards a quantitative method to analyze the long-term innovation diffusion of automated vehicles technology using system dynamics

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ABSTRACT

This paper 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 simulates the innovation diffusion of automated vehicles (AVs) on the long-term. It looks at the system of AVs from a functional perspective and therefore categorizes this technology into six different levels. Each level is represented by its own fleet size, 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 AVs. The model was applied to the Netherlands both for a base and an optimistic scenario (strong political support and technology development) named “AV in-bloom”. In these experiments, we found that the system is highly uncertain with market penetration varying greatly with the scenarios and policies adopted. Having an ‘AV in bloom’ eco-system for AVs is connected with a great acceleration of the market take-up of high levels of automation. As a policy instrument, a focus on more knowledge transfer and the creation of an external fund (e.g. private investment funds or European research funds) has shown to be most effective to realize a positive innovation diffusion for AVs. Providing subsidies may be less effective as these give a short-term impulse to a higher market penetration, but will not be able to create a higher market surplus for vehicle automation.

1. Introduction

Automated vehicles (AVs) may have a strong impact on the future of the transport sector, but also a much wider societal impact in the long-term, on safety, social equity and public health as discussed by Milakis et al. (2017b). A study by Hoogendoorn et al. (2014) shows the potential impact that AVs can have on traffic efficiency, highway capacity and congestion reduction. From a mobility point of view, Correia and van Arem (2016) look at the degrees of freedom that AVs bring in satisfying more trips of a household in the future, showing that AVs can satisfy more trips with some added traffic congestion resulting from the extra empty kilometers. Yap et al. (2016), Scheltes and Correia (2017) and Liang et al. (2016) studied the supply and demand of AVs as a last-mile/first-mile connection to train trips and observed changes in the value of travel time which disrupt the current mobility system as well as changes in the costs of operating these systems. But AVs are classified in different levels in terms of support and automation that they

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offer. Currently, there are driver support systems and partially automated vehicles on the market (intermediate levels of automation) that already have an impact on traffic. A study by Kyriakidis et al. (2015) shows that there could be a significant impact of automation on decreasing the number of traffic accidents, which are estimated by Anderson et al. (2014) at 5.3 million automobile crashes per year in the USA alone.

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 highlighted such as a decrease of travel time, improved traffic safety, and environmental benefits. However, Howard and Dai (2013) claim that: "the ability of automated vehicles to affect transformative change depends largely on how successful the vehicles are in attracting drivers from [conventional] 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 number of consumers towards vehicle automation, there must be a clear value proposition for this technology. The magnitude of the societal changes that will result from this technology will be determined by how consumers adopt AVs as part of their lives. Therefore in this paper, the adoption of vehicle automation is analyzed from the perspective of the end user.

Due to the potential beneficial effects of vehicle automation, there is a high incentive by policy makers to stimulate the development and diffusion of this technology. Governments from various European countries like UK, Finland and the Netherlands (Dutch Ministry of Infrastructure and Environment, 2014) are putting a strong focus on stimulating the development of vehicle automation. However, in order to make beneficial decisions, policymakers should have insights into the interaction between technology development, personal preferences of the end-consumer and entrepreneurial activities around vehicle automation. This is important either to be able to adapt to changes in society due to vehicle automation as well as to guide the direction and speed of this innovation system if they want to be leaders in this technology production.

For the above-mentioned reason, it seems relevant to have a modeling framework that allows gaining more insights into possible adoption scenarios of AVs in the long-term as a function of some future scenarios of mobility evolution and policy decisions that countries can control. As Rosenberg (1983) stated: "One of the most important unresolved issues is the rate at which new and improved technologies are adopted". The difficulty of forecasting the adoption of new technologies in the particular case of vehicles is also underlined by (Shladover et al., 2001) the authors state 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".

The present study is not the first one to aim at obtaining more insights on the diffusion of AVs into society. Some studies have explored the diffusion of AVs using both quantitative and qualitative methods. The methodologies that have been applied in those studies can be divided into historical analogies, expert interviews, panel consensus, trend projections and scenario development. Kyriakidis et al. (2015) studied the diffusion of Advanced Driving Assistance Systems (ADAS) in the period of 2012 to 2015 and compared the market penetration among different European countries. Milakis et al. (2017a) estimated through scenario development 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 AV systems, active safety systems, travel behavior and human factors. Kyriakidis et al. (2014) and De Winter et al. (2014) conducted a survey among, respectively, 4886 and 1517 respondents, which showed that most people expect vehicles to be driving fully automated on public roads around 2030.

The studies use different terminology, like market penetration, market introduction or deployment, nevertheless, their objective has been to understand innovation diffusion of AVs. Table 1 shows an overview of the estimates on the market penetration that have been found in those references. As it can be seen there is no consensus on market penetration for fully-automated vehicles (level 5).

Despite their value as a measure of what travellers are expecting from the transportation systems it is important to state that an estimation of the future car fleet has to be done independently of stated preferences and forecasting done by the consumers, because these can be highly biased. Expert opinion helps but it may be biased as well.

None of these studies have captured the complexity of different interacting factors on market penetration using quantitative

Table 1
Overview of market penetration estimations in literature.

Variable[a]	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	Underwood (2014), Rangarajan and Dunoyer (2014), Juliussen and 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 between 2025 and 2045 25% in 2035 50% in 2035–2050 75% in 2045 – 2060 90% in 2055	Milakis et al. (2017a), Underwood (2014), Rangarajan and Dunoyer (2014), Bierstedt et al. (2014), Litman (2015), Juliussen and Carlson (2014),

[a] Levels explained in Fig. 1.

methods. A framework that is able to capture the different aspects of the system in an unambiguous way and relates these aspects to each other is needed.

In this paper, we apply System Dynamics (SD) to explore the diffusion of AVs accounting for the complexity of several relevant interrelated components. In the current literature, simulation studies and field tests combined form an extensive amount of data on the possible effects of AVs. However, these data are mostly focused on the effects on traffic and not so much on other types of impacts, such as the effect on ownership. Despite a relative lack of information on how this complex system should behave we argue that there are enough indicators available on some of the different model components of this system which can be used to quantify some key relations within the framework. When lacking direct data, an alternative similar system may be observed and tentative relationships may be extracted to fill in the gaps. This work is not supposed to be a closed and final model of how this technology will evolve. It is a first tentative on shaping the complex system, formed between society and companies, that leads to vehicle automation development. Later it will be possible to change some of these parameters or relationships according to more knowledge that is being gathered year by year, therefore the contribution of this paper is mostly done on the discussion of the modeling framework with a critical perspective and some initial conclusions on the model application to the Dutch case-study under different scenarios.

Furthermore, due to a lack of common terminology, a clear distinction between different types of automated driving is not always done in past studies. A clear framework can also solve this ambiguity in terminology. The aim of this research is to create this framework and gain more knowledge about the factors that influence the diffusion of AVs so that it is possible to better understand the interaction of policies and their potential effects on the diffusion of the different automation levels. The purpose is to reflect on this framework providing a first iteration on what will be a path to reach a more robust quantitative model that can simulate the speed and direction of the diffusion of AVs over a medium to a long-term run.

In the next section, we describe the methodology. This is followed by the description of a proposed SD model structure that results from this methodology. The paper continues with the application of the model to the Dutch case-study in order to assess its applicability. The paper ends with the main conclusions that can be taken from the model construction and from the application of the model to the Dutch reality.

2. Methodology

2.1. Taxonomy

The technology of self-driving vehicles is best described as a movement of two game changers as introduced by Wilmink and Schuurman (2014): the movement from autonomous towards cooperative systems and the movement from manual control towards automated control of the vehicle. Both the first and the second game changer could happen independently from each other. Within the scope of this research, the main focus will be on the movement from manual control towards vehicle automation, either autonomously or in a more cooperative form. The adoption and diffusion of cooperative systems are out of the scope of this research.

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 such as highways. This paper will look at the system of AVs with the view of the functional pathway. The way the innovation system of vehicle automation is modeled through SD in this work best fits a functional pathway. In this paper technology gradually evolves towards a higher level of automation due to interdependent factors. The spatial element is not taken into account as this requires other modeling techniques.

The steps in the functional pathway from driver support, partial automation, high automation and full automation are divided into specific levels. In this study, the standards of SAE (2014) are used. These standards range from level 0 (no-automation) to level 5 (full-automation). We decided to reproduce the full description of these levels according to SAE in this paper because they are the basis of the whole model that has been developed and there is no better way of describing their differences (Fig. 1).

2.2. Geographical scope

The system of AV diffusion 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 are 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 et al. (2007).

The innovation system of AVs is not bound to a specific country or region. As the innovation is across borders, the system is not geographically specific. Hekkert et al. (2007) specify these systems as a Technology Specific Innovation System (TSIS). Nevertheless, there are regional differences in determining 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 observed in the different adoption rates across the globe of innovations like mobile phones, solar power, and electric vehicles.

The current state of the infrastructure and automobile fleet size in a specific region can be a determinant factor for the speed of innovation of AVs as well. Statistics show that, for example, the registration of new cars in developing countries in Africa and China grows much more rapidly (annual growth rate of 11.4%) than in Europe and USA (with respectively 1.4% and 0.8%) (Gao et al., 2014). This difference in growth rate can have a major impact on the adoption rate of new technologies, such as vehicle automation, in these regions. An example of regional differences in adoption rates can also be seen by comparing the market penetration of ADAS

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**

Fig. 1. Overview of levels of automation by SAE Standard J3016. .
Source: (SAE, 2014)

across different parts of Europe (Kyriakidis et al., 2015). Countries with a low GDP like Romania, Croatia, Latvia, and Estonia have much lower market penetration (between 10% and 15%) than countries with a high GDP like Germany, Sweden, Austria and Luxembourg (between 30% and 50% market penetration).

Due to the sensitivity of innovation diffusion to regional differences, any kind of model should be sensitive to the type of region to which is being applied. Hence our model is intended to be general and has a holistic perspective within the boundaries of developed countries. However, to represent the whole developed world would make the model unnecessary complex and we would not have the information available for designing such framework. In order to test the model in a proper fashion, data from a specific region has to be collected for a case-study. Therefore the Netherlands is chosen as a geographic region for this case-study. As the Netherlands is a small country with a relatively high availability of data we are convinced that this case-study has the necessary conditions to be a first good example for the purpose of this research. Furthermore, the Netherlands has shown to be very active in the field of transportation and vehicle automation (Dutch Ministry of Infrastructure and Environment, 2014), so new data is likely to occur in the near future on the system components that are part of the model. When data is missing for a specific model component in the Netherlands, this will be complemented with data from other comparable regions.

2.3. Choosing a modeling approach

When analyzing the innovation system of AVs three main characteristics can be identified. The innovation system of AVs is uncertain, complex and dynamic. First of all, the system is uncertain because there is a lack of knowledge about its structure and the factors that have an effect on the development of the technology and diffusion of the different levels of automation. As such this paper provides a first tentative approach on modeling the adoption of this technology. There is also a lack of data about the magnitude of some specific factors in this system. A second characteristic is that the factors in the innovation system are quite interrelated. As we will show there are various feedback loops in this innovation system, which makes the system a complex one. The third characteristic of the innovation system is that the factors that affect the adoption rate are mostly endogenous to the system and thus have a tendency to change over time. A multitude of highly connected endogenous factors makes the behavior of the system unpredictable and dynamic.

In order to gain quantitative insight in the diffusion of AVs over the long-term, we must choose a modeling method that can be applied to uncertain, complex and dynamic systems. AVs are totally new products that are in the beginning of the product lifetime cycle; hence this needs to be taken into account when studying the future demand and diffusion into society.

Table 2
Comparison system dynamics and agent-based modeling.

	System Dynamics (SD)	Agent-Based Modeling (ABM)
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

The method should be able to show the future behavior of the speed and direction of the diffusion of AVs. This way, relations between factors might come to light that have a strong influence on one another. Due to the many factors that are involved with the diffusion of AVs, a large time horizon needs to be taken into account. To learn more about the speed and direction of the diffusion of AVs over this long time horizon the general average behavior on an aggregated level of the system is more feasible to be used.

In the search for an appropriate method that meets the above-mentioned requirements, a widespread number of research methodologies have been looked upon. Simulation seems to be applicable for the innovation system of AVs and seems to meet the method requirements. 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”. There are two simulation techniques that seem appropriate to model an uncertain, complex and dynamic system: System Dynamics (SD) and Agent-Based Modeling (ABM).

When comparing SD with ABM it can be seen that both techniques are capable of simulating complex systems that show nonlinear behavior. SD uses a continuous approach in which the behavior of an innovation system is driven by its feedback loops and accumulations. 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. Agent-Based Modeling has a bottom-up approach whereby the system results from describing the behavior of the smallest model components (agents) interacting with each other and with the environment. It is an approach that is based on the emergence of aggregate realistic behavior from describing the disaggregate relations.

The distinction between both approaches can also be categorized as macroscopic (SD) versus microscopic (ABM). Table 2 shows an overview of the comparison between SD and ABM.

Borshchev and Filippov (2004) argues that ABM is the most suitable method to use when not much is known about the macroscopic behavior of the system, but when more information is available about the individual behavior of agents. However in the innovation system of AVs, the opposite seems to be the case: little knowledge is available about the detailed behavior of possible future actors, their objectives and their relations over the long-term of the system. More knowledge seems to be available about possible aggregate phenomena that could occur and the overall structure of the system, or at least some assumptions can be taken by observing similar systems or looking at results from other aggregate studies or event disaggregate (like ABM).

SD seems to be most suitable to capture the complex and dynamic nature of this innovation system. 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.

3. The system dynamics model

3.1. High-level description of the model

By using the TSIS framework of Hekkert et al. (2007), the innovation diffusion theory of Rogers (2003) and the Abernathy and Utterback (1978) dynamics of innovation model five important system components have been identified that complement our framework of the innovation system of AVs. All of these system components are represented by a stock in the model and interact with each other by various dynamic loops.

In system dynamics, stocks, (also known as levels, accumulations, or state variables) are used to represent the real-world processes (e.g. stocks of material, knowledge, people, money). They change their value continuously over time with the given flows. Flows, also known as rates, change the value of stocks. In turn, stocks in a system determine the values of flows.

The five stocks (system components) in our model 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 fleet size and adoption rate of the various levels of automation and (5) the dynamic interaction between car-ownership and carsharing. A high level system overview of the components and their dynamic loops is shown in Fig. 2.

An example of a feedback loop that is not included in this model is the impact of the usage of AVs on traffic congestion. Congestion has an impact on travel behavior, which by its turn has an impact back on the usage of AVs. This has been well documented and there are studies showing how automation and cooperation can change traffic capacity and general performance in different elements of the transport system such as urban vs interurban environments (Letter and Elefteriadou, 2017; Luo et al., 2016; Talebpour and Mahmassani, 2016). Other elements such as changes in traffic safety or emissions are not being considered either. This

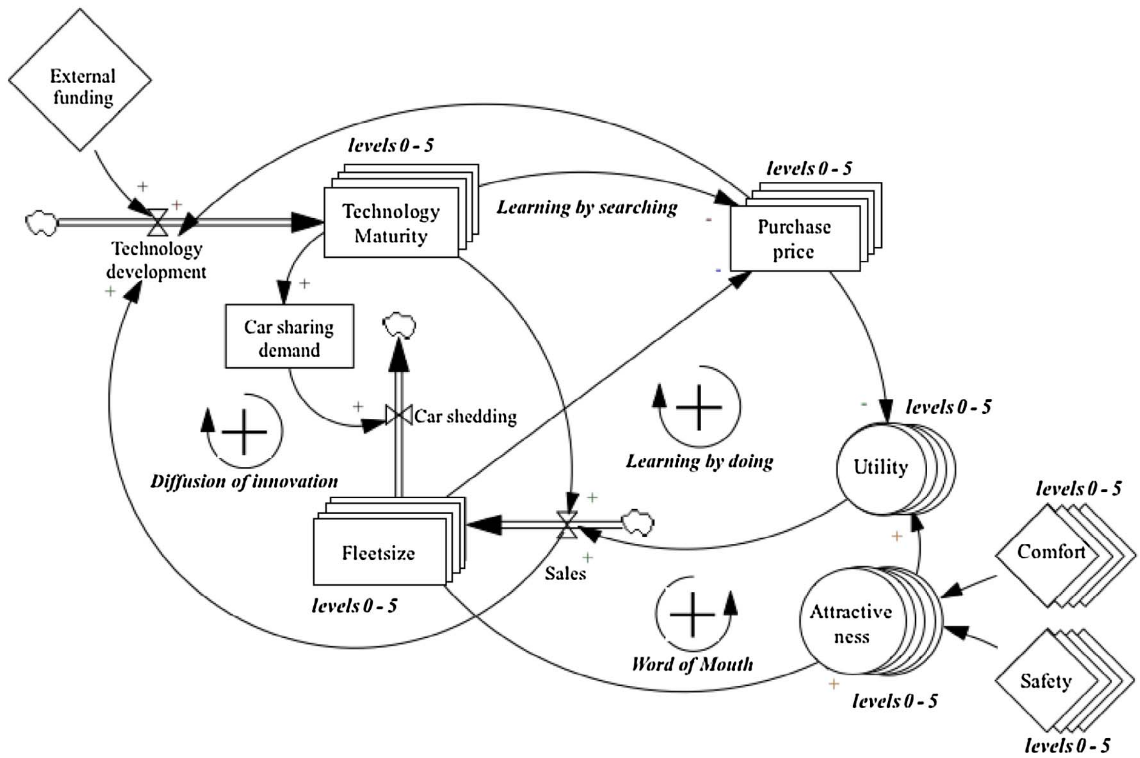

Fig. 2. System components and dynamic loops.

choice has mainly to do with the non-geographical nature of an SD model whereby applying it to a country is not going to allow distinguishing its different regions: a city will benefit in a different way compared to the country side. But these are certainly elements that are relevant in future research.

3.1.1. Technology maturity

The technology development of AVs is driven by the amount of R&D investment that is put into technology, and by how these funds are turned into knowledge. This representation of knowledge accumulation intends to reproduce the process by which in the real world softer innovation factors such as creativity and coincidence play an important role. Due to the level of aggregation of the model, one assumes that the right innovation factors are in place in order to develop the technology.

Investment in R&D is based on the potential gains of a technology and thus on its current and future market size. In the model, this is represented as the Sales. The dynamics that are being described in the model are on a higher level than individual companies. In this model, Sales is not being described as the sales of an AV by one specific company, rather it represents the sales of AVs in general. When the sales of AVs of a specific level increase the market becomes more interesting for companies to invest in the R&D of this specific level.

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 0–100%, although it could be argued that a technology can always be improved 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.

3.1.2. Purchase price

As the technology develops through R&D, this will have an effect on the purchase price. The purchase price will decrease through learning by searching effects. When the fleet size 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 fleet size will thus lower the purchase price for the end consumer. The purchase price has a negative effect on the utility of a specific vehicle so when the price decreases, the utility will therefore increase. This will further lead to more vehicles of this type being bought.

3.1.3. Utility of the automation level

Each level of automation will be appointed with a certain level of comfort and safety. It should be clearly stated that these 'soft' variables are simplified in order to make them quantifiable and usable. The parameter chosen for both comfort and safety are relative amongst the different levels of automation and do not represent anything outside the context of this model. E.g. a parameter '0' chosen for comfort does not mean that the level of automation is not comfortable at all, but merely that it is less comfortable than other levels of automation in the model that have a value above 0. This comfort and safety are exogenous to the model and contribute to the attractiveness of each automation level. If the fleet size of a certain level of automation grows, the probability of people finding this level of automation on the street will increase hence consumers will get more familiar with the concept of AVs.

Likewise, the interest of the media on the topic of AVs will grow as the sales and fleet size increase in the early days of the technology. As people see more examples around them, they 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 (2003) 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 has been coined as the dynamic feedback loop of word-of-mouth.

3.1.4. Fleet size and adoption rate

The number of vehicles in use at a certain moment in time in a certain region is specified as the fleet size. 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. Each of the six levels of automation will be represented by its own fleet size and therefore they will form its own 'market'. The economic size of each market is specified as the number of vehicles sold multiplied by the average price of the vehicles.

The fleet size of a specific level of automation increases through sales. 'Sales' represents a transition in the number of cars in the total car fleet from one level to another level. Whether these cars are being disposed and new cars are being purchased or whether these cars are being retrofitted to a better automation level is not being distinguished in the model. This is due to the level of aggregation in which the model operates. Sales are 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 there is going to be a positive effect on sales. There are, naturally, different adoption rates among the population as it is so well known in marketing theory and practice. After the early adopters who are always keen on adopting new technologies, a bigger group of people follow when the technology is more mature. In a later stage another part of the population starts using the technology once is the technology has fully matured. This usually results in an S-shaped adoption rate, as we will see later in this paper.

The market penetration of one level is specified as the percentage of the fleet size of this specific level of automation compared to the total fleet size. The sum of the market penetration of level 0 up to level 5 is 100% at any given moment. The diffusion of innovation represents a dynamic feedback loop in the model between the technology development and the fleet size of AVs. This fleet size is increased by the sales, of which the relative speed is expressed as the adoption rate.

3.1.5. Carsharing

In this study, the fleet size is assumed to consist of vehicles which can either belong to individuals or to a fleet-owner, such as a taxi company or a carsharing company. Two significant trends could disrupt this ownership of vehicles in the upcoming decades: carsharing and a lower average vehicle lifetime. Bierstedt et al. (2014) talk about a likely significant shift in car ownership over the next decades due to the introduction of AVs. Cars currently are in use for an average of ten years. "With new business model opportunities and carsharing applications, this could speed up the car replacement and thus the replacement of new technologies." According to Shaheen and Cohen (2007), carsharing has a major impact on car ownership. She states that "carsharing provides a flexible alternative that meets the diverse transportation needs across the globe while reducing the negative impacts of private vehicle ownership." Automation is a game changer for car-sharing, various studies from Correia and Antunes (2012), Jorge and Correia (2013), Jorge et al. (2015) show the importance of the fact that automation enables providing this mode at a lower price since the system can be operated without the high costs and management complexity of relocating vehicles in the city, which currently has to be done with normal cars.

The model takes into account the impact that vehicle automation can have on the growth of the carsharing market. The other effect that is taken into account in the model is the effect that carsharing can have on the ownership rate which can lead to the shedding of cars by individuals who previously owned a car. A growth in the carsharing market can, therefore, lead to a decrease in fleet size over the long haul.

3.2. Specification of the mathematical structure

The system components are specified separately in the model for each of the 5 individual levels of automation. This means that level 1 has its own purchase price, technology maturity and fleet size, which is different than those of, for example, level 3. The levels are represented with an index $j = [0, \ldots, 5]$.

The endogenous variables in the equations are all time dependent. For simplicity reasons, we have chosen not to write this time dependence in every variable. So, for example, the purchase price, $p_j (t)$, is depicted just 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 we have 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, *egr.* This combination of letters should not be seen as a multiplication between various variables, but just as one variable. In the 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 $M_j\ (0)\ =\ M_{j0}$.

3.2.1. Technology maturity

R&D expenditure is traditionally a low percentage of the total revenue of a market. In the model, the annual revenue of the market is specified as the product of the annual number of sold vehicles and the average purchase price of a vehicle. The technology development of the six levels of automation is 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, for example, level 3 automation is therefore dependent on the sales of level 3 vehicles. This is a simplification because some of the same components are needed for all the automation levels. It is safe to say that manufacturers are offering commercial available systems up to level 2 currently. Research on level 3 and 4 by both traditional car makers and IT companies is taking place although little information on their actual performance and operational design domain is available in scientific literature.

To simulate the concept of learning and forgetting we have chosen to configure a knowledge stock. In this stock, the knowledge gathered through R&D is accumulated. 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 it is translated in a monetary way. The stock 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 related to level j, rd_j is given by:

R&D expenditure

$$rd_j = s_j * p_j * frd \tag{1}$$

where s_j are the sales of level j, p_j is the purchase price of level j, and frd is the R&D percentage of annual earnings.

The 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 (see Eq. (2)).

Knowledge stock

$$\frac{dK_j}{dt} = rd_j - (K_j * \partial) \tag{2}$$

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 and in order to do so, a variable is added that represents the ‘total knowledge that is needed’, an_j, for a fully matured technology. This variable is imaginary and does not 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 somehow be estimated ex-ante, for example by looking at the potential market size or looking at earlier investment amounts in fully matured technology in the automotive sector (see Eq. (3)).

Normalized knowledge of level j

$$nK_j = \frac{K_j}{MAX\,(K_j, an_j)} \tag{3}$$

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 represents the development of the maturity level. A gap is specified as the inverse of the maturity:

Maturity gap of level j

$$gap_j = 1 - M_j \tag{4}$$

The sum of the maturity and the gap will therefore always be 1.

The normalized knowledge is multiplied by the gap to ensure the maturity stock, M_j, will not grow lager 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 (see Eq. (5)).

Maturity stock

$$\frac{dM_j}{dt} = +(nK_j * gap_j * ef) \tag{5}$$

We have 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 built between the gathering of knowledge and the growth of maturity. This also causes that maturity to be less sensitive to 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 which increase when the technology gets more mature. At the end, it takes considerable knowledge to slightly increase the maturity. 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, K_{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 (Eq. (6)).

Initial knowledge stock

$$K_{0j} = nK_j * M_{0j} * df \tag{6}$$

3.2.2. Purchase price

The purchase price, p_j, is the sum of the baseline price, bp_j, and the retrofit price, rp_j (Eq. (7)).

Purchase price

$$p_j = bp_j + rp_j \tag{7}$$

Whereby the base line price is given by:

Base line price

$$bp_j = bp_{0j}\left(\frac{E_j}{E_{0j}}\right)^{lcd} \tag{8}$$

where bp_{0j} is the initial baseline price for level j, E_j are the experience levels, and lcd is the learning-by-doing curve.

Both the baseline price and the retrofit price (expression supplied in Eq. (16)) 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 (Eq. (9)). 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 (Eq. (10)).

Learning-by-doing curve

$$lcd = \log_{\omega}(1-x) \tag{9}$$

Learning-by-searching curve

$$lcs = \log_{\Omega}(1-\mu) \tag{10}$$

3.2.2.1. 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 is 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 time (Eq. (11)).

Accumulation of experience

$$\frac{dEj}{dt} = \sum_{i=0}^{(j-1)} s_{ij} \tag{11}$$

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 $0 \leqslant lbd \leqslant 1$ (Eq. (12)).

Learning-by-doing variable

$$lbd_j = 1-\left(\frac{E_j}{E_{0j}}\right)^{lcd} \tag{12}$$

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 (Eq. (13)).

Baseline price stock

$$\frac{dBP_j}{dt} = -dc_j \tag{13}$$

The desired baseline price, dbp, represents the asymptote that the baseline price will reach. This desired baseline price is constant. A 'price gap' variable, $pricegap_j$, will be specified as the baseline price minus the desired price (Eq. (14)).

Specification of the price gap

$$pricegap_j = BP_j - dbp \tag{14}$$

The reduction of price is a product of the learning-by-doing variable, the price gap, and a learning effect delay factor. This

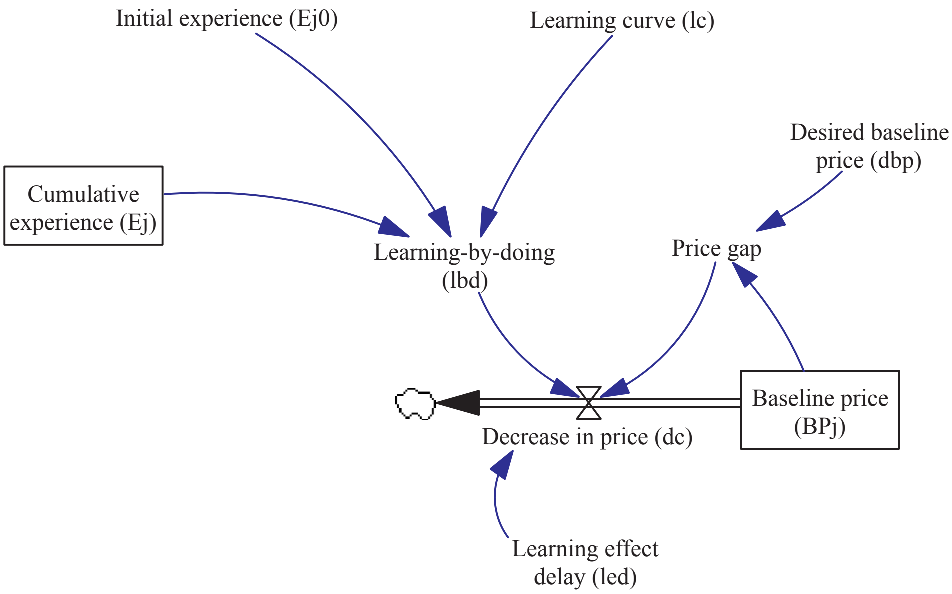

Fig. 3. Structure of the new specification of Baseline price.

function represents the real world phenomenon that the baseline price of a vehicle decreases when the industry recognizes that there is 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 decrease too much. If this market is growing the costs will decrease through the process of innovation, which leads to learning-by-doing effects. The cumulative experience that is built up has a direct effect on the learning-by-doing. This effect, however, is never so direct in the real system because 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 (Eq. (15)). This 'learning effect delay', *led*, has a dimension of 1 / delay [in years] and is constant.

Decrease of price for level *j*

$$dc_j = pricegap_j * lbd_j * led \tag{15}$$

The total specification of the baseline price is depicted in Fig. 3.

3.2.2.2. 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 (Eq. (16)). With every multiplication Ω of the maturity of a technology, the retrofit price decreases with a fraction μ (remember Eq. (10)).

Retrofit price

$$rp_j = rp_{j0}\left(\frac{M_j}{M_{j0}}\right)^{lcs} \tag{16}$$

3.2.3. Utility of an automation level

The utility of a specific level of automation, U_j, is the sum of the attractiveness, a_j, and the normalized price, np_j, both multiplied by a weight (Eq. (17)).

Utility function

$$U_j = (np_j * ß_1) + (a_j * ß_2) \tag{17}$$

The utility is represented with a value between 0 and 1. For this reason, the purchase price has to be normalized, np_j. To normalize the purchase price this is divided by the highest price of all the levels of automation at a specific time instant (Eq. (18)).

Normalized price

$$np_j = p_j/(MAX(p_n)) \text{ with } n = [0,...,5] \tag{18}$$

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 for each technology *j* in the model (Eq. (19)).

Attractiveness

$$a_j = (sf_j * ß_3) + (cf_j * ß_4) + (pc_j * ß_5) \tag{19}$$

The β parameters that can be found in Eqs. (17) and (19) represent a weight value. These parameters indicate the weight that customers put on a specific attribute of the utility function. The weight factors are constants in the simulation model and we assume an average population.

The familiarity, pc_j, consists of the ratio of the fleet size of j compared with the total fleet size. This illustrates the word of mouth principle, which states that people will get more familiar with the automation level j if they see j around them more often when compared to the other levels of automation.

The total fleet size of the model is given by:

Total fleet size

$$V = \sum_{n=0}^{5} V_n \tag{20}$$

3.2.4. Fleet size

The fleet size is the total number of vehicles of each level of automation $j = [0, \dots, 5]$, V_j. Each fleet size starts with an initial value. This variable accumulates all the change of vehicles from i to j, c_{ij}, with $i = [0, \dots, j-1]$. All the changes of vehicles from j to the other levels of automation k, c_{jk} with $k = [+1, \dots, 5]$, are subtracted from the stock. Each fleet size is also growing by an exogenous growth rate, egr_j (Eq. (22)).

Fleet size stock

$$\frac{dVj}{dt} = \sum_{i=0}^{(j-1)} c_{ij} + egr_j - \sum_{k=(j+1)}^{5} c_{jk} \tag{21}$$

The exogenous growth rate, egr_j, is the product of the total fleet size, the change in fleet size and the market penetration of level j. The change of vehicles in the fleet size, cV, will be explained further on in this paper (Eq. (35)).

Exogenous growth rate of the vehicle fleet size

$$egr_j = V * cV * \left(\frac{V_j}{V}\right) \tag{22}$$

Variable c_{ij} in Eq. (21) represents the number of vehicles that "transfer" from automation level i to automation level j. The word transfer is used to mean that a vehicle of level i disappears and one of level j is created in the model which can happen through shedding or retrofitting. It is assumed that vehicles can only transfer towards a higher automation level ($i < j$). It is possible to transfer a vehicle from any lower level of automation to any higher level of automation. So $i = [0,\dots,j-1]$. This specification assumes a continuous flow of the fleet size 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 at a later stage.

The change of vehicles from level i to level j depends on the fleet size 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 (Eq. (23)) in which the utility of j is divided by the utility of i and j combined. In this model the second hand market does not exist thus it is not considred that older technology may be adopted by other people.

Change of vehicles from level i to level j

$$c_{ij} = V_i * (1/\alpha) * M_j * \frac{U_j}{U_i + U_j} \tag{23}$$

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 with respect to i, the likelihood increases that people will favor level j over the level i. An illustration of this structure of change between the levels is depicted in Fig. 4. 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.

The likelihood of people changing to level j will always be with respect to each of the individual levels $i < j$, but not to the sum of all the levels together. This is in contrast to a normal logit function as described in Train and Winston (2007) and McFadden (1974). This function represents the probability that j is chosen over all the other alternatives (Eq. (24)).

Logit function

$$P_j = \frac{e^{U_j}}{\sum_{j=0}^{5} e^{U_j}} \tag{24}$$

The 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 with respect to level 1,

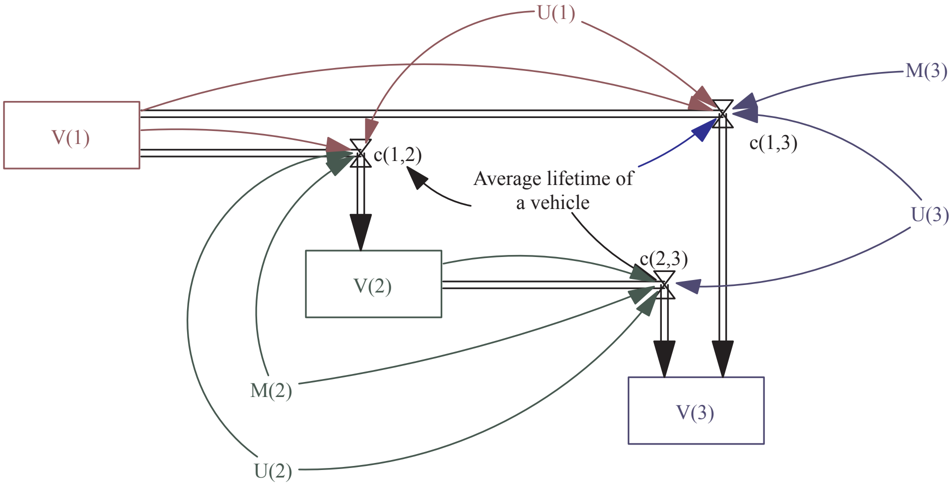

Fig. 4. Illustration of change of vehicles between the levels in VensimPro.

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 into the function.

3.2.5. 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 have not adopted carsharing yet is specified as the potential adopters, PA. The potential adopters are specified by the total population, N, minus the number of adopters (Eq. (25)). 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.

Potential adopters

$$PA = N-A \tag{25}$$

The total population is a stock that varies with the flow of births and deaths:

Population

$$\frac{dN}{dt} = birth\ ratedeath\ rate \tag{26}$$

The carsharing users, with unit "person", are split into users with a car, A_c, and a group without a car, A_{wc} (Eq. (27)).

Number of carsharing users

$$A = A_c + A_{wc} \tag{27}$$

The carsharing users' stocks, with and without a car, both increase through the same construction. The stock is the integral of the adoption rate of carsharing, ar_{cs}, times 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 section and is shown in Eq. (34).

Carsharing users with a car

$$\frac{dA_c}{dt} = (\mathrm{ar_{cs}}*f_c)-abr \tag{28}$$

Carsharing users without a car

$$\frac{dA_{wc}}{dt} = (\mathrm{ar_{cs}}*f_{wc}) + abr \tag{29}$$

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

Fraction of users with a car

$$f_c = \frac{V}{N} \tag{30}$$

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.

Adoption rate carsharing users

$$ar_{cs} = g*PA*\frac{A}{N} \tag{31}$$

Eq. (31) 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 rises, this slowing factor reduces. This results in a phase of massive adoption. As the group of potential adopters decreases, the word-of-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 in 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 growth rate g consists of the sum of a normal market growth rate, g_m, and a growth rate through vehicle automation, g_{va} (Eq. (32)).

Growth rate of carsharing

$$g = g_m + g_{va} \tag{32}$$

We have identified a knowledge gap about the impact of vehicle automation on the growth of the carsharing market. Although various studies refer to this impact, such as one by Le Vine et al. (2014), none can give clear indications of the magnitude of the impact.

In our model, the growth rate of carsharing 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 rate of carsharing (Eq. (33)). 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 (Shaheen and Cohen, 2012). 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 fact level 4 vehicles could also be considered under some modes of operation, namely in city centers, however in this study we decide not to assume volume of trips being done in the different types of environments.

Growth rate carsharing through vehicle automation level 5

$$g_{va} = IF\ \ THEN\ \ ELSE\ (M_j > 0.4, tm, 0) \tag{33}$$

In the real system, a product would not become available on the market until the technology has reached a certain threshold maturity. Until this threshold, the manufacturers are unsure about the reliability and performance of the product. In our model we assume the first 10% of maturity as a phase of 'product development'. A phase of 'testing and validation' of the technology is assumed at a maturity of 10–40%. The deployment wouldn't start until 40% maturity. Thus the effect of vehicle automation on the growth rate of carsharing is only active after the maturity of level 5 has reached the threshold value of 40%. This aspect of a threshold value is recognized as a limitation of SD modeling as it gives a discrete representation of a continuous real-world phenomenon. However, without a threshold value the deployment of a new AV level would already occur at a very low maturity, which is not representative. The threshold of 40% is an assumption and is taken from various expert interviews realized during the AVs Symposium in Ann Arbor from July 21 until July 24, 2015.

Various studies, such as Robert (2000), Cervero and Tsai (2003), Rydén and Morin (2005), Martin et al. (2010), and Schoettle and Sivak (2015), show that there is a rate between 10% and 43% of car shedding among carsharing users, meaning people abandoning 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* (Eq. (34)). The abandoning rate is specified as a flow of users from A_c to A_{cw}.

Abandoning rate of cars due to carsharing

$$abr = A_c*sr \tag{34}$$

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 fleet size *V*. The abandoning rate (in *[person/year]*) is translated into a yearly number of shedded cars (in *[cars/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 fleet size to create an annual percentage of shedded cars (Eq. (35)).

Change in vehicle fleet size

$$cV = \frac{abr*f_c}{V} \tag{35}$$

The total vehicle fleet size is changed through an exogenous growth rate, egr_j, at each of the levels of automation as described earlier in this section.

3.2.6. Performance indicators

Various endogenous indicators are produced in the model, which have no influence on the dynamics of the model, but that can be used in the validation process.

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 fleet size.

Adoption rate of vehicle automation

$$ar_{va,j} = \frac{\sum_{s=0}^{j-1} s_j}{V} \quad (36)$$

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

$$d_j = \frac{V_j}{V} \quad (37)$$

The number of households, hh, is a quotient of the total population (N) and the average household size, shh:
Number of households

$$hh = \frac{N}{shh} \quad (38)$$

The number of cars per household, chh, results from dividing the total vehicle fleet size by the total number of households.
Number of cars per household

$$chh = \frac{V}{N/shh} \quad (39)$$

The travel demand is the product of the travel demand per person, ptd, and the total population:
Total travel demand

$$td = ptd*N \quad (40)$$

The distance traveled per car, tc, is another indicator. It represents the quotient of the total travel demand, td, and the total vehicle fleet size:
Distance travelled by car

$$tc = \frac{td}{V} \quad (41)$$

An overview of the equations of the stocks and the endogenous variables can be found in Table 3.

4. Case-study in the Netherlands

4.1. Scenarios

In this section, we show the results of using the model by applying it to the case-study of the Netherlands. By using the model we aim at learning more about the applicability of the model itself and about the dynamics of the system of AVs adoption. We aim at learning more on how to change the direction and the speed of the adoption rate of AVs and on how policy and technological development contributes to this adoption rate under the assumptions that we have made in the previous section.

The case-study will be run on a base line scenario (more pessimistic) and on an optimistic scenario studied by Milakis et al. (2017a). Milakis et al. (2017a) applied the intuitive logics scenario approach in expert-based workshops to identify plausible development paths of AVs in the Netherlands. Four scenarios (AV in standby, AV in bloom, AV in demand, AV in doubt) were developed around permutations of two driving forces for the development of AVs: technology and policy. Moreover, the four scenarios involved variations of other relevant driving forces (i.e. customers' attitude, economy, and environment). The 'AV in bloom' scenario was chosen as input for the case-study in this paper due to the use of comparable components of the innovation system and due to the longer time horizon that the authors have used (100 years). Moreover the Netherlands is a country that is currently positioning itself on the forefront of the research and development of these technologies therefore it makes sense to look at the possible adoption rates of automation as a result of this trend.

In the model described in the previous section some of the equations use static parameters. A set of these parameters is chosen for a base run of the model. It is impossible to transcribe in this paper all the data sources and considerations when establishing this base run scenario. In some cases like the initial fleet size for 2000 it was possible to obtain data (CBS Statline, 2015) but in others such as the initial baseline price of each level had to be considered by the authors by comparison with current prices. Some of the parameters were obtained by expert estimation during the Automated Vehicle Symposium in Ann Arbor from July 21 to July 24, 2015. All the parameters can be found in Appendix A where an extra column shows how certain/uncertain the authors are regarding their levels in qualitative way. A final column shows the result of the sensitivity analysis done to the model results regarding each and every parameter. The value of all the input parameters in the model was changed by −10% and +10%. The effect of these changes was checked and:

- when the indicators do not change by altering a specific input parameter, the sensitivity of the model on these input parameters is considered "low".
- when a numerical change is noticed, the sensitivity is considered "medium".

Table 3
Full model equations.

Name	Notation	Expression	Unit[a]	Equations
Annual R&D expenditure	rd_j	$rd_j = s_j*p_j*frd$	Euro/year	Eq. (1)
Knowledge	K_j	$\frac{dK_j}{dt} = \mathrm{rd}_j-(\mathrm{K_j}*\partial)$	Euro	Eq. (2)
Normalized knowledge	nK_j	$nK_j = \frac{K_j}{MAX(K_j,an_j)}$	Dmnl	Eq. (3)
Maturity gap	gap_j	$gap_j = 1-M_jBP_j$	Dmnl	Eq. (4)
Maturity	M_j	$pricegap_j$	Dmnl	Eq. (5)
Initial Knowledge stock	K_{0j}	$K_{0j} = nK_j*M_{0j}*df$	Euro	Eq. (6)
Purchase price	p_j	$p_j = bp_j + rp_j$	Euro/car	Eq. (7)
Baseline price	bp_j	$bp_j = bp_{0j}\left(\frac{E_j}{E_{0j}}\right)^{lcd}$	Euro/car	Eq. (8)
Learning-by-doing	lcd	$lcd = \log_{\omega}(1-x)$	Dmnl	Eq. (9)
Learning by searching	lcs	$lcs = \log_{\Omega}(1-\mu)$	Dmnl	Eq. (10)
Cumulative experience	E_j	$\frac{dEj}{dt} = \sum_{i=0}^{(j-1)} s_{ij}$	Car	Eq. (11)
Learning-by-doing	lbd_j	$lbd_j = 1-(\frac{E_j}{E_{0j}})^{lcd}$	Dmnl	Eq. (12)
Baseline price stock	BP_j	$\frac{dBP_j}{dt} = -dc_j$	Euro/car	Eq. (13)
Price gap	$pricegap_j$	$pricegap_j = BP_j-dbp$	Dmnl	Eq. (14)
Decrease of price	dc_j	$dc_j = pricegap_j*lbd_j*led$	Dmnl	Eq. (15)
Retrofit price	rp_j	$rp_j = rp_{0j}\left(\frac{M_j}{M_{0j}}\right)^{lcs}$	Euro/car	Eq. (16)
Utility	U_j	$U_j = (np_j*ß_1) + (a_j*ß_2)$	Dmnl	Eq. (17)
Normalized price	np_j	$np_j = p_j/((MAX(p_n), withn = [0,...,5])$	Dmnl	Eq. (18)
Attractiveness	a_j	egr_j	Dmnl	Eq. (19)
Total fleet size	V	$V = \sum_{n=0}^{5} V_n$	Car	Eq. (20)
Fleet size	V_j	$\frac{dVj}{dt} = \sum_{i=0}^{(j-1)} s_{ij} + g_j- \sum_{k=(j+1)}^{5} c_{jk}$	Car	Eq. (21)
Exogenous growth rate of the vehicle fleet size	egr_j	$egr_j = V*cV*(\frac{V_j}{V})$	Car/year	Eq. (22)
Sales	c_{ij}	$c_{ij} = V_i*(1/\alpha)*M_j*\frac{U_j}{U_i+U_j}$	Car/year	Eq. (23)
Potential adopters	PA	$PA = N-A$	Person	Eq. (25)
Population	N	$\frac{dN}{dt} = birthrate-deathrate$	persons	Eq. (26)
Total number of carsharing users	A	$A = A_c + A_{wc}$	Person	Eq. (27)
Carsharing users with car	A_c	$\frac{dA_c}{dt} = (\mathrm{ar_{cs}}*f_c)-abr$	Person	Eq. (28)
Carsharing users without car	A_{wc}	$\frac{dA_{wc}}{dt} = (\mathrm{ar_{cs}}*f_{wc}) + abr$	Person	Eq. (29)
Fraction of cars per person	f_c	$f_c = \frac{V}{N}$	Car/person	Eq. (30)
Adoption rate carsharing	ar_{cs}	$ar_{cs} = g*PA*\frac{A}{N}$	Person/year	Eq. (31)
Growth rate carsharing	g	$g = g_m + g_{va}$	1/year	Eq. (32)
Growth rate carsharing through vehicle automation	g_{va}	$g_{va} = IF\ THEN\ ELSE\ (M_j > 0.4, tm, 0)$	1/year	Eq. (33)
Abandoning rate of cars due to carsharing	abr	$abr = A_c*sr$	persons	Eq. (34)
Change in vehicle fleet size	cV	$cV = \frac{abr*f_c}{V}$	1/year	Eq. (35)
Adoption rate vehicle automation	$ar_{va,j}$	$ar_{va,j} = \frac{\sum_{s=0}^{j-1} s_{ij}}{V}$	1/year	Eq. (36)
Market penetration	d_j	$d_j = \frac{V_j}{V}$	Dmnl	Eq. (37)
Number of households	hh	$hh = \frac{N}{shh}$	Household	Eq. (38)
Cars per household	chh	$chh = \frac{V}{hh}$	Car/household	Eq. (39)
Total travel demand	td	$td = ptd*N$	km/year	Eq. (40)
Distance traveled per car	tc	$tc = \frac{td}{V}$	km/car/year	Eq. (41)

[a] "Dmnl" in this column will refer to dimensionless units.

- when a behavioral change in the indicators is noticed (curves change their shapes), the sensitivity of the model for this specific input parameter is considered "high".

For the base scenario several other model runs were executed in order to conclude about the effect of different policies on the market penetration of the different levels. We individually test the effect of price reductions through taxes or benefits, knowledge transfer boost, extra funds to support research, and looking at different carsharing success rates.

In the ‘AV in bloom’ scenario, the customer attitude is positive, economic growth is strong, the technology development is high and the policy is supportive. The parameter values and initial values of the variables had to be set to specify the scenario in the simulation model. All the parameter settings for this scenario run can be found in the Appendix B.

By running the ‘AV in bloom’ scenario on the case-study, we focus on positive policy stimuli towards level 5 (full automation), as this level is likely to be most beneficial in a policy perspective. Some of the parameter values had to be changed to specify the scenario in the simulation model. To illustrate a positive customer attitude towards AV, the importance of the price will be decreased in the perceived utility of AV. As shown in Eq. (17) the utility of a specific level of automation, U_j, is the sum of the attractiveness, a_j, and the normalized price, np_j, both multiplied by a weight. By decreasing the weight on the price, the attractiveness (comfort, safety and familiarity) of AVs becomes more important.

The economic growth within the scenario will be illustrated by an annual increase in the total number of vehicles in the model at each level, which represents the extra car sales due to economical prosperity. This is operationalized via an exogenous variable, called 'growth rate through economic effects', that is added to the equation of annual change in vehicle fleet (Eq. (35)). In the base run this annual change in vehicle size is affected by the abandoning rate of cars through carsharing, so the variable is mainly negative. Through an exogenous variable this annual change in vehicles is artificially increased with 1 percent per year in the conservative scenario and 3 percent per year in the progressive scenario.

The high technology development will be illustrated by a parameter change on three different factors: An increased effectiveness of knowledge transfer; A higher percentage to R&D, representing the percentage of the total budget out of vehicles sales that the industry spends on R&D; the third factor is a decreased depreciation rate, which means the knowledge in the knowledge stock is depreciating slower and thus leading to a high maturity level faster.

A subsidy on the purchase price of level 4 and level 5 vehicles will account for the supportive policy. The operationalization of this subsidy is described in Section 4.2.1.1. As a last policy instrument an artificial fund is created in the simulation model that has to boost the technology development of level 4 and level 5. The operationalization of this factor is described in detail in Section 4.2.1.3. The parameter settings for the AV in bloom will be specified both conservatively and progressively. All the settings for the scenarios are shown in Table 4

4.2. Results

The model was implemented in VensimPro 6.3. The unit for time is ‘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 results. The integration type was set to Euler.

4.2.1. Base run and variations

The simulation was run between the year 2000 and year 2100 whereby the year 2015 is considered to be the last year for which there is data available. The first thing that can be noticed with the curves of the fleet size of all the levels as shown in Fig. 5 (total number of cars per level) and Fig. 6 (proportion of each level on the total fleet) is that the fleet size of level 0 starts declining right from the start of the simulation run. The fleet size of level 1 and level 2 starts increasing from this point onward. This results in a fleet size in 2015: 2.8 M (level 0); 1.3 M (level 1); 1.9 M (level 2) and 235 K (level 3) vehicles. The fleet size of level 4 and 5 are still very low at this point at respectively 3345 and 2795 vehicles.

The total fleet size stays constant at this moment in time. What is noticeable is the high number of AVs of various levels that are already on the market, determining a high proportion of the total fleet size. Compared to data in the real world this is not very representative. Currently in 2015 there are not so many AVs on the road. Certainly level 3, 4 and 5 are not yet available on the market and a realistic number for their fleet size would be 0 vehicles. The fleet size of level 1 and 2 is less certain. However it is not as high as depicted by the results of the simulation run. The extent to which this is a problem can de discussed. The behavior that is observed here is caused by the fact that the model is biased. The model is intended to produce a change in fleet size among the different vehicle automation levels. These levels are sort of competing amongst each other in terms of number of vehicles. The level with the highest maturity and utility will gain most increase in its fleet size stock. Even if the maturity and the utility of a specific level of automation

Table 4
Parameter settings for Base run and AV in bloom scenario.

Parameter	Default base run	AV in bloom – conservative	AV in bloom – progressive
β1 Weight for price	0.5	0.4	0.2
Growth rate through economic effects	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 funds	0 euro	1B over 10 years	2B over 10 years

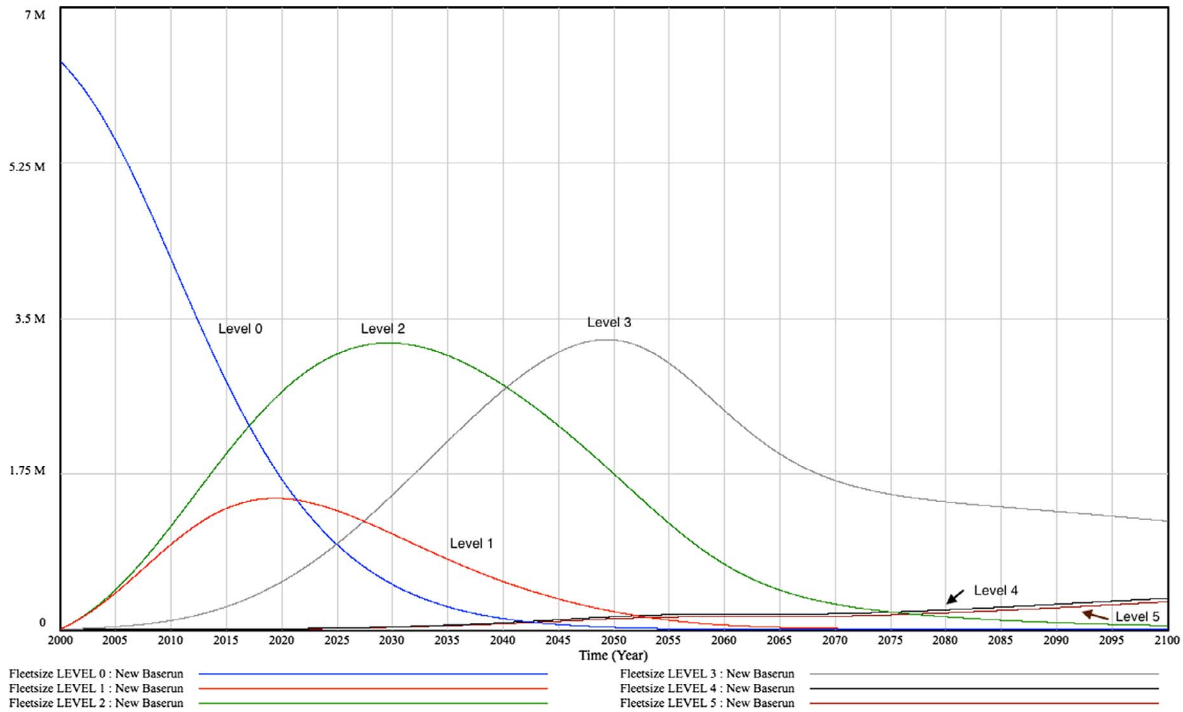

Fig. 5. Fleet size of all levels of automation for the base scenario.

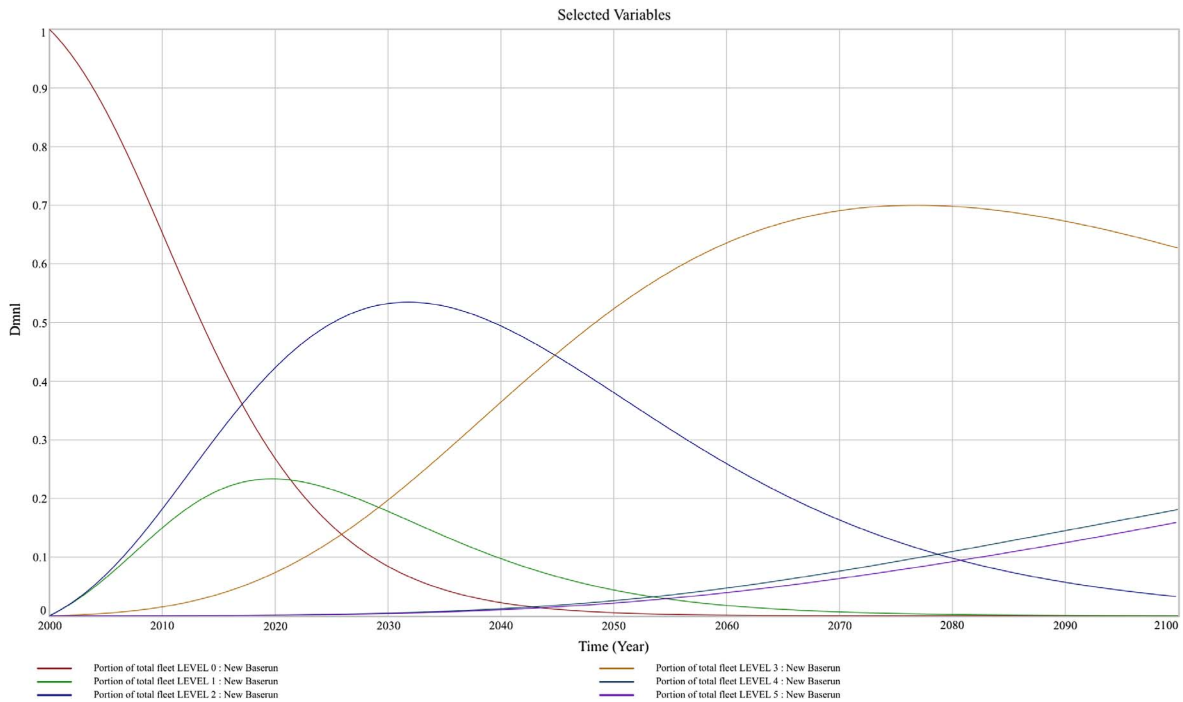

Fig. 6. Market penetration of the different levels of automation for the baserun scenario.

are very low, than still a slight growth in its fleet size can be observed. This is due to the fact that the model is continuous and is built this way. The fleet size 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 fleet size 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 had reached a specific threshold maturity. As the choice was made to have sales and R&D influence each other at the same level 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 comes directly from the sales. If the sales are 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 assume the overestimation of the fleet size of the various levels in this study and will look more at the shape and behavior of the curves than at the exact numerical values at a specific year.

Another aspect that can be noticed is the low fleet size throughout the whole simulation run of level 4 and level 5. Around 2100 the fleet size of these levels are respectively 335 K and 293 K vehicles. The fleet size of level 3 reaches a peak at 2050 of approximately 3.3 M vehicles. However after this peak it starts to decrease towards 1.2 M vehicles in 2100. The reason for this is that the total fleet size also decreases heavily due to the rise of carsharing. Around 2050 the adoption of carsharing is on a maximum of 900.000 new users per year. This leads 220.000 new carsharing users to abandon their car around this time. This could cause a reduction on the total fleet size from 6.4 M to 1.9 M vehicles according to the model assumptions.

Such a big difference between level 3 automation and level 4 and 5 in these results is due to the comfort of level 3 (5/10) which is reasonable for the user and it leads to a reasonable price as well for these vehicles. In the model this gave a trigger to many car sales around 2025. Because of the high sales numbers, the technology development accelerated and this led, through learning effects, to an even lower price. This made level 3 cars in the model so popular that level 4 and level 5 cars never really got a foot on the ground and never reached high enough sales to also gain the rapid technology development and lower prices. It could be argued to be unrealistic since some industry is skipping level 3 and going directly to level 4 and 5, however the latter are also more demanding from a safety point of view.

In the following sub-sections several experiments will be done with the base model to test different scenarios and policies.

4.2.1.1. *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 predefined amount from the purchase price of a vehicle (Eqs. (42) and (43)). However this subtraction is not executed before the maturity of a vehicle automation level is above 40%. This way there will be a step in the purchase price at the moment that the maturity reaches 40%.

Purchase price with discounted subsidy

$$p_j = bp_j + rp_j - Subsidy_j \tag{42}$$

Subsidy function

$$Subsidy_j = IF\ THEN\ ELSE\ (M_j > 0.4{,}5000{,}0) \tag{43}$$

A price reduction of €5000 is considered. Therefore the purchase price of level 3 decreases from 2030 onwards with 5000 euro. This leads to 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 have a sudden jump, there is little to no effect in the adoption rate. Even with a weight of 50% on the price, the model seems to be less 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 fleet size of levels 2 and 3. The subsidy has no effect on levels 4 and 5 as these levels never reach a maturity of 40% within the simulation run time.

4.2.1.2. *Boosting 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 AVs (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 to 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 Fig. 7. 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% is 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%.

4.2.1.3. *Providing external funds*.

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 to the annual R&D expenditure.

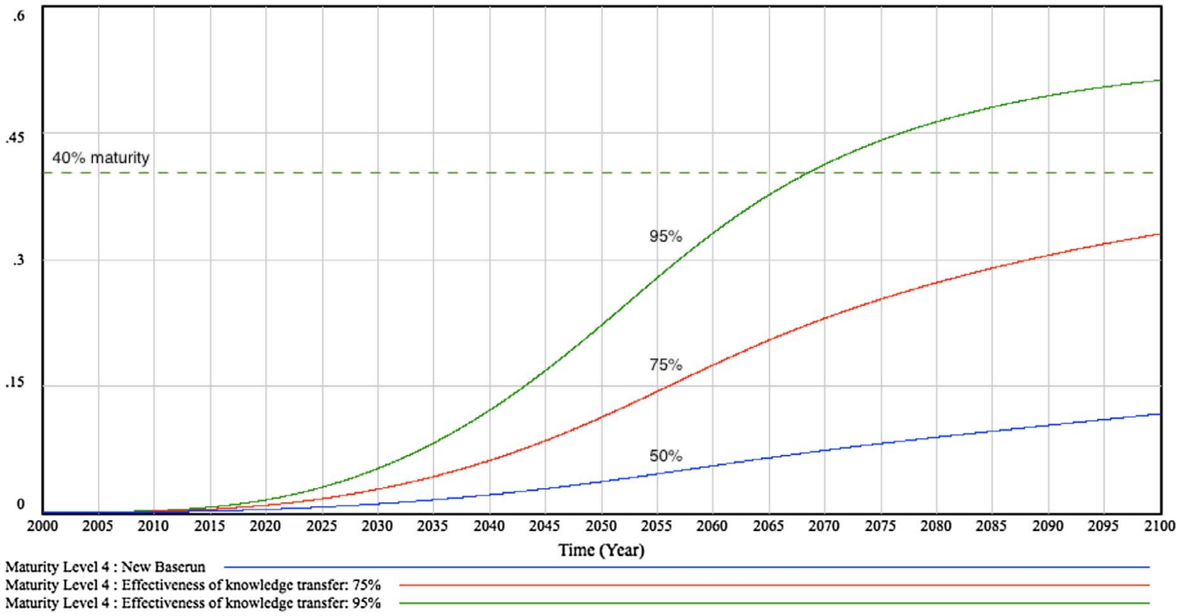

Fig. 7. Maturity curves of level 4 with $\boldsymbol{ef}$ = 50%,75%,95%

External monetary research fund

$$\frac{dF_j}{dt} = Periodical\ allocation\ of\ resources - (F_j * \%) \tag{44}$$

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

Periodical allocation of resources that fills the fund

$$Periodical\ allocation\ of\ resources = STEP(x,2015) - STEP(x,2020) \tag{45}$$

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 = 400 M and pa = 1B.

The effect on the knowledge stock is significant. This stock increases with 250% (pa = 400 M) 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 400 M fund and to 37% with the 1B fund.

4.2.1.4. Carsharing effects on the fleet size. The model showed sensitivity to a 10% change in the value of this parameter (gcs). 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 indicator ‘total fleet size’ (Fig. 8). The behavior is the same but is shifted in time. A change in the growth rate causes the total fleet size to decrease earlier and later. However the total fleet size finds the same asymptote in all cases, as can be seen in Fig. 8.

4.2.1.5. Changing the vehicles’ lifetime. The lifetime of a car is much related to the adoption of vehicle automation. This value was 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 assess the extended sensitivity of the model to this parameter. As an indicator it is chosen to look at the adoption rate of the highest levels of automation. The graphs of these indicators are shown in Figs. 9and 10.

The indicators show both numerical and behavioral changes. This leads to the conclusion that this parameter leads to significant changes. 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 which 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 gets shorter, the decrease of the adoption rate also happens faster.

4.2.2. ‘AV in bloom’ conservative and progressive scenarios

The adoption rate and market penetration of the conservative scenario are shown in Figs. 11 and 12. In 2025 level 3 has the highest adoption rate of nearly 3% per year. Between 2020 and 2030 level 3 has the highest market penetration of 50%. The adoption

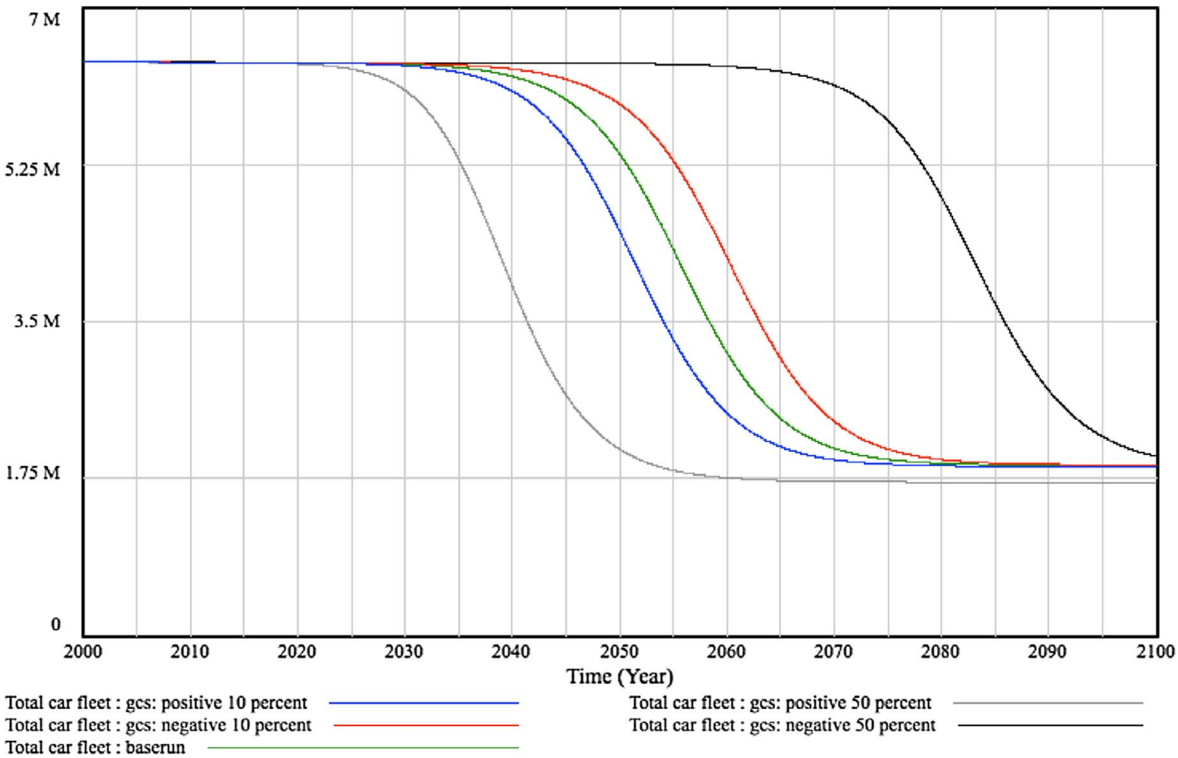

Fig. 8. Total fleet size with sensitivity analysis to the growth rate of carsharing.

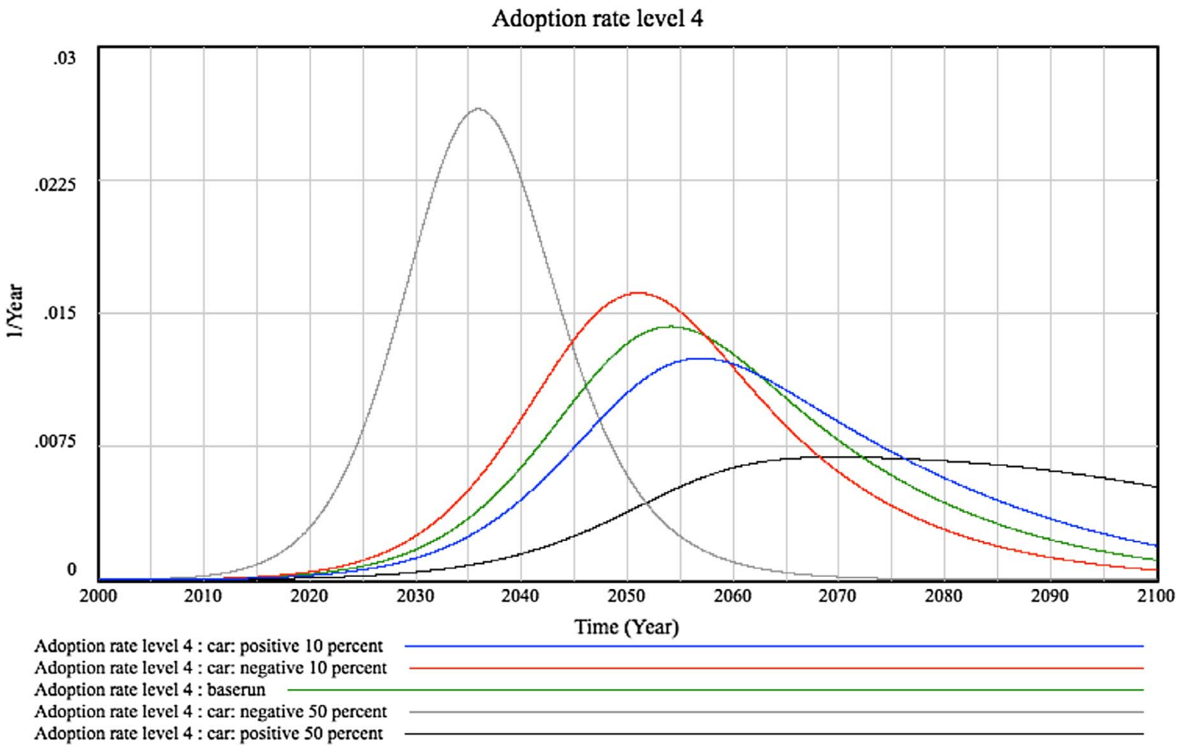

Fig. 9. Adoption rate of level 4 AVs as a result of different vehicle lifetime.

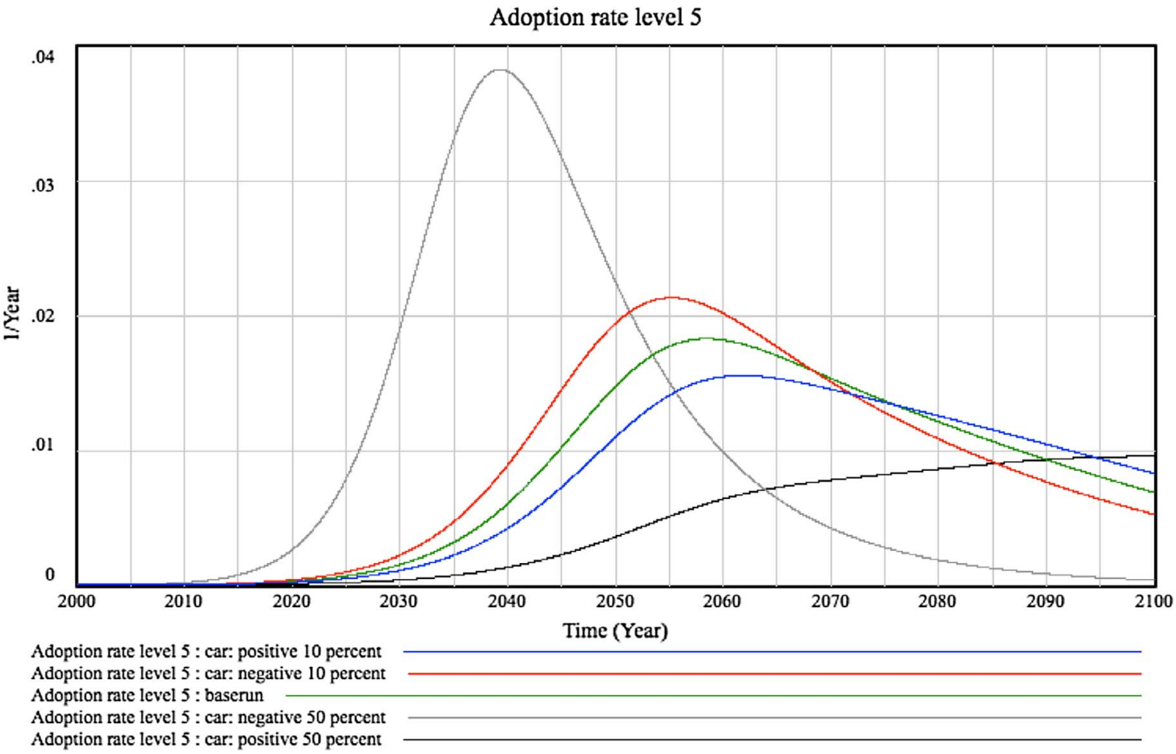

Fig. 10. Adoption rate of level 5 AVs as a result of different vehicle lifetime.

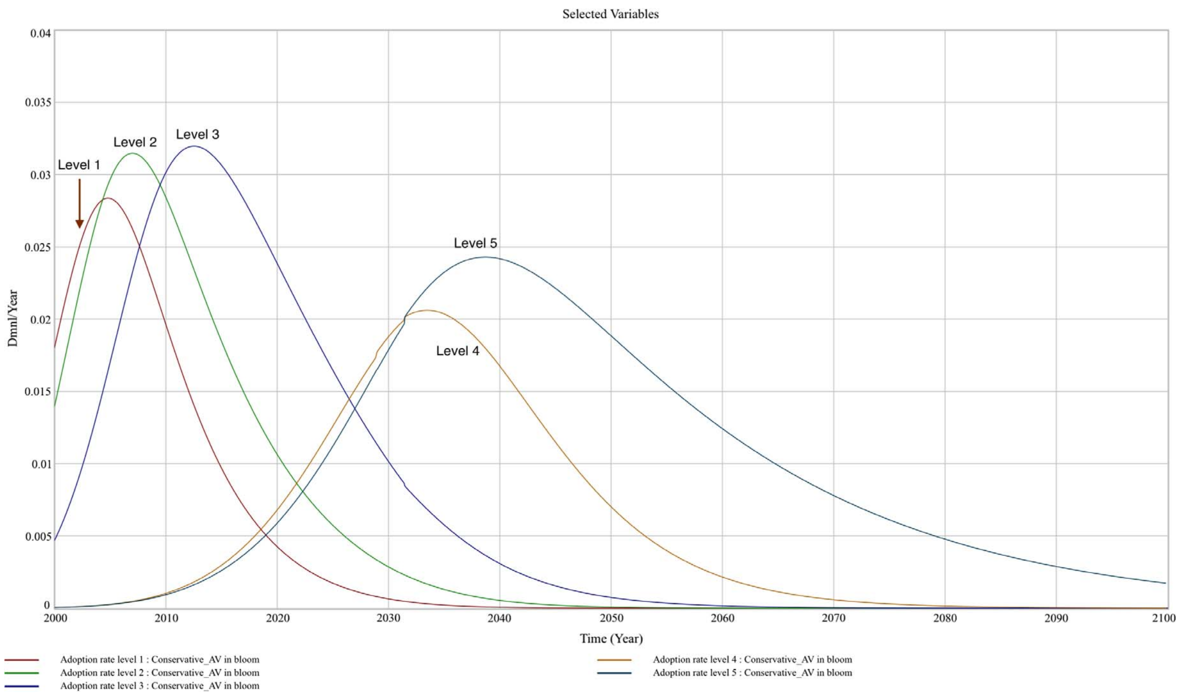

Fig. 11. Adoption rate of AV in bloom conservative scenario.

rate of level 4 and 5 starts increasing rapidly after 2020. Around 2030 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% on the adoption rate. After 2040, level 5 has the most dominant market penetration, which will increase towards 96% in 2100.

The adoption rate and market penetration of the progressive scenario are shown in Figs. 13 and 14. It can be recognized that the

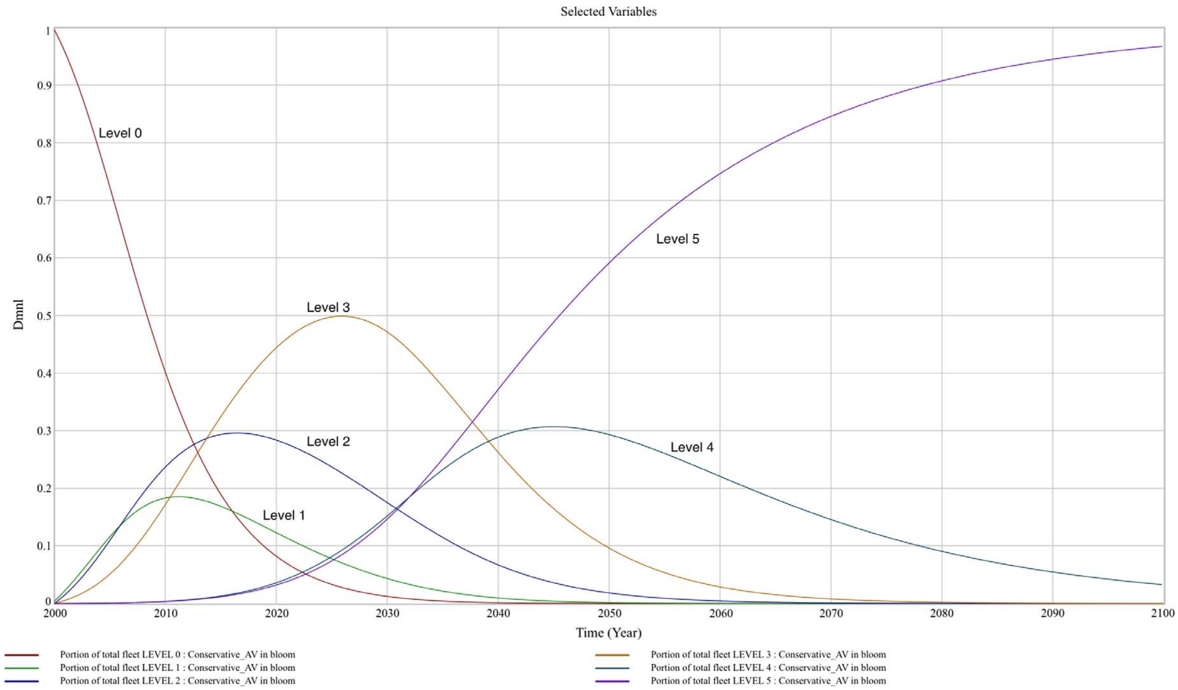

Fig. 12. Market penetration of AV in bloom conservative scenario.

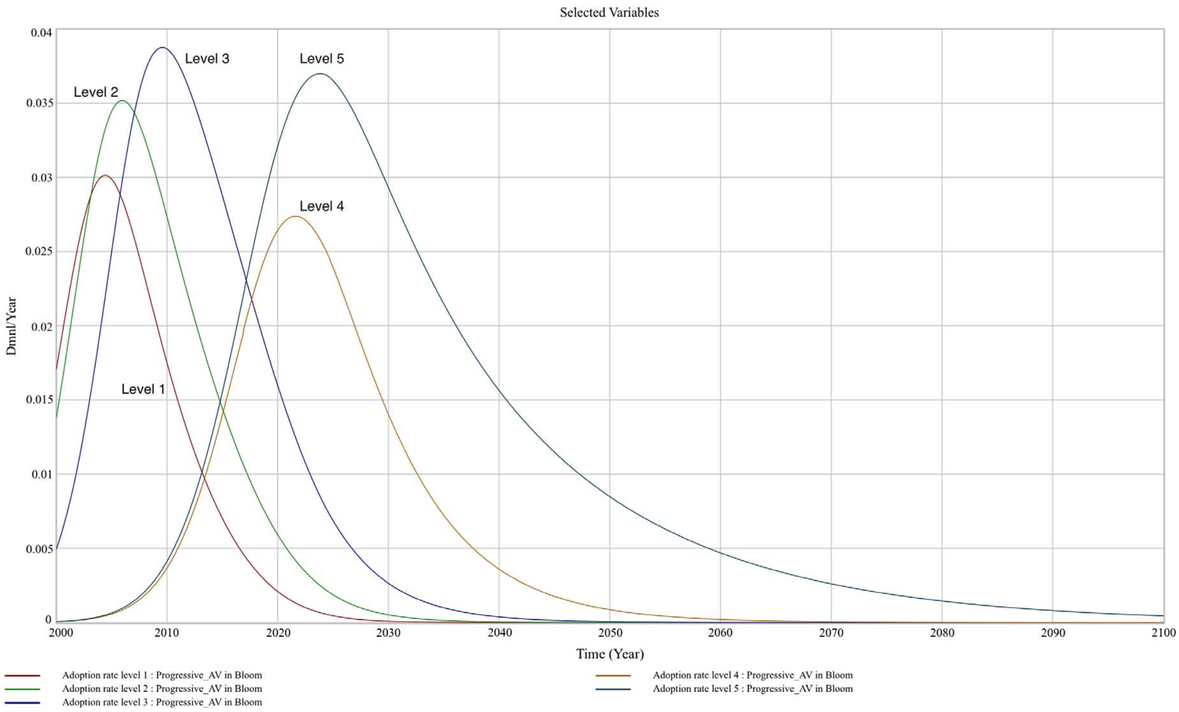

Fig. 13. Adoption rate of AV in bloom progressive scenario.

adoption rate in this scenario is much steeper and higher with all the levels of automation in comparison to the conservative scenario. Another noticeable point is that all the levels of automation reach a peak of their adoption rate before 2040. This could cause a dominant market penetration for level 5 after 2025. In both scenarios, the market penetration of level 0 drops very rapidly after 2015.

These results for the “AV in bloom” conservative and progressive scenarios show in a more evident way that there is a tendency for the model to overestimate the market adoption of the several automation levels, which is a result of the model structure as it was

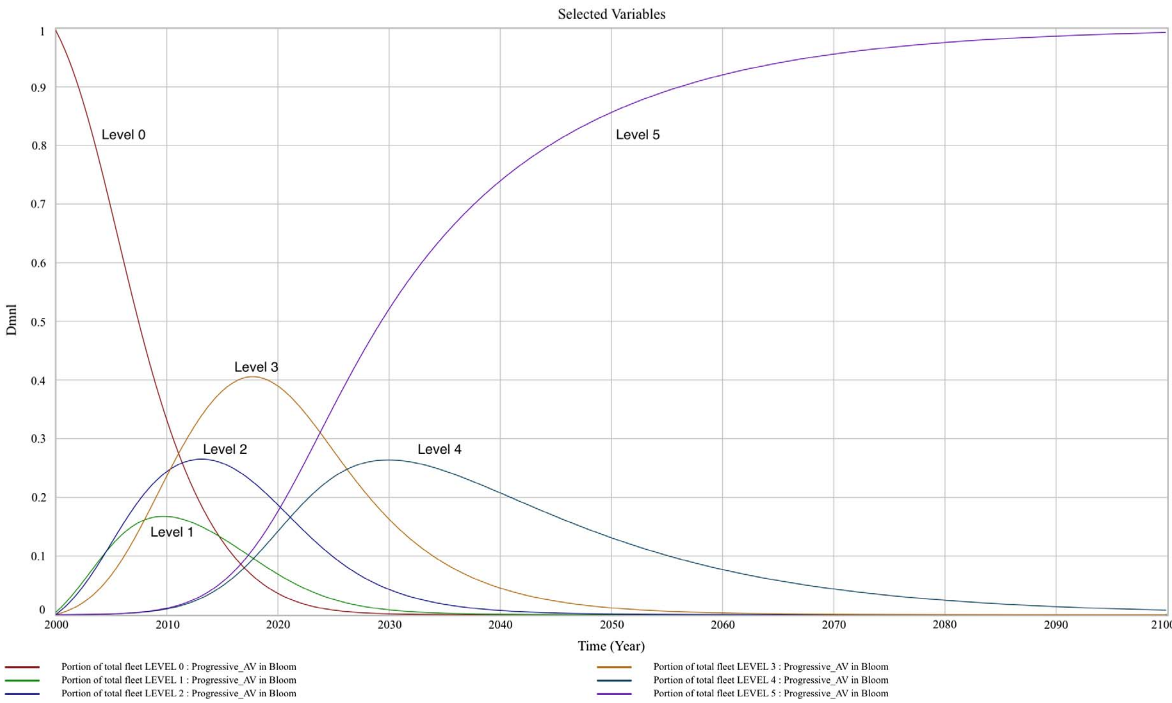

Fig. 14. Market penetration of AV in bloom progressive scenario.

explained before. Nevertheless as support for AVs increases so should the adoption increase and it can be argued that this support was not put into place 20 years ago, certainly not comparable with what governments and companies are doing now.

4.2.3. Summary table for market shares

In Table 5 we summarize the market shares estimated according to the three scenarios that have been modeled above. This allows for a better comparison of the differences that result from the assumptions that have been adopted in each scenario.

With the base run a strong adoption of level 3 can be identified from 2025 onwards to 2100. A possible explanation why Level 3 is so popular in the baserun, is because the comfort that level 3 confers to users was not so low in comparison to levels 4 & 5 (Level 3: 5/10, level 4: 8/10, level 5: 10/10). With this comfort at a reasonable level for the user the price of the level 3 vehicles was also reasonable. In the model this gave a trigger to a lot of car sales around 2025. Because of the high sales numbers, the technology development accelerated and this leads, through learning effects, to an even lower price. This made level 3 cars in the model so

Table 5
Market shared estimated in each scenario for 2025, 2050, 2075 and 2100.

Scenario/year	Levels	2025	2050	2075	2100
Base scenario	0	14%	0%	0%	0%
	1	21%	0%	0%	0%
	2	51%	34%	8%	2%
	3	14%	62%	75%	64%
	4	0%	2%	9%	17%
	5	0%	2%	8%	17%
AV in bloom – conservative	0	4%	0%	0%	0%
	1	8%	0%	0%	0%
	2	24%	3%	0%	0%
	3	49%	9%	1%	0%
	4	7%	29%	22%	4%
	5	8%	59%	77%	96%
AV in bloom – progressive	0	1%	0%	0%	0%
	1	3%	0%	0%	0%
	2	10%	0%	0%	0%
	3	28%	1%	0%	0%
	4	23%	13%	4%	1%
	5	35%	86%	96%	99%

popular that level 4 and level 5 cars never really got a foot on the ground and never reached high enough sales to also gain the rapid technology development and lower prices.

The AV in bloom conservative and progressive scenario's both show the same kind of behavior. In 2025 the market penetration of level 3 and lower is still on a considerable level, but from 2025 onwards the market penetration of both level 4 and 5 increase dramatically. A possible explanation of the big market penetration of level 4 and 5 could be the multiple policy instruments that are applied to boost the technology development of level 4 and level 5. With a boost in the technology maturity, the price decreases faster over time through learning effects. This decrease in price gives a boost to the sales of the level 4 and level 5 vehicles, which creates extra budget for R&D. Two policy instruments that externally influence this feedback loop, the external resources fund and the subsidy on the price, only show little effect to this loop. These policy instruments only show a sudden increase in market penetration somewhere in time and could function as a kickstarter, but do not give a sustainable boost to the market penetration of AVs. The policy instruments that are part of the feedback loop, such as the increased percentage to R&D and the decreased knowledge depreciation rate, show a significant effect on both scenarios. The reason for this is that their effect is re-enforced by their own success. From 2050 the market penetration of level 4 decreases and the level 5 market penetration quickly increases towards a nearly full market penetration in 2100. The reason for this is that level 5 is more attractive to users than level 4 on all points, and due to learning effect has the same price as level 4 from 2050 onwards. Remarkable to note is the difference between the conservative and progressive scenario between 2075 and 2100. What can be seen is that the market penetration of level 4 (4%) and level 5 (96%) of the progressive scenario in 2075 is the same as that of the conservative scenario in 2100. This means that on the progressive scenario the market penetration is accelerated with 25 years in comparison to the conservative policy instruments.

4.2.4. A critical note on the use of SD

One should take into account that the model presented in this paper is a first representation of the real-world system regarding vehicle technology evolution. Although the structure and input values have been carefully chosen as much as it is currently possible, the model is still biased and surely it contains some limitations, namely in what concerns to data availability and lacking model components. One of the limitations of using SD as a stimulation technique is that all the stock variables in the model need an initial value in order to start the simulation. Zero is not an option since rates of variation cannot change this value. For this reason the initial value of both the fleet size of level 4 and level 5 were set to '2'. This does not represent the real world as level 4 and level 5 are not yet on the market. Another limitation with the initial values in the model was with the price of level 4 and level 5 AVs. As these vehicles are not yet on the market, the initial price had to be set arbitrarily. In order to gain confidence in the initial value and its impact on the model a careful uncertainty analysis has been executed.

Most of the relationships in the model are based on solid innovation theory from other market sectors or from the automobile sector or as a last resort to common understanding and expert interview on the Automated Vehicles Symposium in Ann Arbor from July 21–24, 2015. However some relationships are describing phenomenon that are harder to relate to in the real world. An example of this is the knowledge stock and the way this knowledge is accumulated into technology maturity. The model is intended for analysts to use with their own data and test different parameter values of the model to gain better insight into the dynamics of the system. Fuzzy variables in the model make it harder for people to test the model with, as they miss a reference point in the real world. Although we have confidence in the robustness of the variables in the model, we recognize these fuzzy variables as a serious limitation of the model.

There are several aspects of mobility behavior that are not expressed in this model due to lack of data and because this has a high level of aggregation. One of the recommendations for future research is to work on a hybrid version of the current SD model combining it with a more disaggregated modeling type such as ABM. SD has been widely used for modeling the forces of a market because in cases such as innovation diffusion, disaggregating the process in several companies with their corresponding characterization of behavior would be very difficult. Whilst for other components of the model, like modeling traffic behavior, an approach such as ABM could be better suited.

5. Conclusions

In this research, a novel quantitative model is constructed that can be used to learn more about the dynamic and complex nature of the innovation system of AVs. The feedback loops between the model components form a dynamic behavior that influences the diffusion of AVs. The model takes the approach of the functional pathway of vehicle automation. In this approach vehicle technology is represented in 6 different levels varying from no automation (level 0) to full automation (level 5).

Each level of automation technology has its own technology maturity. This maturity is developed through funding that is created by the (potential) market size 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 done 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 one attained by the higher level of automation. Because of these changes of vehicles by the end-users the fleet size of each level of automation gradually shifts over time. This effect causes the diffusion of vehicle automation into society.

The model was applied to the case-study of the Netherlands. A base scenario and an 'AV in bloom' scenario for AV development in the Netherlands were selected, this later describing a supportive AV policy and high technology development (see Milakis et al., 2017a). In these experiments, we found that the system is highly uncertain with market penetration varying greatly with the scenarios and policies adopted. Having an 'AV in bloom' eco-system for AVs is connected with a great acceleration of the market take-up of high levels of automation. As a policy instrument, a focus on more knowledge transfer and the creation of an external fund has shown to be most effective to realize a positive innovation diffusion for AVs. Subsidies have shown to be less effective as they give a short-term impulse to a higher market penetration, but will not create a higher market surplus for vehicle automation.

We believe that this model should be classified in the category of a model with the purpose to simulate a system in order to know it. With future possibilities of being used as a model with the purpose to simulate a system in order to change it. The paper launches a first discussion of how to quantify the evolution of AVs which is a novelty regarding the previous approaches which are mainly qualitative. The model can be used for the objective of gaining more knowledge about the factors that influence the diffusion of AVs and to better understand the interaction of complex policies and their potential effects on the diffusion of AVs.

Acknowledgements

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Appendix A

Parameter settings for the base run scenario

Parameter	Notation	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 fleet size Level 0	$V_{0,0}$	6,390,000	Car	Low	Low
Initial fleet size Level 1	$V_{0,1}$	1000	Car	Medium	Low
Initial fleet size Level 2	$V_{0,2}$	2	Car	Medium	Low
Initial fleet size Level 3	$V_{0,3}$	2	Car	Low	Low
Initial fleet size Level 4	$V_{0,4}$	2	Car	Low	Low
Initial fleet size 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
β1 Weight Price	β_1	0.5	Dmnl	High	Medium
β2 Weight Attractiveness	β_2	0.5	Dmnl	High	Medium
β3 Weight Familiarity	β_3	0.2	Dmnl	High	Low
β4 Weight Comfort	β_4	0.6	Dmnl	High	Low
β5 Weight Safety	β_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
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	Medium
Amount needed for full maturity Level 5	an_1	100 Billion	Euro	High	Medium
Average lifetime of a car	a	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	Dmnl	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
Delay	led	0.20	%	Low	Low

Appendix B

Parameter settings 'AV in bloom' scenario

Parameter	Notation	Value	Unit
Initial Maturity Level 0	$M_{0,0}$	1	Dmnl
Initial Maturity Level 1	$M_{0,1}$	0.4	Dmnl
Initial Maturity Level 2	$M_{0,2}$	0.3	Dmnl
Initial Maturity Level 3	$M_{0,3}$	0.1	Dmnl
Initial Maturity Level 4	$M_{0,4}$	0.001	Dmnl
Initial Maturity Level 5	$M_{0,5}$	0.001	Dmnl
Initial fleet size Level 0	$V_{0,0}$	7,902,290	Car
Initial fleet size Level 1	$V_{0,1}$	30,000	Car
Initial fleet size Level 2	$V_{0,2}$	1000	Car
Initial fleet size Level 3	$V_{0,3}$	2	Car
Initial fleet size Level 4	$V_{0,4}$	2	Car
Initial fleet size Level 5	$V_{0,5}$	2	Car
Initial Baseline price Level 0	$bp_{0,0}$	20,000	Euro/Car
Initial Baseline price Level 1	$bp_{0,1}$	25,000	Euro/Car
Initial Baseline price Level 2	$bp_{0,2}$	35,000	Euro/Car
Initial Baseline price Level 3	$bp_{0,3}$	50,000	Euro/Car
Initial Baseline price Level 4	$bp_{0,4}$	180,000	Euro/Car
Initial Baseline price Level 5	$bp_{0,5}$	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	$rp_{0,4}$	100,000	Euro/Car
Initial price of retrofit Level 5	$rp_{0,5}$	300,000	Euro/Car
Initial car-share users	A_0	16,000	Person
Initial population	N_0	16,829,289	Person
β1 Weight Price	β_1	0.5	Dmnl
β2 Weight Attractiveness	β_2	0.5	Dmnl
β3 Weight Familiarity	β_3	0.2	Dmnl
β4 Weight Comfort	β_4	0.6	Dmnl

β5 Weight Safety	β_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	gcs	0.2	Dmnl
Technology multiplier	tm	0.2	1/Year
Percentage of car shedding among car share users	sh	0.23	Car/person
Delay	led	0.20	%

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