STECCAR

Simulating the Transition to Electric Cars using the Consumat Agent Rationale

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"Just as the wave cannot exist for itself, but is ever a part of the heaving surface of the ocean, so must I never live my life for itself, but always in the experience which is going on around me."

— Albert Schweitzer

Abstract

This thesis presents the STECCAR model: a newly developed agent-based model of the Dutch consumer car market, constructed to study the diffusion of electric vehicles in the Netherlands. In agent-based modelling, the micro-level characteristics of numerous, often heterogeneous, agents are initialised, and the emerging macro-level behaviour of the population is studied.

The underlying rationale of the agents in our model is structured through the Consumat approach; a cognitive framework based on theories from psychology and economics. Within this approach, agents are defined by their individual needs, abilities, decision-making process, and personality. The results of 1.795 survey respondents were used to initialise each individual agent after a Dutch citizen with its own characteristics and driving behaviour.

At the shared car market, agents may purchase gasoline vehicles, plug-in hybrid electric vehicles and battery-electric vehicles. Each fuel technology comes with its own functional and financial characteristics. Mimicking the actual Dutch car market, three types of agents are defined using the input survey: lessees, purchasers of new vehicles, and occasion buyers. Within this context, the first two agent types determine the supply of cars to the occasion market.

Validation of the model is performed using recent consumer data about Dutch yearly sale figures, occasion market size, ownership characteristics and scrappage data. The model is subsequently used to study the effects of different policies and technological advancements on the diffusion process of electric vehicles. Some of the specific findings include that 'bijtelling' policy has a strong regulatory effect on the diffusion of electric cars and that a rapid realization of a nation-wide fast charge network is an important step towards making battery-electric vehicles competitively attractive.

More generally, simulations using the STECCAR model show that the effect of measures can be strengthened by combining measures, or by applying them in a specific temporal order. Additionally, targeting measures at battery-electric vehicles specifically, but not at plug-in hybrid electric vehicles, could lead to a larger overall reduction in carbon emissions. Long term scenarios show that a quick diffusion of electric vehicles results in unconventional behaviour on the occasion market.

We conclude that agent-based models can provide unique and valuable insights into how to influence complex relations within interactive social systems, such as the Dutch car market. Implications of using an agent-based model to study the diffusion of electric cars are described. Regarding agent-based modelling in general, the importance of proper validation and the benefits of using a psychologically-founded cognitive framework are discussed.

Contents

1 Introduction

In the current age when global warming and rising oil prices are governing our news, the transition to energy-efficient techniques is becoming increasingly important. The electric vehicle (EV) is one such promising solution. With zero tail-pipe emissions and the capability of being powered by renewable energy sources, it can help navigate our path to a sustainable future.

The aim of this thesis is to gain insight into the diffusion process of EVs in the Netherlands through the method of agent-based modelling. Using artificial agents and a computational representation of the Dutch car market, the initial adoption of both battery-only electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) is explored.

The rest of this chapter discusses why an agent-based model of the diffusion of electric cars is an interesting topic to investigate, which exact research questions we aim to answer, what the place of this project is within the field of artificial intelligence, and how the rest of this thesis is structured.

1.1 Problem description

Although in 2012 the number of EVs sold in the Netherlands was almost five times higher than in the year before, the market share of EVs within the domain of all passenger cars purchased in 2012 was still only 1% [46]. This percentage further increased to 4.3% in 2013, which indicates an increasing popularity of EVs even though the absolute numbers are still small. In order to push the adoption of this alternative fuel technology further, multiple stakeholders are trying to influence both the perception and the utility of electric vehicles. The government has instated road tax exemption for low-emission vehicles, start-up companies are building towards a nation-covering fast charge station network and car manufacturing companies such as Tesla Motors and BMW design luxury electric sports cars that could influence the public's opinion on the appearance of electric vehicles.

Any of these measures could help stimulate the diffusion of EVs, but which policies and advances are most influential and how these measures interact in the complex social systems of our world remains a difficult theoretical exercise. Statistical analysis of consumer survey data can provide a first insight into the current obstacles to a wide-spread adoption of EVs and the effectiveness of different measures. One example of such a questionnaire is a study Bockarjova conducted among driving license holders in the Netherlands in June 2012. So far, this study has shed light on how personal concerns influence close and distant measures of adoption [8] and how consumers perceive the generalized costs of EV ownership [9].

However, when the effects of multiple factors are taken into account and the question is how these measures influence societal dynamics over time, even these methods run into scalability problems. The larger and more complex a statistical model becomes, the harder it will be for others to interpret the results and discuss the underlying assumptions. Moreover, to study these factors and the effect of different policies and technological advances over the course of years in the real world is simply impractical. Needless to say, there are many ethical arguments against turning our society into a controlled research environment.

In situations like this, multi-agent systems (or 'agent-based models', see Section 3.3) can play an important role. In this sub-field of artificial intelligence, persons are represented by digital agents acting according to their personal beliefs and needs [98]. Through interactions and individual behaviours, these agents together make up a complex artificial society in which different kinds of scenarios can be studied. Ideally, the motivations of these agents are initialised using empirical data from a real population, and the resulting behaviour of the agents is validated using an equally empirical source of real world data. This process of initialising (or 'calibrating') and validating an agent-based model is identified as one of the key challenges in the field [24]. But if done well, the resulting simulation represents a simplified version of our own society and provides a powerful estimator of future developments.

In this thesis, the questionnaire by Bockarjova delivers the input data to initialise an agent-based model of the Dutch car market. In this model, 1.795 respondents are instantiated as individual agents, causing the end result to be an empirically parametrised simulation in which the effects of new policies and technological advancements can be explored. Because Bockarjova's questionnaire was not conducted for the purpose of creating an agent-based model, challenges arise in how to fit the obtained data to the model in a plausible way.

Related to this aspect is a very critical modelling decision: according to which principles do the artificial agents transform any kind of input data into meaningful behaviour? To answer this question, a cognitive framework is required that captures the essence, but also simplifies, real world decision making. Our chosen approach is an agent framework called the Consumat [49, 52]. This framework has been used to model decision making in many different contexts, such as farmers committing to a crop, pedestrians deciding whether to litter of throw their rubbish in a bin, or consumers deciding which brand to buy. Modelling the Dutch car market, however, incorporates a new level of complexity. Different types of consumers interact in a shared market where the decisions of individuals who lease or purchase new cars determine the supply of vehicles to individuals who purchase occasions. Applying the Consumat framework to such a large and dynamic model brings additional challenges to this project.

1.2 Research questions

From the problem description, two very broad research questions arise. On the one hand, we want to know whether a valuable agent-based model of the Dutch car market can be created. On the other hand, we want to inspect what such a model can teach us about the diffusion of electric vehicles in the Netherlands. These two research questions are formulated below. Additionally, specific sub-questions are defined to frame how we aim to answer our main questions.

1. *Can we create an agent-based model using which the diffusion of electric vehicles in the Netherlands can be explored?*

   (a) *Does the Consumat framework provide a suitable cognitive framework to model artificial consumer agents in an agent-based model of the Dutch car market?*

(b) *Is the data from Bockarjova et al.'s 2012 survey sufficient to initialise artificial consumer agents in an agent-based model of the Dutch car market?*

(c) *Can an agent-based model realistically capture the dynamics of the Dutch car market according to Dutch consumer data from recent years?*

2. *What can we learn from an agent-based model about the diffusion of electric cars in the Netherlands?*

   (a) *Which measures are most effective in stimulating the initial diffusion of electric cars?*

   (b) *Does the simultaneous effect of some combination of measures have a stronger influence on the diffusion of electric cars, than the summation of the effects when these measures are applied separately?*

   (c) *What is the relation between the diffusion of electric cars and the reduction in carbon emissions of the car fleet?*

   (d) *Given favourable circumstances, within what time frame is full diffusion of electric cars possible?*

   (e) *Will a quick diffusion of electric cars among newly bought vehicles resonate to the occasion market, resulting in a quick adoption of electric vehicles among occasion buyers?*

1.3 Placement within the field of AI

The field of artificial intelligence (AI) is inherently interdisciplinary. It integrates topics from biology, psychology, mathematics, computer science, linguistics and possibly any other field in which humans are active, in order to understand, aid and surpass human reasoning. In its pursuit, countless sub-approaches have been established, such as knowledge representation, natural-language processing and machine learning. All approaches make continuous progress in many specialised areas, but nevertheless a holistic solution to the problem of 'general AI' does not seem close to being reached. In this respect, intelligent agents are sometimes said to be the closest thing to obtaining an integrated form of AI [80].

The study of intelligent agents is one of the newest approaches within AI. It is concerned with artificial entities that possess autonomy, social abilities, reactivity to the environment and pro-activity with regard to reaching specific goals [99]. Although our understanding of a 'wholly' intelligent system is still limited, this field is making a modest head start using the insights and technologies that are available today.

Multi-agent systems extend on this concept by studying or utilizing emerging phenomena that arise from interactions between numerous intelligent agents. Due to time and processing constraints that arise when working with fast numbers of agents, a single agent's cognitive components (e.g. memory, perception, reasoning) can often embody only a fraction of the complexity of the state-of-the-art work in related AI sub-disciplines. The modeller must therefore select cognitive components that make the agent only sufficiently intelligent for the domain to which it is applied. Additionally, if the goal is to represent human behaviour and therefore to develop an agent that *thinks* like a human, then many typical techniques from the field of AI are off-limits [80]. Learning and decision making techniques such as support vector machines and neural networks, for instance, provide good results when applied to numerous domains.

However, these techniques only *act* like humans but do not *think* like humans, and therefore their results are not generalizable to the behaviour of a human population.

This places the research in this thesis within an integrative field of AI called multi-agent systems, as well as associating it with the usual disciplines that together constitute AI. However, because this specific multi-agent system is used to explore human consumer behaviour in our actual society, the scope of research is extended even further. In the case of this thesis, additional disciplines are sociology, public policy, system analysis and economics.

1.4 Thesis structure

Chapter 2 provides background information and dives deeper into the history of electric vehicles (EVs), the current state of EVs and the concept of product diffusion. In Chapter 3, agent-based models and the Consumat framework are discussed. The newly developed STECCAR model is presented in Chapter 4 and the subsequent parametrisation of the model using the 2012 survey is described in Chapter 5. Chapter 6 shows the validation of the model by comparing its behaviour to recent Dutch consumer data, while Chapters 7 and 8 show the results of playing out simple and more complex scenarios in the simulation respectively. Chapter 9 closes off with a discussion of the research questions, recommendations for further work and an overall conclusion.

2 Electric vehicles and diffusion

Chapter 1 defined the scope of our research problem and the specific research questions that we aim to answer. This chapter and Chapter 3 fill in the gap of information between these research questions and our proposed agent-based model, needed in order to obtain relevant answers. Important background information, concepts and terminology are introduced before Chapter 4 continues with the theoretical specifications of the developed agent-based model.

2.1 Overview

Sections 2.2 and 2.3 give an overview of the history and current state of electric vehicles (EVs), respectively. The most important terminology introduced is the distinction between battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). While the first type of vehicle is propelled by electricity only, the latter also uses an internal-combustion engine which can extend the range of the vehicle once the battery is depleted. At the end of this chapter, Section 2.4 introduces theory related to product diffusion.

2.2 History of electric vehicles

Electric cars may seem like a recent discovery in our society as a reaction to the pressing issues related to oil scarcity and climate change. However, their development goes almost as far back as the first employment of automobiles in general. Here, an overview is presented from the first small scale models in the mid eighteen hundreds to the competitive cars available in the present day and age. Interwoven is an analysis of the electric vehicle's apparent failure to thrive during the course of recent history. Understanding the past may help in pinpointing factors that are still relevant during the present diffusion of electric cars.

Even though the early introduction of mechanical transportation in Europe diverges from the American history at certain points [70], this section has a strong focus on the United States due to a better documentation of its automobile history. However, to gain a general understanding of the different issues and perspectives that have influenced the diffusion of electric vehicles in the past, a dominant focus on America is acceptable.

2.2.1 1828 - 1915

At the end of the 19th century the rapid urbanization and industrialisation of American cities led to an increased demand in horses as a mode of local transportation. In Boston for example, the ratio of roughly forty humans for each horse in 1841 quickly dropped to 25 humans per horse in 1880 [69]. However, McShane and Tarr argue that with a significant increase in horses, issues such as stabling costs and manure volume rose to problematic levels, while the value of manure plummeted and regulations became tighter. As horses were increasingly perceived as a nuisance, opportunities arose for the diffusion of new transportation technologies. Although it might seem as if cars then simply substituted horses as both competed in the same market, Geels argues that historical dynamics were more complex [35]. The following paragraphs briefly outline some historical dynamics which played a role during the initial diffusion of the personal vehicle.

New modes of transportation. Due to the application of steel in boiler engines, lighter and smaller steam vehicles became possible in the 1860s and steam cars were employed on racetracks and in circus parades [35]. However, even though these vehicles were further improved in the 1870s and 1880s, they did not catch on in the long run. Public resistance due to unprecedented speeds, smoke, steam exhaust and widely publicized explosions caused steam cars to ultimately phase out from the streets [68, 40]. Britain even adopted legislation against steam-powered vehicles [23].

Shortly after the invention of steam vehicles, electric and gasoline vehicles also came into use. The first electric vehicle models were developed by various inventors. Between 1828 and 1835 the Hungarian Ányos Jedlik, the Scottish Robert Anderson, the Dutch Professor Sibrandus Stratingh and the American Thomas Davenport all developed their own, often small scale, electric vehicles. But none of these designs would have become practical for everyday use if the French chemist Gaston Planté had not demonstrated the first rechargeable battery, the lead-acid cell, in 1859 [26]. In 1881 the French chemical engineer Camille Alphonse Faure increased the capacity of Planté's cell by coating the lead plates with a paste of lead dioxide and sulfuric acid. This finding also reduced the formation time of the plates from months to hours and therefore became the standard in lead-acid battery production. Both Planté's and Faure's inventions pushed the development of electric vehicles forward.

Society welcomes personal vehicles. In the 1890s, the first electric vehicles on the road used small electric motors close to the wheels. Public reception was positive because EVs were considered clean, quiet, reliable and easy to handle [35]. By adopting the same mechanical controllers used in electrical trams, easy starting and acceleration became possible. This in contrast to the first gasoline cars which needed a clutch to change gears and easily stalled at low speeds. Among important people, the electric car was considered 'the car of tomorrow' [70]. However, among civilians, both electric and gasoline vehicles mostly remained luxury toys for the upper class. Horses continued to be a popular mode of transport in freight and also professional groups such as salesmen and rich farmers did not catch on until 1905 [35].

Geels identifies four niche markets for the earliest automobiles and suggests that during the first years, these distinct niches withheld competition between gasoline and electric vehicles [35]. First of all, horse-drawn carriages were enthusiastically replaced by electric cars in urban taxi fleets (Figure 2.1a). Because of the low speeds and frequent stops of taxi rides, gasoline vehicles were initially unsuited for this job. Electric cars were also popular in a second niche among members of the upper class who used their vehicle for promenading in parks. When the ban on personal vehicles was lifted in these green spaces, initially only electric cars were allowed because their lower noise level was less likely to scare horses. Geels states that the short range of electric cars was not a problem in this domain. A third niche was the racing circuit. Although electric cars did well on short range circuits, gasoline vehicles were superior on long-distance tracks. Electric cars were capable of producing high speeds or crossing relatively large distances, but not both at the same time. Geels argues that these races had an important influence on the public's perception of what a personal vehicle should be able to do, thereby increasing the popularity of gasoline cars. Finally, in a fourth niche, touring the country-side became increasingly popular around the turn of the century. While cities became more crowded and more polluted, driving automobiles outside of urban areas was perceived as a health activity. Also in this niche, gasoline vehicles were the more popular choice due to their greater range.

Public transport goes mechanical. Whereas automobiles did not immediately replace personal horse drawn carriages, the story was quite different in the mass transit sector. Electric trams replaced horse powered trams almost completely within 14 years after their first occurrence in 1888 [42]. Operational costs were much lower, speeds doubled and the pressing problems around horse manure were eliminated. Additionally, there was a general public enthusiasm for electricity and multiple social groups were in favour of electric trams. These included horse tram companies looking to reduce costs, real estate promoters who saw their land value increase as they invested in tram lines, and electric light companies which foresaw a new day-time market that could complement their night-time market in lighting [35].

Geels argues that the diffusion of the electric tram led to several cultural changes. Among others, lower classes could now engage in tourism, people's perception of high-speed vehicles was adjusted and the function of streets changed. Instead of being a social meeting place, streets now predominantly became domains for transportation vehicles and social meetings were shifted towards parks and open places. These changes in society were important underlying effects influencing the further diffusion of personal vehicles.

Gasoline cars take over the market. According to Geels, the electric tram lost popularity in favour of automobiles after approximately 1910, due to a number of political, social and economic reasons. Trams had become increasingly crowded, and due to a wider adoption of personal vehicles, the public perception of speed changed, causing trams to be perceived as relatively slow. Additionally, while automobiles were subsidised in the United States, trams were strongly regulated. This inhibited tram companies from raising fares while overhead expense increased.

However, the increased recognition of personal vehicles did not benefit cars of all fuel technologies equally. Due to Ford's pioneering of the assembly line, the price of the Model T gasoline car dropped from $850,- in 1908 to $360,- in 1916 [35]. Electric cars did not settle into a stable design and therefore remained relatively costly; in 1912, electric vehicles were available starting from $1750,- [2]. This made them financially more inaccessible for more consumers than gasoline cars.

Further sub-urbanisation and intercity road improvements also increased demand for vehicles with a long range, which was still a limiting factor for battery powered vehicles at that time. In contrast to gasoline cars, electric vehicle owners experienced difficulties with finding electrical recharge facilities in rural areas. These factors entailed that planning was an important aspect of owning an electric vehicle. This planning aspect was also found in vehicle maintenance. Partly discharged or defective lead batteries had to be recharged or repaired immediately in order to prevent capacity loss, while defect gasoline cars could easily be stalled to be repaired at a more convenient time [70].

Also important was the discovery of vast oil reserves in Texas. With gasoline still being a by-product of the oil industry, fuel prices decreased and the number of gasoline service stations rose [2]. Furthermore, electric starters became available to gasoline cars by 1912 and made these vehicles easier to handle.

Electric-gasoline hybrid cars, such as the Lohner-Porsche Mixte Hybrid shown in 1900, could have overcome these difficulties by providing the best of two worlds. However, Hoyer writes that due to cost problems, this fuel technology did not advance in the early days of the automobile [45]. For all these reasons, the gasoline car ultimately became the dominant mode of personal transport.

2.2.2 1915 - 1990

Hoyer provides an overview of electric vehicle developments in the years 1915 to 1990 [45]. During the First World War, European interest in electric vehicles temporarily increased in order to conserve gasoline for the war. However, demand fell once the war was over and plummeted even further after the stock market crash of 1929, which left many electric vehicle companies bankrupt. A short peak in demand was once again observed during the Second World War, likewise caused by the demand for gasoline at the war front. Germany applied tax-exemption regulation to promote the adoption of electric vehicles. In Great Britain, a fleet of 30.000 milk vans ran on electricity, their quietness being a significant benefit during morning rounds. After the war, interest once again dropped, although electric vehicles remained important in Japan until 1952 due to a problematic gasoline shortage. A Japanese company that would later merge with Nissan developed the Tama electric car, which utilised a lead-acid battery with a range of 95 kilometres and a top speed of 35 kilometres an hour (Figure 2.1b).

In the 1960s, 70s and 80s, the rise of the environmental movement put alternative energy sources on the political agenda and sparked a renewed interest in electric vehicles. The British Ford Motor Company and US General Motors, as well as multiple other manufacturing companies, each created prototypes that eventually never came into full production. Batteries proved to be too expensive in competition with gasoline cars and the second generation zinc-air batteries was still not reliable enough.

2.2.3 1990 - 2007

Several initiatives to stimulate electric vehicle development arose in the United States in the 1990s. At the start of the decade, the California Air Resources Board (CARB) introduced a mandate that obliged major car manufacturers to produce and sell zero-emission vehicles if they were to remain in business in California [2]. In 1993, the Clinton administration announced the 'Partnership for a New Generation of Vehicles' initiative that aimed to stimulate the development of low-emission vehicles. Notably, these measures motivated the development of all-electric cars by the General Motors Corporation and the Toyota Motor Corporation: the EV1 and RAV4.

Between 1996 and 1999, 1,117 General Motors EV1s were made available through a leasing programme in several US cities (Figure 2.1c). While first versions used traditional lead-acid batteries, the last version to be released used a more expensive nickel metal hydride (NiMH) battery pack that increased the vehicle's range. Around the same time, the all-electric Toyota RAV4 was also available for lease and sale in Japan and California. Around 1,900 RAV4s were sold between 1996 and 2003, with some reportedly still being on the road in 2013 [76]. After the CARB mandate was loosened to include other low-emission vehicles, motivation to pursue an all electric vehicle declined. Both General Motors and Toyota discontinued leasing plans of their electric vehicles and General Motors repossessed all EV1s, claiming that its continuation would be unprofitable.

Even more than for all-electric cars, the turn of the millennium was an important period for the rise of gasoline-electric hybrid vehicles [45]. In 1997, Toyota released the hybrid Prius in Japan and three years later, the car model became available on the American market as well. The Honda Motor Corporation introduced two hybrids on the American market: the Insight in 1999 and the Civic Hybrid in 2003. All three hybrids originally employed a NiMH battery and became commercial successes. In 2005, more than 100,000 units of the Toyota Prius were sold in the US alone [21]. Hybrid vehicles combined high fuel economy with the convenience of operating a gasoline vehicle and their availability weakened interest in all-electric cars once again [76].

Ultimately, Hoyer concluded in 2007 that the 1990s and the first years of the new millennium were an important period for the development of all-electric and hybrid cars. All major car manufacturers were in some form involved in research and development to realize a viable electric vehicle. However, all this effort did not bring about a return of the 'golden age' of electric vehicles as the world had experienced one century earlier [45].

2.2.4 2008 - now

One year after Hoyer's conclusion, the electric vehicle market received a sudden impulse when Tesla Motors brought its all-electric Roadster sports car on the market in 2008 (Figure 2.1d). The Roadster was the first electric vehicle to use a much lighter and powerful lithium-ion battery pack and also the first to obtain a range of more than 320 kilometres per charge [76]. With an average range of 400 kilometres, it broke records by driving the entire 504 kilometres of Australia's Global Green Challenge on a single charge.

Other electric vehicles running on lithium-ion batteries followed suit. According to the CEO of General Motors, Robert Lutz, the announcement of the Tesla Roadster flipped a switch that renewed serious interest in electric vehicles within General Motors: "All the geniuses here at General Motors kept saying lithium-ion technology is ten years away, and Toyota agrees with us, and, boom, along comes Tesla. [...] That was the crowbar that helped break up the logjam".[1] Additionally, according to Lutz, the success of the Toyota Prius hybrid gave Toyota a 'green' image that rose the market share of the entire Toyota Motor Company. To tap into this success, General Motors started production of the plug-in hybrid Chevrolet Volt, which was released in 2010 .

Fast forward to 2014 and most major vehicle manufacturers have a commercially available all-electric vehicle in their assortment. Prominent vehicles include the Tesla Model S, Nissan Leaf, Renault Zoe, Ford Focus Electric, Volk-

[1] Friend, T., The New Yorker. January 7, 2009. "Plugged In", obtained November 21, 2014. http://www.newyorker.com/magazine/2009/08/24/plugged-in

(a) Bersey Taxi Cab (1897)[2]

(b) Tama Electric Car (1947)[3]

(c) General Motors EV1 (1996)

(d) Tesla Roadster (2008)

Figure 2.1: Examples of electric vehicles over the course of history.

swagen e-Golf, BMW i3 and Mitsubishi i-MiEV. Additionally, multiple plug-in hybrids have been released. These electric vehicles can be charged using a regular power-plug and can drive on batteries only. However, once their batteries are depleted an internal combustion engine (ICE) can kick in, thereby increasing the vehicle's range and eliminating any potential range anxiety of the driver. To discern between different forms of electric cars, all-electric vehicles are subsequently referred to as battery electric vehicles (BEVs) and their plug-in hybrid counter-parts are referred to as plug-in hybrid electric vehicles (PHEVs). When the general term electric vehicle (EV) is used, both fuel technologies are implied.

2.2.5 Reflection

From the previous sections, it becomes apparent that all attempts in the past at reintroducing the electric vehicle were so far short lived. The EV's initial introduction was overshadowed by contextual developments that were in favour of gasoline vehicles. Every consecutive endeavour to revive electric cars failed once the initial stimulus to do so was removed; during both World Wars, EVs only remained popular while gasoline supply was tight, while in the 1990s, the willingness to pursue EVs dwindled once regulation was loosened. Just as the gasoline vehicle once won over the market because its characteristics were favourable from many different perspectives, it seems as if the diffusion of EVs might only thrive under similarly multi-perspective beneficial conditions.

[2] Credit: Science Museum, London
[3] Credit: Nissan Global website

2.3 Current state of electric vehicles

Given the turbulent history of the electric vehicle, the question is whether EVs are here to stay or whether society is experiencing one of its many temporary booms. When looking at the political, technological and social context in which the current adoption of electric vehicles is taking place, it is tempting to assume that the current marketing of EVs is significantly different than previous attempts at its revival. The following sections describe how the contemporary demand for electric vehicles is simultaneously addressed from multiple angles.

2.3.1 Political context

Since the uprise of the environmental movement in the 1970s, the stimulation of alternative energy sources and reduction of air pollution has retained a prominent position on the international political agenda. An example of this interest is the 1990 California Air Resources Board (CARB) mandate, mentioned in Subsection 2.2.3. Although the CARB mandate was eventually modified, new regulations required car manufacturers to produce 58,000 PHEVs between 2012 and 2014.[4] In 2007, the US Bush administration created the Advanced Technology Vehicles Manufacturing Loan Program. This programme helped motor companies such as Tesla Motors to develop zero-emission vehicles. The previous section already showed that the subsequent realization of the all-electric Tesla Roadster was an important catalyst for the development of EVs by other major car companies.

Furthermore, in recent years, multiple countries have instated tax benefits for purchasers and owners of EVs in order to reach internationally agreed carbon emission cuts. For instance in the Netherlands, all vehicles emitting less than 50 g CO_2 per kilometre are exempt from paying road taxes and fall in lower 'bijtelling' tax categories until at least 2016. The latter is a specific tax that only applies to lessees.

Less conventional political measures are also taken. Norway allows battery electric vehicles on bus lanes as part of its plan to reach 50,000 zero-emission vehicles on the road by 2017. An informal test showed that this measure reduces the duration of a standard trip during morning rush hour in Oslo from 51 minutes for gasoline cars to 19 minutes for BEVs.[5] Other incentives in Norway include exemption from toll payments and exemption from paying ferryboat fees and public parking fees for BEV owners.

As a result of differing policies, differences in composition of electric vehicle fleets are observed between countries. In Norway, only BEVs apply for the incentives mentioned above. As a result, in October 2014, 94.5% of the country's electric fleet consisted of BEVs and only 5.5% was a plug-in hybrid.[6]. In the Netherlands, many government incentives favour both types of electric vehicles. As a result, only 14% of the Dutch electric personal car fleet was a BEV in October 2014, the other 86% being PHEVs.[7]

[4] California Environmental Protection Agency, March 27, 2008. "The Zero Emission Vehicle Programme - 2008", obtained November 20, 2014. http://www.arb.ca.gov

[5] Mejlbo, K. Budstikka, December 9, 2013 'This fast is an electric car compared to a gasoline car' (translated from Norwegian), obtained November 20, 2014 http://www.budstikka.no/%C3%B8konomi-bolig/sa-rask-er-el-bilen-kontra-bensinbilen-1.8202727

[6] Gronn Bil, obtained November 20, 2014 http://www.gronnbil.no/statistikk/?lang=en_US

[7] Rijksdienst voor Ondernemend Nederland (RVO), obtained November 20, 2014. 'Numbers electric transport' (translated from Dutch) http://www.rvo.nl/onderwerpen/duurzaam-ondernemen/energie-en-milieu-innovaties/elektrisch-rijden/stand-van-zaken/cijfers

2.3.2 Technological context

The development of lithium-ion batteries allowed electric vehicles to make a functionally interesting come-back in recent years. They have double the energy density of NiMH batteries and four times that of their lead acid historical counter parts, while increasing the cycle life time with a similar degree [76]. Although prices are still high, they are steadily decreasing and initiatives such as the 'Tesla Gigafactory' can presumably further decrease the price of lithium-ion battery prices in upcoming years. Companies such as Toyota and BMW have set up research programmes to investigate commercial viability of lithium-air batteries, which could hold 5 to 10 times the energy of lithium-ion batteries of the same weight [76].

Multiple initiatives focus on realizing a reliable recharge infrastructure that can extend a BEV's trip beyond the range of a single charge. While Tesla is rolling out 'free for life' fast charge stations where customers can recharge their vehicle in 30 minutes in countries such as the United States and Norway, Renault allows its French customers one hour of daily free charging at any of their more than 800 chargers across the country. Independent start-up initiatives are also taking off, such as a Dutch company called Fastned which is building towards a nation-covering fast charge network by 2016.

A diverse range of other approaches are also taken by the industry to offset the perception of electric vehicles' limitations. To reduce the initial purchase price and the uncertainty about the battery's life span, companies such as Nissan and Renault sell their EVs with a separate lease plan for the car's battery. Other car manufacturers have set up distinct warranty plans for the vehicle's battery. An interesting approach is also taken by some Dutch lease companies, which temporarily supply their EV customers with a traditional gasoline vehicle in case they wish to undertake a long road trip.[8]

2.3.3 Social context

The rising political interest in renewable energy and privately owned solar panels has also increased public interest in electric vehicles. In the 2011 documentary 'Revenge of the Electric Car', the CEO of Renault/Nissan explains that his company is investing in electric vehicles because the public expects that this fuel technology becomes available. However, as of October 2014, electric vehicles in the Netherlands still make up only 0.5% of the total car fleet. Several studies have therefore pried the public's perception of electric vehicles in recent years.

Information-wise, consumers reported in 2011 that they are aware of the environmental benefits of electric vehicles and understand that EVs are currently characterised by a higher initial purchase price but lower running costs [86]. A majority of consumers was willing to accept this trade-off if the payback time was no more than 4 years. Additionally, the prospect of charging an EV using a power-plug was no reason for concern.

When it comes to the perception of EVs, a study from 2013 found that the EV stereotype is in flux. While traditional negative stereotypes are prevalent and are often linked to lack of knowledge and experience, new stereotypes are on the rise in which EVs are perceived as the cars of the future [14]. A con-

[8] Information on this deal was obtained on November 21, 2014 from Kyotolease: http://www.kyotolease.nl

firmation of the more negative image is portrayed by an online questionnaire among Dutch consumers, which showed that preference for EVs was significantly lower than for conventional gasoline vehicles. The main reasons for this were the limited driving range, long recharge times and limitedly available recharge opportunities [43]. Similar perceptions were found in the US, where consequently more interest was shown in adopting hybrids and PHEVs than BEVs [5]. Positive perceptions of EVs are more likely to occur in individuals with a pro-environmental self-identity [81].

As for actual hands-on experience, a 2014 study among persons who owned their EV for three months, showed that EV drivers were positive about recharging, preferred it over refuelling, and reported no serious concerns over the absence of proper public charging infrastructure [13]. However, a less positive image was obtained from a 2012 study of 40 UK drivers. After a seven-day EV trial period, hesitations for adopting an EV included prioritizing functional needs over environmental benefits, concerns over social perceptions of EVs, and uncertainty over the speed of technological developments that could quickly make current car models obsolete [38].

The above suggests that there is a distinction between the actual experience of owning an electric vehicle and the perception of EVs that many non-EV drivers still have. This can partly be explained by unfounded negative stereotypes, but also by different personal preferences of the early EV adopters in comparison to current gasoline owners.

2.4 Diffusion and adaptive policies

Product diffusion by itself is a difficult theoretical concept. Due to its open-ended nature, a precise definition of its success or failure is impossible. Complete diffusion would only occur when each individual in a society selects the same behavioural option. This is a situation that is unrealistic in the real world. Therefore, the objective of a diffusion model is to present the level of spread of an innovation, amongst a set of consumers, over time [63].

Rogers identified different segments of consumers, called 'adopter categories', that each play a prominent role during different moments of the diffusion process [79]. While the relatively small *innovators* and *early adopters* categories are the first to get acquainted with a new innovation, the *early- and late majority* follow thereafter and consist of the largest bulk of consumers. *Laggards* are again fewer in number and are the last to adopt an innovation. Figure 2.2 illustrates this process and shows how the market share of an innovation follows an S-shaped curve, resembling a logistic sigmoid function, due to the structure of the underlying adopter categories.

It is important to keep in mind that different adopter categories are driven by different needs when committing to a new product [79]. Mahajan argues that while early adopters often have a lot to gain from the functionality of the new product, slow adopters put great value on normative influences and will only be convinced after a significant number of others have committed to the innovation, causing the product to be a new social norm [65]. Because of these different preferences of different adopter categories and the inherent uncertainty of operating in the real world, different policies can become of use at different stages of the diffusion process. Such adaptive policies allow the adoption of a new product to be robust in a changing world [93].

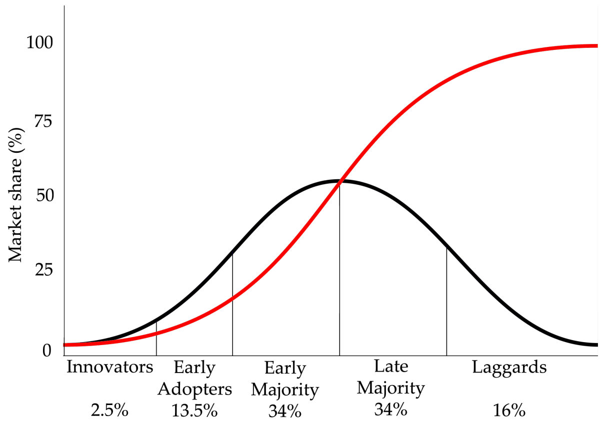

Figure 2.2: Diffusion of innovations. During different moments in the diffusion process (red line), different adopter categories play a role (black line) (adapted from: [79])

To gain some insight into the complex and often chaotic world of innovation diffusion, computer simulations can provide an environment in which this process can be studied. Besides allowing the operator of the simulation to explore the effects of different policies and re-innovations on the rate of the diffusion process, they can also provide insight into the reasons why some policies work better than others. Moreover, they can show effects of the diffusion process on other aspects of the environment that may have been overlooked otherwise. Agent-based models are particularly well suited for this task, as they allow the inspection of the reasoning of individual consumers for adopting an innovation or for sticking to their traditional behaviour.

3 Agent-based computing

While Chapter 2 provided background information on the domain to which our model is applied, this chapter describes literature concerning our method - agent-based computing - and the Consumat framework more specifically. The theory from this chapter provides the foundation for our model, which is presented in Chapter 4.

3.1 Overview

The first part of this chapter discusses basic concepts and terminology within the domain of agent-based modelling. The notion of an 'agent' (Section 3.2) and the different approaches within agent-based computing (Section 3.3) are explained first. the chapter then provides a brief overview of different agent-based modelling toolkits and arguments are given for using one of these toolkits for our implementation (Section 3.4). Next, examples are given of cognitive frameworks which are applied to artificial agents (Section 3.5), followed by requirements to which a useful cognitive framework in the domain of social simulations could adhere (Section 3.6). Important aspects of the Consumat agent framework are described in Section 3.7, followed by an a-priori evaluation of possible advantages and disadvantages of applying the Consumat framework to the domain of electric vehicles (Section 3.8).

3.2 Agents

A universal definition of an agent is not agreed upon, but a common summation of properties is that agents possess: *autonomy* (operating without intervention of others), *social ability* (interacting with others), *reactivity* (responding to changes in a perceived environment), and *pro-activity* (taking initiative to reach predetermined goals) [99]. A stronger notion of an agent is also identified within the field of artificial intelligence. According to this notion, agents must possess a mental state, described in human-like concepts such as beliefs, decisions, intentions and obligations [83].

Agent-based computing is then a programming paradigm in which computational agents are employed. While some computer systems may consist of a single agent (such as a web crawler that independently indexes a web domain), many systems consist of multiple agents that interact. Multi-agent systems represent the latter field, and its application can range widely from distributed problem solving [54] to flocking behaviour of birds [74]. Simulations using this type of agent-oriented programming can advance our understanding of social processes [29]. When applied to the field of sociology, they can help explain how macro-level structures emerge from the micro-level interactions between autonomous individuals.

3.3 Multi-agent systems vs agent-based models

Within the domain of agent-based computing, a distinction is often made between on the one hand small systems containing intelligent and diverse agents, and on the other hand simulations of large numbers of relatively simple and uniform agents [71, 22].

Within the first approach, researchers are predominantly interested in the (cognitive) functions of the agents themselves. Simulations of the agents are used to validate the assumptions of the underlying model. Typically this approach uses specialised agents to solve or study a certain practical problem. This is referred to as multi-agent systems (MAS). Its origin can be found in the field of Artificial Intelligence, where more specifically computer science, logic and cognitive science have been of influence [22]. MAS is applied to problems in which a multi-perspective provides benefits over trying to solve the problem from a single point of view, or where multiple locations and lack of central control make a single software system inviable. Examples are on-line trading, cooperating robots and networking technologies.

In the second approach agents are typically used as a means to study global or emergent phenomena in complex systems. This is referred to by a wide variety of names, the most common being social simulation, agent-based modelling (ABM), individual-based modelling (IBM), and agent-based simulations (ABS) [62]. This approach is widely used in the ecological and social sciences. Examples are simulations of the spread of epidemics, predator-prey relationships or crowds responding to a panic situation. The major concern is not for the agents to be competitively intelligent in comparison to actual humans; they only need to be sufficiently complex to provide useful insight into the phenomenon that is being studied.

Of course the distinction between these two approaches is not always clear-cut and systems may be positioned anywhere on the range from a specialised multi-agent system to a general agent-based simulation. Moreover, terminology is often used inconsistently and sometimes any approach using agents is referred to as a multi-agent system [72].

The model discussed in this thesis was primarily developed to study the diffusion of electric vehicles in Dutch society. This places the model on the side of ABM and its goal to understand social systems. However as will become clear in Section 3.7, a cognitive framework is applied to put the agents' mental states and decision-making processes in line with basic psychological understandings. Both this framework, which increases the agents' cognitive complexity, and the rich environment in which the agents are situated, places the model closer to the MAS side of the spectrum. Ultimately, we have chosen to describe our model as an ABM rather than a MAS in order to emphasize our research goal, but the reader is cautioned to remember the somewhat vague boundaries between these terms.

3.4 Agent simulation toolkits

Agent-based models are typically characterised by a large number of agents, all sharing the same environment and often connected in some form of social network. Additionally, simulations are run over a certain time frame, consisting of 'ticks' (also called 'steps' or 'epochs'). During each tick, actions are performed, often in a predetermined order. Although agents can be heterogeneous, they may share a large number of characteristics, such as abilities and needs.

Knowing this, it is possible to develop a computational representation of an agent-based model from the ground up. However, often it is much more economical to rely on an existing toolkit that provides the underlying infrastructure that almost all ABMs use. Relying on existing toolkits also enhances the distribution of social simulations, as it allows for easy instalment of software on different systems.

A well known free cross-platform and open-source ABM toolkit is the Recursive Porous Agent Simulation Toolkit (Repast) [73].[1] Repast is an agent-based modelling and simulation toolkit that supports implementations in multiple programming languages (ReLogo, Java, C++) within the domain of social science. Depending on the scale and computational complexity of the eventual model, one of the more expressive languages may be used. This in contrast to the popular and user-friendly NetLogo modelling environment.[2] Netlogo relies on a similar-named programming language, designed for use by persons without a programming background. Since this concern is not applicable in our case, the selection of an ABM toolkit can be made on more fundamental grounds. A comparison between toolkits showed that Repast has a higher execution speed than NetLogo, with a toolkit called MASON being the fastest [75].[3] However, due to the less mature nature of MASON and the fact that difference in execution speed seems to decrease with the complexity of the model, the decision was made to rely on the more widely adopted Repast. A Java based implementation was chosen within the Repast Simphony 2.1 version, released on August 13, 2013.

3.5 An overview of agent frameworks

One of the main challenges in working with simulated agents is to construct a cognitive framework that is both rich enough to realistically capture an individual's decision-making process given the circumstances, but also simple enough to remain computationally efficient and comprehensible to the modeller. Especially when working with a large number of agents, one must put restrictions on the number of factors taken into account. Although in certain cases ad-hoc models are created to suit the needs of a specific type of system, several more general frameworks have been developed over the years.

The *belief-desire-intention (BDI)* software model uses high-level mental concepts for planning and problem solving [10, 77]. The agents use modal logics to reason about their beliefs about the world, their desires which they wish to accomplish, and their intentions and plan on how to accomplish these goals. The BDI model has been a useful approach for technical problems in the area of multi-agent systems. For instance, embedded in a framework called *procedural reasoning system (PRS)*, it was successfully used in fault diagnosis for Space Shuttle missions and in controlling overload of telecommunication networks [48]. However, the framework is not based on sound psychological theory of human behaviour in the real world. Rather it is founded in logic and philosophy [36]. Moreover, in the traditional BDI model the agents do not possess a mechanism to learn from past experiences and to adapt to new situations [39]. With our current understanding of human reasoning, this makes the BDI

[1] Repast, http://repast.sourceforge.net/
[2] NetLogo, http://ccl.northwestern.edu/netlogo/
[3] MASON, http://cs.gmu.edu/eclab/projects/mason/

model too simplistic to realistically capture human decision-making processes in agent-based models.

A different approach is taken by cognitive frameworks such as *Soar* [58, 57] and *ACT-R* [3]. These kinds of elaborate architectures are strongly embedded in cognitive psychology and typically contain: both short-term and long-term memories; the organisation of memories into larger mental structures; and low-level functional processes that operate on these structures [59]. Artificial agents equipped with these cognitive frameworks should demonstrate similar capabilities as humans in a broad range of domains. However, these kinds of architectures are needlessly complicated when applied to social simulations such as the one developed for this thesis. For instance, when investigating the effect of several policies on the proportion of consumers adopting an electric vehicle, one is not interested in fine-tuning each agent's latency of information retrieval from memory. Furthermore, applying such a thorough framework to thousands of agents would result in unmanageably high computational costs. Consequently these cognitive frameworks are typically used for areas such as testing and explaining psychological phenomena, developing intelligent computer tutoring systems and creating realistic agents for simulated training environments [59].

CoJACK is a hybrid system between the high-level mental concepts of the BDI model and the low-level cognitive structures of the ACT-R architecture [78]. This architecture is used to develop more realistic simulated human entities. However, the reliance on the logic-based BDI model still results in an unsubstantiated representation of actual human behaviour due to its lack of foundation in cognitive psychology. It would therefore be dubious to apply a system such as CoJACK to social simulations, as outcomes would not be generalisable to the real world. It seems that the field of agent-based modelling requires frameworks that capture high level mental concepts and avoid cluttering of unnecessary details, but at the same time are also based on sound empirically-based theory.

3.6 Requirements for a cognitive agent framework

Because of the limitations when applying the cognitive frameworks mentioned in Section 3.5 to social simulations, Jager and Janssen address the need for a meta-theory that organises different social, psychological and economical theories in a unified conceptual framework for agent-based models [51]. Key components of such a framework that need special attention are the agent's needs and its decision-making processes.

Jager and Janssen [51] argue that agents in many social simulations are motivated by a single need: consuming a certain good. However, humans are characterised by their pursuit of satisfying various needs at the same time [51]. Maslow's hierarchy of needs is perhaps one of the most well known theories to this respect [66]. Maslow discerns between physiological, safety, belonging, esteem and self-actualisation needs. The first four are regarded as basic needs that must be satisfied before an individual can commit to self-actualization, or becoming "everything one is capable of becoming". Balancing different needs means that humans will not always aim to maximise the utility of one specific need. In many situations they are forced to compromise. For instance, driving an electric vehicle with a sufficient range may satisfy the need to reach destinations on time, but it may negatively affect the need to feel connected with friends that are still predominantly driving a fuel car. Depending on the domain that is being modelled, one must take into account the dominant needs that influence the individual under those specific circumstances.

Regarding theoretical constructs of decision-making processes, the notion of a rational agent, or homo economicus, has been a dominant influence in the field of economics for many decades. This theory claims that humans are principally self-interested and make rational decisions with the desire to optimise their own wealth. Strongly linked to this concept is rational choice theory, which dictates that all human actions are rational and calculative, denying the existence of habitual or emotional actions [82]. Perhaps unsurprisingly, psychological experiments show that optimising does not always take place but that people often resort to heuristics. For instance, one study found no empirical proof of homo economicus behaviour in any of the observed 15 small scale societies [41]. Also in lab and field settings, participants cooperate more often than theory would predict and defect in situations where cooperation would lead to a higher utility [37].

An alternative perspective on human decision-making is provided by Simon, whose notion of bounded rationality indicates that humans optimise their entire decision making process (*procedural rationality*) instead of only the outcomes (*substantive rationality*) [84]. Therefore, individuals may decide to invest less cognitive efforts in relatively unimportant problems than in others. This strategy that selects a suboptimal but acceptable behaviour is termed '*satisficing*' [85]. A second key insight from psychology is that people who are uncertain of their situation will engage in social processing [30]. By obtaining information on the beliefs of similar others, individuals aim to reduce their perceived level of uncertainty of their attitudes, perceptions and behaviour [44].

Using these concepts derived from psychology, Jager constructed a cognitive framework of consumer decision-making processes: the Consumat [49]. This framework is further discussed in Section 3.7 and provides the basic underlying rationale of the agents in the agent-based model of this project.

3.7 Consumat framework

The Consumat approach captures the main behavioural principles of consumer decision making in a conceptual framework for agent-based modelling [49, 52]. It is a collection of psychological meta-models and has the capacity to model consumer behaviour in many different contexts. Over the years, it has been successfully applied to areas such as flood management [11], household dynamics [53] and adaptation to climate change by farmers [1]. Recently, a revised version of the Consumat approach was proposed by Jager and Janssen: the Consumat II framework [50]. This section outlines the components as specified in the revised version.

3.7.1 Summary of core concepts

Consumat agents interact and perform behaviour in a shared environment. Key components of the agent are its decision-making process, its needs and its abilities. Needs can be satisfied through behaviour, whereas abilities are required to perform a behaviour. Two aspects of the agent's mental state determine the decision strategy the agent will use to select a suitable behaviour. These aspects correspond to the level of satisfaction and the level of uncertainty that the agent experiences with respect to its current situation. This is in line with

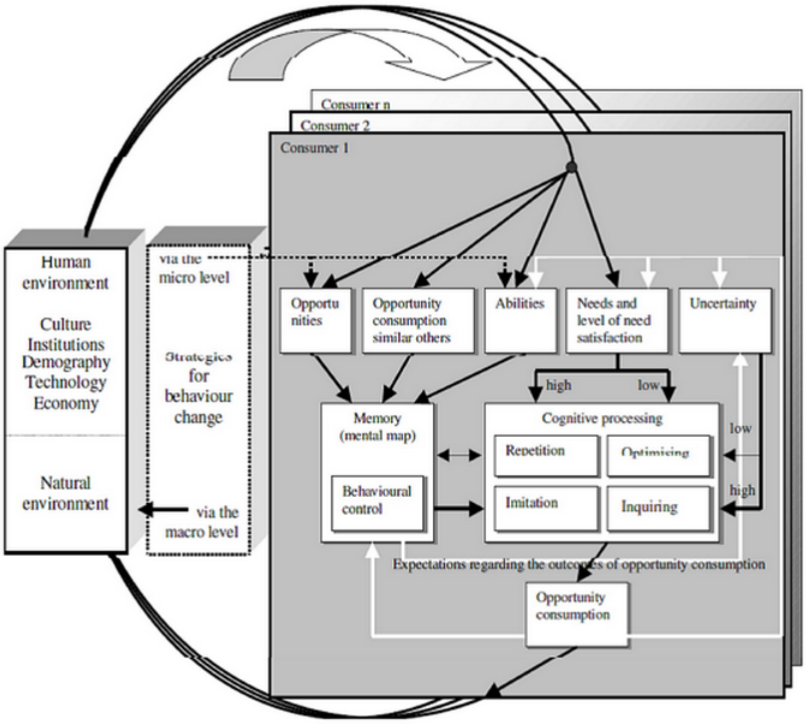

Figure 3.1: Schematic overview of the Consumat approach (source: [49])

psychological theories introduced in Section 3.6. A schematic overview of the Consumat approach is shown in Figure 3.1.

3.7.2 Needs

In the Consumat framework, three basic types of needs are identified: Existence needs, social needs and preferences. These loosely correspond to the three behavioural motives distinguished in Goal Frame Theory: Respectively gain motives, normative motives and hedonic motives [61]. *Existence* needs refer to the economic resources of the agent, such as food, money and housing. Agents will act in order to avoid depletion of these resources over time. The *social* need refers to interaction with other agents and corresponds to the strong ties persons have to others. Three social components are important here: Consumat agents want to conform to the behaviour of the majority, but they also want unique and better opportunities compared to others. This individual trade-off between conformity, anti-conformity and superiority can be modelled using a different weighting factor for each agent. The existence of both conformity and anti-conformity drives has long been suggested by research, in which a third drive is also specified: non-conformity [96]. This last aspect is incorporated in the Consumat approach by assigning a very low importance to the social need overall; this results in agents that do not act upon either conformity of anti-conformity tendencies. Finally *preferences* reflect the agent's personal taste with respect to other life values, such as religion, the environment or enjoyment of life.

3.7.3 Decision strategies

After evaluating its different needs, a Consumat agent's mental state can be satisfied or unsatisfied, and certain or uncertain. Depending on these two factors, the agent selects a decision strategy that includes 'satisficing' and/or social processing (Section 3.6). When a Consumat agent is satisfied and certain, there is no need for high cognitive or social processing and therefore the agent will simply repeat its current behaviour. When it is satisfied but uncertain, it will resort to its social network and through imitation it will copy the behaviour of successful peers. A dissatisfied and uncertain agent will consider the behaviour and knowledge of even more agents through inquiring, causing more possibilities to open up at the expense of using more cognitive processes. Finally, a dissatisfied but certain agent will choose optimising and investigate all possible behavioural options, through for instance the web, news and papers. This may lead to options not yet exploited by other agents.

3.7.4 Personality

Agents also possess a unique personality. Three notable aspects of an agent's personality are its ambition level (whether the agent is quickly satisfied or not), its uncertainty tolerance (how well the agent can deal with uncertain situations) and its time perspective (whether the agent takes possibilities in the far future into account). The greater an agent's time perspective, the more its need satisfaction will be affected by possible future threats. Another important aspect of an agent's personality is how the agent balances the importance of its different needs. While some agents can be mostly motivated by the drive to manage economical resources (existence need), others can be more susceptible to the influences of other agents (social need).

3.7.5 Other concepts

Besides needs, decision strategies and a personality, a few other concepts define the Consumat agent. First, the agent has abilities that determine which behaviours are available. Examples of abilities are income or the possibility to charge an electric car at home or at work. Second, the agent has a memory in which it stores information on behavioural opportunities, namely from its own experience, the experience of others and information from media. Finally, the agent is part of a social network and is more likely to interact with agents that are similar in terms of for instance age, income and opinions. These interpersonal communications are an important influence on the diffusion process in social systems [64]. Garcia and Jager argue that they play a key role in the success or failure of a diffusion process through raising awareness of new products and by changing normative pressures [34].

3.8 A priori evaluation of the Consumat framework

The introduction of Section 3.7 mentioned numerous consumer domains to which the Consumat approach has been successfully applied. Presumably, this framework will also be a good fit for the input data and modelling domain of our research project.

First of all, for most aspects there seems to be a direct mapping between the individual Consumat components and the questionnaire which supplies the input data for our model. For instance, the respondents' ambition level and uncertainty tolerance can be obtained from the questionnaire, as well as the importance that respondents place on several life values. The latter may be used to initialise how an agent balances its different needs. Like most questionnaires, demographical information such as age, income and location are also available. These aspects allow the instantiation of the social network of the Consumat agents, since research shows that individuals who are more similar in such aspects, are more likely to communicate [67].

Next, we predict that the Consumat framework can be adapted to instantiate three different types of agents. Within the Dutch car market, lessees share the road with individuals who purchase new cars and those who buy occasions. In this context, lessees and new buyers determine the supply of vehicles to occasion buyers. These different types of agents can share the same basic Consumat framework, but have slightly adjusted evaluation functions for specific needs. A lessee for instance, will not be interested in road taxes, but will focus on 'bijtelling' instead. The latter is a specific Dutch tax which only applies to individuals who lease their vehicle. A challenge when modelling these different types of agents, however, is that an additional car market infrastructure needs to be built around the Consumat agents in order to obtain realistic market dynamics.

One concern with the traditional Consumat framework, is that needs are not ordered, but only balanced according to a personal weighing function. It is unlikely however, that financial and symbolic aspects would counteract a car model's inability to meet the owner's driving behaviour. If that were the case, then individuals would buy a car model for financial or environmental reasons, even if the car in question had insufficient range to meet the driver's transport needs on a daily basis. In line with Maslow's theory on hierarchical needs [66], we therefore assume that being able to travel intended distances is a more basic need, and the inability to do so results in a penalty on the overall need satisfaction level of an agent.

Furthermore, the question arises whether the Consumat's heuristic-based decision-making process also applies to purchasing an expensive good such as a personal vehicle. It seems somewhat far fetched that an individual will switch its current vehicle for the same model that its friends use, as soon as its uncertainty rises. In the absence of data, we assume that cars are too much of a financial investment to think about switching vehicles this lightly. On the other hand, research shows that similar heuristics as defined in the Consumat framework do occur as *information seeking strategies* among vehicle purchasers [33]. Furse, Punj and Steward showed that individuals with low self-confidence in their ability to evaluate a product employ social processing heuristics by turning towards knowledgeable others. In contrast, experienced car buyers that are satisfied with their previous purchases do not spend much time searching out new information. If they do seek information, they rather turn towards advertising than towards other persons. Therefore, in this thesis, the notion of 'decision strategies' in the Consumat approach is adapted to 'information seeking strategies'.

With these considerations in mind, Chapter 4 continues with the theoretical foundation of the developed agent-based model.

4 Model

In Section 3.7 a theoretical outline of the general Consumat II framework was given. This chapter describes how the Consumat framework is applied specifically to a model of the personal vehicle market which has been given the name STECCAR (*Simulating the Transition to Electric Cars using the Consumat Agent Rationale*).[1] Chapter 5 continues with the parametrisation of this model and describes how a survey from June 2012 [9] was used to empirically initialise the Consumat agents. For now, it suffices to mention that each respondent to this survey is modelled as an individual Consumat agent in the STECCAR simulation.

4.1 Overview

The core of the STECCAR model is a set of agents that each own a personal vehicle to satisfy their needs. Vehicles using different fuel technologies exist within the agents' world: traditional gasoline cars, battery electric vehicles, and plug-in hybrid electric vehicles (Section 4.2). Agents are restricted in their behaviour through the amount of money they have and their ability to refuel cars that use alternative fuel technologies (Section 4.3).

Each tick of the simulation represents one week in the agent's world. Therefore on each tick, every agent has seven opportunities to travel a daily distance with its personal vehicle. During this drive, the vehicle will need refuelling when it runs out of energy and failures may occur (Section 4.4). After each trip, the agent decides how satisfied it is with its vehicle's costs and functionality and updates its knowledge about its current vehicle (Section 4.5).

At the end of the week the agent makes a comprehensive evaluation of its current vehicle, during which the agent not only focuses on its finances and the functionality of its car, but also aims to optimise its social and environmentalism needs (Section 4.6). This evaluation is combined with the agent's personality, which determines how easily the agent is satisfied or uncertain (Section 4.7). The result is the agent's mental state which indicates whether the agent perceives itself as satisfied and certain (Section 4.8).

Depending on its mental state, the agent decides whether to engage in an information seeking strategy to possibly increase its knowledge of other vehicles on the market (Section 4.9). Agents can find new information through communication with other agents (Section 4.10) and through the media (Section 4.11). If an agent is repeatedly unsatisfied, it may decide to purchase a new vehicle that better satisfies its needs (Section 4.12).

Figure 4.1 provides a visual overview of the STECCAR model.

[1] An additional reason for choosing the name STECCAR is its very appropriate close resemblance to the Dutch word for power plug: 'stekker'.

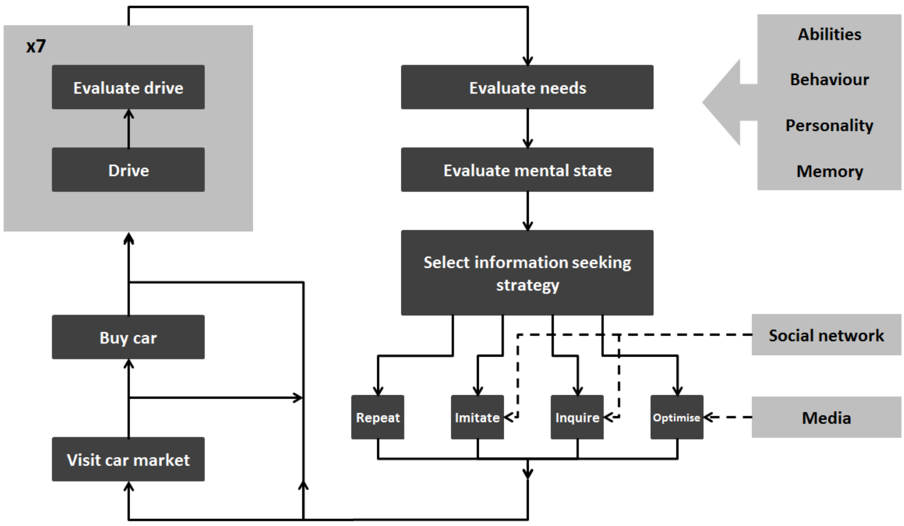

Figure 4.1: Abstract overview of the STECCAR model

4.2 Vehicles

Each car model available to the agents is defined by its fuel technology, price, range and emissions. More general aspects such as size, weight, cargo capacity and appearance are excluded, as respondents to the survey were instructed to assume that these are exactly the same across all models. What follows is an overview of the vehicles' aspects, which can be studied by introducing new car models to the market.

4.2.1 Fuel technology

All vehicles are propelled by either gasoline, electricity or a combination of both. These options correspond to three different fuel technologies that are available to the agents: gasoline vehicles, battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). Each fuel technology calls for different refuelling methods and maintenance costs, which results in a different driving experience to the agents (Section 4.4).

4.2.2 Price

The new price of a car model is set upon introduction and does not change during the course of the simulation. The actual value of the car decreases with time and affects agents selling or buying their vehicle from the occasion market. At tick t, the value of a vehicle v which was first purchased at tick $t_{\text{purchase, v}}$ is given by:

$$\text{value}_v = \text{depreciation}^{\frac{t - t_{\text{purchase, v}}}{52}} * \text{new price}_v \tag{4.2.1}$$

Although import taxes and purchase subsidies are not explicitly included in the model, their effect can easily be explored by altering the initial price of different car models.

4.2.3 Range

All vehicles can travel a limited range until their energy is depleted. To constrain the complexity of the model, a fixed range is chosen upon introduction of each gasoline vehicle, rather than specifying the capacity of the fuel tank and the car's fuel economy. For electric batteries, a fixed capacity (kWh) and fuel economy (kWh/km) *are* specified. This allows the modelling of decreasing battery costs by altering their price per kWh. Notice that in theory, including a fuel economy parameter allows agents to improve the range of their electric car by purchasing a new, more efficient battery. In the current STECCAR model however, that option is not developed further. PHEVs use both gasoline and electricity, and thus have both a fixed range from their gasoline tank and a battery capacity which determines their electric range.

$$\text{range}_{\text{electric}} = \frac{\text{capacity}}{\text{fuel economy}} \tag{4.2.2}$$

4.2.4 Emissions

Upon introduction, the emissions (g CO_2/km) of a car model are set fixed. Emissions influence both the tax category the vehicle falls in and the perceived environmental impact of the model. Notice that although emissions are fixed, a vehicle's tax category is not, because new tax policies may be introduced during the simulation. To reduce the complexity of the model, emissions are decoupled from driving costs. This entails that a reduction in carbon emission output of a gasoline vehicle has no effect on the gasoline costs per driven kilometre, although one would expect such a relationship in the real world.

4.3 Abilities

An agent's abilities influence which behavioural options are available and to a large extent determine whether the agent can satisfy its needs. The most prominent ability of an agent is to drive its personal vehicle, but also its money and its access to electric charge stations affect the agent's behaviour to a great extent.

4.3.1 Vehicle ownership

Each agent owns a personal vehicle at all times and is initially assigned a car whose fuel type, price class, age and kilometrage match its survey respondent's current vehicle as closely as possible.

There are three types of vehicle ownership which are determined and set fixed upon initialisation. Each agent is one of the following types: a lease owner, a buyer of new vehicles, or a buyer of occasions. The type of ownership influences which vehicles are available to the agent when it purchases a new vehicle and how the agent evaluates the costs of different car models.

4.3.2 Money

Agents have a personal money account which accumulates a portion p_{money} of their income each week. The update of the money account of an agent a is given by:

$$\text{money}_t = \text{money}_{t-1} + \text{yearly income}_a * p_{\text{money}} * \frac{1}{52}, \qquad (4.3.1)$$

with

$$\text{money}_0 = \text{yearly income}_a * \frac{1}{2} p_{\text{money}} * \text{ownership duration},$$

under the assumption that agents have initially saved half of their portion p_{money} to save for a new car since they last purchased a vehicle. This account is used for paying off maintenance costs and saving towards a new car. Since agents can generally only buy a vehicle when they have sufficient funds, the inclusion of money appoints a penalty to purchasing vehicles and it prevents agents from continuously buying new cars whenever they remain unsatisfied.

Agents that encounter higher failure costs than their budget allows will end up in debt and are prevented from buying a new vehicle once they are unsatisfied with their current car. They will however still purchase a new vehicle when their current one is total loss, as is further described in Section 4.12.

4.3.3 Refuelling

Whereas a gasoline vehicle can always and only fuel up along the road, electric vehicles can potentially refuel at three different types of locations; namely at home, at work and on the road. What enables an agent to charge at any of these locations is described below.

Home charge Agents that have access to their own garage, carport, drive way or other personal parking lot immediately possess the ability to recharge the batteries of their vehicle at home using a regular power plug. Agents that use a public parking space must rely on publicly available slow charge stations in their neighbourhood. A global property $\theta_{\text{charge, home}}$ determines which proportion of the population has access to a public charger near their house. Each tick, random agents are selected and given the ability to charge at home until the proportion of agents with access to a home charger equals that which $\theta_{\text{charge, home}}$ indicates. This ability is permanent, meaning that $\theta_{\text{charge, home}}$ only influences the agents' abilities when its value is increased.

Work charge Similar to the ability to charge at home, a property called $\theta_{\text{charge, work}}$ regulates the proportion of agents that can charge their vehicle at work. As with home charge, once an agent obtains the ability to charge at work, this ability is permanent.

Road charge A global property $\theta_{\text{charge, road}}$ indicates the probability that an agent has access to fast charge stations during its trip. Contrary to charging at home or at work, the ability to charge on the road is not fixed and is newly determined at the start of every drive the agent makes. The assumption is that long distances are not commonly travelled along the same route, unless the trip is a commute to work which is already captured in the previous paragraph. Since road charging only plays a role when agents drive long distances, it is likely that the ability to use a fast charge station differs between trips.

4.4 Driving

Each tick, an agent is given the opportunity to make seven drives, each drive corresponding to one day in the agents' world. The distances the agent drives correspond to the actual driving pattern of its respondent and are initialised at the beginning of the simulation and again every 52 ticks, or 'after each year'. During its drive, the agent may encounter failures and opportunities to refuel.

4.4.1 Refuelling

Agents have different preferred moments to refuel. While some seek new energy when their tank is still 50% full, others wait until their fuel depletes to 25% or even 10% of the tank's full capacity. The way the agent can refuel depends on the fuel technology of its vehicle.

Gasoline vehicles Modelled after the current situation, gasoline car models can only be refuelled on the road (i.e. not at home or at work) and these service stations are always readily available. Because the vehicle must be refilled during the drive, a delay is inevitable when refuelling is needed. Due to the extensive range of a gasoline car, the typical gasoline driver will not refuel daily. This entails that the agent may encounter price fluctuations with a delay, or in the case of a quick rise and fall, perhaps not even at all.

Battery electric vehicles An electric car can potentially be charged on the road, at home and at work. Section 4.3.3 described how agents may be able to charge at any or all of these locations. If the agent is able to charge at home, its vehicle's energy will be fully restored at the end of its drive. Home charging agents thus start each day with a full 'tank'. If the agent has the ability to charge at work, its battery will fill up completely halfway during a work drive, causing no delay to the agent as it is working while its vehicle charges. It is assumed that a work drive is a direct commute from home to work and back. During its trip, the agent may use fast charge service stations on the road. A different price is used for fast charging than for slow charging at work or at home. Modelled after the current situation, fast charging may only refuel the battery up to a certain proportion of its full capacity. As with gasoline cars, charging on the road results in a delay to the agent.

Because none of these charge locations are a given, some trips may be inaccessible to certain agents driving a BEV. Before a distance is travelled, it is therefore determined whether the drive will succeed or not, taking into account the current energy level of the car and the possibility to fast charge on the road or slow charge at work. A global property $\theta_{\text{charge, road}}$ determines the probability that the agent encounters fast charge service stations along its route. If no service station is encountered and the agent is predicted to run out of energy before it completes its planned distance, it will not drive but instead set this day's trip to 'failed'. A failed ride decreases the overall satisfaction that an agent experiences with its car, as is further explained in Section 4.8.

Plug-in Hybrid electric vehicles PHEVs use a combination of gasoline and electricity. Although they always start their drives using electricity, they are not limited by the electric range of their vehicle and will switch to gasoline if their battery runs out of power. Just like BEVs, PHEVs are charged at home or at work if the agent has the opportunity to do so. Since the survey respondents did not indicate how they prefer the trade-off between driving on gasoline or stopping to fast charge their battery, it is assumed that agents only fast charge with probability $\theta_{\text{charge, road}}$ if they need to stop to fill up their gasoline tank anyway.

4.4.2 Maintenance

Three different failures, or maintenance jobs, are encountered by the agents: small (€ 50), medium (€ 500) and large (€ 2000). Every d kilometress, failures occur with a probability that is specific to the vehicle's fuel type. To capture the increasing maintenance costs of older and more heavily used vehicles, d increases with the relative age of the vehicle. The relative age of a vehicle is determined by taking either its true age in years, or its total kilometrage divided by the average Dutch kilometrage per year[2], whichever one is larger (Equation 4.4.1). The distance d after which the chance of a failure occurs for a vehicle v is then given by Equation 4.4.2, where d_{max} is the largest distance after which failures can occur and d_{min} the smallest.

$$\text{relative age}_v = \max\left(\frac{t - t_{\text{purchase},v}}{52}, \frac{\text{kilometrage}_c}{13000}\right) \tag{4.4.1}$$

$$d_v = \max\left(d_{min}, d_{max} - \text{relative age}_v\right) \tag{4.4.2}$$

Battery maintenance On top of regular failures, an electric vehicle's battery also loses power and needs replacement after a certain time. Cugnet showed that battery life varies between 5 and 20 years and is dependent on multiple factors, such as outside temperature, depth of (dis)charge and method of charging.[3] However, only the method of charging (fast or slow) is taken to affect the battery's power in the simulation. Warm weather is assumed to be a relatively small issue given the moderate climate in the Netherlands and no survey information is available on whether participants value a deeper (dis)charge over a shorter battery life or vice versa.

Two life times are defined in the simulation: battery life_{slow} indicates the average battery life time if only slow charge is used, while battery life_{fast} represents the average life time of a battery that is solely powered using fast charge. When an electric vehicle v charges, the probability that the battery's range decreases by one kilometre is then given by Equation 4.4.3.

$$p(\text{range decrease}) = \frac{\text{new energy}}{\text{kilometrage} * \text{battery life}_x} * (\text{original range}_v * \text{max decrease}) \tag{4.4.3}$$

Here, new energy is the energy in kilometres that is gained through the current charge, x represents the average battery life time of either $fast$ or $slow$ charge, original range indicates the range of the vehicle v upon its first purchase and max decrease is the proportion of power the battery is allowed to lose until it is written off. The kilometrage is the yearly kilometrage upon which the

[2] Obtained from Statistics Netherlands (CBS). In 2012, the average yearly kilometrage in the Netherlands was 13.059 km (http://www.cbs.nl).

[3] Cugnet, M.G. Research presentation at a meeting of the American Chemical Society April 10, 2013. 'Understanding the Life of Lithium Ion Batteries in Electric Vehicles', obtained March 25, 2014. http://www.chemistry2011.org/news/PhysicalChemistry/Electrochemistry/UnderstandingTheLifeOfLithiumIonBatteriesInElectricVehicles

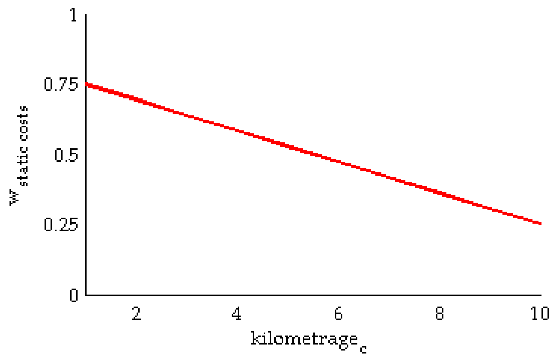

Figure 4.2: The linear static cost weight function which determines how much agents emphasize taxes over energy and maintenance costs (Equation 4.4.4)

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estimation of the battery's life time is made, this is further explained in Section 5.4.3.

If the battery's range drops further than max decrease allows, i.e. range < original range ∗ max decrease, the battery is written off. Section 4.12 describes whether the agent buys a new vehicle or a new battery when this happens. In case a new battery is bought, this is done at the price per kWh that is currently prevalent in the simulation.

4.4.3 Evaluation

At the end of each day, the agent evaluates its trip and updates its existence satisfaction, resulting in seven updates per tick. The agent separates the different components of its driving evaluation into two groups: finances and functionality. These groups correspond to the agent's two existence needs, which are further explained in Section 4.6. The aspects which the agent includes in its evaluation are now described further. It is important to notice that all evaluations are constrained by a minimum value of 0 at the lowest, and of 1 at the highest. If an equation results in an evaluation outside this range, it is cut off at the minimum or maximum value.

Finances In the finance group, the agent's maintenance-, energy- and tax satisfaction are combined into a single measure of financial satisfaction. A distinction is made between variable costs which depend on the extent to which the vehicle is used, and static costs which remain constant even when the vehicle is not in use. The first includes the maintenance and energy costs, while the latter consists of taxes. Depending on the kilometrage category c in which the agent's driving pattern falls, more emphasis is placed on either static or variables costs. The static costs weight is chosen such that the lowest kilometrage category emphasizes the static costs with a factor 0.75, while the highest category weighs these with a factor 0.25 (Figure 4.2).

Equations 4.4.4 to 4.4.7 show how the financial satisfaction is computed. Next, the different components (maintenance, energy and taxes) of the financial evaluation are described in more detail.

$$
\begin{aligned}
s_{\text{finances, t}} &= w_{\text{static costs}} * s_{\text{static costs, t}} + \\
&\quad (1 - w_{\text{static costs}}) * s_{\text{variable costs, t}} \quad , \qquad (4.4.4)
\end{aligned}
$$

where

$$w_{\text{static costs}} = -\frac{1}{18} * \text{kilometrage}_c + \frac{29}{36} \qquad (4.4.5)$$

$$s_{\text{static costs, t}} = \begin{cases} s_{\text{bijtelling, t}} & \text{if ownership = lease} \\ s_{\text{taxes, t}} & \text{otherwise} \end{cases} \qquad (4.4.6)$$

$$s_{\text{variable costs, t}} = s_{\text{maintenance, t}} + s_{\text{energy, t}} \qquad (4.4.7)$$

After each drive during which as an agent encounters a failure, the agent's failure satisfaction drops to the multiplicative inverse of the maintenance costs. The satisfaction is restored exponentially after each subsequent drive, causing large failures to have a longer lasting effect than small ones. The equation to determine the maintenance satisfaction at time t is then given by:

$$s_{\text{maintenance, t}} = \begin{cases} \frac{1}{\text{costs}_t} & \text{if costs}_t > 0 \\ s_{\text{maintenance, t-1}} * 1.5 & \text{otherwise} \end{cases} \qquad (4.4.8)$$

Even when the agent did not refuel during its drive at time t, it still evaluates its satisfaction with the energy price it encountered the last time it refuelled (Equation 4.4.9). The agent's satisfaction with its vehicle's current energy costs consists of three components. The basic satisfaction is a sigmoid function, leaving the agent completely satisfied with an energy price of 0 € /km and completely dissatisfied when the price reaches 0.20 € /km. The latter corresponds to a gasoline price of approximately 3.30 € /litre. A sigmoid was chosen under the assumptions that price alterations in the low- and high end of the range have a smaller effect than those around the middle. The basic energy satisfaction is given by Equation 4.4.10 and depicted in Figure 4.3 for clarity.

The second component reacts to sudden fluctuations in energy prices. It decreases or increases the energy satisfaction, depending on whether the energy price rose or fell since the previous time the agent refuelled (Equation 4.4.11).

Within the last component, previous (dis)satisfaction with energy price fluctuations are taken into account and added or subtracted to the basic satisfaction. This is represented by Equation 4.4.12, which takes the discrepancy between what the energy price satisfaction should have been previously if no fluctuations had taken place, and what the satisfaction actually was. This difference is reduced by a factor 0.8, ensuring that past price fluctuations have an ever decreasing effect on the present.

The final energy satisfaction is given by combining the three components in Equation 4.4.13.

$$\text{price}_{\text{energy, t}} = \begin{cases} \text{price}_{\text{energy, t}} & \text{if costs}_{\text{energy, t}} > 0 \\ \text{price}_{\text{energy, t}-1} & \text{otherwise} \end{cases} \qquad (4.4.9)$$

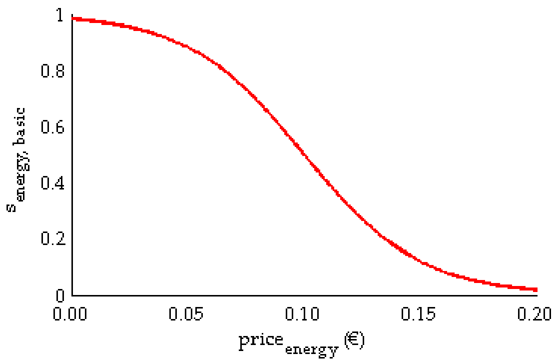


Figure 4.3: Sigmoid function which depicts the basic energy satisfaction equation (Equation 4.4.10)

$$s_{\text{energy, basic, t}} = 0.5 - 0.5 * \tanh(2 * 10 * (\text{price}_{\text{energy, t}} - 0.1)) \quad (4.4.10)$$

$$s_{\text{energy, fluctuation, t}} = \frac{\text{price}_t - \text{price}_{\text{energy, t}-1}}{\text{price}_{\text{energy, t}-1}} \quad (4.4.11)$$

$$s_{\text{energy, past, t}} = 0.8(s_{\text{energy, basic, t-1}} - s_{\text{energy, t-1}}) \quad (4.4.12)$$

$$s_{\text{energy, t}} = s_{\text{energy, basic, t}} - s_{\text{energy, fluctuation, t}} - s_{\text{energy, past, t}} \quad (4.4.13)$$

Because taxes are something that individuals are continuously confronted with during their vehicle ownership, agents also take into account their tax satisfaction at the end of each drive by comparing the taxes they pay to the maximum taxes they could be paying:

$$s_{\text{taxes, t}} = 1 - \frac{\text{taxes}_t}{\text{max taxes}_t} \quad (4.4.14)$$

In the Netherlands, lease owners pay taxes through a tax construct called 'bijtelling', instead of paying regular taxes. Alternatively to Equation 4.4.14, lease agents therefore use Equation 4.4.15 to evaluate their tax satisfaction.

$$s_{\text{bijtelling, t}} = 1 - \frac{\text{bijtelling}_t}{\text{max bijtelling}_t} \quad (4.4.15)$$

Functionality Only its satisfaction with the duration of the drive determines how satisfied the agent is with the functionality of its vehicle. When battery electric vehicles are unable to travel a desired distance due to insufficient range and charge stations, the agent's satisfaction also severely decreases. This aspect is also part of the vehicle's functionality, but it is assumed to have a much stronger impact because it defies the most prominent reason for owning a car: getting from A to B. The inability to travel a certain distance therefore influences the total satisfaction of the agent (Section 4.8) instead of solely the functionality need.

Agents encounter time delays when they refuel on the road. They become less satisfied with this duration when their refuel time is longer than they are willing to wait. After a drive at time t, first the maximum acceptable delay (in minutes) is computed, using the maximum highway refuel time the agent is willing to accept and the maximum distance over which the agent is willing to encounter this (Equation 4.4.16). Next, the actual delay is divided by this acceptable delay to obtain the agent's functionality satisfaction (Equation 4.4.17).

$$\text{acceptable delay}_t = \frac{\text{distance}_t}{\text{max distance}} * \text{max time}_{\text{highway, a}} \tag{4.4.16}$$

$$s_{\text{functionality, t}} = 1 - \frac{\text{delay}_t}{\text{acceptable delay}_t} \tag{4.4.17}$$

4.5 Memory

In its memory, the agent keeps track of its driving experiences, its knowledge of different vehicle models and fuel types, and its knowledge of the agents in its social network.

Both the agent's driving experience and its knowledge on vehicles is continuously updated using the exponentially-weighted moving average (EWMA, Equation 4.5.1). This method, also called exponential smoothing, was initially introduced by Brown to predict future values [12]. It is also a computationally efficient way to compute the weighted average of a continuous stream of data, because no storage of old values is required. By increasing or decreasing α, one can respectively place more or less emphasis on recent information over past information.

$$\mu_{x,t} = \alpha x_t + (1-\alpha)\mu_{x,t-1} \tag{4.5.1}$$

The agents also keep track of the variance of information they encounter. Equation 4.5.2 is a slightly adjusted version of the formulas by Welford and West and shows the weighted variance which corresponds to the EWMA [94, 95].

$$\sigma^2_{x,t} = \alpha(x_t - \mu_{x,t-1})(x_t - \mu_{x,t}) + (1-\alpha)\sigma^2_{x,t-1} \tag{4.5.2}$$

Together, the moving average and variance are used to compute the coefficient of variation (COV). The COV is the ratio of the standard deviation to the mean and is the direct representation of an agent's uncertainty with a certain piece of information (Equation 4.5.3). Next, the exact forms of information that are stored and updated in memory are described in more detail.

$$\text{COV}_{x,t} = \frac{\sigma_{x,t}}{\mu_{x,t}} \tag{4.5.3}$$

4.5.1 Drive experience

After the financial satisfaction and functionality satisfaction at time t are determined (Section 4.4.3), the overall satisfaction and uncertainty of these two needs are updated according to Equation 4.5.1 and 4.5.3 respectively, using an α of 0.1. This entails that the most recent measure of satisfaction always influences the overall satisfaction and uncertainty by 10%. This information is later used, in combination with the agent's social- and environmental satisfaction, to evaluate whether the agent perceives itself as overall satisfied with its current vehicle (Section 4.8).

4.5.2 Beliefs about vehicles

Because each conversation or media message may transfer different beliefs, the agent continuously updates its estimated value and variance of vehicle models' characteristics. This information is later used to determine the agent's satisfaction and certainty with its existence and environmentalism needs. The agent updates the believed characteristics of its currently owned car model after each drive, and updates the information of other models after a communication has taken place or a media message has been read. This means that the agent's beliefs about its own vehicle's characteristics are not influenced by the opinions of others. This is done under the assumption that for obvious vehicle properties such as range and energy costs, the owner knows best.

A distinction is made between aspects related to vehicle models (Section 4.2) and those belonging specifically to different fuel technologies (Section 4.4). All aspects are updated using Equation 4.5.1 and 4.5.2. When updating through the agent's own experience or the media, a fixed α of 0.1 is used. Information from other agents uses an α that corresponds to the other agent's informative weight, which ranges between 0 and 0.1 and is further explained in Section 4.10.3.

Vehicle models For each car model on the market, the agent keeps track of its estimated price, range, emissions and taxes. Concerning beliefs about its own vehicle, the price and emissions remain constant over time and are therefore not updated. The estimated range of the agent's own vehicle will only change when the agent drives an electric vehicle and the battery capacity decreases. This entails that agents who drive a gasoline vehicle only update their beliefs about the taxes of their currently owned car model, since for the other characteristics there is no adjustment to take place. Because different communication partners and media outlets provide alternative beliefs, all characteristics of vehicle models that the agent does not own are always updated.

Upon initialisation, all agents are familiar with their current vehicle. However, to ensure that agents have some awareness of electric vehicles at the start of the simulation, an agent may also know about other electric vehicles currently on the market. For each electric car on the market, the probability that an agent knows about this car model is equal to the agent's expertise in alternative fuel technologies, which is a value between 0 and 1.

Fuel technologies The agent forms a belief about the charge time, the energy costs per kilometre and the maintenance costs per kilometre of each different fuel technology available. For battery electric vehicles, the agent maintains separate beliefs about the charge time of normal charging at home or at work, and of fast charging along the road. Because all these aspects can vary over time, all are constantly updated regardless of whether the information is obtained from personal experience, other agents or the media.

When an agent updates its beliefs about the energy costs of its current vehicle, it uses the costs of the last time it refuelled divided by the amount of energy (in km) that was gained. This way, EV drivers each have a personally tailored belief about their energy costs per km, depending on how often they use normal versus fast charge stations or even gasoline stations in the case of PHEVs. For updating its estimated maintenance costs, the agent uses the total maintenance costs it has paid for so far, divided by the total kilometrage it has driven in this car. The refuel duration of its current vehicle is simply the actual refuel time as is currently prevalent in the simulation.

Although not all vehicle models have to be known by every agent, it is crucial for the agents to have initial beliefs about the three different fuel technologies in order to reason about car models using alternative fuels. A survey respondent's self-indicated expertise in alternative fuels ranges between 0 and 1. The larger this expertise, the larger the probability that the agent's beliefs about different fuel technology characteristics are initialised close to their true value. The agent's expertise of the fuel technology it currently uses is always set to 1. This dynamic allows the simulation to start with a diverse range of beliefs about the characteristics of different fuel types. Equation 4.5.4 & 4.5.5 show how the expertise influences the initial value of a fuel technology's aspect x. A larger expertise results is a smaller possible deviation. The function $\text{Rand}(min, max)$ selects a random number between min and max.

$$\text{deviation} = 1 - \text{expertise} \tag{4.5.4}$$

$$x = x - \text{Rand}\left(-\text{deviation} * x, \text{deviation} * x\right) \tag{4.5.5}$$

4.5.3 Social information

Lastly, the agent's memory stores information on the agents in its social network (Section 4.10). More specifically, the agent stores what fuel types the other agents use and what the existence satisfaction of the other agents is. This information is used to perform social comparison (Section 4.6.3). Because fuel types are nominal values and cannot be averaged intuitively, these aspects are stored for every agent that the agent communicates with, rather than being updated through a moving average as is done with the information described in the previous two sections. Since the number of communication partners of any agent is limited, this does not pose a serious concern for computational costs.

4.6 Needs

An agent's needs are the different aspects of its life that it tries to keep in balance. The original Consumat framework identifies three types of needs: existence, social and personality. Social refers to the agent's place within its network, while personality reflects the agent's style and taste. Existence refers to having means for a continuous life, such as housing, food and clothing. Money and transportation are two elements of the existence need that individuals particularly need to balance when considering car ownership. The survey provided results on how respondents value these elements separately, but no data was available on how they value the need for existence as a whole. Simply combining the importance the respondents place on these two elements was not a satisfying option, as they are too different to compare. The finance and transportation aspects of the existence need were therefore modelled as two separate needs, leaving the Consumat agents with four needs in total.

At the end of each week, agents evaluate how satisfied and how certain they are with respect to their four needs (Section 4.8). In case they are prolongedly unsatisfied, they will look for a new vehicle by comparing the estimated satisfaction and certainty of other vehicles they know (Section 4.12.2). A distinction is made between determining the satisfaction of a currently owned vehicle and the satisfaction of a potential new model, as true ownership satisfaction is assumed to be of a different kind than expected ownership satisfaction. The first is based on actual experience, while the latter inevitably needs to rely on heuristics of expected utility. This distinction only holds for the two existence needs, as estimations of social and environmental satisfaction are presumably unaltered by actual ownership. For each need, the exact satisfaction and uncertainty evaluations are now explained further.

4.6.1 Financial need

The financial need aims to keep the amount of money an agent spends on its vehicle as low as possible. The financial satisfaction and uncertainty of actual ownership depend on previous driving experiences of the agent, as was described in Section 4.4.3. An overall measure of the financial ownership satisfaction and uncertainty are then directly obtained from memory (Section 4.5.1). The rest of this section explains the process of estimating the satisfaction and uncertainty whenever an agent searches for a new car.

Satisfaction When an agent contemplates purchasing a new vehicle, it cannot rely on financial experiences with all the car models it compares. It therefore approximates the yearly costs of all car models within its price range, denoted by set M. Such an estimation is also made for its currently owned vehicle, in order to make a fair comparison to other models. The agent then estimates its satisfaction with the financial aspects of a potential new model m, by determining the proportional difference between the yearly costs s of m and the cheapest model in set M:

$$s_{\text{finances, } m} = 1 - \frac{c_m - \min_{i \in M} c_i}{\min_{i \in M} c_i} \tag{4.6.1}$$

The yearly costs are a summation of a vehicle's depreciation, energy, maintenance and tax costs for agents who drive a private vehicle. Agents who lease their car aggregate the energy, maintenance and 'bijtelling' costs to obtain their estimated yearly expenses. Car insurance is independent of fuel technology and therefore, given the purpose of this model, excluded. The costs of aspects of the agent's currently owned model are always derived from personal experience, while estimated costs of other models and alternative fuel technologies can only be obtained through beliefs that the agent formed in its memory through communication or the media (Section 4.5.2). Next, the expected yearly costs of these aspects are described in more detail.

$$c_m = \begin{cases} c_{\text{lease, } m} & \text{if ownership}_a = \text{lease} \\ c_{\text{private, } m} & \text{otherwise} \end{cases}, \tag{4.6.2}$$

where

$$c_{\text{private, } m} = c_{\text{depreciation, } m} + c_{\text{energy, } m} + c_{\text{maintenance, } m} + c_{\text{taxes, } m} \tag{4.6.3}$$

$$c_{\text{lease, } m} = c_{\text{energy, } m} + c_{\text{maintenance, } m} + c_{\text{bijtelling, } m} \tag{4.6.4}$$

The yearly depreciation is taken as the average depreciation over 4 years, which is the average ownership time in the Netherlands [92]. While agents who buy new vehicles always use their believed new price as the model's initial value, agents who buy occasions will assume that their occasion is 8 years old on average and will thus reduce this new price with a depreciation of 8 years using Equation 4.2.1. Agents who lease their vehicle do not take depreciation into account. When estimating the depreciation of the car model the agent currently owns, it uses the value of its current vehicle as long as it is not beyond repair. The yearly depreciation costs c of model m are then given by:

$$c_{\text{depreciation, } m} = \text{value}_m * \frac{1 - \text{depreciation}_m{}^4}{4} \tag{4.6.5}$$

To estimate the energy costs on a yearly basis, agent a multiplies the energy costs per kilometre of the fuel technology f that car model m uses, by its own estimated yearly kilometrage:

$$c_{\text{energy, } m} = \text{energy km costs}_f * \text{kilometrage}_a \tag{4.6.6}$$

A similar computation is made for the maintenance costs. The average maintenance costs per kilometre of car model m's fuel technology f is again multiplied by agent a's yearly kilometrage, shown in Equation 4.6.7. An agent a who evaluates the expected maintenance costs of a battery electric occasion, also takes into account additional costs due to battery breakdown. The yearly costs of replacing the vehicle's battery at some time in the future are obtained by dividing the total costs of replacement by the battery's duration.

$$c_{\text{maintenance, } m} = \text{maintenance km costs}_f * \text{kilometrage}_a + \text{battery costs}_m, \tag{4.6.7}$$

where

$$\text{battery costs}_m = \begin{cases} \frac{\text{capacity}_m * \text{costs per kWh}}{\text{battery duration}} & \text{if Fuel}_m = \text{BEV} \\ & \text{\& ownership}_a = \text{occasion} \\ 0 & \text{otherwise} \end{cases} \tag{4.6.8}$$

Private vehicle owners multiply their monthly taxes by 12 to obtain the yearly tax costs of car model m. Taxes are dependent on the carbon emissions of m. Lease owners do not pay regular taxes in the Netherlands, but instead contribute through a tax system called 'bijtelling'. The 'bijtelling' percentage is determined by m's carbon emissions. This percentage is multiplied by the agent a's income tax percentage and the new price of the car model in question.

$$c_{\text{taxes, } m} = \text{monthly taxes}_m * 12 \tag{4.6.9}$$

$$c_{\text{bijtelling, } m} = \text{bijtelling}_m * \text{income tax}_a * \text{value}_m \tag{4.6.10}$$

Uncertainty The agent obtains the uncertainty about its estimated price, energy, maintenance and tax costs of car model m by averaging the coefficients of variation (COV, Equation 4.5.3) of all four aspects. Agents who lease their vehicles use the uncertainty with the model's 'bijtelling' percentage instead of the model's regular taxes. So with

$$F = \{\text{price}_m, \text{energy km costs}_f, \text{maintenance km costs}_f, \text{monthly taxes}_m\},$$

for agents who buy private vehicles and

$$F = \{\text{price}_m, \text{energy km costs}_f, \text{maintenance km costs}_f, \text{bijtelling}_m\},$$

for agents who lease their vehicle, the financial uncertainty of agent a with model m using fuel technology f is given by:

$$u_{\text{finances, } m} = \frac{1}{\|F\|} \sum_{i \in F} \text{COV}(i), \tag{4.6.11}$$

4.6.2 Functionality need

The functionality need represents the agent's desire for a vehicle that meets its transportation requirements. As with the financial need, the functionality satisfaction and uncertainty of actual ownership depend on previous driving experiences of the agent and are directly obtained from memory (Section 4.5.1). The rest of this section deals with the estimation the functionality satisfaction and uncertainty when an agent compares potential new vehicles.

Satisfaction Whereas an estimation of an unknown car model's costs satisfaction can easily be made with an approximate calculation, it is much less intuitive to estimate the satisfaction with this new model's functionality. If the model in question m and the agent's current vehicle o can both use gasoline to propel themselves, the agent will assume that its satisfaction is equal to its experience with its current car.

An extra assumption is added when m and o are both battery electric vehicles, as the potentially large differences in range between BEVs restrict a direct comparison. In this case, the agent uses a ratio of its current functionality satisfaction in proportion to the range difference.

Finally, if the agent is unfamiliar with the fuel technology of car model m, it will estimate its satisfaction with the model's range and charge time using heuristics described next. As when determining its satisfaction with different components of its driving experience (Section 4.4.3), all satisfactions are constrained by a minimum value of 0 at the lowest and of 1 at the highest.

$$s_{\text{func, } m} = \begin{cases} s_{\text{func, } o} & \text{if } (\text{Fuel}_m \wedge \text{Fuel}_o) \neq \text{BEV} \\ (s_{\text{func, } o} * \text{range}_m)/\text{range}_o & \text{if } (\text{Fuel}_m \wedge \text{Fuel}_o) = \text{BEV} \\ (s_{\text{range, } m} + s_{\text{time, } m})/2 & \text{otherwise} \end{cases} \quad (4.6.12)$$

An agent a determines its satisfaction with a car model m's range in proportion to its minimally desired range:

$$s_{\text{range, } m} = \frac{\text{range}_m}{\text{min range}_a} \quad (4.6.13)$$

Agent a's satisfaction with the refuel time of vehicle model m using fuel technology f is given by Equation 4.6.14 to Equation 4.6.17. Let L be the set of all refuel locations available for the fuel technology used by model m. Refuel stations along highways can potentially be used by any fuel technology and therefore 'highway' is always included in L. If the model is a battery electric vehicle, the agent also computes its satisfaction with the charge time at home and at work. For BEVs, $\text{time}_{\text{home, } f}$ and $\text{time}_{\text{work, } f}$ are the normal charge times of an electric vehicle and $\text{time}_{\text{highway, } f}$ equals an electric vehicle's fast charge time. For gasoline models and PHEVs, $\text{time}_{\text{highway, } f}$ is equal to the time it takes to refill a gasoline tank. Notice that BEV users are completely unsatisfied with home or work charging when they do not have the ability to charge at these locations.

$$s_{\text{time, home, } m} = \begin{cases} 1 - \dfrac{\text{time}_{\text{home, } f}}{\max \text{time}_{\text{home, } a}} & \text{if } \theta_{\text{charge, home, } a} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{4.6.14}$$

$$s_{\text{time, work, } m} = \begin{cases} 1 - \dfrac{\text{time}_{\text{work, } f}}{\max \text{time}_{\text{work, } a}} & \text{if } \theta_{\text{charge, work, } a} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{4.6.15}$$

$$s_{\text{time, highway, } m} = 1 - \frac{\text{time}_{\text{highway, } f}}{\max \text{time}_{\text{highway, } a}} \tag{4.6.16}$$

$$s_{\text{time, } m} = \frac{1}{\|L\|} \sum_{i \in L} s_{\text{time, } i, m} \quad , \tag{4.6.17}$$

where

$$L = \begin{cases} \{\text{home, work, highway}\} & \text{if Fuel}_m = \text{BEV} \\ \{\text{highway}\} & \text{otherwise} \end{cases} \tag{4.6.18}$$

Uncertainty The agent's functionality uncertainty with model m which uses fuel technology f is given by the average coefficient of variation (COV, Equation 4.5.3) of the model's range and refuel time:

$$u_{\text{func, } m} = \frac{1}{2} \left(\text{COV}(\text{range}_m) + \frac{1}{2} \left[\text{COV}(\text{time}_{\text{normal, } f}) + \text{COV}(\text{time}_{\text{fast, } f}) \right] \right) \tag{4.6.19}$$

PHEVs can use multiple forms of refuelling, but since they are never restricted by the longer charge times of electricity, agents only take the refuel time of gasoline into account. This entails that $\text{time}_{\text{normal, } f}$ and $\text{time}_{\text{fast, } f}$ are equal for gasoline and PHEV vehicles.

4.6.3 Social need

During each conversation with other agents in its social network (Section 4.10), the agent stores information on its communication partner in its memory (Section 4.5.3). Within the social need, agents use this information to optimise their perceived relation to others. When an agent determines its social satisfaction and uncertainty with its current vehicle at the end of the week, it uses the same method as when it estimates how well its social need would thrive with a potential new model.

Satisfaction An agent's social satisfaction consists of desires for conformity, anti-conformity and existence superiority over others (Equation 4.6.20). While the first aspect drives an agent to adopt similar behaviour to those around it, the second aspect tries to obtain the direct opposite: being unique and therefore performing different behaviour than others. The superiority aspect reflects the tendency of individuals to seek a better standard of living than their direct acquaintances in order to feel socially superior. Each agent places a different emphasis on these three components of their social need by using a different set of social weights. The evaluations of the three components are now explained further.

$$s_{\text{social, } m} = w_{\text{conformity, } a} * s_{\text{conformity, } m} + w_{\text{anti-conf, } a} * s_{\text{anti-conf, } m} + w_{\text{superiority, } a} * s_{\text{superiority, } m} \tag{4.6.20}$$

Let A denote the set of agents in agent a's social network. For the conformity satisfaction of a with its current or potential vehicle model m, a looks at the proportion of agents in A whose vehicle n uses the same fuel technology as m. The anti-conformity satisfaction is the proportion of agents which use a different fuel technology and is therefore simply 1 subtracted by the conformity satisfaction. The more similar two agents are, the greater the influence the other agent poses on a's (anti-)conformity satisfaction . This is indicated by w_{norm} and further explained in Section 4.10.3.

$$s_{\text{conformity, } m} = \frac{1}{\sum_{i \in A} w_{\text{norm},i}} \sum_{i \in A} \begin{cases} w_{\text{norm, } i} & \text{if Fuel}_a = \text{Fuel}_i \\ 0 & \text{otherwise} \end{cases} \tag{4.6.21}$$

$$s_{\text{anti-conf, } m} = 1 - s_{\text{conformity, } m} \tag{4.6.22}$$

The superiority satisfaction is given by the proportion of agents in set A which have a lower existence satisfaction with their vehicle n than agent a has with its own or potential car model m. The existence satisfaction is given by the average of an agent's financial and functionality satisfaction with their current or potential vehicle. Again, more similar agents have a greater influence on a's superiority satisfaction.

$$s_{\text{superiority, } m} = \frac{1}{\sum_{i \in A} w_{\text{norm},i}} \sum_{i \in A} \begin{cases} w_{\text{norm, } i} & \text{if } s_{\text{exist},a} > s_{\text{exist},i} \\ 0 & \text{otherwise} \end{cases} \tag{4.6.23}$$

where

$$s_{\text{exist}} = \frac{1}{2}(s_{\text{finances}} + s_{\text{func}}) \tag{4.6.24}$$

Uncertainty When more agents switch from a vehicle that uses fuel technology f to a vehicle that does not use f, the agent's social uncertainty with a vehicle that uses fuel technology f increases. Set A_f consists of the agents in agent a's social network that currently use fuel technology f and H_f denotes the set of all agents in a's network that use fuel technology f now or did so at some time in the past. The social uncertainty of an agent with car model m which uses fuel technology f is then given by:

$$u_{\text{social, } m} = 1 - \begin{cases} \frac{\|A_f\|}{\|H_f\|} & \text{if} \|H_f\| > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.6.25}$$

4.6.4 Environmentalism need

In the Consumat framework, aspects such as personal style and taste are included in the personality need. When considering the market for (electric) vehicles, both the appearance and environmental impact of car models are expected to influence consumer decisions. To reduce the complexity of the STECCAR model, the model's scope is restricted to the propulsion systems of different cars and appearance is excluded from the framework. The personality need therefore solely relates to the individual's environmental values and how the agent evaluates the environmental friendliness of different vehicle models. A benefit of this decision is reduced complexity in an already elaborate model. As with the social need, the agent's environmentalism satisfaction and uncertainty with a certain car model m are computed using the same method, whether m is currently owned by the agent or not.

Satisfaction It is assumed that agents with a greater concern for environmental problems will be less easily satisfied with the level of carbon emissions of their vehicles. To determine an agent a's environmental satisfaction with its current or potential new model m, a's preferred emissions are divided by m's carbon emissions. As with other forms of satisfaction encountered earlier, the environmentalism satisfaction ranges between 0 and 1 and its value is cut off if it surpasses this range on either side.

$$s_{\text{environm},\, m} = 1 - \frac{\text{emissions}_m}{\text{max emissions}_a} \tag{4.6.26}$$

Uncertainty The agent's environmental uncertainty is given by the coefficient of variation (COV, Equation 4.5.3) of model m's carbon emissions, since only this aspect influences the agent's environmentalism need.

$$u_{\text{environm},\, m} = \text{COV}(\text{emissions}_m) \tag{4.6.27}$$

4.7 Personality

All agents come with unique characteristics which make them value one need more than another and which affect how they respond to uncertain or unsatisfying situations.

Need weights Section 4.6 described how an agent determines the satisfaction and uncertainty of its four different needs. The agent's need weights regulate how these need evaluations are combined into a general measure of satisfaction and uncertainty. They ensure that a diverse range of agents with different values exist by indicating which needs an agent emphasizes. For each agent, the summation of W, the set of the four need weights, results in 1. In other words $\|W\| = 1$. Two examples are given for clarity.

Agent a has a need weights set W_a, where $W_a = \{w_{\text{finances}} = 0.5, w_{\text{func}} = 0.15, w_{\text{social}} = 0.05, w_{\text{environm}} = 0.3\}$. This is a plausible set as $\|W_a\| = 1$. Agent a will put most of its effort into optimising its finances by driving a vehicle which costs less on a yearly basis than other car models. Somewhat less important but still relatively essential to agent a, is that the carbon emissions of its vehicle are not significantly greater that its preferred limit. Whether agent a's vehicle matches its driving behaviour is somewhat relevant, but not to the same extent as the previous two needs. The agent is practically unaffected by what the other agents in its social network do. So even though a may potentially have a relatively large conformity weight, this does not have an effect on its behaviour because a's social weight is very low. This is called 'non-conformist' behaviour.

Agent b, who possesses the need weights set $W_b = \{w_{\text{finances}} = 0.15, w_{\text{func}} = 0.25, w_{\text{social}} = 0.6, w_{\text{environm}} = 0.1\}$ will have other preoccupations than agent a. Agents b's social need plays a far more important role than any of the other needs. Therefore, depending on the social aspect which is most prevalent in agent b, it will seek the vehicle that makes him most similar, most dissimilar or better off compared to other agents.

Ambition The more ambitious an agent is, the more it takes for the agent to be satisfied. The ambition level is scaled between 0 and 1 and has two effects on the agent's behaviour. First, it acts as a threshold to decide when the agent's mental state is content with its current vehicle. While agents with a relatively low ambition are very likely to feel overall satisfied even when their satisfaction with their personal vehicle is very low, ambitious agents will need to be highly satisfied with their current car before they stop searching for a different model. This dynamic is explained in more detail in Section 4.9. Second, the ambition level acts as a weight when balancing the estimated uncertainty and satisfaction of a potential new car model m. The higher the agent's ambition in comparison to its uncertainty tolerance, the more emphasis the agent places on its estimated satisfaction of m instead of its estimated uncertainty. Section 4.12.2 elaborates on this process.

Uncertainty tolerance The agent's uncertainty tolerance is linked to different consumer segments as proposed by Rogers [79]. The more risk taking an individual is concerning innovative products, the higher its uncertainty tolerance. Similar to the ambition, the uncertainty tolerance ranges between 0 and 1 and functions both as a threshold for the agent's uncertainty with its current vehicle, and as a weight for the agent to balance the estimated uncertainty and satisfaction with a potential new vehicle.

4.8 Mental state

The mental state of the agent represents its current outlook. It dictates whether the agent perceives itself as satisfied or unsatisfied and as certain or uncertain. The evaluations of the agent's four different needs are combined with the agent's need weights, in order to obtain a general evaluation of the agent's current mental state. Notice that the satisfaction and uncertainty of the agent's financial and functionality needs with its current vehicle are derived from its direct driving experience (Section 4.5.1), while its social and environmental needs are evaluated using the heuristics described in Sections 4.6.3 and 4.6.4 respectively.

If N is the set of all four needs, the general measures of the agent's satisfaction and uncertainty with its current vehicle are obtained using Equation 4.8.1 and 4.8.2 respectively. A satisfaction penalty is given for each day that the agent was unable to complete its ride due to insufficient range and charge stations (Section 4.4.1). The assumption here is that the main functionality of a vehicle, getting an agent from A to B, is so influential that an agent cannot be satisfied if its vehicle fails to provide this.

$$s = \frac{\text{succesful rides}}{7} \sum_{i \in N} s_i * w_i \tag{4.8.1}$$

$$u = \sum_{i \in N} u_i * w_i \tag{4.8.2}$$

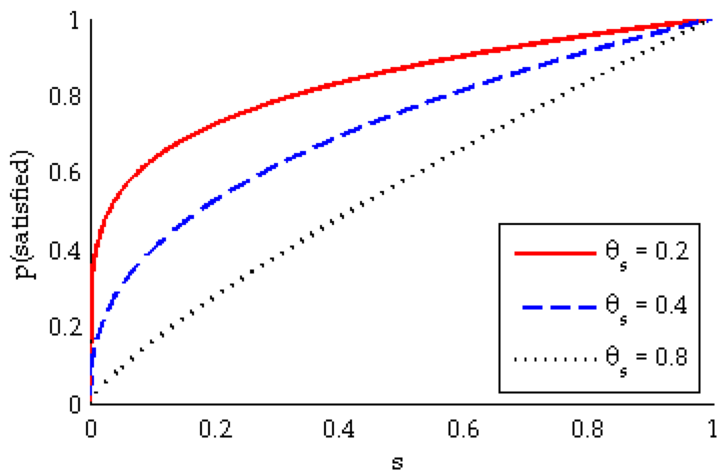


Figure 4.4: The probability that an agent perceives itself as satisfied, given various values of its ambition level θ_s. The lower the agent's ambition level, the greater the probability that it is satisfied.

Because these general measures result in an evaluation between 0 and 1, a stochastic process controls whether the agent's current mental state is ultimately satisfied and/or certain. The agent's ambition level θ_s regulates this process for the agent's satisfaction. The probability that an agent perceives itself as satisfied is then given by s^{θ_s}. For the agent's uncertainty, the uncertainty tolerance θ_u plays a similar role and u^{θ_u} gives the probability that the agent perceives itself as uncertain. More ambitious agents are harder to satisfy and agents with a higher uncertainty tolerance can handle more uncertainty before they perceive their current state as uncertain. Figure 4.4 illustrates the influence of different ambition values on the probability that an agent feels satisfied. A similar figure would hold for the agent's uncertainty tolerance.

4.9 Information seeking strategies

After an agent has evaluated its mental state, it decides whether to seek out more information on other car models. Which information seeking strategy it selects is dependent on whether the agent perceives itself as generally satisfied and/or uncertain.

The four different information seeking strategies available to the agent mirror the behavioural options of agents in the original Consumat framework. In general, being unsatisfied results in a search for new information, while being uncertain causes agents to explore what other agents do. Agents that are satisfied and certain will repeat their current behaviour without contemplating different possibilities. Satisfied but uncertain agents use social comparison to imitate the knowledge of similar others. They turn towards other agents in their network and ask them how they perceive their current vehicle. Unsatisfied but certain agents optimise their knowledge by seeking new information through the media. A combination of both, being unsatisfied and uncertain, results in agents that seek new information by inquiring which car models others are familiar with. Table 4.1 summarizes the strategies available to the agents while the following sections explain each of them in more depth.

Table 4.1: Information seeking strategies available to the Consumat agents. X is a uniformly distributed random variable between 0 and 1

		Satisfied	
		$X > s^{\theta_s}$	$X \leqslant s^{\theta_s}$
Uncertain	$X \leqslant u^{\theta_u}$	Optimising	Repetition
	$X > u^{\theta_u}$	Inquiring	Imitation

4.9.1 Repitition

Satisfied and certain agents have no reason to expend their knowledge of other car models. They do not seek new information but immediately decide whether they will visit the car market or not (Section 4.12). Notice that these agents *can* still obtain new knowledge when other agents are uncertain enough and approach them.

4.9.2 Imitation

Agents who resort to imitation feel uncertain with their current vehicle, but are also satisfied. This removes the need for deep cognitive processing and searching for new information. A simple survey of the current vehicles used by other agents suffices.

Each agent within the agent's social network (Section 4.10) is approached. The probability that the agent will communicate with a contact is obtained by squaring their similarity: let X be a uniformly distributed random variable between 0 and 1, then communication will take place if $X < \text{similarity}^2$. Once communication is initiated, both agents inform each other of the price, range, carbon emissions and taxes of their current vehicle and of their estimated energy costs, maintenance costs and refuel time of the fuel technology their current car uses. Section 4.5.2 explained how both agents then update their beliefs about the other agent's car model and fuel technology. Additionally, agents inform each other of their personal existence satisfaction, which is used within the agent's social need during the following week.

4.9.3 Inquiring

Similar to agents who use an imitating information seeking strategy, inquiring agents turn towards their social network to alleviate their uncertainty. However, inquiring agents feel both uncertain and unsatisfied, and will thus put more effort into learning new information. Instead of only sharing information about one another's current vehicle, every car model that both agents know has a chance of being discussed.

It is assumed that these deep and long conversations occur with a smaller number of contacts than the trivial conversations that take place within the imitation strategy. A conversation therefore takes place when $X < \text{similarity}^4$, where X is again a uniformly distributed random variable between 0 and 1. Figure 4.5 illustrates the difference in communication probability between the imitation and the inquiring strategies.

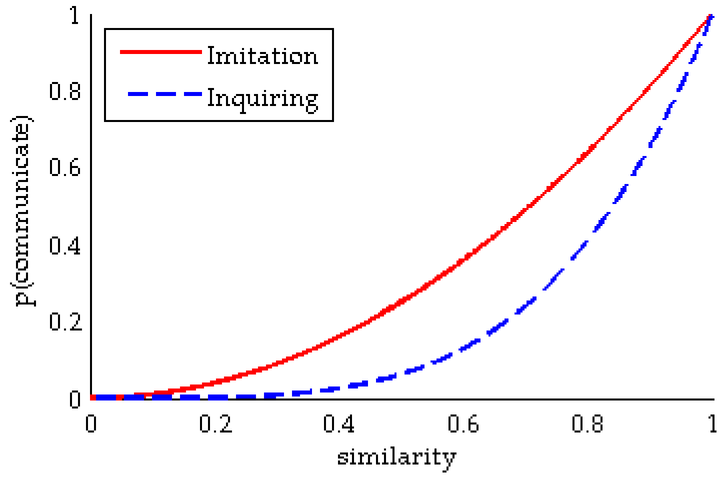


Figure 4.5: The probability that two agents communicate during the imitation and inquiring information seeking strategies.

The same information is exchanged as in the imitation strategy. Additionally, the believed price, range, carbon emissions and taxes of each car model that the other agent is familiar with, is shared with the inquiring agent with a probability of 0.5. If a shared car model uses an alternative fuel technology to those already discussed, the estimated energy costs, maintenance costs and refuel time of this technology are shared as well. Similar beliefs on each car model that the inquiring agent knows is also shared with the other agent with a probability of 0.5. The estimated aspects of all discussed car models are then updated by both agents, as is described in Section 4.5.2.

4.9.4 Optimising

Optimising agents are unsatisfied but not uncertain and will therefore seek new information without consulting their social network. Instead, optimising agents utilize the media by searching for recent news messages. This is the only strategy that can deliver information on new car models, still unknown by the other agents.

Although the media frequently publish messages, a message is only obtained by an agent with a probability of $0.9^{t-t_{\text{publish}}}$, with a minimum probability of 0.01. Here, t is the tick at which the agent chooses to optimise and t_{publish} is the tick at which the news message was published. This results in a bias for more recent news messages but ensures that old news may still pop up. A maximum of 5 messages is retrieved by any optimising agent. A news item contains either information on the price, range and carbon emissions of a certain car model, or it contains information on the energy costs, maintenance costs and refuel time of a certain fuel technology. How these messages are used to update the inquiring agent's beliefs was explained in Section 4.5.2.

4.10 Social network

Central to any social simulation is the network through which the agents are connected with one another. It is well established that individuals are more likely to communicate, with a certain probability, to others that are more similar to them [67]. This is termed 'homophily'.

4.10.1 Initialising friends

In the STECCAR model each agent is connected to a fixed number of communication partners which are assigned upon initialisation. During this process, each agent is compared to a subset of the other agents. Those agents that are most similar to the agent are selected as its communication partners, or 'friends'. Because only a subset of the agents is considered, it is not guaranteed that the most similar agents in the model are connected. Additionally, connections are not automatically symmetric. Meaning that agent A may consider agent B as one of its friends, while agent B has no connection to agent A in return.

4.10.2 Factors of similarity

Six factors are included to determine the similarity between two agents a and b. These are described in the following paragraphs. The relative importance of each of these factors is uncertain and absent in the survey data and literature. It is therefore assumed that all factors contribute equally to determine the similarity between agents. If F is the set of all factors that determine the similarity between two agents, then the similarity between these to agents is given by:

$$\text{similarity} = \frac{1}{\|F\|} \sum_{i \in F} \text{similarity}_i \tag{4.10.1}$$

Geographical proximity Numerous studies show that the closer two individuals are located, the more likely they will form a bond and thus communicate often [7, 87, 89]. For the purposes of this model, geographical proximity is expected to be of particular importance because it also reflects similar driving infrastructure. Individuals in the rural North will more likely consider experiences of proximal peers, than those of individuals in the urban West when deciding which vehicle best suits their needs.

To determine the geographical similarity between two agents, a hard line is drawn by comparing their postal code areas. If both agents share the same general postal code area (e.g. both are within range 1000 - 1999) they are considered maximally geographically similar, otherwise their similarity is maximally dissimilar. This way, the local neighbourhood effect plays an important role in the simulation.

$$\text{similarity}_{\text{geography}} = \begin{cases} 1 & \text{if location}_a = \text{location}_b \\ 0 & \text{otherwise} \end{cases} \tag{4.10.2}$$

Income Research indicates that income is a relatively unimportant predictor of friendships [87]. However, the correlation between income and probability of communication may be much higher. At work, most colleagues will have a comparable income level and conversations about vehicles may take place on the work floor even though strong friendships do not form. Moreover, individuals with similar income levels are assumed to be more likely to ask each other for advice concerning expensive purchases such as vehicles. Therefore despite absence of empirical evidence, income is assumed to influence the probability that two agents exchange thoughts about cars.

The annual income of the agents is divided into ten categories. The absolute difference between two income categories then linearly determines the income similarity of the respective agents. This causes agents in equal income categories to be maximally similar, while agents in the lowest category are maximally dissimilar to those in the highest.

$$\text{similarity}_{\text{income}} = 1 - \frac{|\ \text{income}_a - \text{income}_b|}{10} \tag{4.10.3}$$

Values The more similar the attitudes of two individuals are, the more these individuals are attracted to each other [15, 16]. Also, the more individuals in one's environment, the less diversity in attitudes and beliefs there is within friendships [6]. In other words, when given the option to choose between potential friends, as the group size increases, individuals with more similar attitudes are preferred.

Translated to the Consumat agents, this means that if two agents place similar relative importance on their needs, they are more likely to have a similar outlook on life and thus more likely to communicate. Therefore the balance between the weights of the agents' four needs is taken as a measure of similarity. The absolute difference between the weights of each need n is subtracted from 1, while a negative similarity is not allowed. This causes agents with equal weights to be maximally similar and agents with a need weight difference of 1 or higher to be maximally dissimilar.

$$\text{similarity}_{\text{values}} = \max\left(0, 1 - \sum_{n} |w_{\text{needs, a}} - w_{\text{needs, b}}|\right) \tag{4.10.4}$$

Ambition Similarity in the level of ambition is an important predictor of friendship [87]. It is also likely that equally ambitious individuals will more often meet in work settings and thus communicate. As the agent's ambition level is already scaled between 0 and 1, it directly linearly influences the ambition similarity between two agents.

$$\text{similarity}_{\text{ambition}} = 1 - |\ \text{ambition}_a - \text{ambition}_b| \tag{4.10.5}$$

Behaviour and preferences Similar activities are an important predictor of friendships [87]. Two behaviours can be discerned as particularly characterizing the agents: the type of vehicle an agent drives and its yearly kilometrage. Since the agents' vehicle type is flexible, including it as a measure of similarity would introduce network dynamics: once individuals buy an electric vehicle, they could be more likely to seek out other EV owners through for instance online communities. Strengthening the ties with these EV owners will result in a stronger social certainty which can influence the overall behaviour of the simulation. This would however introduce assumptions on how ties with older friends are weakened and how strongly EV owners seek new connections to like minded consumers. It was chosen to side pass these assumptions due to absence of data, and not include vehicle type ownership as a measure of behavioural similarity.

It is assumed that individuals with similar kilometrage are more likely to seek advice from one another. Those who travel long distances on a daily basis will more readily relate to each other's experiences than to those who only use their vehicle for the occasional leisure activity. The agents' estimated kilometrage is categorized and fixed and therefore lends itself to be easily compared. As with income, ten categories are discerned whose difference results in a linear decreasing behavioural similarity.

$$\text{similarity}_{\text{behaviour}} = 1 - \frac{|\text{kilometrage}_a - \text{kilometrage}_b|}{10} \tag{4.10.6}$$

Age Age plays an important part in friendship formation of high school students [55]; some of these friendships will last all the way up to adulthood. McPherson et al. discuss multiple studies that show the influence of age on social network structures in adults [67]. Likelihood of friendship seems to drop exponentially as the age gap widens. For instance in Detroit, 38% of a man's close friends are within two years of his age, while 72% are within eight years [31].

The age difference between two agents therefore influences their age similarity exponentially. Agents are most dissimilar when their age difference is 40 or higher, assuming that 40 is roughly the largest age difference on the work floor and the moment when the lives of two individuals diverge too much.

$$\text{similarity}_{\text{age}} = \begin{cases} \left(1 - \frac{|\text{age}_a - \text{age}_b|}{40}\right)^2 & \text{if } |\text{age}_a - \text{age}_b| \leqslant 40 \\ 0 & \text{otherwise} \end{cases} \tag{4.10.7}$$

Other measures of similarity Gender similarity is associated with strong friendships and initial contact but not with 'friendly' or neutral relationships [89, 60]. Additionally, the link between gender and network ties is not very strong [67]. It was therefore decided not to include gender as a factor that determines the probability of a network tie.

4.10.3 Weights

Not all information that is shared between agents counts equally. As described in the original Consumat framework, information from similar others and information from experts may carry a greater weight. These two aspects are represented by the normative and informative weights respectively.

Normative weight The normative weight is equal to the similarity between two agents. It determines how much a communication partner influences the conformity, anti-conformity and superiority satisfaction of an agent's social need under the assumption that more similar others have a greater influence on how we perceive our social position.

Informative weight After each inquiry into another agent and after each media message that an agent reads, the agent's expert level is increased by 1. The informative weight that agent a then puts on agent b, is agent b's expert level divided by ten times the maximum expert level that agent a has so far encountered, resulting in a value between 0 and 0.1. This entails that agent b has differing informative weights when communicating with different agents. b may carry a large informative weight when communicating with agent a, who only knows agents that do not inquire or optimise much. However, its informative weight may be relatively low when communicating with agent c, who happens to know a very ambitious agent that seeks out new information on a regular basis.

The informative weight influences how much the other agent updates its beliefs after a conversation takes place, as was described in Section 4.5.2.

4.11 Media

At the start of each tick, the media publishes messages on the different car models available in the car market and on the current state of different fuel technologies. In case the message focuses on a specific car model, it mentions this model's fuel technology, price, range and carbon emissions. When the focus is on a fuel technology, the energy costs, maintenance costs and refuel duration of this technology are described. The probability that a message about a certain car model m which was introduced at tick $t_{\text{intro, m}}$ is published at tick t decreases exponentially and is given by Equation 4.11.1. The probability that the media publishes a message on fuel technology f is always 0.5.

$$p(\text{message}_m) = \max\left(0, 1 - \frac{t - t_{\text{intro, m}}}{104}\right) \quad (4.11.1)$$

Four different types of media can be selected upon initialisation of the simulation, namely those that always report true values, those that report random deviations from the true values, and that who announce values that are either specifically in the favour of electric vehicles or against them.

A random deviation is always an overestimate or underestimate between 0 and 30% of the actual value. An overestimate means that the aspect is reported more favourably than is actually the case, by for example mentioning energy costs which are lower than the true refuel costs. An underestimate reports a more pessimistic view, such as describing a longer charge time than is actually the case. The media in favour of electric vehicles always overestimate values related to electric and hybrid fuel technologies and car models by 0 to 30%, while they underrate values of gasoline models by 0 to 30%. The opposite is the case for the media which are specifically against electric vehicles: while the characteristics of gasoline cars are overestimated by 0 to 30%, those of car using electricity are consequently underestimated 0 to 30%.

4.12 The car market

The car market is the place that keeps track of all available car models. Here, agents can lease a vehicle or purchase a new vehicle or an occasion. New car models can be introduced to the car market to investigate the effects of technological advancements or cost adjustments. Each agent has access to the car market where it may buy, sell or lease a vehicle, depending on the agent's ownership type (Section 4.3.1). Whenever a new model is introduced, it is unlimitedly available to agents that lease or buy new vehicles. Agents that buy occasions, however, are limited to the used cars available on the occasions market. Whenever an agent buys a vehicle or finishes its lease contract, its current vehicle is added to the occasion market, as long as its current maintenance costs are not higher than the remaining value of the car. This occasion market dynamic captures the lag in diffusion of new models, because not all consumers have the finances to invest in a new, better or even more financially attractive vehicle and need to resort to suboptimal models that are available second hand.

4.12.1 Deciding whether to buy

At the end of each tick - after an agent has made its drives, has evaluated its satisfaction and has optionally engaged in an information seeking strategy - agents who own a private car evaluate their past week's maintenance costs and how often, on average, they are satisfied. Both aspects determine whether an agent will visit the car market in search of a different vehicle. This does not hold for those who lease their vehicle, as these agents always and only choose a new car after their lease contract has ended. The selection of a new car is further explained in the following section.

To determine whether an agent that privately owns its vehicle is satisfied on average, it inspects the proportion of times it perceived itself as satisfied in the previous X weeks (Section 4.8). If this proportion surpasses the threshold $\theta_{satisfied}$, the agent is satisfied enough to continue using its current car. If an agent is satisfied and its car is not total loss, it will finish its turn by paying for any maintenance costs that emerged during the previous week. Agents that drive an electric vehicle, will also buy a new battery in case the current one has lost more capacity than allowed. All maintenance and new battery costs go from the agent's money account (Section 4.3.2), unless the agent still has warranty on its vehicle or battery, or if the agent leases the battery instead of owning it.

When a vehicle is total loss, however, the agent always decides to purchase a new vehicle. A vehicle is total loss when its maintenance costs, including a battery replacement, are higher than its remaining value. The owner of a total loss car will look for a new car model as described in the following section.

If a vehicle is still worth more than its maintenance costs but its owner is unsatisfied on average, the agent will decide whether buying a new vehicle will result in a higher level of satisfaction than keeping the current one, by comparing the different car models it knows.

4.12.2 Comparing car models

When looking for a new vehicle, agents first estimate their overall satisfaction and uncertainty with each car model that is within their price class using Equations 4.12.1 and 4.12.2 respectively. The satisfactions and uncertainties of the four different needs in set N are now all based on the heuristics described in Section 4.6 and no longer on direct driving experiences. As a different method is used to estimate the evaluations of the financial and functionality needs, the agent's current vehicle may be more or less satisfying than the agent perceived it earlier.

$$s = \sum_{i \in N} s_i * w_i \tag{4.12.1}$$

$$u = \sum_{i \in N} u_i * w_i \tag{4.12.2}$$

This similarity may be further reduced. Similar to determining the agent's mental state, it is assumed that the need to successfully travel desired ranges transcends all other needs. An expected inability to do so results in a penalty to the corresponding car model's satisfaction.

As Section 5.2.3 in the chapter on parametrisation of the model explains further, each survey respondent indicated how often they make drives within six different distance ranges (for instance, between 10 and 50 kilometres). It is therefore known whether agents drive these distance ranges never or at least once a week, month or year. Set R contains all the distance ranges of which the maximum distances are larger than model m's range. Each of these distances r reduces the agent's limitation satisfaction depending on how frequently it is driven by the agent. A distance which is driven only a few times a year has a relatively large influence on the agent's limitation satisfaction. This is in line with accounts of non-EV drivers overestimating their need for driving infrequent distances [90]. Equation 4.12.3 gives the final expected satisfaction with a car model.

$$s = \sum_{r \in R} \begin{cases} s - 0.4s(1 - \theta_{\text{charge, road}}) & \text{if } r = \text{weekly} \\ s - 0.2s(1 - \theta_{\text{charge, road}}) & \text{if } r = \text{monthly} \\ s - 0.1s(1 - \theta_{\text{charge, road}}) & \text{if } r = \text{yearly} \\ 0 & \text{otherwise} \end{cases} \tag{4.12.3}$$

If set M is the set containing all known car models in the agent's price class, then the agent selects its desired model d using Equation 4.12.4, where θ_s and θ_u are the agent's ambition and uncertainty level respectively (Section 4.7).

$$d = \arg\max_{m \in M} \left(s_m \theta_s + (1 - u_m)(1 - \theta_u)\right) \tag{4.12.4}$$

In other words, agents prefer the car model which is expected to be the most satisfying and most certain. Lease agents directly swap their current vehicle for their desired car model. Agents that privately own their vehicle will immediately purchase their desired car model if it is different than their current model and if the agent has sufficient funds to purchase the new car. The agent's funds include the money in its account and the (scrap) value of its current vehicle. When the desired car model is the same as the agent's current car, or the agent does not have sufficient funds yet, it will only buy its desired model if its current vehicle is total loss.

Finding the best occasion Agents that buy occasion vehicles need to perform one more action before they can purchase their desired car model from the car market: they need to select the most optimal occasion d_{occ}. Let O_d be the set of all available occasions of the agent's desired car model d within the agent's price class. The agent then seeks the most optimal occasion d_{occ} by judging the proportional value and kilometrage of each occasion o in O. Both aspects should be as low as possible. Whether the agent emphasizes the vehicle's value or kilometrage is dependent on its income category and represented by the income weight w_{inc}.

$$d_{occ} = \arg\max_{o \in O_d} \left(w_{inc} \left[1 - \frac{\text{value}_o}{\sum_{i \in O_d} \text{value}_i} \right] + (1 - w_{inc}) \left[1 - \frac{\text{km}_o}{\sum_{i \in O_d} \text{km}_i} \right] \right) \tag{4.12.5}$$

The income weight is a linear function equivalent to the static cost weight described in Section 4.4.3 and illustrated in Figure 4.2. However, instead of using the kilometrage category of the agent, the income category which also ranges between 1 and 10 is used.

$$w_{inc} = -\frac{1}{18} * income_c + \frac{29}{36} \tag{4.12.6}$$

4.12.3 Purchasing a new vehicle

Once an agent has decided to purchase a new vehicle, its current one is sold to either the occasion market or the wreckage site, depending on whether it is total loss or not. Agents who privately own their vehicle can use the returned value of their previous car to pay for their new one. A newly purchased vehicle is always delivered with a full tank and upon purchasing, the agent resets its previous satisfaction estimates and starts off with a clean slate.

4.12.4 Export

Import and export of occasion vehicles is an important aspect of the real world occasion market. In 2013, 279.00 thousand occasions were exported while 88.500 were imported [92]. This entails a net removal of almost 200.000 vehicles from the occasion market, which is large compared to the volume of the occasion stocks in the Netherlands: around 300.000 vehicles. To accurately capture the dynamics of import and export goes beyond the scope of this model. Therefore, a heuristic is used to restrict to occasion market from growing too much.

When the proportion of occasions of a specific car model on the occasion market is more than double the proportion with which this model is owned within the agent population, any additional occasions of this car model are 'exported', or in other words, removed from the simulation. However, a minimum of two occasions of each car model is always allowed on the occasion market, independent of how popular this model is within the agent population. This ensures that new car models are not immediately removed from the simulation once they are traded in as an occasion.

Parametrisation 5

Chapter 4 described the theoretical framework of the STECCAR model. This chapter presents the parametrisation and initialisation of the model, which relies on empirical data obtained from a 2012 Dutch questionnaire. In Chapter 6, the behaviour of the simulation under these selected modelling and parametrisation choices is validated using real world data.

5.1 Overview

The following is an overview of all parameters used in the theoretical framework of the STECCAR model and of which the instantiation is described in this chapter. For readability, parameters have been grouped into themes.

Agents (Section 5.2)

- Demographics (Section 5.2.1)
  - Age
  - Postal code
  - Yearly income
  - Income tax
- Personality (Section 5.2.2)
  - Need weights
  - Ambition
  - Uncertainty tolerance
  - Social weights
  - Expertise in EVs
- Driving behaviour (Section 5.2.3)
  - Yearly kilometrage
  - Driving frequency
  - Daily driving distances
  - Work trips
  - Refuel moment
  - Access to home charge
- Vehicle preferences (Section 5.2.4)
  - Ownership type
  - Vehicle price class
  - Minimum range

  - Maximum charge times
  - Maximum charge time distance
  - Maximum carbon emissions
- Initial vehicle (Section 5.2.5)
  - Vehicle age
  - Kilometrage
  - Ownership duration
  - Fuel technology
  - Car model
- Other (Section 5.2.6)
  - Proportion of income towards vehicle
  - Friends
  - Satisfaction threshold

VEHICLES (Section 5.3)

- Car models (Section 5.3.1)
  - Battery electric vehicles
  - Plug-in Hybrid electric vehicles
  - Gasoline vehicles
- General aspects (Section 5.3.2)
  - Introduction
  - Depreciation
  - Fuel economy
  - Price per kWh
  - End of lease contract

INFRASTRUCTURE (Section 5.4)

- Car market (Section 5.4.1)
  - Initial occasions
- Refuel stations (Section 5.4.2)
  - Access to home charge
  - Access to work charge
  - Probability of road charge
  - Refuel time
  - Refuel costs
  - Maximum recharge capacity
- Maintenance (Section 5.4.3)
  - Failure distances

- Failure probabilities
- Failure ratios of EVs
- Battery life
- Maximum battery capacity decrease
- Battery warranty

◦ Taxes (Section 5.4.4)

- Road taxes
- 'Bijtelling'

◦ Media (Section 5.4.5)

- Level of truth

5.2 Agents

To initialise the STECCAR model agents, data from a Dutch on-line questionnaire from June 2012 was used [9]. The 2.977 valid respondents were obtained through a commercial marketing research company called Panel Inzicht. Appendix A provides an English translation of a subset of the questionnaire; only the questions which were used for the purposes of this model are given. Respondents were removed from the data set if one of the following criteria was applicable:

- Incomplete data
- Unknown yearly household income
- Main vehicle that drives on natural gas or LPG
- Inconsistent frequency of driving distances

After applying these criteria, 1.795 respondents proved to be suitable candidates for the initialisation of the simulation. Each remaining respondent is instantiated as a single agent in the simulation, resulting in an agent pool of 1.795 agents in total. The rest of this section describes the link between the data from the questionnaire and the agent parameters which surfaced in Chapter 4. Within several subsections, it is explained exactly how the respondent data is transformed into STECCAR agents. The satisfaction threshold parameter described in Section 5.2.6 is of special importance because its optimal value helped obtain a valid simulation output in Chapter 6.

5.2.1 Demographical information

Age Q21 gives the year in which the respondent was born. By subtracting this number from the year in which the survey was held, 2012, the age of the agent is obtained.

$$\text{age} = 2012 - \text{Q21} \tag{5.2.1}$$

Postal code Q22 provides the four digit postal code of the respondent. The first number of this code is stored as an indication of the agent's location.

Yearly income Q23 indicates in which income category the household of the respondent falls. The first item, *less than €15.000*, corresponds to category 1 and the last item, *unknown / will not say*, to category 11. Notice that respondents with an unknown income are removed from the data set, causing category 10 to be the highest possible income category available to the agents.

The category is converted to an approximate monetary value, by taking the halfway value of its corresponding range. For instance, if the respondent selected the 6th item, *€40.001 to €50.000*, the agent's income category will be 6 and its absolute yearly income will be €45.000. For the lowest income category, *less than €15.000*, a random yearly income between €1.000 and €15.000 is selected upon initialisation. For the highest category, *more than €95.000*, a random yearly income between €95.000 and €400.000 is drawn.

$$\text{income} = \frac{1}{2}(\mathrm{min}(Q23) + \mathrm{max}(Q23)) \tag{5.2.2}$$

Income tax Income tax is initialised according to the tax groups which were used in the Netherlands in 2012. It is only relevant to lease owners and is derived from the agent's income category. Categories 2 and below (i.e. lower than €20.000) result in a tax percentage of 33.1%. Agents that fall in categories 3 to 7 (between €20.000 and €60.000) pay 42% in taxes and agents in all categories higher than 7 pay 52%.

5.2.2 Personality

Need weights Q16 asks the respondents how important ten different values are in their life. The answers for each value range between 1 and 9. The first nine items of the question are used to determine how much emphasis each agent places on each of its four different needs (Section 4.7).

The financial need directly corresponds to the answer to item 4 (wealth). The functionality need weight is derived from the average of the answers to items 3 (pleasure) and 7 (enjoyment of life). The assumption behind this decision is that individuals who are hedonically oriented will be more interested in the direct driving experience of a car.

The social need weight is somewhat more complicated as no items directly apply. Items 1 (equality), 2 (power), 5 (authority) and 6 (social justice) all have a social aspect, but are typically not valued highly all at the same time. Whereas the first and last refer to a cooperative social strategy, items 2 and 5 are more closely related to a competitive strategy. Therefore, the average answer to items 1 and 6 is computed, as is the average answer to items 2 and 5. The higher value of these two averages is used a measure of the agent's social need weight.

Finally, the environmentalism need weight corresponds to the average of the answers to items 8 (protection of the environment) and 9 (prevention of pollution). The values that correspond to each need weight are normalised by dividing them by the sum of all the need weight values W. This ensures that the final four need weights always sum up to 1 and that conservative respondents are not treated differently than extravagant respondents.

$$w_{\text{finances}} = \frac{1}{||W||} Q16.4 \quad (5.2.3)$$

$$w_{\text{functionality}} = \frac{1}{||W||} \frac{1}{2}(Q16.3 + Q16.7) \quad (5.2.4)$$

$$w_{\text{social}} = \frac{1}{||W||} \max\left(\frac{1}{2}(Q16.1 + Q16.6), \frac{1}{2}(Q16.2 + Q16.5)\right) \quad (5.2.5)$$

$$w_{\text{functionality}} = \frac{1}{||W||} \frac{1}{2}(Q16.8 + Q16.9) \quad (5.2.6)$$

AMBITION The 10th item of Question Q16 (ambitious) is used to set the agent's ambition level (Section 4.7). The answer to this item, which again ranges between 1 and 9, is divided by 10. This results in an ambition level that is 0 at its lowest (i.e. the agent is always satisfied) and 0.9 at its highest.

UNCERTAINTY TOLERANCE In Q15, five options are presented which reflect the different consumer segments of technology adoption as described by Rogers [79] (Section 2.4). For the parametrisation of the STECCAR model, these options are linked to the uncertainty tolerance of the agents (Section 4.7). Respondents who describe themselves as someone 'who dares to take risks' and are thus perceived as Innovators by Rogers, correspond to agents with a very high uncertainty tolerance, i.e. 1. With each option in which the willingness to adopt innovative technology at an early stage drops, the uncertainty tolerance decreases with 0.2 as well. This entails that the second most risk taking agents have an uncertainty tolerance of 0.8, and the least risk taking agents have an uncertainty tolerance of 0.2.

SOCIAL WEIGHTS The social need consists of three aspects: conformity, anti-conformity and superiority (Section 4.6.3). To initialize the weights for each of these aspects, the answers to Q13, which range between 1 and 6, are used. Item 1 corresponds to the anti-conformity weight, while the average value of items 2 and 3 reflects the superiority weight. No data was available to represent the conformity weight, therefore a random sample X of a normal distribution ($\mu = 3.5, \sigma^2 = 0.85$) is drawn for each agent at the moment of initialisation, where X cannot be smaller than 1 or larger than 6. The values that correspond to each weight are normalised by dividing them by the sum of all social weights.

EXPERTISE IN EVS Q14 consists of three items, all ranging between 1 and 6, of which the answers give a self-described indication of the respondent's level of knowledge on the current state of alternative fuel technologies. The average of these three answers is divided by six, to obtain the agent's expertise value that ranges between 0 and 1 (Section 4.5).

$$\text{expertise} = \frac{1}{3 * 6}(Q14.1 + Q14.2 + Q14.3) \quad (5.2.7)$$

5.2.3 DRIVING BEHAVIOUR

YEARLY KILOMETRAGE The average yearly kilometrage category of an agent is obtained from Q6. The first item, *less than 5.000 kilometres*, corresponds to category 1 and the second last item, *45.000 to 50.000 kilometres*, to category 10.

The last item, *More than 50.000 kilometres, namely ...* is grouped together with category 10 as well to keep comparisons simple.

The category is converted to an approximate yearly kilometrage, by taking the halfway value of its corresponding range. For instance, if the respondent selected the 4th item, *15.000 to 20.000 kilometres*, the agent's kilometrage category will be 4 and its absolute yearly kilometrage will be 17.500 kilometre. If the respondent selected the last item, *More than 50.000 kilometres, namely ...*, its exact yearly kilometrage is known and directly applied to the agent.

$$\text{yearly kilometrage} = \frac{1}{2}(\min(Q6) + \max(Q6)) \tag{5.2.8}$$

Driving frequency The answers to Q7 provide an elaborate overview of the frequency with which certain distances are driven by the respondent. The answers are copied without any adjustments and used to initialise the distances of the daily drives the agent makes (see following paragraph and Section 4.4) and to estimate whether a given car model will fit the agent's driving needs (Section 4.12.2).

Daily driving distances At the start of each agent year (once every 52 ticks, where one tick represents one week in the agents' world), the daily distances which the agent will travel during the year are initialised using the table obtained in the previous paragraph (Q7). When the yearly distances are initialised, distance ranges that are driven least frequently are selected first, thereby skipping ranges that are driven (almost) never.

First, it is randomly decided whether each range that is driven at least once per year is driven one or any number up to eleven days this year (if it was driven on more than eleven days, the respondent would have selected that it was driven at least once per month, not per year). A similar process then proceeds for all distance ranges that are driven at least once per month. A random number is drawn to determine whether each range is driven 12 or any number up to 51 days this year (more days would entail that the range is driven at least once per week, which the respondent did not indicate). Finally, the distance ranges which are driven at least once per week are selected. Each of these ranges is at least driven on 52 days, while the remaining days of the year are randomly dispersed over the weekly ranges.

At the end of this process, all days of the year correspond to one of the distance ranges from the original table and each distance range occurs in the frequency indicated by the respondent. The days are shuffled and for each day of the year, a random distance is drawn within the limits of the corresponding distance range. When the distance range corresponds to the first item of the table, *0 km (car is not being used)*, the selected distance always equals 0. If the range corresponds to the last item, *More than 500 km in one day*, the upper limit is set to 1500 kilometres.

Work trips A daily trip is flagged as a trip to work if its total distance is between 10 and 200 kilometres and the respondent indicated that it is driven once or multiple times per week. During a trip to work, agents are able to recharge their electric car if they have the ability to charge at work (Section 4.3.3).

Refuel moment The agent's preferred moment of refuelling is obtained from Q8. The three options from which the respondent can choose are converted to a tank state at which the agent wants to refuel its vehicle 4.4.1. Preferring to refuel when the tank is half empty corresponds to a tank state of 50% full, moderately empty corresponds to 25% full and almost empty equals only 10% full.

Access to home charge Through Q9, respondents indicate whether they have access to a personal parking place. If the respondent owns or rents a garage, carport, driveway or private parking place, it is assumed that the agent can charge an electric vehicle at home (although a financial investment must likely be made). If the respondent does not have access to any of these options, home charging is initially not an option for the agent.

5.2.4 Vehicle preferences

Ownership type All agents fall into one of three categories when it comes to obtaining new vehicles. Either they buy new cars, they buy occasions, or they lease their vehicle for a fixed amount of time/kilometrage (Section 4.3.1). To determine whether the agent leases its vehicle, Q2 and Q3 are used. The latter states which car is the respondent's main vehicle, while the former delivers information on whether this main vehicle is a lease or private car. If the respondent's main vehicle is leased, the agent is defined as one who leases its vehicle. If the main vehicle is a private car, Q10 is used to classify the agent as either one who purchases new vehicles, or one who only buys occasions.

Vehicle price class Agents who purchase new vehicles or occasions are restricted to a specific price class (Section 4.12.2). Depending on the agent's ownership type, either Q11 (for new buyers) or Q12 (for occasion buyers) is used. Either way, a range is obtained within which the price of a potential new car must be situated. Because the questions do not state an upper limit for the highest price range, these are defined as € 150.000 for new vehicles and € 50.000 for occasions.

Minimum range From Q20, a direct answer is obtained for the desired minimum range of an electric vehicle. Agents use this range when estimating their satisfaction with the functionality of an EV if they do not yet own such a vehicle. 4.6.2.

Maximum charge times When estimating how satisfied they will be with a potential new car, agents determine their refuel time satisfaction at three locations, depending on the fuel technology their vehicle uses (Section 4.6.2). Using Q19, the maximally accepted charge time at each of these locations is obtained.

Maximum distance for charge time Although the previous paragraph provides information on how long agents are willing to wait when refuelling, it does not answer the question *how often* agents are willing to wait this long, which is of importance when determining the time satisfaction of a daily drive (Section 4.4.3, Equation 4.4.16). The assumption is made that agents are willing to wait their maximally accepted refuel time once for every 200 kilometres they have driven that day.

Maximum carbon emissions To determine an agent's satisfaction with the environmental impact of a vehicle, an upper limit must be set from where on all vehicles are perceived as minimally environmentally friendly (Section 4.6.4). This limit is a fraction of 250 gCO_2/km, depending on the respondent's level of concern with environmental issues. The more concerned the respondent, the smaller the fraction and thus the carbon emissions limit the agent uses.

The items I of Q17 and Q18 indicate how severe and how likely to happen an agent perceives environmental consequences of petroleum cars respectively. The maximum carbon emission limit is then obtained through the following equation:

$$\text{max emissions} = \left(1 - \frac{1}{\|N\|} \sum_{i \in I} Q17.i * Q18.i\right) * 250 \tag{5.2.9}$$

5.2.5 Initial vehicle

Vehicle age To determine the age of the agent's current car at the moment of initialisation, Q2 and Q3 are used. The latter states which car is the respondent's main vehicle, while the former delivers information on this vehicle's build year. By subtracting the build year from the year 2012, the approximate age of the vehicle is obtained. This value is then multiplied by 52 to obtain the vehicle's age in weeks, the conventional unit for time measurement in the STECCAR model. To ensure that vehicles with the same build year have somewhat differing ages, the final age of the vehicle ranges between 6 months (26 weeks) prior and 6 months post its approximate age.

$$\text{vehicle age} = (2012 - \text{build year}(Q2)) * 52 + Rand(-26, 26) \tag{5.2.10}$$

Kilometrage By multiplying the vehicle's approximate age with the agent's yearly kilometrage (Section 5.2.3), the total number of kilometres travelled with the vehicle so far are determined. Notice that this approximation assumes that any previous owners had a similar yearly kilometrage as the current owner of the vehicle. Without information about previous ownership, this assumption suffices.

$$\text{kilometrage} = \text{yearly kilometrage} * \text{vehicle age} \tag{5.2.11}$$

Ownership duration The ownership duration of the agent's current vehicle is derived from the respondent's answer to Q4. By subtracting the purchase year from the year 2012, the approximate duration of ownership is obtained. As with the vehicle's age, the final ownership duration ranges between 6 months prior and 6 months post the approximate duration.

$$\text{ownership duration} = (2012 - Q4)) * 52 + Rand(-26, 26) \tag{5.2.12}$$

Fuel technology The answer to Q5 determines what fuel technology the agent's initial vehicle uses. Owners of LPG or natural gas vehicles were removed from the data set, while agents of which the respondent drives a diesel vehicle were assigned a gasoline car to simplify the model. The brand and model of hybrid vehicles were checked using Q2 and Q3 to determine whether the respondent drives a plug-in hybrid electric vehicle or a conventional hybrid. At the end of this process, it turned out that all 1.795 agents initially drive a gasoline vehicle.

CAR MODEL The model of the agent's initial car depends on the price class within which the agent shops (Section 5.2.4) and the fuel technology as obtained in the previous paragraph. For agents who buy new vehicles, the new price of the initial vehicle must fall exactly between the agent's preferred price range as indicated by Q11. For an occasion buyer, the original price of the vehicle it is currently driving must first be estimated, since only the price that the agent is willing to pay for an occasion vehicle is known through Q12. The original price is obtained using an adaptation of Equation 4.2.1. The preferred new price of a vehicle for agent a with an occasion vehicle v which was purchased by its first owner at $t_{1st,\,v}$ and purchased by agent a at $t_{owner,\,v}$ is given by:

$$\begin{aligned} min(\text{price class new})_a &= min(Q12)_a/\text{depreciation}^{\frac{t_{1st,\,v}-t_{owner,\,v}}{52}} \\ max(\text{price class new})_a &= max(Q12)_a/\text{depreciation}^{\frac{t_{1st,\,v}-t_{owner,\,v}}{52}} \end{aligned} \quad (5.2.13)$$

The agent is then assigned a model of which the new price falls within that price class.

5.2.6 Other

In contrast to the parameters described above, the values of the agent parameters described in this section could not be initialised using the survey data. Where possible, other data was used. If not, an assumption was made of which the influence can be inspected by altering the value and observing possible behaviour changes in the simulation.

PROPORTION OF INCOME TOWARDS VEHICLE As a very rough estimate, Dutch drivers spend 10% of their income on their personal vehicle [91], while the Dutch National Institute for Family Finance Information indicates that around 50% of a vehicle's costs are in its maintenance and its depreciation.[1] Therefore each step, agents direct 5% of their income to an account which goes to paying off failure costs and saving towards a new car.

FRIENDS When the friends of agent a are selected upon initialisation, only a subset of the complete agent pool is considered (Section 4.10.1). The chance that the similarity between two agents is computed is 20%. Then out of these agents of which the similarity is known, the 15 most similar agents are selected as agent a's friends. These are the agents that agent a approaches during its imitation and inquiring information seeking strategies. Remember that friendships are not necessarily symmetrical, and therefore the actual number that this agent communicates with may be higher. If the subset of agents under consideration is smaller than 15 agents, additional agents are selected at random.

SATISFACTION THRESHOLD An agent must determine whether it is satisfied on average when deciding if it should buy a new vehicle (Section 4.12.1).

[1] NIBUD, "What do you pay for the car?" (translated from Dutch), http://www.nibud.nl/uitgaven/huishouden/auto.html (July 17, 2014)

During this process, the agent reflects on the past 10 weeks that its vehicle was in its possession. If it is satisfied during at least 4 of these 10 weeks, then it is satisfied enough with it current vehicle and does not look for a new car. If the vehicle is bought more recently than 10 weeks ago, than the agent does not have enough experience yet and will perceive itself as satisfied. This entails that agents will always keep a vehicle for at least 10 weeks before purchasing a new one.

The time frame and threshold described in this paragraph proved to be important determinants of the simulation's behaviour. Optimal values were selected after performing a parameter sweep of which the outcome was inspected using the validation themes described in Chapter 6.

5.3 Vehicles

Although agents are central in any social simulation, vehicles play an important role in this model as well. This section describes the car models that are available at the start of the simulation and the initialisation of general aspects belonging to the vehicles.

5.3.1 Car models

Table 5.1 gives an overview of the car models that are available at the start of the simulation. Electric vehicles are approximations of the car models that were available on the market in 2012. Their specifications are derived from Wikipedia, the Royal Dutch Touring Club (ANWB) and dealers' websites. The following paragraphs explain for each fuel technology why these models and their characteristics were chosen.

Battery electric vehicles Two BEVs are available at the start of the simulation: the iON for agents willing to spend between € 30.000,- and € 35.000,- on their vehicle and the ROADSTER for those in the highest price class. Although more battery electric car models were available in the Netherlands in June 2012, many were positioned in the same price class and had similar ranges.

For instance, the Peugeot iON, Citroën C-Zero and Mitsubishi i-MiEV are rebadged versions of the same vehicle and were sold for roughly € 34.500 with an EPA cycle range of 100 kilometres and a Japanese cycle range of 160 kilometres. The Nissan Leaf sold for € 33.000 in 2012 and had an EPA cycle range of 117 and an NEDC cycle range of 175 kilometres. Therefore only one representation of these car models is included in the simulation (named iON). The Renault Fluence Z.E. could have been included as it would have been positioned one price class lower than the iON. However, Renault sells its BEVs without a battery and offers batteries for lease instead, which is an option that has been left out of this version of the STECCAR model to reduce complexity. A representation of the Smart Fortwo electric drive was also left out, as this vehicle only fits two passengers and is therefore not comparable to other vehicles within the simulation.

Plug-in hybrid electric vehicles In 2012, PHEVs were available in the highest four price classes. The Plug-in Hybrid version of the Toyota Prius was released in the summer of 2012. The Chevrolet Volt (and its rebadged Opel Ampera) were the cleanest and sold relatively well. Their price was around

Table 5.1: Specifications of all car models available upon initialisation of the simulation. Cars are defined as having an internal combustion engine (ICE), being a battery electric vehicle (BEV) or being a plug-in hybrid electric vehicle (PHEV).

Fuel	Model	Price	Gasoline range (km)	Capacity (kWh)	gCO_2/km
BEV	iON	34500		25	0
BEV	ROADSTER	120000		80	0
PHEV	PRIUS	39500	750	4	49
PHEV	VOLT	44500	550	10	27
PHEV	OUTLANDER	49500	750	8	44
PHEV	KARMA	110000	320	8	47
ICE	TINY	8500	700		105
ICE	MINI	11000	700		105
ICE	SMALL	16000	700		110
ICE	JOE	21000	700		120
ICE	LARGE	26000	750		125
ICE	BIG	31000	800		135
ICE	BIGGER	36000	850		140
ICE	HUGE	41000	900		155
ICE	HUMONGOUS	46000	1000		160
ICE	EXTRAORDINARY	60000	1100		170

€ 43.000, they obtained an EPA cycle electric range of 56 kilometres and consequently had emissions as low as 27 gCO˙2/km. The Mitsubishi Outlander PHEV was available to consumers in the second highest price class while the luxury Fisker Karma was sold to those willing to spend the most. The latter was added for completion, even though it is presumably not a very competitive addition to the simulation because both its gasoline and its electric range are limited compared to other vehicles, while its attractive appearance is not taken into account.

Gasoline vehicles At the beginning of the simulation, gasoline vehicles are available within each consumer price class as described in Section 5.2.4. They are positioned at the lower end of a price range, to make their initial purchase price more attractive than those of EVs in the same price class. Because more expensive often means a more powerful engine, it is a general tendency that the range and carbon emissions per kilometre increase when the price of a gasoline vehicle goes up.

5.3.2 General aspects

Introduction As will become clear when describing simulation scenarios in the following chapters, car models can be replaced by an upgraded version on a yearly basis. To prevent that all initial car models are taken off the market and upgraded at the same time, a random moment of introduction ranging from -52 to 0 is selected for each model upon initialisation of the simulation.

Depreciation All vehicles owned by agents or waiting on the occasion market lose value each week. Exact car depreciation rates would be dependent on the specific model, market demand and driver style, but a depreciation rate of 15% per year is assumed to be an adequate approximation.[2] The same depreciation rate is applied to both gasoline vehicles and EVs. Although some predict that EVs will lose value more quickly due to degradation of their expensive batteries, there is no data to support this conclusion and an analysis of 100.000 Dutch occasions suggests that depreciation rates are actually very similar (gasoline: 12%, diesel: 16%, BEVs: 15%).[3]

Fuel economy As explained in Section 4.2.3, the electric range of a vehicle is dependent on the fuel economy of its battery. This fuel economy is initialised at a fixed value of 20 kWh/100 km, roughly the prevalent fuel economy of BEVs available in 2014 [28].

Price per kWh According to a report published by McKinsey in 2012, battery prices were between $500 to $600 per kilowatt hour around that time.[4] Battery prices in the model are therefore initialised at € 500 at the start of the simulation.

[2] L. Lazarony. *Bankrate*, December 2002. 'Know the deal on auto depreciation', obtained July 16, 2014. http://www.bankrate.com/brm/news/auto/20011226a.asp

[3] W. van Loon. *z24 Business News*, November 2013. 'Buying an occasion? Take a look at hybrids' (Translated from Dutch), obtained July 16, 2014. http://www.z24.nl/ondernemen/auto/occasion-kopen-kijk-eens-naar-een-hybride-409087

[4] R. Hensley, J. Newman, and M. Rogers. *McKinsey Quarterly*, July 2012. 'Battery technology charges ahead', obtained October 22, 2014. http://www.mckinsey.com/insights/energy_resources_materials/battery_technology_charges_ahead

End of lease contract Lease contracts end after 4 years or after the agent has driven 140.000 kilometres, whichever comes first.[5] Because this is a generalisation, some agents possess a lease vehicle at the start of the simulation which is more than 4 years old or has driven more kilometres than allowed. These agents immediately select a new car at the first tick of the simulation.

5.4 Infrastructure

The remaining parameters deal with the infrastructure that supports the purchasing and driving of vehicles within the simulation. Four types of infrastructure are discerned: the car market, refuel stations, car maintenance and taxes.

5.4.1 Car market

Initial occasions In 2012, the size of the Dutch occasion market was 304.000 vehicles while the the entire Dutch car fleet consisted of 7.858.712 vehicles [92, 19]. If the same proportion should hold for the simulation in which the total car fleet size is 1.795 vehicles, then roughly 70 cars should be on the occasion market at the start of the simulation. After each agent has been assigned an initial car model that most closely resembles the information given by its respondent, the distribution of car models in the agent population is applied to the occasion market. In other words, if one fifth of the agents owns car model M, then one fifth of the available occasions will be of model M as well. Each occasion is randomly assigned a kilometrage between 10.000 and 150.000 kilometres and an age between 6 months and 10 years.

5.4.2 Refuel stations

Access to home charge The proportion of agents having the ability to charge an EV at home, $\theta_{\text{charge, home}}$, is set equal to the proportion of agents that received the ability to home charge through the data indicated by the respondents (Section sec:param:agents:driving).

Access to work charge No data could be found on the proportion of the Dutch population having access to work charge stations. The assumption was made that 5% of the population could currently get access to such a station, either because it is already available or because the work place is willing to install a charge station upon request. $\theta_{\text{charge, work}}$ is therefore set to 0.05.

Probability of encountering road charge The probability to use a fast charge service station along the road is initialised at 0 at the start of the simulation. Although some fast charge stations were active (15 in December 2012[6]), this number seems insignificantly small to have a direct effect on the simulation and thus for simplicity, a probability of 0 was taken.

[5] M Keswiel. NUZakelijk, February 2011. 'A lease car as a gravel tile' (Translated from Dutch) http://www.nuzakelijk.nl/special-zakelijk-rijden/2436696/leaseauto-als-grindtegel.html

[6] Rijksdienst voor Ondernemend Nederland (RVO), obtained August 25, 2014. 'Numbers electric transport' (translated from Dutch) http://www.rvo.nl/onderwerpen/duurzaam-ondernemen/energie-en-milieu-innovaties/elektrisch-rijden/stand-van-zaken/cijfers

Refuel time Three different kinds of refuelling are discerned in the STEC-CAR model: gasoline along the road, normal electric charging at home or at work, and fast electric charging along the road (Section 4.4.1). While gasoline refuelling is initialised at 5 minutes, fast charging initially takes 30 minutes per vehicle (independent of the capacity of the vehicle's battery) and normal charging takes 8 hours.

Refuel costs Each refuelling type described in the paragraph above comes with a specific cost per kilometre of energy gained. Gasoline costs are initialised at €0.11/km, or in other words, €1.83/litre for cars with a fuel economy of 6 litres/100km. Fast and normal electric charging cost €0.045 and €0.03 per kilometre respectively. Or, in more conventional terms, €0.225 and €0.15 per kilowatt hour.

Maximum recharge capacity At fast charge service stations in the simulation, agents can recharge their electric vehicles up to 80% of their full capacity. This is in line with all major providers currently offering fast charge services in the Netherlands.

5.4.3 Maintenance

Failure distances The number of kilometres d after which a failure may occur is given by Equation 4.4.2 in Section 4.4.2. This equation ensures that the probability of a failure increases with vehicle age. Here, d_{max} is the largest distance after which failures can occur and d_{min} the smallest, meaning that brand new vehicles may encounter failures each d_{max} kilometres and increasingly older vehicles will not encounter the probability of a failure more often than every d_{min} kilometres. For reasons which will become clear in the following paragraph, d_{max} is set to 55 and d_{min} to 40 kilometres.

Failure probabilities Section 4.4.2 described three different failures which the agents may encounter after each d kilometres of a drive: small (€50), medium (€500) and large (€2000). The probability of encountering each of these failures after d kilometres is described in this paragraph. Although much is dependent on specific vehicle properties and driver style, the Royal Dutch Touring Club estimates the maintenance costs of the average Dutch vehicle around 3 to 5 cents per kilometre.[7] Therefore on average, maintenance costs of gasoline cars in the simulation are set to 4 cents per kilometre using the following set of probabilities:

$$P(failure_{small}) = 0.01,$$
$$P(failure_{medium}) = 0.001,$$
$$P(failure_{large}) = 0.0005$$

This results in an average cost of $0.01 * €50 + 0.001 * €500 + 0.0005 * €2000 = €2$ per d kilometres, or €0.036/km for brand new vehicles (d = 55 km) and €0.05/km for very old vehicles (d = 40 km).

[7] ANWB, "Preventive maintenance" (translated from Dutch), obtained July 16, 2014. http://www.anwb.nl/auto/onderhoud-en-reparatie/onderhoud-en-garage/preventief-onderhoud

Failure ratios of electric vehicles According to the Institute for Automobile Economics, the maintenance costs of BEVs are assume to be 35% lower than those of conventional gasoline vehicles.[8] The average maintenance costs of BEVs are therefore 65% of gasoline vehicles, resulting in €0.026/km using the following set of probabilities:

$$P(\text{failure}_{\text{small}}) = 0.0065,$$
$$P(\text{failure}_{\text{medium}}) = 0.00065,$$
$$P(\text{failure}_{\text{large}}) = 0.000325$$

Because PHEVs possess the same complexity as conventional gasoline cars that use an internal combustion engine, Edmunds.com, an on-line resource for automotive information, claims that their maintenance costs are similar to gasoline vehicles as well. Without any other data, this indeed sounds like a reasonable assumption and therefore PHEVs use the same failure probabilities as gasoline vehicles in the simulation.[9]

Battery life Besides general failures, Section 4.4.2 also describes the capacity decrease of vehicle batteries. battery life_{slow} indicates the average battery life when only slow charging is used, while battery life_{fast} gives the average battery life if the owner would solely use fast charging. These values are initialised at 20 years and 5 years respectively based on the work of battery modelling by Mikael G. Cugnet.[10] To come to these life expectancies, Cugnet used an average yearly kilometrage of 10.000 kilometres (personal communication, April 3, 2014), which is also the kilometrage used in Equation 4.4.3

Maximum battery capacity decrease A battery is written off when its capacity has decreased more than 20%.[11]

Battery warranty If a battery has lost more than 20% of its capacity within 8 years or before 100.000 kilometres have been driven, then warranty covers the replacement costs of a new battery. This is a generalisation of the differing battery warranty services that manufacturers provide. For instance, at the moment the model was created (2014), Tesla offered 8 years of battery warranty for its Model S with a limit of 200.000 kilometres if the owner has opted for the 60 kWh battery over the 85 kWh. Nissan's battery warranty holds for 5 years or 100.000 kilometres, whichever one comes first. For the BMW i3, battery warranty expires after 8 years of 100.000 kilometres.

5.4.4 Taxes

Road taxes At the start of the simulation, vehicles with carbon emissions lower than 50 g/km are exempt for road taxes. This is modelled after the

[8] G. Steiler. *Institut für Automobilwirtschaft*, November 2012. 'Elektroautos sind relativ günstig im Unterhalt'

[9] Edmunds.com, September 2013. 'The Real Costs of Owning a Hybrid', obtained May 7, 2014. http://www.edmunds.com/fuel-economy/the-real-costs-of-owning-a-hybrid.html

[10] Cugnet, M.G. Research presentation at a meeting of the American Chemical Society April 10, 2013. 'Understanding the Life of Lithium Ion Batteries in Electric Vehicles', obtained March 25, 2014. http://www.chemistry2011.org/news/PhysicalChemistry/Electrochemistry/UnderstandingTheLifeOfLithiumIonBatteriesInElectricVehicles

[11] See footnote 10

current situation in the Netherlands, which will hold until at least January 2016. Dutch road taxes of more polluting vehicles are dependent on vehicle mass, which is a factor that is excluded from the STECCAR model. Therefore all vehicles that are not exempt for road taxes pay the same amount of monthly taxes: € 50,-.

'Bijtelling' In June 2012, owners of low carbon emission vehicles ($<$ 50 gCO˙2/km) were exempt from paying 'bijtelling', which is a special tax that only holds for lease owners. Three other 'bijtelling' categories remained for the more polluting vehicles: 14% ($>$ 50 g/km and $<$ 110 g/km), 20% ($>$ 110 g/km and $<$ 140 g/km) 14% ($>$ 140 g/km).

5.4.5 Media

Level of truth By default, the 'random media' is selected (Section 4.11). This media publishes vehicle information with a random deviation between 0 to 30% from the vehicle's true characteristics.

Validation 6

From the STECCAR model described in Chapter 4 and subsequent parametrisation described in Chapter 5, a simulation has been developed which enables the construction and inspection of hypotheses concerning the diffusion of electric vehicles. To investigate the legitimacy of this simulation, a validation of the underlying assumptions must be made by comparing the behaviour of a basic scenario to the real world. Whereas behaviour of individual agents cannot be validated due to the isolated nature of the survey which was used to instantiate them, global patterns will be observed and validated using recent consumer data. After validation, this basic scenario will also function as a control scenario for the experiments performed in Chapters 7 and 8.

6.1 Overview

A basic scenario has been constructed, using developments in the vehicle market from July 2012 to June 2014 and hypothetical developments envisioned until June 2025 (Section 6.2). This scenario is presented to the STECCAR model and the resulting behaviour is compared to real world data.

Validation is done within four themes: market stability (Section 6.2), ownership aspects (Section 6.4), scrappage characteristics (Section 6.5) and diffusion of electric vehicles (Section 6.6). Additionally, the perception of different fuel technologies during the scenario is evaluated (Section 6.7). To conclude, we have found that the behaviour of the basic scenario closely resembles real world data (Section 6.8).

6.2 Scenario

The survey data through which the agents were initialised was collected in July 2012, two years before STECCAR was developed. Therefore, the first part of the basic scenario spans the course of this same time frame: 104 ticks, where every tick represents one week in the agent's world. By tailoring a scenario that represents the actual developments in the most recent two years, the simulation's results can be compared to accurate and recent real world data. The second part of the scenario consists of hypothetical developments. It extends the basic scenario's time frame to 676 ticks, which represents June 2025. Although any results past the initial 104 ticks cannot be empirically validated, a longer interval provides crucial insight into the stability of the simulation's behaviour.

The rest of this section elaborates which developments were incorporated in the basic scenario. The sections thereafter describe the simulation's behaviour under these conditions. All results as described in the upcoming sections are obtained by aggregating the simulation output over 10 runs.

Table 6.1: Specifications of all car models introduced during the basic scenario.

Tick	Fuel	Model	Price	Gasoline range (km)	Capacity (kWh)	gCO_2/km
50	BEV	S85	85000		80	0
54	BEV	FOCUS	39500		30	0
60	PHEV	V60	64500	1100	8	49
72	BEV	EGOLF	34500		30	0
78	BEV	LEAF	29500		30	0
90	PHEV	VOLT2	39500	550	11	27
130	PHEV	CMAX	34500	850	6	46
145	BEV	OHM	44500		32	0
156	BEV	JOULE	49500		32	0
260	PHEV	FARADAY	29500	700	8	38
390	BEV	HERTZ	24500		30	0
434	PHEV	COULOMB	24500	700	8	32
530	BEV	WEBER	19500		30	0
610	PHEV	HENRY	19500	700	8	28

New car models

Table 6.1 shows the new car models that are introduced in the basic scenario. A distinction is made between models released between July 2012 and June 2014 (above the line break) and hypothetical models released after June 2014 (below the line break). All specifications are based on freely available information from Wikipedia, the Royal Dutch Touring Club (ANWB) and dealers' websites. In most cases the liberty was taken to reduce the electric range specified by the manufacturers to better fit driving experiences expressed in both anecdotal and professional on-line reviews, as specified ranges often do not live up to real world usage [27]. Prices are approximations and are slightly adjusted to ensure that the electric models end up on the upper limit of their price class.

Battery electric vehicles Three noteworthy all-electric vehicles were released in the period between July 2012 and June 2014. The Ford Focus, Tesla Model S and Volkswagen e-Golf. Although the Model S serves the same high-end price class as the already available Tesla Roadster, it is significantly cheaper and therefore an attractive addition to the market. Additionally, a newer version of the Nissan Leaf was released, with a longer range and reduced price. Since the Leaf is not included as one of the initial models, its price and range being too close to the Peugeot Ion, its updated version is introduced as a new model in the basic scenario.

In the extended scenario, plausible but mostly hypothetical car models are introduced. It is assumed that the remaining high end price classes will be saturated in the upcoming years with models similar in range as currently available in the medium range price classes (OHM and JOULE). All subsequent models are introduced at a moment when battery prices are expected to have decreased enough to make their production economically feasible (See 'Battery costs' below).

Plug-in hybrid electric vehicles Multiple plug-in hybrids entered the scene in the past two years. However, most were within the same price class as the already available Chevrolet Volt and provided no increase in range or reduction in emissions. Since appearance is not included in the simulation, these car models would not be a competitive addition and are therefore excluded from the basic scenario. The only notable new PHEV model was the Volvo V60. The Chevrolet released an update of its Volt, thereby reducing its price and slightly increasing its range.

The Ford C-Max Energi is expected to be available by January 2015 and will position itself in a lower price class than the PHEVs previously available.[1] It is assumed that due to decreasing battery costs and advancements in technology, consumers of even lower price classes will also have the ability to purchase a PHEV as time progresses.

Upgraded car models

To simplify the process of introducing improved vehicles to the new market, car models may be annually replaced by an updated model that either has lower emissions or an increased battery capacity. Updated car models are introduced with a unique suffix to ensure that agents can reason and communicate about specific versions of a model. Agents may initially hear about an updated model through the media or by visiting the car market, upon which they automatically learn which of the models they know have received an update.

Electric vehicles Each year, BEV and PHEV models are replaced by a model with an increased battery capacity, depending on how much the battery costs have dropped. Upon introduction to the car market, a distinction is made between how much the electric car itself costs and how much money is reserved for its battery pack. The latter is computed by multiplying the car model's capacity with the battery costs per kWh that is prevalent at the moment of introduction. The proportion of money that is spent on the vehicle's battery does not change over the years. Therefore, when an electric vehicle is taken off the market and replaced with a new model, the battery capacity of this new model is computed by dividing the money that is reserved for the car's battery by the currently prevalent battery costs. An example is given below, in the section which discusses battery costs.

Gasoline vehicles One year after each gasoline and PHEVs model's introduction, it is taken off the market and replaced by a model with carbon emissions that are 0.93 times lower, but which is equal in all other aspects. This represents the trend that since 2008, the average carbon emissions of newly registered vehicles in the Netherlands decreases by 7% [17]. Because this trend cannot continue indefinitely, gasoline car emissions reduce only 0.98 each year after 208 ticks.

[1] Groen7 news site, August 26, 2014. 'Ford announces price of C-MAX Energi plug-in hybride' (translated from Dutch)http://www.groen7.nl/ford-maakt-prijs-bekend-van-c-max-energi-plug-in-hybride/

Purchase power

The amount of money agents can spend on maintenance and saving towards a new car steadily increases from 5% of their current household income at tick 104, to 10% at the end of the scenario. Notice that the implicit assumption is made that household incomes will rise due to economic growth, enabling agents to spend more money on personal items.

Service stations

The probability of encountering a fast charge service station during a trip steadily increases from 0% at tick 104 to 95% at the end of the scenario. During the same time period, the proportion of agents with access to home and work chargers increases to 80% and 60% respectively. At the moment that fast charge stations along the highways start occurring (tick 104), the price of fast charging per kWh increases to €0.15/km, or €0.75/kWh for EVs with a fuel economy of 20 kWh/100km. This reflects the high costs that recently built fast charge stations in the Netherlands charge consumers.[2] Starting from tick 156, the fast charge price steadily decreases again to €0.09/km at the end of the scenario. The price of gasoline increases between tick 104 and the end of the simulation to €0.15/km, which would equal €2.50/litre for vehicle with a fuel economy of 6 litres/100km.

Battery costs

The price per kWh of batteries steadily decreases between tick 104 and 676 to €300. This price drop affects both the range of existing electric vehicles and the possibility to introduce completely new and cheaper electric car models. An example is given for clarification.

When the LEAF is introduced for €29500 at tick 78, battery costs are €500 per kWh and the LEAF thus designates €500/kWh $*$ 30kWh = €15000 to its battery pack, which leaves €14500 for the construction costs of the car itself.

When car model HERTZ is introduced for €24500 at tick 390, the costs per kWh has dropped $(390 - 104) * \frac{€500 - €300}{104 - 676}$ = €-100. HERTZ thus designates €400/kWh $*$ 30kWh = €12000 to its battery pack, leaving €12500 for the build costs of the car itself. At this same tick, the current version of the LEAF is taken off the market and replaced with a newer model. As shown above, the LEAF's battery budget is €15000. Therefore with the currently prevalent battery costs, its upgraded version will have a battery capacity of $\frac{€15000}{€400}$ = 38kWh.

Taxes

All vehicles with carbon emissions lower than 50 g/km are exempt from road taxes in the Netherlands until January 2016. Therefore in the basic scenario, all car models with carbon emissions lower than 50 g/km are tax free during the first 182 ticks while all other models come with a monthly tax of €50,-. Road taxes are expected to be less favourable for EVs after this date, which is translated to a monthly tax of €25,- for vehicles with emissions lower than 50 gCO˙2/km and €50,- for all other car models in the simulation, starting at tick 183.

[2] Fastned, obtained September 10, 2014. http://www.fastned.nl/

Table 6.2: Changes in the 'bijtelling' policy during the basic scenario.

Tick	0%	4%	7%	14%	20%	25%
26	50	-	-	95	124	125>
78	-	0	50	88	117	118>
130	-	0	50	82	110	111>
182	-	0	45	76	104	105>
234	-	0	45	70	98	99>
286	-	0	40	64	92	93>
338	-	0	40	58	86	87>
390	-	0	38	55	83	84>
442	-	0	38	52	80	81>
494	-	0	35	50	78	79>
546	-	0	35	50	75	76>
598	-	0	32	50	72	73>
650	-	0	32	50	70	71>

The Dutch government has confirmed that until January 2015, the 'bijtelling' categories are slightly tightened each year. At the moment of validation, it is uncertain what future policy will be and it is therefore assumed that the current trend will continue, albeit somewhat less strictly after 338 ticks once the emission boundaries are very low. Table 6.2 gives an overview of the changes in 'bijtelling' policy during the basic scenario. Maximum carbon emissions (gCO_2/km) are given for each 'bijtelling' category. Again, a distinction is made between confirmed (above the line break) and hypothetical (below the line break) policy.

6.3 Market

Stability of the car market is crucial for a realistic representation of the diffusion of new vehicles. If there are insufficient cars on the occasion market, too many dissatisfied agents will continue driving their current vehicle even when they have the resources to purchase a more satisfying one. If there are too many occasions available, unused cars will lose value over time without being driven, leaving occasion buyers with unrealistically attractive cars to choose from.

Related to this dynamic is the number of new cars that are sold per year. If fewer new cars are sold in the model than in the real world, there will later on be less opportunities for other agents to buy occasions. If too many new cars are sold, then the diffusion of new car models may occur quicker than can be realistically expected. Both aspects are further examined in this section.

6.3.1 New versus occasion sales

According to data from Statistics Netherlands, 502.445 and 416.816 new cars were sold in the Netherlands in 2012 and 2013 respectively [18] while the total number of registered personal vehicles on the road was close to 8.000.000

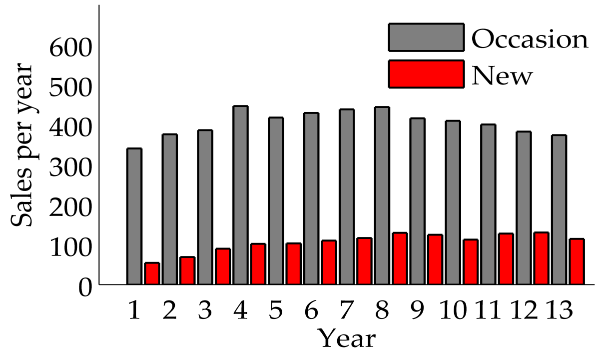


Figure 6.1: Validation: yearly sale figures for both new cars and occasions.

[19]. The number of occasions sold to consumers was 1.774.638 in 2012,[3] and 1.719.885 in 2013.[4] This entails that each year, the sale figure of newly registered cars is roughly 5.5% of the total automobile fleet. This proportion is around 21.5% for occasion sales.

Converting these numbers to the STECCAR model where a total of 1.795 personal vehicles are continuously on the road, approximately 100 new cars and 400 occasions should be sold each year. Figure 6.1 shows the aggregated results over 10 runs of the basic scenario. Sale numbers are split into 13 bins of 52 ticks (1 year) each, resulting in 13 years of information in total. For each year, the number of new cars (including sales from new lease contracts) and the number of occasion sales are shown. It takes two years for the number of new sales to reach 100 per year and during the first year, the occasion market also attracts fewer costumers than later. Other than that, both sale figures remain close to their appropriate values.

6.3.2 Occasion market stability

As described in Chapter 5.4.1, there should be roughly 72 vehicles on the occasion market at all times. Figure 6.2 shows the stability of the occasion market during the basic scenario. The number of occasions initially declines to 35 agents, which can be explained by the smaller number of new car sales during this period as was observed above. Once more new vehicles are sold, the occasion market grows back to its normal level. The number of gasoline occasions slowly decreases while the number of electric vehicles waiting for a new owner grows. At the end of the 13 year scenario, two out of three occasions are gasoline, while plug-in hybrids make up 18% of the occasion market en battery electric vehicles 14%.

[3] Voertuiginformatie en -documentatie (VWE), January 4, 2013. 'Slight decrease occasion sales in 2012' (translated from Dutch) http://www.vwe.nl/Nieuws/Pers/Persberichten/Archief/lichte-daling-occasionverkopen-in-2012.aspx

[4] Voertuiginformatie en -documentatie (VWE), January 3, 2014. 'Occasion sales 2.7% decreased in 2013' (translated from Dutch) http://www.vwe.nl/Nieuws/Pers/Persberichten/Archief/occasionverkopen-27-gedaald-in-2013.aspx

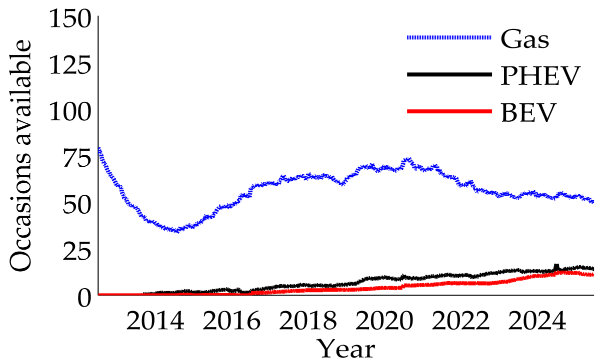


Figure 6.2: Validation: number of vehicles on the occasion market by fuel technology.

6.4 Ownership

Three aspects of ownership are taken into account when validating basic scenario of the STECCAR model. Average ownership duration and the average age of the owned vehicles are the first two aspects. The Dutch trend is an increasing ownership duration and rising vehicle age, presumably due to the loss in purchase power that households have experienced since the financial crisis in 2008. The basic scenario's output should match this development. The third aspect is the percentage of the population that is in debt. Having debts restricts agents in their consumer freedom and therefore the number of agents in debt should be a plausible proportion when compared to actual data.

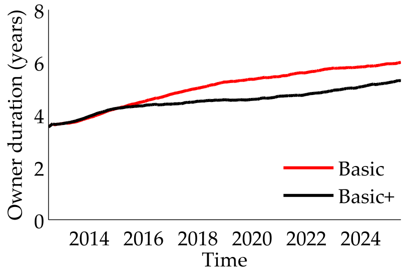
To explore the effects of purchase power, the results of an alternative validation scenario were also aggregated over 10 runs. After the initial 104 ticks of this alternative scenario, agents instantly assign twice as much money from their household income (10%) to vehicle maintenance costs and saving towards a new car, instead of the slow increase in purchase power during the basic scenario.

6.4.1 Duration

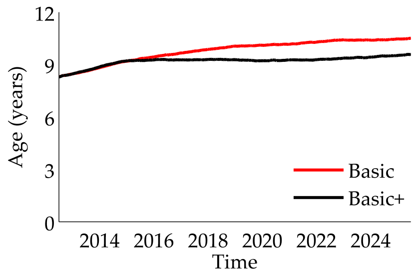
Dutch vehicle ownership duration has steadily increased from 3.6 years in 2010 to 3.85 years in 2013 [92]. An increasing duration trend is also seen in the basic scenario, where average ownership duration increases from 3.5 to 4 years after 104 ticks (Figure 6.3a). While the purchase power of the agents increases, this trend slows down and remains stable at an average ownership duration of 6 years by the end of the scenario. The results of the alternative scenario are shown in black. It can be seen that with an instant increase in purchase power, the increase of ownership duration slows down much faster. The STECCAR model therefore acknowledges that the onset of the financial crisis and subsequent reduction in household purchase power is a plausible explanation for the longer ownership duration of vehicles in the Dutch society.

6.4.2 Average vehicle age

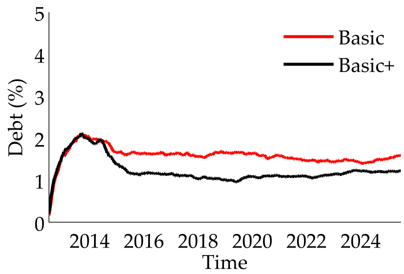
As with ownership duration, the average age of personally owned vehicles increases in the Netherlands. While the average age was 7 years in 2000, it has increased to 9.1 years in 2013 [47]. An ageing car fleet is also the result of the



(a) Average ownership duration



(b) Average age of owned vehicles



(c) Percentage of agents in debt

Figure 6.3: Validation: ownership aspects during the regular scenario (red) and alternative scenario (black) in which agent purchase power is increased.

basic scenario, as depicted in Figure 6.3b. The average age starts off at 8.25 years, reaches 9 years at tick 104 and then slowly stops increasing as purchase power rises. At the end of the scenario, the average vehicle age is 10.5 years. The results of the alternative scenario show that with an instantly increased purchase power, the average vehicle age stops rising immediately. Again, this is in line with assumptions that rising vehicle age is directly related to the consequences of the financial crisis.

6.4.3 Debt

5 to 7% of Dutch households are in problematic debt, of which the cause is often contributed to over-expenditure on luxury consumer products [56]. Although not all of these debts are the result of solely overspending on vehicle ownership, this aspect presumably plays a role in part of the cases. Figure 6.3c shows the percentage of agents that are in debt at any given time during the validation scenario. No agents start in debt, but this number initially rises to 2% of the agent population and then very slowly decreases as purchase power is increased. The results of the alternative scenario show that this percentage declines rapidly if purchase power is instantly increased.

6.5 Scrappage

Once a vehicle is total loss it is removed from the agents' world, or in other words 'scrapped'. Both the yearly volume of scrapped vehicles and the average scrappage age can be compared to recent Dutch data, thereby providing an indication of the soundness of the internal dynamics of the model.

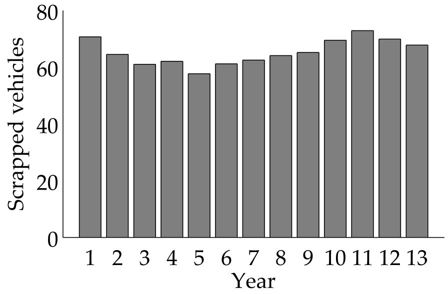


Figure 6.4: Validation: yearly amount of scrapped vehicles.

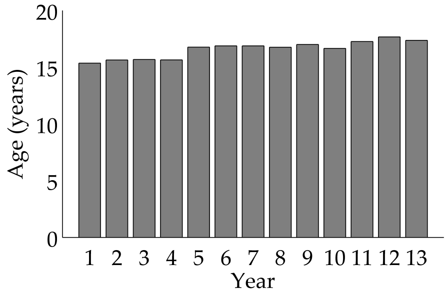


Figure 6.5: Validation: average age of scrapped vehicles.

According to Statistics Netherlands, 219.836 personal vehicles were scrapped in 2013 [20]. Converted to the car fleet size in STECCAR, this entails that roughly 50 vehicles should be scrapped each year. Figure 6.4 shows the yearly scrappage during the basic scenario by splitting the output into 13 bins of 52 ticks each. Results are consistently around 65 scrapped vehicles per year, which is somewhat higher than real world data but not so much to raise concerns.

In 2012, the average age of scrapped vehicles in the Netherlands was 17 years.[5] Figure 6.5 shows how the age of scrapped vehicles during the basic scenario starts off somewhat lower, 14 years but grows after a few years and then stays between 16.5 and 17.5 years, close to the real world data.

6.6 Diffusion

Due to the small volume of electric vehicles currently registered in the Netherlands, and the even smaller sample of agents in the simulation, validating the diffusion of electric cars is difficult. A trend which is clearly observed in the real world however, is a greater interest in plug-in hybrids than in fully electric cars. Under current conditions, a similar tendency should be the result of the simulation's behaviour.

At the end of June 2014, 0.064% of the cars on the road in the Netherlands was a BEV and 0.4% was a PHEV.[6] The validation results are somewhat higher, 0.22% and 0.83%, which is important to keep in mind when interpreting the results of future experiments. However, since we are dealing with such small numbers and the aim of this project is not to mimic and predict the exact diffusion of electric vehicles but to show trends which can be extrapolated to the outside world, it suffices that the tendency to purchase a PHEV in favour of a BEV is observed in the simulation's behaviour.

Figure 6.6 shows the diffusion of electric cars over the entire scenario. Error bars indicate the standard deviation at each moment in time. For PHEVs, episodes of increased growth are especially noticeable upon the introduction of lower priced models. Both the FARADAY, introduced halfway 2017, and the 2024 HENRY give the diffusion of PHEVs a large push forward. At the end of the scenario the proportion of agents who own a PHEV has increased to 10.3%.

[5] Voertuiginformatie en -documentatie (VWE), February 26, 2013. 'Porsches in the back of the line to the car scrappage' (translated from Dutch) http://www.vwe.nl/Nieuws/Pers/Persberichten/Archief/porsches-achteraan-in-de-rij-naar-de-autosloop.aspx

[6] Rijksdienst voor Ondernemend Nederland (RVO), obtained August 25, 2014. 'Numbers electric transport' (translated from Dutch) http://www.rvo.nl/onderwerpen/duurzaam-ondernemen/energie-en-milieu-innovaties/elektrisch-rijden/stand-van-zaken/cijfers

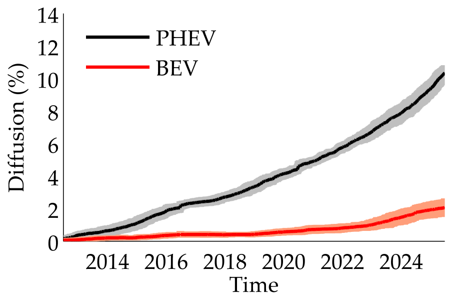


Figure 6.6: Validation: diffusion of electric vehicles.

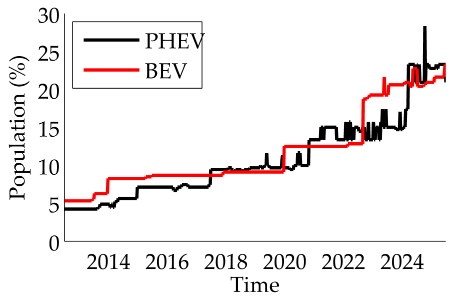


Figure 6.7: Validation: proportion of agents able to purchase an electric vehicle.

To further inspect the effect of lower priced car models on agents' ability to purchase an EV, an extra simulation run was performed in which the proportion of agents able to purchase a PHEV or BEV over the course of the scenario was documented. Agents were defined as 'able to purchase an EV' if at least one EV model was available in their price range on either the new or occasion market, depending on their preferred purchase method. Notice that an agent might not be aware that this car model exists and might therefore not consider this vehicle a viable option. Figure 6.7 shows the results of this extra run. Clearly, the HENRY opens up a particularly large portion of the market. The actual potential of this car model may therefore have been left undiscovered as it was introduced relatively late during the scenario.

The diffusion of fully electric vehicles hardly takes off and stays far below the numbers observed for PHEVs. The most noticeable increase in BEV sales occurs after the introduction of the WEBER halfway 2022. However, sales once again slow down when the HENRY is introduced and opens up PHEVs to consumers of the same price class as the WEBER. At the end of the scenario, only 2.08% of the agents own a BEV. The standard deviations indicate that there is relatively more variability between the final BEV diffusion states of individual runs than between the final PHEV diffusion states.

These results indicate that lower priced EVs are crucial to reach a significant proportion of consumers and thus push the diffusion of EVs forward, but this inclusion alone is insufficient to attract potential buyers towards fully electric vehicles. Interestingly, under the conditions of the basic scenario, the diffusion of EVs in the STECCAR model is close to reaching the Dutch government's target of 12.5% on the road by 2025.[7]

6.7 Perception

Although satisfaction and uncertainty are abstract properties of Consumat agents and cannot be validated with data from the real world, their development over time provides insight into the behaviour of the simulation. In this section, the perceptions of different car models are aggregated by fuel technology. At each tick, each agent estimates its satisfaction and uncertainty with every car model which it knows and is currently available on the new market and within its price class. This entails that the opinions on gasoline cars are based on a larger set of agents than the opinions on electric cars, because the latter are initially

[7] See footnote 6

only available to agents who purchase new vehicles in the higher price classes or who lease.

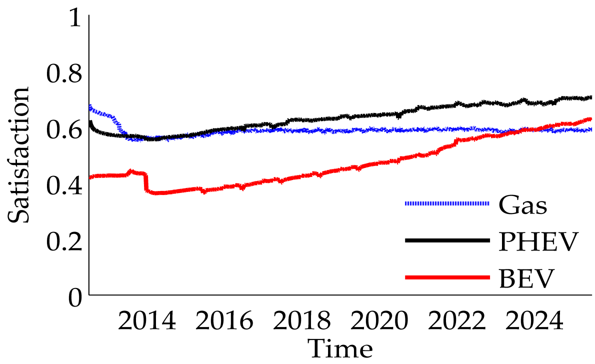


Figure 6.8: Validation: expected average satisfaction with different fuel technologies

6.7.1 Satisfaction

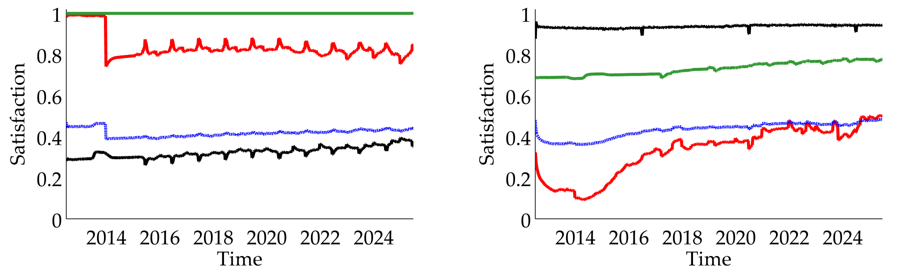
Figure 6.8 shows the development of the estimated satisfaction with different fuel technologies during the basic scenario. At the start of 2014, a drop occurs for BEVs, which is a direct consequence from abolishing the 0% 'bijtelling' for low carbon emission vehicles. Interestingly enough, this policy change does not seem to influence the satisfaction with PHEVs. Figure 6.9 provides more insight into this effect by showing the satisfaction with both types of electric vehicles, broken down by the agents' four different needs.[8] While the attraction of BEVs stems from having the lowest costs and carbon emissions, PHEVs are characterised by a high functionality and environmentalism satisfaction and low to intermediate cost satisfaction in comparison to BEVs.[9] Making electric cars less financially attractive therefore poses a larger burden on the attractiveness of BEVs than on PHEVs.

Changes in 'bijtelling' policy have a direct effect on the attractiveness of electric vehicles, but the abolishment of road tax exemption for low carbon emission vehicles at the beginning of 2016 causes no such response. Because most agents who can purchase an electric vehicle are initially lease owners, general taxes have far less impact than taxes targeted at lease ownership.

As a direct effect from steadily increasing the number of fast charge service stations in the agents' world, the expected satisfaction with BEVs continuously rises starting from halfway 2014. By 2025, BEVs are on par with gasoline vehicles and perceived almost as satisfactory as PHEVs. A scenario is which the

[8] The annual 'spikes' in Figure 6.9a are caused by updates of the S85. Right after a yearly update is introduced, most agents are still unaware of this newer model's existence and thus their opinion on this model is not taken into account for the purposes of this section. The figure then shows that when the S85 is temporarily not taken into account, the agents perceive the average BEV as less functional but more financially attractive.

[9] The relatively low cost satisfaction of PHEVs in Figure 6.9b deserves an explanation: because cost satisfaction is dependent on the other car models within a price class, the PHEVs are almost always compared to BEVs and therefore evaluated as sub-optimally financially attractive. Gasoline cars, however, are only compared to other gasoline cars by agents who are restricted to the lower price classes. This results in a very high cost satisfaction simply because no better alternatives are available. The figure should therefore not be interpreted as an absolute representation of the attractiveness of different fuel technologies, but as an aggregation over relative attractiveness given the possibilities available to each agent.



(a) Battery electric vehicles (BEV) **(b)** Plug-in hybrid electric vehicles (PHEV)

Figure 6.9: Validation: expected average satisfaction with electric vehicles broken down by need: costs (red), functionality (black), social (blue), environment (green).

development of fast charge stations occurs quicker can show what effect this increased satisfaction may have on the diffusion of BEVs versus PHEVs.

6.7.2 Uncertainty

The most prominent change in perceived uncertainty is also seen at the start of 2014, with the abolishment of the 0% 'bijtelling'. Due to a large change in tax policy, the uncertainty increases for both types of electric vehicles. No further peaks are encountered during the small yearly adjustments in 'bijtelling'.

Around 2016, the uncertainty of BEVs and PHEVs start to diverge. This corresponds to an increase in PHEV sales (Section 6.6) which reduces the social uncertainty of this type of fuel technology. The uncertainty with gasoline vehicles slowly increases during the basic scenario. Again, this is explained by the adoption of EVs by an increasing number of agents, causing the social uncertainty of owners of gasoline vehicles to rise.

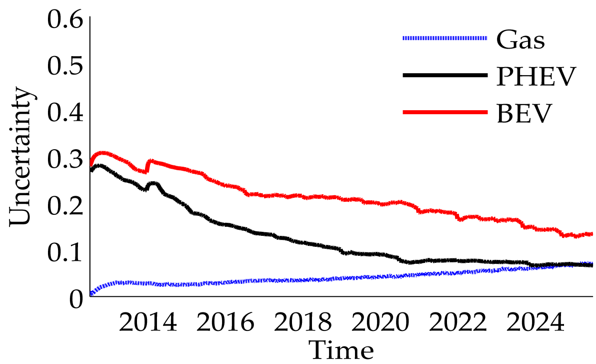


Figure 6.10: Validation: expected average uncertainty with different fuel technologies

6.8 Conclusion

The previous sections show that the parametrisation of the STECCAR model results in a simulation that is well validated against real world data. Purchase behaviour is an adequate reflection of actual sale figures, while the occasion market keeps itself in balance. Vehicle age, scrappage amount and ownership duration match the numbers and trends in Dutch society and the diffusion process develops in realistic proportions when compared to the actual EV diffusion over the previous two years.

It should be noted however, that whereas validation of consumer behaviour under normal circumstances is to some extent possible, the relatively new introduction of electric vehicles to the car market makes the validation of the exact speed and volume of the diffusion of electric vehicles troublesome, if not impossible. One should therefore caution against using this simulation, or any of its kind, as a predictive tool. Instead, its competency lies in visualizing the possible interactions and effects of mechanisms in a complex social system. It should be seen as an accessible policy planning tool, through which both obvious and surprising dynamics can be inspected in a relatively effortless way. Once the diffusion of electric vehicles moves further ahead, the model and parametrisation may be updated using additional insights and data.

7 Single measure scenarios

Now that a theoretically founded framework and an empirically parametrised and validated simulation has been constructed, scenarios can be run to observe the effects of different measures on the perception and diffusion of electric vehicles. This chapter describes several scenarios that implement a single adjustment to the basic scenario described in Chapter 6.2 to pinpoint the influence of isolated changes to society. Chapter 8 describes more complex scenarios in which multiple measures are combined.

7.1 Overview

The single adjustment scenarios in this chapter are divided into two themes: government policy and technological developments. The following is an overview of the scenarios within each theme.

Policy scenarios *The government takes charge.* (Section 7.2)

- 'Bijtelling' exemption (Section 7.2.1)
- Fuel excise duties & subsidies (Section 7.2.2)
- Purchase subsidies (Section 7.2.3)

Development scenarios *Technology powers up.* (Section 7.3)

- Charge time reduction (Section 7.3.1)
- Battery price reduction (Section 7.3.2)
- Charge probability increase (Section 7.3.3)

At the end of this chapter, a reflection is given on the different diffusion results and a comparison is made between the final reduction in carbon gas emissions at the end of each scenario (Section 7.4).

7.2 Policy scenarios: The government takes charge

With international agreements to significantly reduce carbon emissions over the coming years, governments need to seek for leverage points which have the largest effect on nation wide emission outputs for the lowest possible costs. This section elaborates on four different measures that a government could take and compares their effects to the basic scenario.

7.2.1 'Bijtelling' exemption

In January 2014, the Dutch 0% 'bijtelling' policy for car models with emissions lower than 50 gCO_2/km was abolished. Instead, owners of cars with 0 gCO_2/km or fewer than 50 gCO_2/km are charged 4% and 7% 'bijtelling' respectively. At the moment of writing, it is uncertain what the government's

Table 7.1: Changes in the 'bijtelling' policy during the BIJTELLING[1] and BIJTELLING:BEV[2] scenarios.

Tick	0%[1]	0%[2]	4%	7%	14%	20%	25%
26	50	50	-	-	95	124	125>
78	-	-	0	50	88	117	118>
130	-	-	0	50	82	110	111>
182	45	0	-	-	76	104	105>
234	45	0	-	-	70	98	99>
286	40	0	-	-	64	92	93>
338	40	0	-	-	58	86	87>
390	38	0	-	-	55	83	84>
442	38	0	-	-	52	80	81>
494	35	0	-	-	50	78	79>
546	35	0	-	-	50	75	76>
598	32	0	-	-	50	72	73>
650	32	0	-	-	50	70	71>

'bijtelling' policy will be from January 2016. This section therefore inspects the effect of reinstating the 'bijtelling' exemption for low carbon emission vehicles.

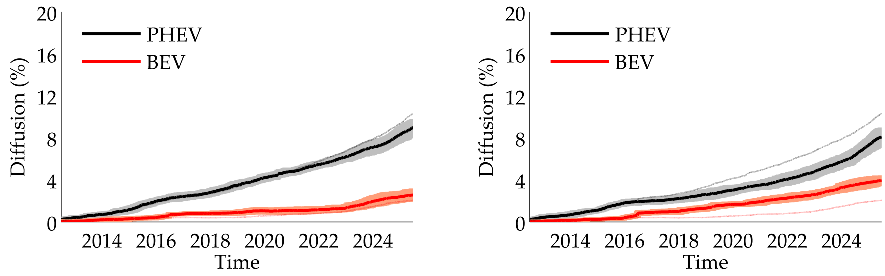
Two scenarios were developed. In the BIJTELLING scenario, 'bijtelling' exemption is reinstated for all vehicles that fall within the 4% and 7% categories in the BASIC scenario. In the BIJTELLING:BEV scenario, a policy more strongly in favour of battery electric vehicles (BEVs) is enacted. Here, only zero-emission car models are favoured for 'bijtelling' exemption, while the 7% category from the BASIC scenario is scrapped. This entails that plug-in hybrid electric vehicles (PHEVs) will fall in the 14% category, along with regular hybrid vehicles. The policy changes in both scenarios are shown in Table 7.1.

Results

The average diffusion process over 10 runs of the scenarios is given in Figure 7.1. Because the lease market is relatively small, 'bijtelling' exemption interestingly enough does not result in an increase of electric vehicle (EV) owners overall. It does however create competition between PHEVs and BEVs.

The results show that reinstating 'bijtelling' exemption for all low emission vehicles results in a small preference of BEVs over PHEVs. 13% fewer plug-in hybrid electric vehicles (PHEVs) are sold (8.97%) compared to the BASIC scenario (10.30%), while the total proportion of BEVs is 24% higher (BIJTELLING: 2.57%, BASIC: 2.08%). This is in line with findings in Section 6.6 that costs are a more important aspect for potential BEV owners than for those who consider a PHEV. More strongly, these results suggest that BEVs become favourable over PHEVs for certain consumers when the initial price is taken out of the equation and only usage costs (refuelling and maintenance) are taken into account.

The effect of the BIJTELLING:BEV scenario is even stronger. When PHEVs are treated less favourably than is currently the case and zero-emission vehicles fall in the 0% 'bijtelling' category again, 90% more BEVs are sold in the BIJTELLING:BEV scenario (3.95%) compared to the BASIC scenario. The op-



(a) BIJTELLING **(b)** BIJTELLING:BEV

Figure 7.1: Average diffusion of plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) during the BIJTELLING and BIJTELLING:BEV scenarios in which 0% 'bijtelling' was reinstated for low carbon emission and zero-carbon emission vehicles respectively. Standard deviations are added to show variability between runs. The average diffusion process during the BASIC scenario is added for reference (dotted line).

posite holds for PHEVs, of which the sales drop 21% to a final diffusion of 8.12%.

7.2.2 Fuel excise duties & subsidies

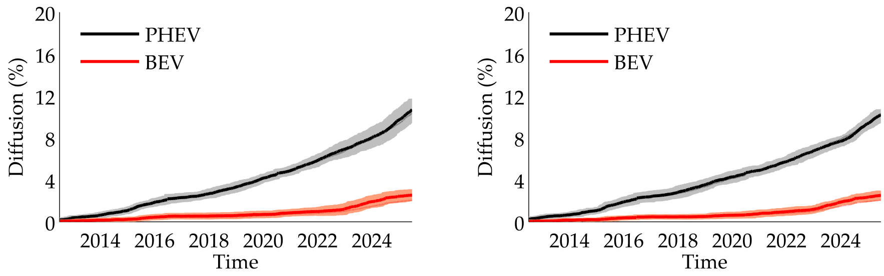
In scenario GASCOSTS, the excise duties on gasoline are increased yearly. Starting from July 2015 (tick 156), gasoline prices are instantly raised €0.005/km at the start of each year. This results in a final gasoline price of €0.20/km, or €3.33/litre for cars that have a fuel economy of 6 litres/100km, at the end of the scenario.

Instead of increasing excise duties on gasoline, the government could also subsidise the price of electricity at fast charge service stations. Scenario CHARGECOSTS is constructed to observe what the effects of this single measure would be. Starting from tick 156, the costs of electricity at fast charge stations is reduced €0.005/km once every 52 ticks. The final fast charge price is then €0.04/km at the end of the scenario, which coincides with €0.20/kWh when a fuel economy of 20 kWh/100km is used.

Results

Figure 7.2a shows the average diffusion process over 10 runs of the GASCOSTS scenario. No large deviations from the BASIC scenario are observed. The final diffusion of BEVs is 2.55%. This is a slight increase compared to the BASIC scenario, but since the standard deviations clearly overlap it is uncertain whether this is a result of increased gasoline prices or if it is caused by accidental variability between runs.

Similarly, simply further reducing the fast charge electricity price without taking any other measures has no observable effect on the diffusion of electric vehicles (Figure 7.2b). The final diffusion of BEVs is 2.52%, but again, this effect is too small to draw any conclusions.



(a) GASCOSTS **(b)** CHARGECOSTS

Figure 7.2: Average diffusion of plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) during the GASCOSTS and CHARGECOSTS scenarios in which respectively gasoline costs are increased yearly or fast charge costs are decreased yearly. Standard deviations are added to show variability between runs. The average diffusion process during the BASIC scenario is added for reference (dotted line) but is hardly visible due to overlap with the experimental results.

7.2.3 Purchase subsidies

One limiting factor to a quick diffusion of electric vehicles could be their high initial purchase costs. Since EVs are only available in the higher price classes, they are initially off limits to the largest bulk of agents who prefer to buy vehicles in the lowest price classes. By subsidising the purchase of EVs, the government could allow these alternative fuel technologies to compete in a larger segment of the market at an earlier moment in time.

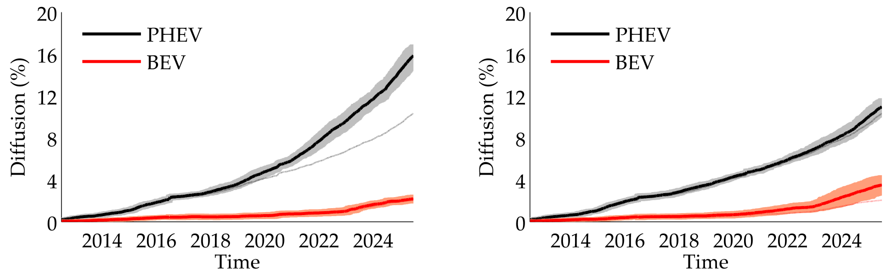
In the SUBSIDIES scenario, the purchase price of all EVs introduced after July 2015 (tick 156) is reduced by € 5000. This amount was chosen to ensure that each EV is placed one price class lower than in the BASIC scenario. Two extra car models were introduced to fill in the gaps between price classes which would otherwise arise. At tick 193, a PHEV is introduced with the same characteristics that the FARADAY model has in the BASIC scenario. At tick 224, a BEV with the same characteristics as the HERTZ model in the BASIC scenario is introduced. This ensures that a PHEV is available to agents who shop in the € 25000 to € 30000 price class and a BEV is available for those restricted to the € 20000 to € 25000 price class.

In the SUBSIDIES:BEV scenario, a different approach to purchase subsidies is taken. Now, only the BEVs introduced after tick 156 are € 5000 reduced in price. All PHEVs have the same purchase price as in the BASIC scenario, and therefore no extra PHEV is introduced at tick 194.

Results

As Figures 7.3 shows, the SUBSIDIES and SUBSIDIES:BEV scenarios have very different effects on the car market and diffusion of electric vehicles.

The SUBSIDIES scenario results in a 54% higher proportion of PHEVs on the road at the end of the scenario(SUBSIDIES: 15.86%, BASIC: 10.30%). As the figure shows, this is a large increase over previous scenarios. The average final proportion of agents who own a BEV is only slightly higher in this scenario (2.2%) than in the BASIC scenario (2.08%). However, due to the small volume of sold BEVs and the variability between runs, this effect is too small to draw



(a) subsidies **(b)** subsidies:bev

Figure 7.3: Average diffusion of plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) during the subsidies and subsidies:bev scenarios in which subsidies reduce the purchase price of all EVs or of BEVs only respectively. Standard deviations are added to show variability between runs. The average diffusion process during the basic scenario is added for reference (dotted line) but is not always visible due to overlap with the experimental results.

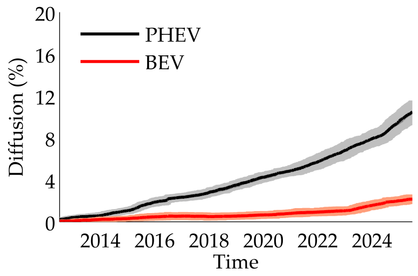
any conclusions. These results indicate that when EVs become available in lower price classes, the diffusion trend in the basic scenario is strengthened but not altered. This in contrast to the bijtelling scenario, where an actual difference in the proportion of BEV to PHEV sales was observed.

In the subsidies:bev scenario, the diffusion of PHEVs is not affected by the subsidies that only apply to BEVs. The final proportion of PHEV owners is negligibly higherthan in the basic scenario. The proportion of agents that own a BEV by the end of the scenario (3.5%) however, has increased 68% in comparison to the basic scenario. Subsidies can therefore increase the sales in zero-emission vehicles, but this effect is diminished if other low-emission vehicles receive similar benefits.

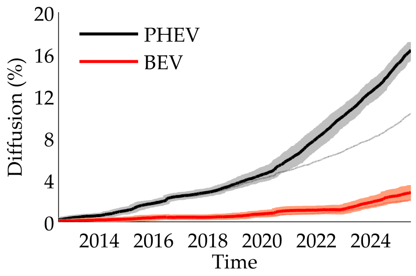
An interesting finding is that although purchase subsidies were introduced in 2015, their effect does not become noticeable until 2023. At the very least, one would expect that the number of BEV owners would start to increase in 2020, which is the moment when a vehicle becomes available in the € 15000 to € 20000 price class and the diffusion of BEVs takes off in the basic scenario. A reason for this delay is likely the slow onset of a reliable network of fast charge service stations and consequently the limited range of BEVs, which initially reduces their estimated satisfaction. For most agents, a BEV only becomes a viable option once a sufficient fast charge network is in place or their vehicle has a range which meets their daily travel needs. The results of this scenario show that although making electric vehicles accessible to consumers in lower price classes is important to push their diffusion forward, more measures are necessary to create an optimal diffusion process.

7.3 Development scenarios: Technology powers up

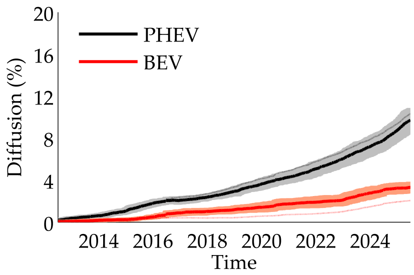
Technological advancements may push the diffusion of electric vehicles forward. To investigate their relative influence on the diffusion process, three scenarios were created that each implement a specific adjustment to the basic scenario. These scenarios are described next.



(a) CHARGETIME



(b) BATTERY



(c) CHARGEPROB

Figure 7.4: Average diffusion of plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) during the CHARGETIME, BATTERY and CHARGEPROB scenarios in which respectively the charge time is reduced, battery prices are continuously lowered or the probability of encountering a fast charge service station is more quickly increased. Standard deviations are added to show variability between runs. The average diffusion process during the BASIC scenario is added for reference (dotted line) but is not always visible due to overlap with the experimental results.

7.3.1 Charge time reduction

The CHARGETIME scenario is used to evaluate the influence of a reducing fast charge time. Between July 2014 (tick 104) and the end of the scenario, the time it takes to recharge an electric car along the highway is stably reduced from 30 minutes to 5 minutes.

Results

Figure 7.4a shows the average diffusion process over 10 runs of the CHARGETIME scenario along with the standard deviations. No difference can be observed when comparing the results to the BASIC scenario. Both the diffusion of BEVs and PHEVs follow a similar path. Apparently, other or additional measures are necessary to make BEVs more desirable to consumers.

7.3.2 Battery price reduction

In the BATTERY scenario, a quicker reduction in battery prices is explored. Instead of the price decreasing €200/kWh between ticks July 2014 and June 2025, prices decrease €350/kWh, resulting in a final price of €150/kWh at the end of the simulation. As explained in Section 6.2, battery price reduction affects both the range of vehicles currently on the market and the introduction rate

Table 7.2: Specifications of all car models introduced during the BATTERY scenario.

Tick	Fuel	Model	Price	Gasoline range (km)	Capacity (kWh)	gCO_2/km
52	BEV	S85	85000		80	0
54	BEV	FOCUS	39500		30	0
60	PHEV	V60	64500	1100	8	49
72	BEV	EGOLF	34500		30	0
78	BEV	LEAF	29500		30	0
90	PHEV	VOLT2	39500	550	11	27
130	PHEV	CMAX	34500	850	6	46
145	BEV	OHM	44500		32	0
156	BEV	JOULE	49500		32	0
193	PHEV	FARADAY	29500	700	8	43
267	BEV	HERTZ	24500		30	0
293	PHEV	COULOMB	24500	700	8	37
347	BEV	WEBER	19500		30	0
393	PHEV	HENRY	19500	700	8	34
530	BEV	PLANTE	14500		30	0
610	PHEV	JUNGNER	14500	700	8	28

of new, cheaper vehicles. Because battery prices drop quicker and further in this scenario than in the BASIC scenario, new car models should also be introduced more rapidly. For instance, while HERTZ was previously introduced in January 2020 (tick 390) when the battery price was €400/kWh, this same price is already reached halfway 2017 (tick 267) in the BATTERY scenario.

Table 7.2 gives an overview of the car models introduced during the BATTERY scenario. The introduction times of OHM and JOULE have not been changed, since high battery prices were never a limiting factor to the introduction of these high price class models. Notice that two extra car models in cheaper price classes are added at the end of the scenario. Due to the drop in battery prices, it is likely that EVs will become available in an even lower segment by that time.

Results

Figure 7.4b shows the diffusion results over 10 runs of the BATTERY scenario. A stronger reduction in battery prices clearly has a powerful effect on the diffusion of BEVs and PHEVs. Both types of vehicles are adopted quicker than in the BASIC scenario, although more deviation between runs is also a result of the adjustments as is indicated by the larger error bars, especially towards the end of the scenario. For BEVs, a 30% diffusion increase is observed (BATTERY: 2.70%, BASIC: 2.08%), while PHEVs ownership has increased 59% (BATTERY: 16.38%, BASIC: 10.30%).

Because a reduction in battery price leads to both cars with an increased range and a quicker introduction of EVs in lower price classes, it is important to determine which one of these two consequences plays the most important role. One indication may be the relatively late effect of battery price decrease on the diffusion of BEVs, which was also observed in Section 7.2.3 when purchase subsidies allowed BEVs to become more quickly available in lower price classes. There we saw that the effect of subsidies presented itself much later than expected because presumably, the lack of a sufficient range held off potential BEV buyers. If the increased range in the BATTERY scenario would be adequate for potential buyers, one might expect some increase in BEV sales around 2019, which is the moment the WEBER becomes available and the diffusion of BEVs takes off in the BASIC scenario. However, BEV sales start increasing, although at a quicker rate, around the same time as in the BASIC scenario, which suggests that the increase in range has less effect than making EVs available to lower price classes.

7.3.3 Charge probability increase

Scenario CHARGEPROB was created to investigate the influence of a quick realisation of fast charge infrastructure in the Netherlands. Current plans aim for a nation-wide network by 2016, two years from the moment of writing. Therefore in the CHARGEPROB scenario, the probability of encountering fast charge service stations increases to 95% between ticks July 2014 (tick 104) and June 2016 (tick 208).

Results

The average diffusion process over 10 runs of the CHARGEPROB scenario is shown in Figure 7.4c. The diffusion of BEVs is positively influenced by a quicker nation-wide network of fast charge stations, thereby slightly affecting and decreasing the diffusion of PHEVs. This positive influence becomes noticeable directly after the infrastructure is complete. However, because the total number of BEVs on the road remains relatively low during the first couple of years, it is not until 2019 that the number of BEV sales in the CHARGEPROB scenario clearly starts to diverge from the BASIC scenario. At the end of the scenario, there are 60% more BEV owners (3.32%) and 6% less PHEV owners (9.7%) than in the BASIC scenario. However, this entails that the total number of EV owners has remained relatively similar with 12.42% of the agent population in the CHARGEPROB scenario and 12.38% in the BASIC scenario. These results indicate that a quick realisation of a nation-wide fast charging network will make BEVs more competitive with PHEVs, but this development will likely not increase the total number of EV owners by itself.

7.4 Reflection

A reduction in the time it takes to fast charge a battery electric vehicle (BEV) and altering the costs of gasoline and electricity do not have a strong influence on the diffusion of electric vehicles (EVs) when they are applied as single measures. However, a quicker nation-wide coverage of fast charge service stations does turn out to be essential in making BEVs competitively attractive over plug-in hybrid vehicles (PHEVs). Perhaps the potential of the earlier mentioned measures will only show within a scenario that already utilizes a nation-wide fast charge network. This hypothesis will be further tested in Chapter 8.

Out of the government policies that were inspected, 'Bijtelling' exemption and purchase subsidies had very different effects. The first resulted in an increase in BEV sales at a cost for the diffusion of PHEVs, especially when the exemption only held for zero-emission vehicles. This is explained by the relatively small proportion of agents to which the 'bijtelling' rule applies. Making full electric vehicles more financially attractive therefore draws potential PHEV leasers towards BEVs. Purchase subsidies on the other hand push the diffusion of all EVs, as they allow these alternative fuel technologies to become available in lower price classes and thereby increase the pool of potential buyers. However, if subsidies become available to all low-emission vehicles and no other measures are taken, the positive effect is much stronger for PHEVs than for BEVs. In the long term, it might not be beneficial that many agents commit to a PHEV in favour of BEVs, as this might stand in the way of reducing carbon emissions to the lowest possible degree in the nearby future. The final part of this section therefore compares the carbon emissions at the end of each scenario in order to better understand what the diffusion rates of each scenario entail.

For the diffusion of PHEVs, the most effective technological development in the chapter was a reduction in battery prices as this would lead both to cars with an increased electric range and to cars available in lower price classes. For BEVs, reduced battery prices resulted in slightly more sales towards the end of the scenario, but the late onset of this effect suggests that more is necessary to make BEVs attractive enough for consumers. The answer for BEVs might lie in a quicker realization of nation-wide fast charge service stations. Chapter 8 will therefore inspect what the effects of reduced battery prices will be in combination with an almost complete coverage of fast charge stations. Additional measures will also be included to see how the diffusion of EVs could be pushed full force.

Emission reduction

Besides comparing the proportion of agents which own an EV at the end of each scenario, a comparison can also be made between how much carbon emissions are actually reduced. Figure 7.5 shows the average weekly tail pipe carbon emissions per kilometre at the end of each scenario. Standard deviations are included as error bars. For PHEVs, the emissions during all-electric drive are 0 g/km. When the vehicle switches to gasoline mode, emissions equal the average carbon emissions of gasoline vehicles that were on the new market when the PHEV was bought. This way, the effect of PHEV owners who do not possess a home charger or who frequently use their vehicle for very long distances is taken into account, something that would be overlooked if the average carbon emissions that determine into which tax category the PHEV falls were used instead.

Although changes might seem small, an average weekly reduction of 1 gCO_2 per kilometre would result in a yearly reduction of 106.400 tons CO_2 when extrapolated to the Dutch car park. This equals the yearly total direct carbon emissions of 13.300 typical Dutch households.[1]

The standard deviations indicate that the variability between runs is relatively high for most scenarios. The only scenario that stands out in terms of carbon emission reduction is the one where BEVs received 'bijtelling' exemption (Section 7.2.1). Interestingly, at the of this scenario the total number of EV owners was not higher than in the BASIC scenario; only the proportion

[1] Milieu Centraal, obtained October 7, 2014. 'Calculate your CO_2 emissions' (translated from Dutch).http://www.milieucentraal.nl/themas/klimaat-en-milieuproblemen/klimaatverandering/klimaatcompensatie/bereken-uw-co2-uitstoot

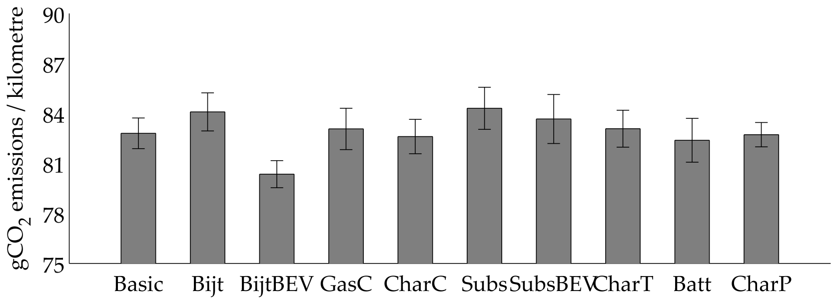


Figure 7.5: Average gCO_2 emissions per kilometre and standard deviations at the end of each single measure scenario: BASIC (Section 6.2), BIJTELLING ('Bijt', Section 7.2.1), BIJTELLING:BEV ('BijtBEV', Section 7.2.1), GASCOSTS ('GasC', Section 7.2.2), CHARGECOSTS ('CharC', Section 7.2.2), SUBSIDIES ('Subs', Section 7.2.3), SUBSIDIES:BEV ('SubsBEV', Section 7.2.3), CHARGE-TIME ('CharT', Section 7.3.1), BATTERY ('Batt', Section 7.3.2), CHARGEPROB ('CharP', Section 7.3.3)

of PHEV owners to BEV owners was altered in favour of the latter. The scenario in which battery costs were lowered (Section 7.3.2), shows no significant reduction in carbon emissions even though the end result was a higher diffusion of EVs. Apparently the effect of additional PHEVs on the road does not contribute as strongly as replacing some of the PHEVs with zero-emission battery-only electric vehicles.

When comparing the two different 'bijtelling' scenarios, 'bijtelling' exemption for BEVs significantly reduces carbon emissions, while providing similar benefits to PHEVs removes any positive effect. It seems that in the case of 'bijtelling' policy, the government could opt for the financially more attractive option in which only zero-emission vehicle owners benefit while PHEV owners are treated similarly to very fuel efficient gasoline cars (i.e. conventional hybrids), and have even better results than if they would financially reinforce potential PHEV buyers as well.

8 Combination scenarios

Chapter 7 showed the effects of simple adjustments on the agents' willingness to purchase electric vehicles (EVs). In this chapter, multiple measures are combined to inspect the influence of their interaction on the diffusion of EVs. The behaviour of the simulation is examined in both more depth and breadth, using additional output data and longer scenarios.

8.1 Overview

Two themes are explored in this chapter. The first theme extends on the knowledge obtained in Chapter 7 and examines whether previously ineffective measures can become useful when combined with a quick realization of a nation wide fast charge station network. The second theme combines all single measures from Chapter 7 to explore the limits of the diffusion of EVs within the STECCAR model. The following is an overview of the scenarios within each theme.

Fast charge scenarios *Light up the highway.* (Section 8.2)

- Better availability and charge time (Section 8.2.1)
- Better availability and costs (Section 8.2.2)
- Better availability, charge time and costs (Section 8.2.3)

Full force scenarios *All parties fuse together.* (Section 8.3)

- Combing all single-measure scenarios (Section 8.3.1)
- Including vehicle appearance (Section 8.3.2)

8.2 Fast charge scenarios: Light up the highway

Section 7.3.3 showed that a quick realization of a nation-covering fast charge network is an important development to make battery electric vehicles (BEVs) more competitive with plug-in hybrid electric vehicles (PHEVs). Other measures, namely slowly reducing charge time and costs at fast charge stations, had no effect if the charge stations were rolled out in a similarly long time span. This section examines whether these ineffective measures may become effective in a scenario where fast charge stations are realized at a quicker speed.

8.2.1 Better availability and charge time

In scenario prob:time, the scenarios from Sections 7.3.1 and 7.3.3 are combined. The probability of encountering a fast charge station increases to 95% between July 2014 (tick 104) and June 2016 (tick 208). Additionally, the time it takes to recharge an electric car along the highway is slowly reduced from 30 minutes in July 2014, to 5 minutes at the end of the scenario, June 2025.

Results

Figure 8.1a gives the average diffusion result over 10 runs of the PROB:TIME scenario. The results of the CHARGEPROB scenario are added for reference (dotted line) but are not visible due to an almost complete overlap between the results of the two scenarios. This indicates that reducing the charge time beyond the current 30 minutes is not an effective leverage point in the diffusion process of EVs, even when a fast charge network is already in place.

8.2.2 Better availability and costs

Scenario PROB:COSTS, combines the scenarios from Sections 7.3.3 and 7.2.2. Again, the probability of encountering a fast charge station increases to 95% between July 2014 and June 2016. Additionally, starting from July 2015 (tick 156) the costs to refuel a vehicle are increased yearly with €0.005/km for gasoline cars and decreased yearly with €0.005/km for agents that use fast charge stations. This results in a final gasoline price of €0.20/km, or €3.33/litre for cars with a fuel economy of 6 litres/100km. Alternatively, owners of EVs end up paying €0.04/km to fast charge their vehicle, or €0.20/kWh when a fuel economy of 20 kWh/100km is prevalent.

Results

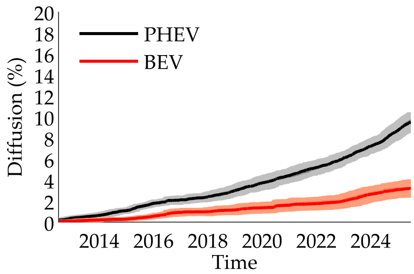
The results of the PROB:COSTS scenario are shown in Figure 8.1b. The final proportion of BEV owners is 4.61%, which is 122% higher than in the BASIC scenario (2.08%) and 39% higher than in the FASTCHARGE scenario alone (3.32%). It seems that making gasoline fuel prices less attractive while making fast charge prices more attractive, has a greater effect when a nation-wide charge network is already in place. On a very small level, these results also show how different adjustments can influence each other and together push the adoption of a new technology forward.

8.2.3 Better availability, charge time and costs

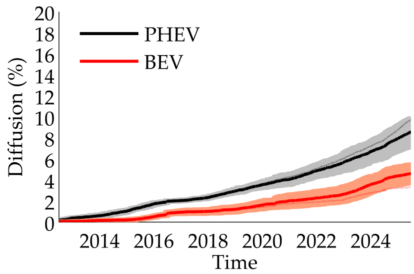
To see whether a reduction in charge time might have a stronger effect when more attractive infrastructure is already in place, the scenarios from Sections 7.3.3, 7.3.1 and 7.2.2 are combined in scenario PROB:TIME:COSTS. Between July 2014 and June 2016, the probability of encountering a fast charge service stations increases to 95% and the time it takes to recharge a vehicles at a fast charge station decreases from 30 minutes in July 2014 to 5 minutes in June 2025. Starting from July 2015, gasoline prices instantly increase €0.005/km on a yearly basis, while at the same time fast charge electricity prices drop €0.005/km.

Results

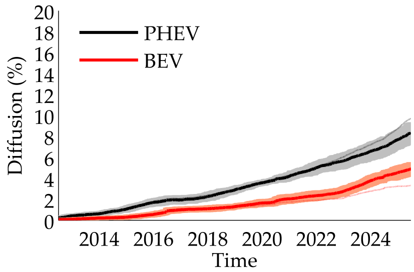
The results are shown in Figure 8.1c. At the end of the scenario, 4.9% of the agent population owns a BEV. This is only slightly higher than in the PROB:COSTS scenario and it thus cannot be taken as an indication that a reduction in charge time has any further effect on the diffusion process.



(a) PROB:TIME



(b) PROB:COSTS



(c) PROB:TIME:COSTS

Figure 8.1: Average diffusion of plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) during alternative versions of the CHARGEPROB scenario (Section 7.3.3) in which a nation-wide fast charge network is quickly realized. In the PROB:TIME and PROB:COSTS scenarios, the charge time and charge costs are reduced respectively. In scenario PROB:TIME:COSTS both are reduced. Standard deviations are added to show variability between runs. The average diffusion process during the CHARGEPROB scenario is added for reference (dotted line) but is not always visible due to overlap with the experimental results.

8.3 Full force scenarios: All parties fuse together

Previous scenarios showed that the transition to a battery-powered car fleet is a relatively slow process. At the current rate at which owners purchase or lease new vehicles and with the prevailing segment of consumers who prefer occasions over new cars, it will take more than a decade until one out of four agents owns an EV, even if electric vehicles become within financial reach optimistically soon.

The scenarios in this section combine all previously explored measures to examine what happens when the initial diffusion of EVs is stimulated as much as possible. Section 8.3.1 explores these scenarios within the now familiar time frame: from July 2012 until June 2025. As will become apparent, these scenarios push the limits of the original STECCAR model.

8.3.1 Combing all single-measure scenarios

Two approaches are taken. In scenario ALL, the technological developments from Section 7.3 are combined with government policies that benefit all low-carbon emission vehicles. In scenario ALL:BEV, the same technological developments are applied, but a distinction is made between BEVs and PHEVs and government policies are applied in favour of BEVs only. Table 8.1 provides an overview of all measures included in these two scenarios, while Table 8.2 shows which new car models are introduced during the course of the scenarios. Notice that because both government subsidies are supplied and battery costs drop sharply, EVs are introduced in price classes twice as low as in the original BASIC scenario.

Results

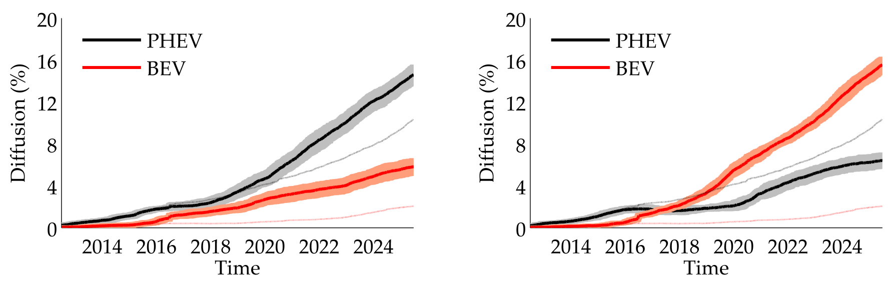
Figure 8.2 shows the average results over 10 runs of the ALL and ALL:BEV scenarios. Under the conditions of the ALL scenario, there are 42% more PHEV owners compared to the BASIC scenario (ALL: 14.62%, BASIC: 10.30%) and 180% more BEV owners (ALL: 5.82%, BASIC: 2.08%). This means that instead of 12.38% of the agent population owning an electric vehicle, 20.44% drives electric by the year 2025. Although the largest absolute increase in new EV adopters is still obtained through PHEV sales, proportion wise, these measures that benefit all electric vehicles have a larger influence on the diffusion on BEVs than on PHEVs.

What happens when measures are specifically targeted at stimulating the diffusion of BEVs, is shown in Figure 8.2b. BEV sales start increasing halfway 2015, similar to the ALL scenario. However, instead of levelling down one year later, the adoption of BEVs keeps growing and overtakes the diffusion of PHEVs halfway 2017. PHEV sales consequently lag behind and do not reach the same numbers as in the BASIC scenario. At the end of the scenario, there are 38% less PHEV owners (6.42%) compared to the BASIC scenario, but almost 650% more BEV adopters (15.57%).

The outcome indicates that with the right combination of measures, for instance those which stimulate the adoption of zero-emission vehicles only, it is possible for BEVs to become more attractive and better sold than PHEVs within a relatively short period of time. As Chapter 7 showed, it is unlikely that a single measure or policy can realize this change.

Table 8.1: All adjustments made in the ALL and ALL:BEV scenarios, in comparison to the BASIC scenario described in Section 6.2.

	ALL	ALL:BEV
Taxes	€ 0 for vehicles with emissions < 50 gCO_2/km	€ 0 for zero-emission vehicles
'Bijtelling' (Section 7.2.1)	See Table 7.1[1]	See Table 7.1[2]
Fast charge costs (Section 7.2.2)		Yearly decrease of € 0.005/km
Gasoline costs (Section 7.2.2)		Yearly increase of € 0.005/km
Subsidies (Section 7.2.3)	-€ 5000 on the purchase price of all electric vehicles	-€ 5000 on the purchase price of zero-emission vehicles
Fast charge time (Section 7.3.1)	Decreases to 5 minutes	Decreases to 5 minutes
Battery price (Section 7.3.2)	Decreases to € 150/kWh	Decreases to € 150/kWh
Fast charge probability (Section 7.3.3)	Increases to 95%	Increases to 95%



(a) ALL (b) ALL:BEV

Figure 8.2: Average diffusion of plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) during the ALL and ALL:BEV scenarios in which multiple policies are combined to stimulate the diffusion of all low carbon emission vehicles or zero-carbon emission vehicles respectively. Standard deviations are added to show variability between runs. The average diffusion process during the BASIC scenario is added for reference (dotted line).

Table 8.2: Specifications of all car models introduced during the ALL and ALL:BEV scenarios. [1] Only introduced in the ALL scenario. [2] €5000 more expensive in the ALL:BEV scenario.

Tick	Fuel	Model	Price	Gasoline range (km)	Capacity (kWh)	gCO_2/km
52	BEV	S85	85000		80	0
54	BEV	FOCUS	39500		30	0
60	PHEV	V60	64500	1100	8	49
72	BEV	EGOLF	34500		30	0
78	BEV	LEAF	29500		30	0
90	PHEV	VOLT2	39500	550	11	27
130	PHEV	CMAX	34500	850	6	46
145	BEV	OHM	44500		32	0
156	BEV	JOULE	49500		32	0
193	PHEV	FARADAY	29500	700	8	43
224	BEV	FAUR	24500		30	0
246	PHEV	DANIELL	24500[1]	700	8	40
267	BEV	HERTZ	19500		30	0
293	PHEV	COULOMB	19500[2]	700	8	37
347	BEV	WEBER	14500		30	0
393	PHEV	HENRY	14500[2]	700	8	34
530	BEV	PLANTE	9500		30	0
610	PHEV	JUNGNER	9500[2]	700	8	28

Reflection

When further inspecting the behaviour of the STECCAR model under the ALL and ALL:BEV scenarios, it becomes apparent that these scenarios push the limits of what can be simulated with the current version of the model. The following paragraphs show what happens to the agents during these scenarios, and why an adaptation to the model is crucial in order to inspect a more distant future. Data from the ALL scenario is used, but the results from the ALL:BEV scenario show the same pattern.

Figure 8.3 depicts the diffusion process of electric vehicles among agents who buy new cars only. Halfway 2025, 12.83% of these agents owns a battery electric vehicle and 41.63% drives a plug-in hybrid. In other words, more than half of the agents who purchase new cars owns an electric vehicle. Keep this in mind when inspecting Figure 8.4. This figure shows the percentage of agents that are satisfied at any given week during the simulation, segregated by the fuel technology that their vehicle uses. Notice that this is not the average satisfaction score that the agents experience, but a binary state indicating whether an agent was satisfied more often than its threshold. In this case that means, if the agent was satisfied during more than 4 weeks in the previous 10 weeks (Section 4.12.1 and Section 5.2.6). Ten weeks after the start of the simulation, agents start determining whether they are satisfied on average and from then on, approximately 3% of the gasoline vehicle owners is unsatisfied each week, causing them to look for a new vehicle. However, after an initial settling period, both PHEV and BEV owners are consistently satisfied and therefore do not feel an urge to purchase a new vehicle. Add to that the lower failure costs of BEVs, and there is no reason for EV owners in the current version of the STECCAR model to purchase new cars on a regular basis.

Indeed this is what happens in the simulation, as depicted in Figure 8.5. Here, the sales of new vehicles during the ALL scenario are compared to those during the BASIC scenario. Once more agents adopt an electric vehicle, a larger segment of the population become persistently satisfied and sale figures drop. More worryingly is the effect this has on the occasion market. Figure 8.6 shows that with decreased sales of new vehicles, the number of occasions on the market plummets. This is similar to the start of the simulation, but this time new sales do not attract and the market does not recover. Notice that the number of EVs of the occasion market remains high, which might be due to a discrepancy between the relatively high value of these cars and the much lower price that the majority of occasion buyers is willing to spend on a vehicle.

As a consequence of the observed behaviour, Figures 8.7 and 8.8 show that the average ownership duration and vehicle age increase once the number of new car sales takes a dive and the simulation's car fleet is no longer consistently replenished with younger vehicles. These figures show how the model can effortlessly visualize its own limitations, and can help pinpoint the right area to intervene.

From the perspective of the model, the observed behaviour makes sense. As Figure 8.9 shows, the experienced satisfaction with EVs is relatively high for all four needs. As one would expect, they are financially attractive and their environmental benefits are high. On a social level, they are equally satisfying as gasoline vehicles. What they lack in satisfying the agent's need for social conformity, they make up for in feelings of social superiority due to a higher existence satisfaction. For agents that possess the ability to home charge, EVs are also functionally satisfying. This holds for all agents once a nation-wide fast

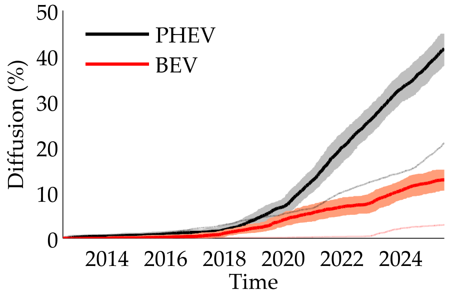


Figure 8.3: Average diffusion among 'new buyers' during the ALL scenario. Standard deviations are added to show variability between runs. The average diffusion process during the BASIC scenario is added for reference (dotted line).

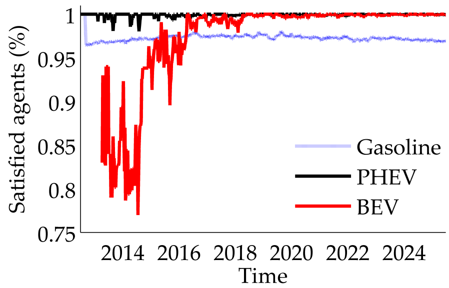


Figure 8.4: Percentage of satisfied agents by fuel technology of their vehicle during the ALL scenario.

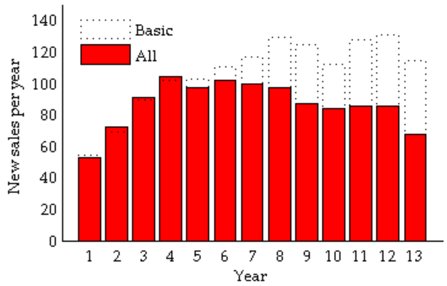


Figure 8.5: Yearly sales of new vehicles during the ALL scenario. For reference, the yearly sale figures of new cars during the BASIC scenario (Figure 6.1) are included.

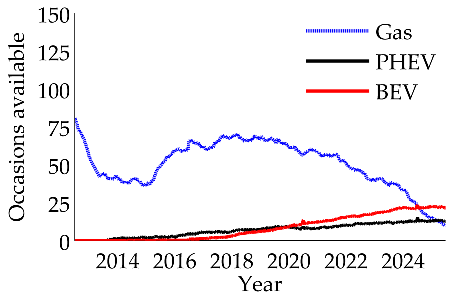


Figure 8.6: Number of vehicles on the occasion market by fuel technology during the ALL scenario.

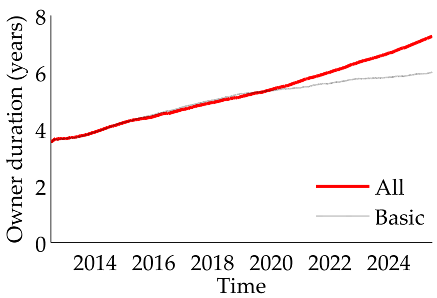


Figure 8.7: Average ownership duration of owned vehicles during the ALL scenario. For reference, the average ownership duration during the BASIC scenario (Figure 6.3a) is included.

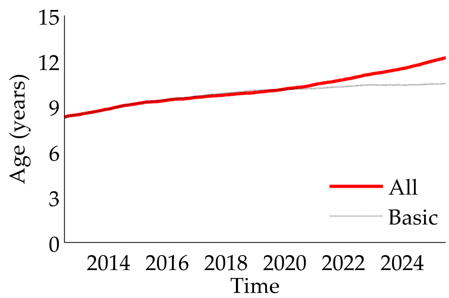
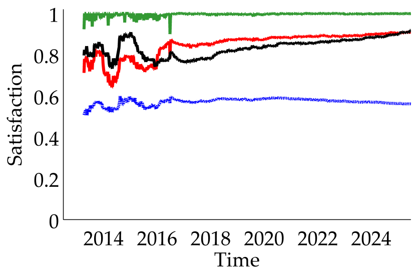
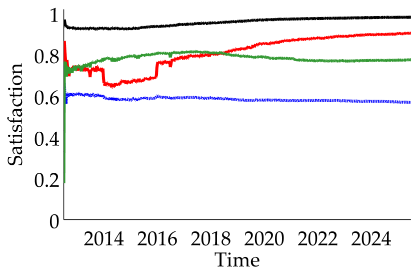


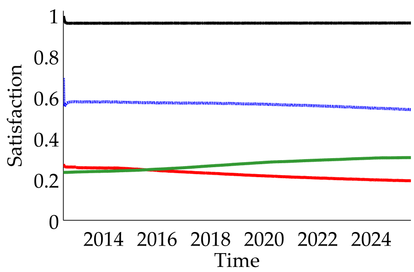
Figure 8.8: Average age of owned vehicles during the ALL scenario. For reference, the average vehicle age during the BASIC scenario (Figure 6.3b) is included.



(a) Battery electric vehicles



(b) Plug-in hybrid electric vehicles



(c) Gasoline vehicles

Figure 8.9: Average experienced satisfaction by fuel technology ownership during the ALL scenario, broken down by need: costs (red), functionality (black), social (blue), environment (green).

charge network is in place and fast charge times have decreased to 5 minutes per charge. A high functionality satisfaction is in line with research indicating that new adopters of EVs experience the ability to charge their vehicle at home as easy, convenient and/or satisfying [32, 38]. At least one survey showed that 85% of new EV owners prefer charging over refuelling after three months time [13]. If agents have a battery at full capacity at the start of each day and they can recharge within a short time frame whenever they need, newer car models no longer provide any functional attraction over continuing to drive one's current vehicle.

One possibility to solve this issue is by including an aspect which was previously deliberately left out of the model to inspect the influence of technological advancements only: the appearance of the car. Cars not only serve functional, social and moral goals, they are also used symbolically to shape an individual's identity [88]. As such, some individuals prefer different and newer car models over continuing to drive an otherwise satisfying vehicle. In the following section, a small adaptation is made to the STECCAR model to observe whether this additional feature is sufficient to stabilize the simulation's behaviour over time.

8.3.2 Including vehicle appearance

The ALL is extended from 676 to 1092 ticks (June 2033). The following measures are added to the scenario in order to prolong the behaviour of the scenario for a longer period of time:

- Gasoline carbon emissions decrease 1% each year

- Percentage of agents with access to home charging increases to 100%
- Percentage of agents with access to work charging increases to 100%
- Probability of encountering a fast charge station increases to 100%
- Battery costs decrease further to € 50,- per kilowatt hour
- The 0% and 14% 'Bijtelling' categories become 1 gCO˙2/km stricter, and the 20% category becomes 2gCO˙2/km stricter every two years.

Additionally, a crude adjustment is made to the STECCAR model. The overall experienced satisfaction of an agent who purchases new vehicles now receives a penalty, depending on the relative newness of the vehicle. After Equation 4.12.3, the following Equation is applied to the agent's satisfaction level:

$$s = s * \frac{20 - Y}{20} \tag{8.3.1}$$

where Y is the number of upgrades that have been put on the market between the release of the agent's current vehicle and the latest upgrade of its current vehicle. The more upgrades have passed, the higher the penalty on the agent's satisfaction level. This scenario is run once to examine its effect on the car market and to inspect whether including a measure of 'vehicle appearance' would improve the STECCAR model's stability over longer periods of time.

Results

Figure 8.10 shows the occasion market during the extended ALL scenario. Sharp fluctuations are observed on a yearly basis, due to the increased interest of agents to purchase upgraded models once they are released. Although the market remains stable for a longer period of time, the number of gasoline occasions reduces to zero towards the end of the scenario. The reason for this is shown in Figures 8.12 and 8.13, which depicts the diffusion process of BEVs and PHEVs among agents who purchase new vehicles and those who lease. In both categories a full diffusion of EVs has taken place by the end of the scenario, stopping the inflow of gasoline vehicles to the occasion market. Due to the adaptation of the STECCAR model, this does not mean that purchases of new vehicles come to a halt. Figure 8.11 shows that the sale figures for new vehicles are actually unrealistically high during the simulation. As a consequence, the total number of vehicles on the occasion market remains high, and there are plenty of electric vehicles for occasion buyers to chose from.

If solely the reduced sales of new vehicles had been the problem in the previous section, than the stability of the simulation should now be repaired. However, Figure 8.11 shows that the number of occasion sales decrease once the number of available gasoline occasions drops. Occasion owners seem uninterested in the available occasion vehicles on the market. Rather than assuming that occasion owners are reluctant to purchase a vehicle with an alternative fuel technology, the reason is sought in the financial dimension. At the end of the scenario, the median prices of BEV and PHEV occasions are € 17.614 and € 15.865 respectively. The latter is a price that only 7.4% of the occasion buyers is willing to spend on a vehicle, while a vehicle with the former price tag would only be bought by 4.2% of the occasion buyer population.

Including a measure of vehicle appearance would therefore not be sufficient to obtain a stable long term simulation. Due to the discrepancy between the

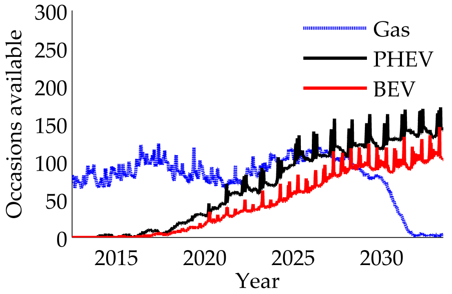


Figure 8.10: Number of vehicles on the occasion market by fuel technology during the EXTENDED ALL scenario.

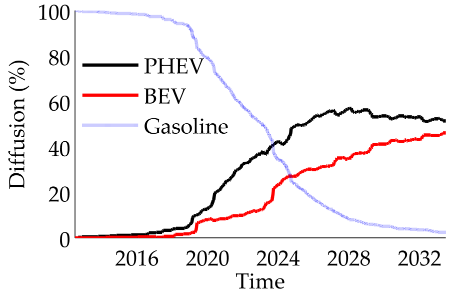


Figure 8.11: Average diffusion among 'new buyers' during the EXTENDED ALL scenario.

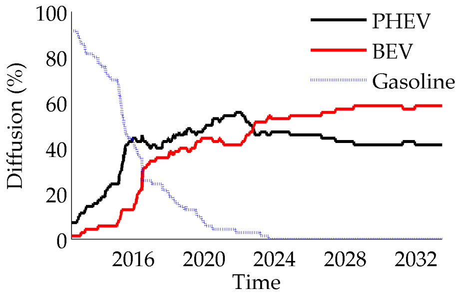


Figure 8.12: Average diffusion among lease owners during the EXTENDED ALL scenario.

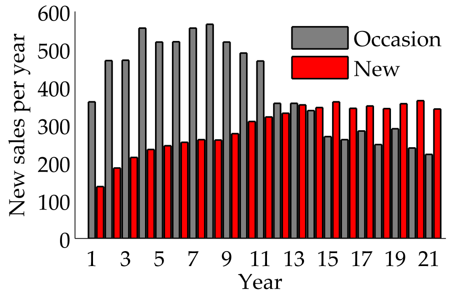


Figure 8.13: Yearly sales of new and occasion vehicles during the EXTENDED ALL scenario.

occasion prices of EVs and the prices that occasion owners are willing to pay, a mismatch arises between offer and demand. In the real world, this problem would be fixed with corrective pricing, perhaps through a stronger depreciation of electric vehicles during the first few years. Another possibility is that proportion wise, more electric vehicles are exported while relatively many gasoline occasions stay in the country.

Setting aside the occasion market mismatch, Figures 8.12 and 8.13 show that the adoption of electric vehicles among those who purchase new vehicles and those who lease, follows the sigmoid diffusion process as proposed by Rogers [79]. The findings suggest that grounded theories of diffusion apply to the new and lease market and that under very favourable conditions, all new vehicles sold by the year 2030 could come with a power plug.

9
Discussion

In Chapter 1, the aims of this research project and the corresponding research questions were introduced. To answer these questions, this chapter reflects upon the insights and results that were obtained through the work in Chapters 2 - 8. Suggestions are made for areas of further research and a concluding section brings this thesis to a close.

9.1 Overview

The most important general findings from exploring the STECCAR model are as follows:

- Applying measures in a specific temporal order may strengthen their influence on the diffusion of electric cars.
- When applied simultaneously, measures may strengthen each other's effect on the diffusion of electric cars.
- Targeting measures at battery-electric vehicles (BEVs) specifically, and not at plug-in hybrid electric vehicles (PHEVs), may increase the number of BEV sales, with larger carbon emission reductions as a result.
- The diffusion of electric cars is a relatively slow process, spanning several decades even under very favourable circumstances.
- More insight into the diffusion process of electric cars in the Netherlands could be obtained by further exploring occasion market dynamics.

9.2 Research questions

Section 1.2 defined two open research questions, each divided into several more specific sub-questions that lay out the path towards deriving an encompassing conclusion. Each research question is separately dealt with in this section, and logically, sub-questions are treated before the overarching research question they belong to.

9.2.1 Feasibility of an agent-based model about electric car diffusion

Research question 1a

Does the Consumat framework provide a suitable cognitive framework to model artificial consumer agents in an agent-based model of the Dutch car market?

In the STECCAR model, lease owners and purchasers of either occasions or new vehicles interact and influence each other, while each of these consumer types perform their own distinct purchasing behaviour and have a specific way of evaluating their needs. An overarching cognitive framework is particularly important in such a case, because it enables a thoughtful definition of where the specifications of the consumer types differ. This in turn benefits comparisons between groups and plausibility of the resulting model.

The Consumat framework showed to be a very flexible solution to this respect. It provided a firm grasp on a theoretically founded but also very intuitive approach, in which small adaptations can be made to better suit one's needs. Examples of these adaptations are the division of the existence need when the nature of the input data made this segmentation desirable. As a consequence, the STECCAR model agents have four needs instead of the conventional three. Additionally, the high financial investment of purchasing a new vehicle seemed to disagree with the ease in which traditional Consumat agents base their consumer behaviour directly upon one of four different decision strategies. Therefore, the notion of Consumat decision strategies has been altered to information seeking strategies in the STECCAR model.

Another notable adjustment to the Consumat approach is the addition of an overarching need for successfully being able to drive a particular distance. This aspect could not simply be included in the agent's functionality need, because in that case, a high social, financial and environmental satisfaction could overrule the agent's need to arrive at the destinations which it desires. However, it is unrealistic to assume that any individual would purchase a car that fails to realize its driving needs on an almost daily basis. Therefore, when modelling consumer evaluations of a product which is as expensive as a personal vehicle, the core functionality of this product must be allowed to overrule the more traditional Consumat needs. This reflects the insights of Maslow that needs are ordered in a specific hierarchy and more fundamental needs must be satisfied before moving on to secondary needs [66].

For all these adaptations, the Consumat framework proved to be very well suited. Extensions to the framework were also effortlessly made, such as including infrastructure that enable the agents' driving behaviour and a car market that regulates vehicle supply.

Besides flexibility, another benefit of the Consumat approach was its foundation in psychological theory. This allowed for an almost direct link between empirically obtained survey data and the instantiation of artificial agents. Although the input data was not specifically gathered for the purposes of creating the STECCAR model but rather for performing statistical analysis, a satisfactory fit was obtained because surveys often focus on attitudes, values and personal characteristics, which are represented as needs, need weights and abilities/personality in the Consumat approach.

Finally, the use of any cognitive framework is invaluable when validating the output of a social simulation. In our case, the Consumat approach made the interpretation of the simulation's results intuitive, because in the absence of reference material on how consumers emotionally respond to changes and developments in the car market, the behaviour of the simulation could still be compared to a subjective sense of how individuals would most likely react. This allowed us to observe the limits of modelling the long-term diffusion of electric cars given the current version of the STECCAR model in which vehicle appearance does not play a role. Furthermore, inspecting the emotional perception and experiences of the agents enables a discussion on whether certain assumptions in the model are sound. This transparency of the model benefits scientific discourse, through which improvements of the model can be made when more empirical findings become available.

From the above considerations, we conclude that the Consumat approach was suitable for the purposes of our research because it provided flexibility and a convenient translation from input data to a structured cognitive framework and it delivered a method to intuitively validate the simulation's output. This is not to say that the Consumat approach itself could not be fundamentally extended or updated with additional insights from psychology, but that is beyond the scope of this thesis.

Research question 1b

Is the data from Bockarjova et al.'s 2012 survey sufficient to initialise artificial consumer agents in an agent-based model of the Dutch car market?

As discussed in the previous section, the input data was particularly well suited for the purposes of this model, which is partly explained by the use of a cognitive framework that is founded in psychological theory. However, the data went further than that and also provided a good insight into the driving behaviour of individuals, such as their preferred moment to refuel and the frequency with which distances are driven. This allowed the instantiation of individually tailored driving experiences upon which the evaluation of the agents' needs is based. Additionally, the survey data also enabled the construction of the three different types of vehicle consumers that are prevalent in the Netherlands. This facilitated the development of a dynamic car market, through which lease owners and consumers of new vehicles determine the supply to the large occasion market. To this end, the data not only met the requirements for instantiating Consumat agents, but specifically enriched the final model with additional information.

As can be expected with a survey that was created for a different purpose than as an application to the agent based modelling domain, certain elements were also missing in the data. Most notable is the absence of how much respondents value the need for conformity. While some questions explicitly targeted the respondent's desire for anti-conformity and superiority, the desire for conformity could not even be implicitly found among less specific questions. For this reason, a Gaussian distribution within the same range as the anti-conformity and superiority values was used to initialise the agents' value for conformity. Another missing aspect is the frequency with which respondents are willing to wait a given amount of time during refuelling or recharging. While the survey provided input on how long respondents are willing to wait at several refuel locations, it did not indicate how often they are willing to undergo this delay. A personal judgement had to made when initialising this aspect. Although the chosen value may therefore differ from reality, adjustments to this parameter within a realistic range did not have a direct effect on the outcome of the simulation's behaviour.

Besides these pronounced missing aspects, the STECCAR model could have benefited from the inclusion of a number of more subtle concepts in the input data. It was for instance unknown what prompts individuals to purchase a new vehicle. Two options were eventually included: agents purchase a new car when their current vehicle is total loss or when the agent's long-term satisfaction is below a predefined threshold. Because this threshold proved to have a strong regulatory effect on the behaviour of the simulation, an empirical initialisation of this aspect could enhance the credibility of the model even further.

Finally, some survey questions would have better fitted the model had they been slightly adjusted. For instance, the values that were used to initialise the agents' need weights represented the respondents' general life values (Q16). Although general values have been shown to influence consumer behaviour, their abstractness allows for individual interpretation [25]. As an example, endorsing the value 'wealth' could mean that an individual does not spend much money on luxury items that devalue quickly in order to increase its wealth, but it could also mean that the individual spends its money on luxury items in order to enjoy wealth to the fullest extent. Rephrasing the question so that the answers represent the respondent's behaviour-specific beliefs would therefore more accurately capture the way that individuals balance their different needs when evaluating personal vehicles.

Ultimately however, any model's strength is found in its abstraction and simplification of reality. The fact that certain questions did not perfectly match the model's requirements should therefore not necessarily be seen as a flaw, as long as a diverse and representative range of agents were instantiated. Keeping this goal in mind, we believe that the rich data set from Bockarjova enabled the instantiation of a sufficiently large and diverse population.

Research question 1c

Can an agent-based model realistically capture the dynamics of the Dutch car market according to Dutch consumer data from recent years?

In Chapter 6, we discussed the validation of the STECCAR model in detail. It showed that many of the simulation's market dynamics, such as sale figures, scrappage age and ownership duration, coincide with current trends in the Netherlands. Therefore we concluded that generally, the model fits the real world data sufficiently well.

However, this chapter also showed that the diffusion of electric cars during the period 2012-2014 is twice as optimistic in the simulation than the actual diffusion in the Netherlands during this same time period. It is important to keep this tendency in mind. Due to the very small sale figures of electric cars more accurate validation was difficult, and we therefore cautioned against using (agent-based) models such as the one constructed here, as factual predictors of future developments.

An aspect which has not been mentioned before, is that the expectations of future utilities as defined in the Consumat approach were not included in the STECCAR model, because of a lack of a sound theory on how to implement this. Therefore, all agents were defined as having a solely reactive nature when evaluating information. This means that for instance they do not make predictions on how particular energy costs are going to rise or fall, or which technological developments may likely take place in upcoming years. As a result, the simulation does not show proactive consumer behaviour, such as the sudden spike in Dutch EV sales at the end of 2013 right before 'bijtelling' exemption was abolished. For the purposes of this model, where the goal is to get better insight into EV diffusion trends rather than obtaining an accurate prediction of exact EV sales, this simplification is not a problem. However, if one would like to extend the model to more accurately fit real world data, a sound theory and input data on how individuals incorporate estimations of several future policies and developments into their present-day vehicle purchases would be crucial.

Finally, very crude assumptions were incorporated to model the effect of the Dutch export market. Under basic circumstances, these assumptions were sufficient to obtain a stable occasion market that reflects realistic occasion numbers. However, as Section 8.3 showed, once the diffusion of electric vehicles took off these assumptions proved to be too simplistic and inflexible to handle the sudden discrepancy between supply and demand.

We conclude that the context in which the diffusion of electric vehicles takes place is well validated, but that the time frame of the diffusion process lacks important data and experience to be equally well legitimized. Additionally, to also realistically capture the vehicle's market behaviour under radically shifted circumstances, more detailed assumptions have to be made when modelling the import and export dynamics of the occasion market.

Research question 1

Can we create an agent-based model using which the diffusion of electric vehicles in the Netherlands can be explored?

In summary, the answers to research questions 1a, 1b and 1c are overall affirmative. Not only do we believe that we succeeded in creating a viable agent-based model to study the diffusion of EVs, the resulting simulation is also fast enough for practical purposes. A run of the 676 ticks long BASIC scenario takes 3 minutes and 28 seconds. On average, this results in 3.25 ticks per second. Considering that each tick, almost 1800 agents must drive, evaluate, interact and compare vehicles, this is a satisfactory result. A significant part of this computational efficiency was obtained by using the exponential weighted moving average and a corresponding moving variance to represent the agent's beliefs. Limiting the size of the agent's social network has undoubtedly also played a part.

Because agents continuously learn about new car models and thereby obtain more information to discuss and compare, the speed of the simulation somewhat slows down during the course of a run. If desired, additional speed reductions could be achieved by reducing the number of vehicles that the agents know over time. Instead of always comparing each car model that is known and within financial reach, agents would thus only consider cars that they have encountered frequently or recently. Especially for occasion owners this could result in a significant speed optimisation.

Several common programming techniques have been applied to structure the relatively large model. Inheritance ensures that new buyers, occasion buyers and lease owners share basic characteristics but differ in important aspects. Similarly, all fuel technologies share the same underlying foundation but each provide a specific driving experience to the user. Static methods enable shared vehicle infrastructure to all agents, such as the car market, recharge stations, a mechanic and the media that publishes advertisements. To maintain readability and reduce the potential for errors, enum types [4] are used wherever appropriate.

To make the exploration of scenarios less cumbersome, additional methods were added to parse scenario files. Currently, the scenario parser can handle (a) the introduction of new car models, and adjustments in (b) purchase power, (c) yearly vehicle emission updates, (d) charge probabilities at home, work and along the road, (e) refuel time and costs at gasoline stations, slow-, and fast chargers, (f) maintenance costs of EVs, (g) battery prices and lifetime duration and (h) taxes and 'bijtelling categories'. For each aspect, the moment and duration of the adjustment can be specified. A simple GUI allows the user to select one of multiple scenarios to use.

Finally, an elaborate data writer was added to further aid exploration of the simulation's results. If enabled, this writer can currently write the output of 116 different aspects to distinct *comma separated value* (csv) files, including information on the diffusion, perception and experience of different fuel technologies, as well as owner characteristics and market dynamics. Matlab scripts were developed to automatically retrieve, parse and visualize this output.

9.2.2 Payoffs of the steccar model for policy

Research question 2a

Which measures are most effective in stimulating the initial diffusion of electric cars?

Chapter 7 showed that adjustments in 'bijtelling' policy have an important regulatory effect on the initial diffusion of electric vehicles. By favouring both BEVs and PHEVs, current trends will persist where most lease owners opt for the functionally save plug-in hybrid vehicle. However, by consistently favouring BEVs over PHEVs, the first type of fuel technology can gain popularity at the expense of PHEVs. This is in line with observations from the diffusion of EVs in Norway, as were described in Section 2.3. Interestingly, the simulation showed that by favouring BEVs over PHEVs, the government could obtain a greater reduction in carbon emissions at lower financial costs. Over the course of a decade, favouring either BEVs or both types of EVs in the 'bijtelling' policy showed to have no effect on the total diffusion of electric vehicles. This is because the total pool of lease owners is relatively small compared to the total population, thereby creating competition between the two types of alternative fuel technology as long as at least one of them is favourable over gasoline cars in the long run.

Measures that could potentially increase the total number of EV owners were purchase subsidies and a further reduction of battery costs. Both measures make electric vehicles available to consumers who shop in lower price classes, and therefore have not had access to EVs so far. Again, the simulation showed that purchase subsidies that favour both types of EVs almost exclusively benefit the adoption of PHEVs, while subsidies specifically targeted at BEVs can increase the market segment of this type of fuel technology only. If no further measures are taken, then a reduction in battery costs also mostly benefits PHEVs. An increased range does not offset the remaining negative aspects of BEVs in comparison to other fuel technologies.

Another important measure to increase the popularity of BEVs was a quick realization of a nation-wide fast charge network. The simulation showed that achieving this infrastructure within two years time instead of eleven, observably increased the market share of BEVs because of a higher perceived and experienced utility satisfaction. This is interesting because it shows that the time frame in which developments take place is important; obtaining desired results is not only about the specific measure that is taken, but also about appropriate timing.

Interestingly, under most single-measure conditions, the number of BEV sales hardly took off until 2023, when a new car model was introduced for slightly less than €20,000 and a nation-wide fast charge network was close to being realized. It seems that both of these measures are crucial in aiding the diffusion of BEVs. Simply introducing cheaper BEVs before a reliable fast charge network was in place, however, did not provide the same results. This indicates that the effectiveness of measures may be strengthened if they are applied in a specific temporal order.

To conclude, the most effective measure to increase the BEV's market segment was reinstating 'bijtelling' exemption for BEVs, but not for PHEVs, resulting in an additional 1.87% of the population owning a BEV by the end of the scenario. A reduction in battery prices had the most effect on PHEV sales and led to an increased market segment of 6.08%. While the latter is more impressive in absolute numbers, in relative terms the increased adoption of BEVs was higher because its market segment is very small under basic conditions. Overall, no single measure had a determining effect in making BEVs more favourable than PHEVs. This reflects the long and turbulent history of the BEV as described in Section 2.2. Here we saw that any single development in favour of the BEV has so far not been enough to push its diffusion further.

Research question 2b

Does the simultaneous effect of some combination of measures have a stronger influence on the diffusion of electric cars, than the summation of the effects when these measures are applied separately?

The results from the experiments mentioned above indicated that a quick development of a reliable fast charge network could be crucial in aiding the diffusion of electric vehicles further. The scenarios in Section 8.2 therefore explored the effect of introducing other measures given the assumption that a charge network was quickly built. We looked specifically at increasing gasoline prices and decreasing fast charge prices, measures that had no observable effect when applied by themselves. The simulation showed that under these conditions, adjusting energy prices suddenly stimulated the diffusion of BEVs further. In other words, increasing gasoline excise duties and providing fast charge subsidies only showed to have an effect if a reliable fast charge network was in place. This entails that an affirmative answer to the above research question is found.

In Section 8.3 we explored the effect of introducing all previously explored measures simultaneously. If all these measures were applied in favour of BEVs only, the simulation showed that BEVs could become more popular than PHEVs by 2017. At the end of the scenario, the market share of BEVs had increased 650%: from 2.08% in the BASIC scenrio, to 15.57%. This increase is much higher than the summation of the results of all single measures applied separately, and again suggests that a well considered team effort is crucial for the BEV to become an important player in the Dutch car market.

Research question 2c

What is the relation between the diffusion of electric cars and the reduction in carbon emissions of the car fleet?

The only scenario that resulted in a noticeable reduction of carbon emissions is reinstating 'bijtelling' exemption for BEVs only, while simultaneously increasing the 'bijtelling' for PHEVs in comparison to 2014. Although this measure did not increase the number of EV owners in total, it observably shifted the preferences of EV owners from PHEVs to BEVs. This shift had a stronger effect on reducing emission outputs than measures which increased the total number of PHEV owners, such as purchase subsidies for all EVs. In other words, the simulation's output suggests that large numbers of PHEV owners do not provide the same carbon emission reduction benefits as a smaller absolute increase in BEV drivers. Perhaps this effect can be mitigated by increasing gasoline prices, thereby stimulating PHEV owners to recharge more.

Rudimentary visual inspection of the results also hints at another reason why these scenarios resulted in these findings. While at the end of the scenario that implemented 'bijtelling' exemption for all EVs, 63% of the PHEV owners possessed the ability to use a home charger, 68% of the PHEV owners had this ability at the end of the 'bijtelling' exemption for BEVs only scenario. Similarly for work charge facilities, 54% had the ability to charge at work in the first scenario, while 59% of PHEV owners could do so in the latter. Perhaps the first scenario lures more agents to purchase a PHEV because of financial benefits, even though they do not have the ability to put this fuel technology to good use.

Research question 2d

Given favourable circumstances, within what time frame is full diffusion of electric cars possible?

An accurate answer to this research question is not as trivial as originally thought. Validation of the time frame of the diffusion process proved difficult, and a further extension of the model is crucial in order to maintain a realistic occasion market once the diffusion of EVs progresses. Keeping in mind that crude validation showed a more optimistic tendency in the STECCAR model than real world data suggests, the simulation's output shows that under very optimistic circumstances, all newly bought vehicles could come with a power plug by 2030.

More important however, is that all scenarios indicate that the diffusion of EVs is a relatively slow process. Because of high initial financial investments and a large occasion market, the diffusion of EVs cannot be compared to other recent innovations such as the diffusion of smartphones or MacBooks, even if all measures and technological advancements are in its favour.

Research question 2e

Will a quick diffusion of electric cars among newly bought vehicles resonate to the occasion market, resulting in a quick adoption of electric vehicles among occasion buyers?

Section 8.3 showed that a very quick diffusion of electric cars among newly bought personal vehicles resulted in unconventional behaviour on the occasion market. The large influx of relatively young and therefore expensive occasions and the slow disappearance of older, cheaper gasoline vehicles brought the demand on the occasion market to a halt.

Time constraints prevented further experimentation, but in the absence of additional data, we assume that the behaviour observed in the simulation would not occur in the real world. First of all, if there really was a large influx of young and expensive occasions for which there is no demand, depreciation of these cars would rise. Secondly, in the absence of interested EV buyers on the occasion market, one expects that a higher export of EVs and a higher import of older gasoline vehicles would take place. Both dynamics are not captured by the assumptions that underlie the occasion market dynamics of the current STECCAR model.

It would therefore be useful to perform additional experiments specifically targeted at the occasion market dynamics, and to alter the underlying market assumptions to see if similar behaviour would still persist. Whether done so using the STECCAR model or some other scientific approach, gaining further insight into the relation between the diffusion of EVs and occasion market dynamics is a fruitful area of research.

Research question 2

What can we learn from an agent-based model about the diffusion of electric cars in the Netherlands?

As the history of electric vehicles already showed, the diffusion of this fuel technology has long been problematic and dependent on multiple interactive factors. From the answers to the research questions above, we conclude that agents-based models, such as the STECCAR model developed for this thesis, can provide crucial insight into the complex elements that are at play. By comparing different scenarios, certain measures showed to be more useful in stimulating the total adoption of EVs, while others mostly regulated the ratio between adopted BEVs and PHEVs. Additionally, results showed that measures can be strengthened in the right combination with other measures, or when applied in a specific temporal order.

Since our aim was only to discover whether a fruitful combination of measures existed, we did not explore more than the tiniest fraction of combinations that are possible. Our findings therefore only hint at the potential of our model, and any of its kind, to find complex relations between multiple measures. Where statistical models can quickly pinpoint bottlenecks in the current uptake of BEVs by the average consumer, an agent-based model such as the STECCAR model can intuitively help discover in which combinations and in what temporal order these constraints should be dealt with.

On a more practical note, the complexity of the diffusion process and the long time frame that all scenarios hint at, show that to get a grip on the diffusion process a vision is required that looks further than the upcoming four or even ten years. Both the combinations of several measures and the temporal order of measures have a long term effect, and therefore policy is required that looks many decades ahead and plans accordingly right from the start. The Dutch government's regulations in previous years have given the PHEV a head start over BEVs. However, behaviour of the STECCAR model suggest that with small changes that are presumably not more expensive to the government, a different path with a higher reduction in carbon emissions could be reached.

9.3 Further work

As with any research, but especially with exploratory work as performed in this thesis, much room remains for further work. This section describes some suggestions for improvements to the STECCAR model, further exploration of the created simulation, and extensions that could lead to additional insights.

Improvements

As mentioned in Section 9.2, all agents have so far been instantiated with a reactive nature when evaluating information. More accurate results, and therefore better validation, would be obtained if a future version of the model includes a solid theory on how proactive consumer behaviour influences decision making. For this, more elaborate input data is crucial.

Another interesting improvement could come from having an empirically founded understanding of how exactly perceptions of different fuel technologies change once consumers switch to an electric vehicle. In line with research data, the simulation's output showed an increased experienced functionality satisfaction with battery electric vehicles (BEVs) compared to the expected satisfaction before adopting an EV (Figures 6.9a and 8.9a) [13]. However, this is a result of generic modelling assumptions and not of a thoroughly embedded theory on how EV adoption changes consumer vehicle perception. Consequently, other research findings such as EV adopters being less satisfied with their level of environmental impact than they presumed, are not identified in the simulation's output. Along similar lines, another missing factor is knowledge on how driving a plug-in hybrid electric vehicle (PHEV) changes a driver's perception of BEVs. Under what circumstances does owning a PHEV influence expected BEV satisfaction in a postive or negative way?

A recent study on the diffusion of EVs in an agent-based model shows that regression analysis can validate the intention of agents to purchase an electric vehicle [97]. This was beyond the scope of our research, but the used input data contains information to allow such an analysis for the STECCAR model as well. To extend on this, it could be useful to re-sample the survey to validate how individual preferences change over time. This does not only hold for the STECCAR model, but would add validity to any agent-based model that tries to accurately gain insight into consumer decision-making processes. Having more data to validate the model would perhaps also allow for a more quantitative analysis of the model's fit. The field of agent-based modelling is still young, but the moment that analysing an entire ABM's goodness of fit becomes practical and a standard procedure, might also be the time that this research approach becomes generally accepted as a tool to draw conclusions from complex data. Especially now that data storage increases at an untraceable rate, further maturity of the field of ABMs could help mankind with untangling bulks of information through new kinds of analytic tools.

Exploration

In our pursuit to uncover as much of the potential of the STECCAR model as possible, many options have not been explored in depth. While much focus was on the effect of individual measures, the number of combinations of measures that were explored can be counted on a single hand. Assuming that a Dutch nation-wide fast charge network will be realized within a couple of years, further exploration of measures could build upon this. Especially the simultaneous effect of 'bijtelling' exemption in combination with a reliable charging infrastructure could lead to interesting results.

Many other single measures have so far not been explored. Possible options are increasing the number of home charge and work charge stations. Or lower-ing the costs of home charge as a result of privately owned solar panels. Also, the effects of increasing the battery's life time or altering general road taxes have so far not been systematically documented.

From a different perspective, more in depth profiling of vehicle owners could be performed. How do early EV adopters differ in ambition levels, uncertainty tolerance and life values ('needs weights') from gasoline drivers? How much and exactly what kind of influence does the agent's social network have on the adoption of an EV? To what extent does the driving behaviour, including yearly kilometrage, travel distance frequency and refuel moments, differ among owners of different fuel technologies? After exploring these questions, the same factors could be adjusted to determine their effect on the diffusion of EVs. This would lead to questions such as 'Does increasing the value that agents place on their environmental need lead to a significant increase in EV sales?' Again, numerous combinations can be made with these adjustments.

Extensions

As Section 8.3 showed, adding a need for 'vehicle appearance' is a crucial extension to maintain the STECCAR model's validity once the diffusion of EVs takes off. A very crude preference for new vehicles was added to exemplify this need, but a future version of the model would do well with a more sensible approach that is calibrated on respondents' input data. Preferably, it should also be taken into account how individuals perceive the appearance of EVs in comparison with gasoline vehicles, since literature shows that negative EV stereotypes are still prevalent [14].

To reduce complexity, no fixed geographical network of fast charge stations was constructed. Agents only possess a probability of encountering a charging station during each ride. Adding such a fixed network would call for additional assumptions (to which exact location are agents driving?) and since expectations are that such a network will soon be realized in the Netherlands, priorities lay elsewhere. However, this does not mean that extending the model with a geographical charging network could not be fruitful, especially if the model is being applied to other countries.

An addition that would particularly increase the model's forecasting validity is including multiple-car households. The input data only provided information on the driving patterns of the respondent's most prominent car, but allowing for additional cars per household would introduce new dynamics that could significantly influence the diffusion process. While many single-car owners may currently have no use for an EV, households with multiple cars could potentially benefit on all aspects by diversifying their personal car fleet.

Finally, multiple developments are taking place in the Dutch car market that may also influence the diffusion of EVs. For instance, private lease is becoming more common and would eliminate the high initial investment when adopting an EV. Also, car manufacturers such as Renault S.A. offer their BEVs without a battery, these must be obtained through a separate lease contract. On top of reducing the initial price of the vehicle, this also reduces uncertainty over battery life times and might make BEVs more attractive on the occasion market. Finally, as was mentioned in Section 2.3, some lease companies provide their BEV lessees with a gasoline vehicle for a few weeks each year. This arrangement could remove hesitations to adopt a new fuel technology that infrequently does not meet the driver's needs.

9.4 Reflection on agent-based models

The aim of this research project was two-fold. On the one hand, we were interested in what an agent-based model (ABM) could show about the possible diffusion of electric vehicles in the Netherlands. On the other hand, this work was exploratory in the sense that we were interested in how a relatively large ABM could be given shape and what issues might arise. From this second challenge, several recommendations and insights have been gained which may help the field of ABMs further.

First of all, the use of a sound cognitive framework seems important for multiple reasons. Psychologically founded frameworks often allow for a direct mapping between input data obtained from surveys and the components of the agents' cognitive framework. This is the case because surveys often focus on attitudes, values and personal characteristics, which are also aspects that a typical cognitive framework needs to instantiate. Consequently, such a framework also facilitates an intuitive mapping from simulation results to hypotheses that could be tested and implemented in the real world. In our case, the framework aided our understanding of the simulation's behaviour, by showing how the need evaluations of agents are affected by different measures. A final benefit is that a framework that combines interdisciplinary insights, aids scientific discourse by making the underlying assumptions of a model more transparent.

To improve the likelihood that the behaviour of an agent-based model has a good fit to reality, it is recommended to use input data that is specifically tailored to the purposes of the ABM and the cognitive framework that is chosen. If such a procedure is impractical, our research showed that an external survey which serves similar outcome purposes can come a long way. In our case, the applied questionnaire was originally designed to find restrictions in the diffusion process of electric cars in the Netherlands, using statistical methods. We saw that even though this survey had no prior link to ABMs, many ABM aspects could easily be instantiated using the data. However, suboptimal modelling decisions also had to be made, for instance by applying general life values to the Consumat need weights, where behaviour-specific beliefs would have likely provided a more valid input.

Another important aspect for the field of ABMs is validating the resulting simulation. Typically, an ABM is initialised on a micro-level (the agent) using empirically obtained individual data, and then validated on an emerging macro-level (the society) using a different set of empirically obtained data. Ideally, validation is performed using quantitative methods such as regression analysis. When doing so, it is also important to define what the 'basic' condition of the simulation is. From this basic condition, deviations can be made, similar to any scientific experiment that uses control groups.

Depending on the field to which the ABM is applied, it is important to pinpoint which macro-level data must be available to validate the simulation's emerging behaviour. In the case of car markets, reliable data on yearly sale figures, scrappage rates and ownership duration is readily available. However, in other domains, macro-level data may be practically absent. This was encountered in our research when validating the actual diffusion process of electric vehicles. In this case, the accuracy of the model could be improved by validating the micro-level behaviour of the model, for instance by re-sampling the input survey after several months using the same respondents. By tracking how real-world individual preferences change, validation can be continuously performed, even in the absence of macro-level data.

Finally, one of the main strengths of ABMs should be their ability to make complex relations easier to understand for human operators. It is therefore important to construct an ABM that is user-friendly and does not have a steep learning curve. Because the STECCAR model is relatively complex and allows for the adjustment of many different parameters, scenario files were constructed which allow the user to predefine and store specific conditions for later reference, thereby increasing the model's ease of use. Although our focus was more on results than on appearance, attractive visualisations can help in a later stage to make an ABM more compelling to the user.

9.5 Conclusion

The history of the electric vehicle has so far been turbulent without satisfactory results. No single development by itself has been able to push its diffusion further. To gain insight into to the complex setting in which the current diffusion of EVs is taking place, we took a thorough approach by artificially simulating its current context in an empirically calibrated social simulation.

Although the resulting agent-based model is best described as exploratory work rather than a final version to guide actual policy, it has shown the importance of such a model in gaining insight into how policies and technological advancements of EVs influence each other over a prolonged period of time. Along the way, the influence of multiple measures on the diffusion of EVs has been described, and observations were made on how these measures interact. Additionally, the agent-perspective allowed us to understand why individual consumers responded to macro-level developments the way they did.

We conclude that agent-based modelling is an important approach in making the complex world in which the diffusion of EVs is taking place comprehensible enough for humans to interpret. Because, as someone allegedly said over a century ago:

"Nothing is particularly hard if you divide it into small jobs."

— Henry Ford

Appendices

A Questionnaire

The following is an English translation of a subset of the Dutch survey questions which were used to initialise the STECCAR simulation [9]. Italic sentences are added for clarification.

Q1 **How many cars are in your household in total (including lease cars)?**

- no cars
- 1 car
- 2 cars
- 3 or more cars

Q2 **Please enter information about your car(s) in the table:**
(*Number of rows depends on answer to Q1*)

	The brand of the car is:	The model of the car is:	The build year of the car is	Is it a lease or a private vehicle?
the first car				
the second car				
the third car				

Q3 **In which car do you drive the most?**
(*Number of items depends on answer to Q1*)

- The first car
- The second car
- The third car

The following questions refer to the car in which the respondent drives the most.

Q4 **Since when do you own/lease your current car?**
(if unknown, make a best possible approximation)

Q5 **Which fuel technology does your car use?**

- Gasoline
- Diesel
- LPG
- Hybrid

- ○ Natural gas
- ○ Electricity
- ○ Other, namely ...

Q6 **How many kilometres on average are driven with this vehicle each year?**

- ○ less than 5.000 kilometres
- ○ 5.000 to 10.000 kilometres
- ○ 10.000 to 15.000 kilometres
- ○ 15.000 to 20.000 kilometres
- ○ 20.000 to 25.000 kilometres
- ○ 25.000 to 30.000 kilometres
- ○ 30.000 to 35.000 kilometres
- ○ 35.000 to 40.000 kilometres
- ○ 40.000 to 45.000 kilometres
- ○ 45.000 to 50.000 kilometres
- ○ More than 50.000 kilometres, namely ...

Q7 **Please indicate approximately how many days occur when the following distances are traveled in total with your car:**

	once or a few times **per week**	once or a few times **per month**	once or a few times **per year**	(almost) never
0 km (car is not being used)	○	○	○	○
1 to 10 km in one day	○	○	○	○
10 to 50 km in one day	○	○	○	○
50 to 100 km in one day	○	○	○	○
100 to 200 km in one day	○	○	○	○
200 to 500 km in one day	○	○	○	○
More than 500 km in one day	○	○	○	○

Q8 **In most cases you refuel a car when...**

- ○ the tank is half empty
- ○ the tank is moderately empty (but not yet ”red”/does not give a warning)
- ○ the tank is almost empty (it is ”red”/gives a warning)

Q9 **To which of the following matters do you have access (through ownership or rental) at your house?**
You may check multiple items.

- ☐ Garage
- ☐ Carport
- ☐ Driveway
- ☐ Private parking place
- ☐ None of the above

Q10 **When you buy an automobile, will you most likely purchase a new vehicle or a used one (occasion)?**

- ○ new
- ○ used/occasion

Q11 **How much do you expect to spend on the purchase of this vehicle?**
(i.e. the purchase price without any trade-in)
(*Asked if answer to Q10 is 'new'*)

- ○ Up to € 10.000
- ○ € 10.000 to € 15.000
- ○ € 15.000 to € 20.000
- ○ € 20.000 to € 25.000
- ○ € 25.000 to € 30.000
- ○ € 30.000 to € 35.000
- ○ € 35.000 to € 40.000
- ○ € 40.000 to € 45.000
- ○ € 45.000 to € 50.000
- ○ More than € 50.000

Q12 **How much do you expect to spend on the purchase of this vehicle?**
(i.e. the purchase price without any trade-in)
(*Asked if answer to Q10 is 'used/occasion'*)

- ○ Up to € 5.000
- ○ € 5.000 to € 7.500
- ○ € 7.500 to € 10.000
- ○ € 10.000 to € 12.500
- ○ € 12.500 to € 15.000
- ○ € 15.000 to € 17.500
- ○ € 17.500 to € 20.000
- ○ € 20.000 to € 22.500
- ○ € 22.500 to € 25.000
- ○ More than € 25.000

Q13 **Could you indicate for each of the following statements to which extent you agree or disagree with them?**
(*Using a 1:6 Likert scale ranging from 'Completely disagree' to 'Completely agree'*)

1 I like to own an innovative product that discerns me from others who do not own this product yet.

2 I like to use innovative products that impress other people.

3 I want to outdo others by purchasing innovative products which they do not posses yet.

Q14 **Please indicate to which extent you agree with the following statements about your knowledge on alternative car technologies (such as fuel cell, electric or hybrid cars)**
(*Using a 1:6 Likert scale ranging from 'Completely disagree' to 'Completely agree'*)

1 I have knowledge of alternative car technologies.

2 I know which potential benefits and drawbacks alternative car technologies have in comparison to gasoline cars.

3 I can explain which differences there are between alternative car technologies and gasoline cars to others (for instance, in environmental impact and functionality)

Q15 **Imagine you are contemplating purchasing a new car. Which of the following descriptions suits you best?**

- I am someone who keeps an eye out for new technological developments and who **dares to take risks** by being the first to try out and purchase innovative cars.
- I am someone who **sees the potential benefits** of an innovative car and who wants to be one of the first to use and profit from that.
- I am someone who likes innovative cars but who is also **pragmatic**. I want to take my time to consider all aspects and to become convinced of the benefits that an innovative car provides. I base my decision (mostly) on the recommendations of existing users.
- I am someone who is not thrilled about innovations and who is rather safe than sorry. It only becomes safe to purchase an innovative car once it has been on the market for some time and has **obvious benefits**.
- I am someone who is **traditional** and who has little affinity with innovative cars; they thoroughly need to prove themselves. I do not like change and will only buy a new type of car when an existing model is no longer produced.

Q16 **Can you indicate how important each of these values is as a guidance in your life?**
(*Using a 1:9 Likert scale, where 1 represents 'goes against my principles' and 2:9 range from 'unimportant' to 'important'*)

1 EQUALITY: equal opportunities for everyone
2 POWER: control over other people, dominance
3 PLEASURE: enjoyment, fulfillment of desires
4 WEALTH: material possessions, money
5 AUTHORITY: the right to lead or delegate
6 SOCIAL JUSTICE: restoration of injustice, care of the weak
7 ENJOYMENT OF LIFE: of food, sex, leisure etc.
8 PROTECTION OF THE ENVIRONMENT: maintenance of environmental quality and nature
9 PREVENTION OF POLLUTION: protecting natural resources
10 AMBITIOUS: hardworking, aspiring, striving

Q17 **The use of petrol cars (such as diesel or gasoline) can have several negative consequences. In general, how severe do you perceive the following potential negative consequences of petrol cars?**
(*Using a 1:6 Likert scale ranging from 'Not at all severe' to 'Very severe'*)

1 Poor air quality in residential areas due to traffic.
2 Pollution due to traffic.
3 Climate change which is accelerated by carbon gas emissions from traffic.

Q18 **In general, how likely do you think it is that your family will be negatively affected by the following problems which are caused by the use of petrol cars?**
(*Using a 1:6 Likert scale ranging from 'Very unlikely, will definitely not happen' to 'Very likely, will definitely happen'*)

1 Poor air quality in residential areas due to traffic.
2 Pollution due to traffic.
3 Climate change which is accelerated by carbon gas emissions from traffic.

Q19 **Could you indicate how long the charging of the battery of an electric car may maximally last for you?**

	up to 15 min	up to 30 min	up to 1 hour	up to 4 hours	up to 8 hours	up to 12 hours	N/A
Home	○	○	○	○	○	○	○
Work	○	○	○	○	○	○	○
Along the highway	○	○	○	○	○	○	○

Q20 **What is the minimum range of an electric car that is acceptable to you?**

Q21 **What is your year of birth?**

Q22 **What is your postal code?**

Q23 **What is your joint annual gross household income?**

- ○ less than € 15.000
- ○ € 15.001 to € 20.000
- ○ € 20.001 to € 25.000
- ○ € 25.001 to € 30.000
- ○ € 30.001 to € 40.000
- ○ € 40.001 to € 50.000
- ○ € 50.001 to € 60.000
- ○ € 60.001 to € 70.000
- ○ € 70.001 to € 95.000
- ○ more than € 95.000
- ○ unknown / will not say

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