Utrecht University

Agent-Based Modelling:

How climate policies influence population dynamics

Master thesis

Artificial Intelligence

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Abbreviations

Abbr.	Explanation	Uitleg
MRB	Motor vehicle tax	Motorrijtuigenbelasting
BPM	Taxation of passenger cars and motorcycles	Belasting van Personenauto's en Motorrijwielen
ABM	Agent-based models	Agent gebaseerde modellen
MAS	Multi-agent systems	Multi-agent systems
ICEV	Internal Combustion Engine Vehicle	Verbrandingsmotor
EV	Electric Vehicle	Electrisch voertuig
TCO	Total Cost of Ownership	Totale eigendomskosten
BEV	Battery Electric Vehicle	Volledig electrische auto
KIM	Netherlands Institute for Transport Policy Analysis	Kennisinstituut voor Mobiliteitsbeleid
BOVAG	Bond of car traders and Garage owners	Bond van Auto(mobiel)handelaren en Garagehouders
CIO	Chief Information Officer	Chief Information Officer
ANWB	Royal Dutch Touring Club	Algemene Nederlandse Wielrijdersbond
RVO	Netherlands Enterprise Agency	Rijksdienst voor Ondernemend Nederland
LISS	Longitudinal Internet Studies for the Social sciences	Longitudinal Internet Studies for the Social sciences
OVIN	Investigation Displacements in the Netherlands	Onderzoek Verplaatsing in Nederland
BDI	Beliefs Desires and Intentions	Overtuigingen Verlangens en intenties
ODD	Overview Design concepts, and Details	Overzicht ontwerpconcepten en details
TCO	Total Cost of Ownership	Totale eigendomskosten
I&W	Ministry of Infrastructure and Water Works	Ministerie van Infrastructuur en Waterstaat
ABSS	Agent-based Social Simulations	Agent-gebaseerde sociale systemen
MIA	Environmental Investment Allowance	Milieu-investeringsaftrek
KEV	Climate and Energy Outlook	Klimaat- en Energieverkenning
CBS	Statistics Netherlands	Centraal Bureau voor de Statistiek
GUI	Graphical User Interface	Grafische gebruikersinterface
VER	Association of electric drivers	Vereniging Elektrische Rijders

Abstract

Climate change is one of the most important global issues the world is facing today. Many governments, including the Dutch government, have agreed to take measures in order to reduce carbon emission and reverse climate change. One of the measures taken by the Dutch government aims to decrease the amount of fossil fuel transportation by encouraging the purchase of battery-only electric vehicles (BEV). By implementing policies, which target different segments of the population, policy-makers try to encourage the population to make the switch from conventional internal combustion engine vehicles (ICEVs) to battery-only electric vehicles (BEVs). Before policies can be introduced, policy-makers want to know whether their targeted policies can be implemented in a cost efficient way. With our research we introduce an Agent-Based Model (ABM) in which the dynamic effects of policies can be observed. The model is created using real world data. The agents in our model behave according to the expectations of policy-makers and other theoretical assumptions. The agent population is subdivided into segments. The effect of the target policies on the different segments is analysed.

Our model allows the users to influence the behaviour of agents by the introduction of target policies, enabling users to observe the effect of target policies on different population segments. Afterwards, we try to assess whether our model can aid policy-makers in determining how cost-effective their policies are. We evaluate the usefulness of our model by letting policy makers validate multiple simulated scenarios. Resulting from our evaluation we are able to show that our model is an easily accessible tool for policy makers, allowing them to test their assumptions, and observe the effects of their policies on the dynamics of the simulation. The behaviour of the simulation can be easily explained and adjusted, allowing policy-makers to observe different hypothetical future scenarios.

From the construction and validation of the Agent-Based Segmentation Model, we are able to generalise our findings and answer our main research goal: how can population segmentation be applied in a useful way within Agent-Based Modelling (ABM). We devise a guideline for the integration of segmentations withing Agent-Based Models as well as how to evaluate the usefulness of such models.

Nederlandse samenvatting

Klimaatverandering is momenteel een groot en belangrijk mondiaal probleem. Veel overheden, waaronder de Nederlandse, hebben afgesproken maatregelen te nemen om de CO2-uitstoot terug te dringen om klimaatverandering tegen te gaan. Een van de maatregelen van de Nederlandse overheid is gericht op het verminderen van het gebruik van voertuigen die gebruik maken van fossiele brandstoffen door de aankoop van elektrische voertuigen op batterijen (BEV) aan te moedigen. Door beleid te implementeren dat gericht is op verschillende segmenten van de bevolking, proberen beleidsmakers de bevolking aan te moedigen de overstap te maken van conventionele voertuigen die gebruik maken van een verbrandingsmotor (ICEV) naar volledig elektrische voertuigen (BEV's). Voordat beleid kan worden ingevoerd, willen beleidsmakers weten of hun beleid op een kosteneffectieve manier kan worden geïmplementeerd. Om beleidsmakers te helpen bij het bepalen van de kosteneffectiviteit van hun beleid, introduceren we een Agent-Based Model (ABM) waarin de dynamische effecten van beleid kunnen worden waargenomen. Het model is gemaakt door gebruik te maken van data vanuit het Ministerie van Infrastructuur en Waterstaat (IenW). De agenten in ons model gedragen zich volgens de verwachtingen van beleidsmakers en andere theoretische aannames. De agentpopulatie is onderverdeeld in segmenten. We analyseren het effect van het doelgerichte beleid op de verschillende segmenten.

Ons model stelt de gebruikers in staat het gedrag van agenten te beïnvloeden doormiddel van de schuifregelaars in de GUI. Hierdoor kunnen gebruikers het effect van doelbeleid op verschillende bevolkingssegmenten observeren. Daarna beoordelen we of ons model beleidsmakers kan helpen om te bepalen hoe kosteneffectief hun beleid is. We evalueren het nut van ons model door beleidsmakers meerdere scenario's, binnen onze modelsimulatie, te laten valideren. Als resultaat van onze evaluatie tonen we aan dat ons model een gemakkelijk en toegankelijk hulpmiddel is voor beleidsmakers. Zij kunnen hierdoor hun aannames testen en de effecten van hun beleid op de dynamiek van de simulatie observeren. Het gedrag van de simulatie kan eenvoudig worden aangepast zodat beleidsmakers, indien nodig, verschillende scenario's in de toekomst kunnen observeren.

Door de constructie en validatie van de Agent-Based Segmentation Model zijn we in staat onze bevindingen te generaliseren en de hoofdvraag van ons onderzoek te beantwoorden: hoe kan bevolkingssegmentatie op een nuttige manier worden toegepast binnen Agent-Based Modelling (ABM). We stellen een richtlijn op voor de integratie van segmentaties binnen Agent-Based-modellen evenals hoe het nut van dergelijke modellen moet worden geëvalueerd.

Contents

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"In this publication we made use of data from the Netherlands Enterprise Agency (RVO): Landelijk reizigersonderzoek, administered by Ministry of Infrastructure and Water management, we also made use of data from the Netherlands Mobility Panel administered by KiM Netherlands Institute for Transport Policy Analysis and the LISS (Longitudinal Internet Studies for the Social sciences) panel administered by CentERdata (Tilburg University, The Netherlands)"

1 Introduction

Climate change is one of the most important global issues the world is facing today. Greenhouse gas emissions and pollution caused by fossil fuel-powered vehicles are one of the many contributors to this issue. Many governments, including the Dutch government, have agreed to take measures to reduce these emissions and reverse climate change. To accomplish this, climate change mitigation policies need to be developed and implemented. For the Dutch government to comply with the climate agreement [1] various measures have been taken, some of these measures can be found in [2]. One of these measures aims to decrease the amount of fossil fuel consumption by stimulating cleaner modes of transport such as the battery-only electric vehicle (BEV). With the capability of being powered by renewable energy and a zero tailpipe emission, BEVs have a place in a sustainable future.
Through the application of specialised targeted policies [3], the Dutch Ministry of Infrastructure and Water Works (I&W) aims to encourage the Dutch population to make the switch from conventional internal combustion engine vehicles (ICEVs) to battery-only electric vehicles (BEVs). Policy developers theorise that certain segments of the population will be more susceptible to certain stimuli. The segmentation is done based on people's behaviour and characteristics. Targeted policies and measures are then applied which aim to influence specific segments of the population. The development of policies is often done under great uncertainty [4].

Policy developers would want to know whether the target segments in combination with corresponding policy-mix increases the probability of someone acquiring a BEV. In other words, they want to know whether the target segments are worthwhile. To determine whether the segmentation is worthwhile, policy-makers would like a better insight into population dynamics. Agent-based modelling (ABM) allows us to model social systems wherein agents learn form experience, as well as by interacting and influencing each other. With ABM we can build a simulation wherein the dynamic effects of policies can be observed. This enables policy developers to investigate the factors involved in the adoption of BEVs. Moreover, the simulations can provide policy-makers with valuable insights that can be used to increase the efficacy of policies.

This thesis is part of a bigger project being conducted by Alexander Melchior [5]. The primary goal, of [5], is to build a framework for policy development using agent-based social simulation design principles (ABSS). Through the use of ABSS, policy-makers are able to make the problem they are trying to solve explicit. The framework enables policy-makers to look at the policy problem from different angles, incorporate it within the right context and reduce biases stemming from their field of expertise.

We will apply Agent-Based modelling within the policy context. The aim of this thesis is to research how the segmentation of a population can be applied within ABM in such a way that it is useful for policy development. The ABM will be applied to our use case, it simulates the problem of targeted policy application with regards to the adoption of BEVs. We will incorporate target segments within our model and determine, via interviews with policy-makers, whether the obtained model is considered to be useful within our context.
From the construction and validation of the Agent-Based Segmentation Model, we are able to generalise our findings and answer our main research: how can population segmentation be applied in a useful way within Agent-Based Modelling (ABM). We devise a guideline for the integration of segmentations within Agent-Based Models as well as how to evaluate the usefulness of such models.

1.1 Motivation

In this section we will provide further motivation for this research. Including the problem description (section 1.1.1), scope (section 1.1.2), stakeholders (section 1.1.3) and the placement of this research within the field of AI (section 1.1.4).

1.1.1 Problem description

In order for the Dutch government to achieve its set climate goals, it develops policies to compel types of behaviours that will decrease the amount of greenhouse gas emissions. These include the policies developed to incentivize people to buy a BEV instead of a conventional ICEV. To develop such policies, an extensive exploration must be done of the factors involved and the alternative courses of action available for addressing the problem. Policy-makers face many uncertainties while developing policy measures. A multitude of external factors can impact the process of policy development. These external factors include the rate of climate change, new technological and economical developments as well as changes in social perspectives, among others.
Policy-makers start from the perspective that the future can be predicted to a certain extent [6]. They develop a plan based on extrapolations of trends to achieve a certain goal. When the prediction does not come to fruition the policy is considered to have failed. Despite having limited information at their disposal, policy-makers have to make good decisions. To develop policies, research and an extensive exploration of the economic and behavioural factors is conducted.
To stimulate the Dutch population to make the switch from an ICEV to a BEV, the Dutch population is divided into target segments according to the type of vehicle they privately own: second-hand car, new car and private lease car. The individuals within these three segments have different characteristics and are therefore theorised to be sensitive to different stimuli. A policy-mix is imposed on the whole population, although the policy-measures primarily aim to influence only one of extent target segments. Any one of these policies could contribute to the transition to a cleaner mode of transport. Which measures have a stronger influence on which segments and which ones have no effect or the opposite effect in our complex social system remains a difficult question.

Every year data is collected by the Royal Dutch Touring Club (ANWB). The ANWB is a travellers association in the Netherlands that offers a wide range of services related to mobility and actively lobbies for consumers within the driving, mobility, travel and recreation sectors. They collect data to determine peoples disposition towards BEV's, this data is used to do a statistical analysis. From this analysis, the effectiveness of adopted policies can be estimated as well as which obstacles hinder the widespread adoption of BEV's. This information is then included in the policy development process.
The statistical method has a scalability restraint, it is unable to capture the full effect policies have within the social dynamics. The more complex a statistical model becomes, the harder it is to interpret the results and the underlying assumptions. Moreover, to truly study the effects policy measures have on the population, some controlled research environment should be created wherein a randomised control trial is conducted [7]. Randomised control trials are extremely costly and do not guarantee a correct result, they are therefore rarely used.
Agent-Based Modelling can be used to fill this gap, it allows us to search for explanatory insights into the collective behaviour of agents obeying simple rules. It also allows us to integrate target segments within ABM such that it can model and simulate the effect of target policies. Agents within the model represent people or groups of people, and agent relationships represent processes of social interaction [8]. This allows for the modelling of these interactions at a certain level of abstraction [9].
The model will be build using available data (Section 2.6). The right data, for Agent-Based Models,

is often hard to obtain because privacy constraints do not permit the tracking of peoples behaviour through time. It is therefore hard to know whether a certain stimuli has affected someone's behaviour and in what way. Often data is collected about peoples intentions, this is not always reflective of what someone really does.
One important thing to mention is that conflict of interest between the different stakeholders can hinder the acquisition of data. The ANWB put a lot of effort into lobbying for policies to support their BEV clients. They are worried that the results from the ABM will lead to the disregard of policies for which they have worked hard to get accepted. This uncertainty of how the results of the model will be interpreted and used leads to a lot of trepidation and unwillingness to collaborate.
The goal of this thesis is to investigate how the segmentation of a population can be applied in a useful way within Agent-Based Modelling. We will investigate whether the Agent-Based Segmentation model, constructed during our research, provides policy-makers with valuable insights into the dynamics of a population. The Agent-Based Segmentation Model will approximate the effects certain policies have on different population segments. The outcome of the model will give an indication of which agents are more susceptible to certain stimuli and which are not. As well as whether the segmentation and the corresponding application of targeted policies have the desired effect. The model will also allow us to identify which data should be collected and suggest efficiencies based on the dynamics within the model. Agent-Based Modelling (ABM) can inform and support policy-makers when making decisions under deep uncertainty. The model should not be used as a prediction tool [10], but rather as a way to give new insights, single out unforeseen scenarios and to develop contingency plans and early warning indicators.

1.1.2 Scope

The scope of this project consists of the number of policies and scenarios to be tested, the number of segments to be analysed and the obtained data. Furthermore the research is multidisciplinary comprising of the following fields:

- Data analysis;
- Agent-Based Modelling through simulations including description and visualisation of the agents;
- Dutch policy development;
- Behavioural theories;

1.1.3 Stakeholders

This research project is conducted by keeping the goals of the stakeholders in mind. In the introduction, we discussed the goal of our research and its placement within a larger project. We highlighted the goal of the research institution, which is one of the stakeholders in this project. Another stakeholder within this project is the Ministry of Infrastructure and Water Works (I&W). We will highlight their goals within this section.
The Ministry agreed to this project to investigate the possibilities Agent-Based Modelling could offer policy developers and the behavioural insights teams (BIT). Policy-makers want to investigate whether Agent-Based Models of population dynamics could provide them with some added value in the sense that it offers them new valuable insights. The Ministry aims to improve the use of data, information and ICT in the policy development process. If it turns out that ABM is indeed valuable, they would like to know whether there is a necessity to enhance collaboration between the BIT and the ministry's data laboratories. Furthermore, they would also like to know whether Agent-Base Models are applicable in a cost-effective way within other fields such as waste disposal

and mobility, among others.
Within our use case, concerning the adoption of electric vehicles, the Ministry would like to investigate whether target segments in combination with the corresponding policy-mix are worthwhile and whether they bring about a significant increase in the number of BEV owners. Furthermore, policy-makers would like to analyse the effect certain policies have on the different target groups. Analysing the effect policies have on the target segments could bring new insights into population dynamics and allow us to discover possible unforeseen side effects resulting from the combined interaction of multiple policies. Policy-makers can use this information to develop a mechanism which allows them to design contingency plans and identify early warning indicators. These insights could help policy developers improve the effectiveness of their policies.

1.1.4 Link to AI

The field of Artificial Intelligence encompasses multiple disciplines from mathematics and computing science to sociology, psychology and linguistics. The study of intelligent agents is one of the newest approaches within AI. There are two main approaches to agent-based computing: the descriptive approach and the prescriptive approach. An example of a prescriptive approach to modelling is multi-agent systems (MAS), which is predominantly interested in the cognitive functions of the agents themselves. Multi-agent systems try to give new analytic insights into how different configurations of agents behave in different circumstances. They are primarily used to solve complex problems using autonomous heterogeneous agents.
Agent-Based Modelling (ABM) is an example of a descriptive way of modelling, used to analyse emergent behaviour from the interaction of a population of individual agents. The agents' autonomy, capacity to adapt and goal-driven interaction will give rise to self-organisation. ABM does not focus on the agents' cognitive complexity but rather on the insights the system provides into the phenomena which are being studied.

Although both methods use agents to represent humans and their interactions. They differ in their methodology, applications, and aim. ABM aims to give an explanatory insight into the collective behaviour of agents while MAS aim to solve a specific practical problem. Within MAS an emphasis is laid on agent architectures where complex goal-oriented processes are formalised. Agent-Based Modelling allows us to study the emergent behaviour of a system. Furthermore, MAS are often small systems containing diverse agents while ABM usually contain a large number of relatively uniform and simple agents [11]. Multi-Agent Systems are primarily used within the computational engineering fields, while Agent-Based Models are primarily used within the social sciences.

The model we will create is developed to study the effects of segmentation and policy practices have on population dynamics. Our research goal is to examine the behaviour of the system and therefore better aligns with the ABM type of approach. Although it does have some characteristics of a MAS, due to the fact that the agents will have high cognitive complexity. The higher cognitive complexity ensures that the agents' decision-making process and mental state will be in line with psychological theories of behaviour. However, the agents will only mimic human behaviour and cannot be considered to be truly intelligent, they do not think or reason like humans. Although the intelligence of each agent within the system is limited the behaviour exhibited by the group will be complex and represent, up to a certain extent, the complexity seen in real life.

1.2 Research approach

In this section, we will describe our research approach. We begin by describing our research methodology (section 1.2.1) followed by the research questions (section 1.2.2) and our research plan (section 1.2.3) which describes how we plan to answer our research questions. We will end this section by discussing the structure of this thesis (section 1.3).

1.2.1 Research methodology

To guide our research process we will use the design science methodology as described in [12]. This process is exemplified in the design cycle given in Figure 1 wherein three phases are represented: Problem investigation, Treatment design and Treatment validation, given in [12].
One starts with identifying a certain problem i.e. the target of the modelling, once we have a better understanding of the problem we begin designing and constructing the model and its algorithms. The final step of the process is the validation of the model within the defined scope of the project. Afterwards, we can again iterate over each of these phases until the model is considered to be satisfactory. This methodology provides us with a better grasp of the problem and with acceptance criteria for the ultimate evaluation of the research results. By iterating across the three stages of the process one ensures that we produce a model that can be useful while being as realistic as possible.

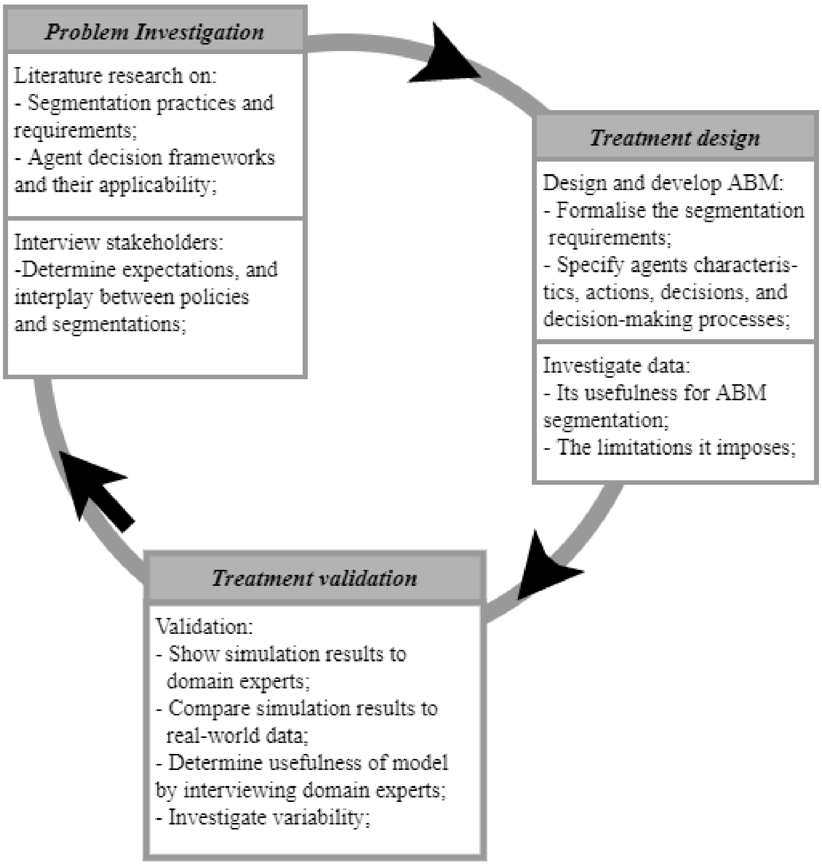


Figure 1: Design cycle

1.2.2 Research questions

The research questions are in accordance with the design cycle discussed earlier. They cover all three aspects of the cycle. Through answering each of the sub-questions below we will gain the knowledge and tools needed to answer the main question.

Main Question: How can population segmentation be applied in a useful way within ABM.

1. **Problem Investigation**
   1.1. What is meant with a target segmentation in our context.
   1.2. What is the interplay between policies and segmentations.
   1.3. What state of the art decision frameworks are available and to what degree are they applicable within our context.
2. **Treatment Design**
   2.1. How do we formalise the segmentation requirements within our model.
   2.2. How can we use available data to build Agent-Based Segmentation Models.
3. **Validation**
   3.1. Does the ABM show behaviour that can be explained by a policy-maker.
   3.2. Does the ABM bring new insights, do the domain experts find it useful.

1.2.3 Research execution

In this section, we will start by defining the problem we are trying to solve, its context and the value of the solution. We will then define how we design our model. Finally, we will describe our verification and validation process.
We will construct an Agent-Based Segmentation Model, using the Repast platform [13], in which the effects of policies on different segmentations will be tested. This will be done by ways of running different simulations, wherein the effects of different policies (section 2.5) will be evaluated. To do a complete analysis we will also evaluate the effects of the interaction of the different policies, through the use of scenarios.
To build such a model we need to be able to model the agents' decision-making process. The behaviour we are interested in is whether or not an agent chooses to buy an electric vehicle. The factors involved in this process are also of interest. These can be external factors such as policies and societal influences as well as internal factors such as the agents' own needs and uncertainties (section 2.2.2).
The outcome of the model should give an indication of which policies have a stronger influence on what parts of the population and on which target segments the policies have no effect or the opposite effect. During the construction phase of the Agent-Based Segmentation Model, we will consult with domain experts to determine the initial goal of the population segmentation. The goal of the population segmentation will give valuable insights into which characteristics and behaviours will be relevant to include within our model. These characteristics will determine the difference in behaviour between agents belonging to different segments. We will also conduct literature research to develop the behavioural algorithms of our agents and substantiate our choices.
The challenge is to define the agents and their environment in such a way that their behaviour conjunctive resembles that of real individuals. This being said it does not imply that the model offers an accurate prediction of the effects policies have on people's behaviour.

To guide our research we will use the Design Science methodology discussed in section 1.2.1. Design science is an agile incremental way of working that allows us to conduct our research in an iterative way such that each process of the models' development is clear and can be analysed. Using this methodology we will construct an action plan which describes how we will solve our research question.
Our goal is to answer the main research question. To do this we need to answer each of the sub-questions given in section 1.2.2. We will cycle through the three phases of the methodology answering the questions within each phase, as exemplified in Figure 1. We will start by defining how we will answer the questions within the problem investigation.

Problem Investigation

We begin our research by conducting a literature study and by interviewing policy developers to discover what exactly they would characterise as useful and what their expectations are of the model (section 1.1.3 gives a short overview of this). We start by identifying the initial goal of the target segmentation from the point of view of the policy developers, this provides us with some insight into the interplay between policies and segmentations. We investigate why certain choices were made regarding the way in which the Ministry segments populations. We also determine how each target segment is expected to be influenced by the policy-mix. We will outline the behavioural theories these expectations were based upon (section 3.3). The policy-mix is discussed in section 2.5. We will compare the requirements for the target segmentations to our general segmentation requirements given in section 2.3.3. This will be used to formalise the segmentation requirements within our model.

To build our model we need to be able to simulate peoples decision-making process. The different factors that influence the agents behaviour should be determined. Some insights into the agents possible behaviour is given in section 3.4. These include the factors that weigh in when an individual acquires a BEV or a traditional car. In section 2.7 we describe the behaviour insights obtained from interviewing domain experts and attending workshops. We investigate the way an agent could be influenced or can influence others in its environment. We will also discuss the difference in behaviour between agent belonging to different segments in section 3.4.
From a modelling perspective, human behaviour is not rational nor is it simple. It is the product of social, mental, physical and emotional aspects. Not all knowledge can be formalised, mechanisms included in the model and those that were not included might turn out to be crucial later. Therefore, there must be a careful deliberation of what to include and what not to include.
Based on a literature study we will decide upon a decision framework which we will implement in our ABM. This will determine how each agent behaves and should therefore be examined carefully. In section 2.2 we give two of such frameworks. Depending on its applicability within our context we might need to alter these frameworks to better suit the purpose of our model, section 3.2. This will determine the kind of behaviour the agent will exhibit, how it will interact and when it will update its cognition.

Treatment design

Regarding the questions within the treatment design, the segmentation requirements will be formalised using the comparison between the general segmentation requirements (section 2.3.3) and the ones defined by the policy-makers, obtained from the problem investigation. The formalisation involves specifying exactly when and why an agent will belong to a certain segment. To do this there needs to be a specification of the agents' characteristics and the kind of decisions an agent can make, how the agents interact and how their actions influence the environment. This specification

will be based on the available data and the literature study conducted during the problem investigation. The behaviour we are most interested in is whether or not someone acquires an electric vehicle. Therefore, the difference between BEV and traditional vehicle needs to be made explicit. These include differences in price, range, recharge options, fuel costs, or total cost of ownership (TCO). In section 2.4 and appendix B we give an overview of some of the characteristics of electric cars. The differences between leasing, buying a new vehicle, or buying a second-hand vehicle also need to be properly defined. As well as all other decisions an agent can perform (section 4.2.3).
We will construct the model using the Repast simulation platform which we discuss in section 2.1.1. Using this platform we will define the agent, its environment and how time progresses, as discussed in section 2.1.3. The agent will be defined using a version of the consumat decision-making framework, obtained from the problem investigation. The policies discussed in section 2.5 are implemented within the model as an environmental influence, for which the agents are susceptible.
We further investigate whether the obtained data (section 2.6) is suitable for building the model structure and initialise the agents within our model. We will discuss the data in section 2.6 and 2.6. We believe that the collected data will be a determining factor in the development of our model on which the agents' initial characteristics will be based. We also believe that the available data will be a determining factor in the segmentation process. The data together with the decision framework will provides us with the necessary tools to develop our ABM. In section 3 discuss our modelling choices and in section 4 we will give a complete overview of our model.

Validation

Besides verifying that our model is debugged and technically correct we must also validate our model. This involves using the techniques discussed in section 2.1.2.
During the construction phase of our model, domain experts were consulted to determine which scenarios would be most useful to simulate. The results of these scenarios are discussed in section 5 and section 6. To validate the Agent-Based Segmentation Model we will consult with domain experts within the Ministry (section 7.1). We will show the models dynamics and results directly to the domain experts to see if they are able to explain them. Thus, whether the dynamic behaviour exhibited by the agents coincides with their expectations. We will also use data about scrappage, and the overall yearly sale figures in the Netherlands to validate our model, section 7.2. The validity of our algorithms will also be discussed in section 7.3. We constructed an overview of the models' algorithms (section C), using a schematic representation, such that it can be reviewed.
During the validation, the aim is to investigate whether the model offers new insights to the policy developers and whether it is perceived to be useful.
From the construction of our model, within our use case, we will be able to generalise our findings and develop a guideline for the integration of target segments within ABM. Thereby answering our main question.

1.3 Thesis structure

Section 2 provides background information about ABM, agent frameworks and segmentation practices. As well as information about the electric vehicle and the ministries measures to promote its diffusion. In section 2 we will also discuss the data used within the model, its requirements and its limitations. We end section 2 by discussing the workshops (section 2.7.1) and survey (section 2.7.2) conducted at the beginning of our model development. In section 3 our modelling choices are given including an overview of the segmentation implementation (section 3.1), our choice for the agents framework (section 3.2), the theoretical basis for our behavioural assumptions (section 3.3) and consumer assumptions (Section 3.4). We give an overview of the model's parametrisation and process overview using the ODD protocol in section 4. In sections 5 and 6 we present the results of playing out single and multiple complex scenarios in the simulation. Section 7 shows the validation of our model. We finish this thesis in section 8 with a discussion of our results, the answers to our research questions and a discussion of the limitations/recommendation for further work. A conclusion is given in section 9.

2 Background information and related works

This section provides the necessary background information about the various disciplines incorporated within our research project. These include an overview of Agent-Based Models (section 2.1) and their various applications, as well as their structure and their modelling protocols and tools. We will also discuss the state of the art cognitive frameworks (section 2.2) used to describe the underlying rationale of agents within an ABM. Finally, we will give an overview of the different approaches to segmentation 2.3.

2.1 Agent based modelling

Agent-Based Models (ABM) are predominantly used in non-computing related scientific domains such as biology [14] to model complex biological systems, epidemiology [15] for predicting the spread of epidemics, anthropology [16] for modelling the rise and fall of ancient civilisations and many more [17, 18]. Agent-Based Modelling is primarily used to simulate dynamic processes that involve autonomous agents [19]. The behaviour of the system as a whole is determined by the effects of the diversity of behaviours and attributes existent among agents. When agents repeatedly execute their actions and interact with other agents, self-organisation can occur. This consists of emergence of patterns, structures and behaviours that are not explicitly programmed beforehand [20]. We give an overview of the articles on ABM by field up until 2008 in Figure 2 given by [18].
The goal of Agent-Based Modelling is to search for explanatory insights into the collective behaviour of agents obeying simple rules.

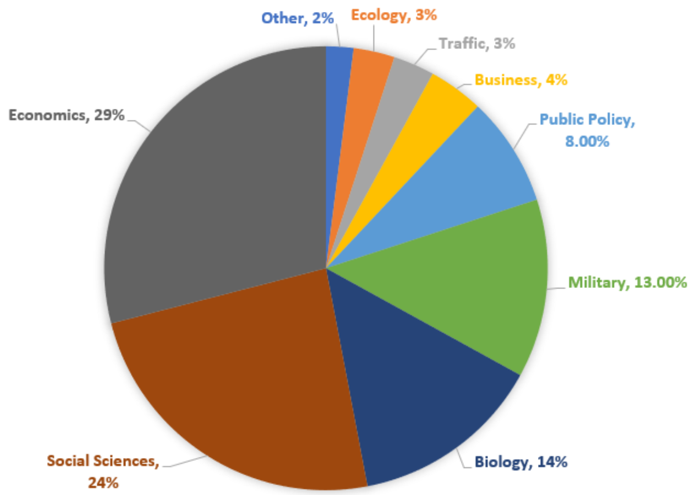


Figure 2: Breakdown of Articles by Field [18]

Agent-Based Modelling techniques have a number of advantages [21]. The models can be made as realistic as one desires. A high degree of heterogeneity can be introduced at the beginning as well as after the model has been completed without this destroying earlier knowledge. Agent-Based Models easily allows for communication between agents and bounded rationality of the agents can be assumed. The models are also intuitive and easy to understand. However, there are downsides to this kind of modelling. One of the most noticeable ones is the lack of adequate data. Furthermore, identifying the processes and mechanisms underlying the agents' behaviour is not a straightforward process, unrealistic model expectations, limited computational time and uncertainty about one's assumptions can lead to erroneous conclusions.

Agent-Based modelling is used by both computer scientists and social scientists. How they are used is, however, wildly different. Computer scientists strive to accurately predict the outcome of certain processes disregarding explainability opting for the “black box” approach. Social scientists, on the other hand, aim to explain why certain behaviours occur and relate it to theory [22]. Explainability and interpretability is therefore key. The models' structure must be based on theoretical knowledge and assumptions about the world. Furthermore, the ethical implications and consequences of the modelling decisions must be taken into account when designing the simulation. Privacy regarding the usage of data must also be taken into consideration.
Agent-Based simulations offer valuable insights into fundamental social processes [23]. As mentioned before agents represent people or groups of people and agent relationships represent processes of social interaction. Agent-Based Models allow for the credible modelling of social interactions at a certain level of abstraction [9]. Social sciences applied in this way is referred to as computational social sciences.

A social agent can be described as a discrete goal-oriented entity with autonomous behaviour, capable of adapting and modifying its behaviours based on its belief system. Models which aim at developing insights into a social process or behaviour usually only include the essential details of a system. Models whose results aim at informing policies and decision-making are modelled in great detail. These models must therefore be subjected to extensive data analysis, verification and validation. To implement an Agent-Based Model some assumptions must be made, namely that:

- The most relevant aspects of behaviours can be described;
- We can algorithmically represent and describe the mechanisms by which agents interact;
- We can use the bottom-up method to build a system which models complex social processes;

Agent-Based Modelling has also been applied to the policy development process. More specifically, within the medical [24], agricultural [25] and public health domain [26], among others. Policy-makers are often involved in a continuous amendment process wherein they adapt their plans ad-hoc to new situations. Agent-Based Modelling can assist policy developers in this continuous amendment process by simulating possible population dynamics and giving new insights. Models used to inform policy-makers cannot be used as prediction methods [10]. The assumptions made while developing the model might bear little resemblance to reality. These assumptions are often based on unverified empirical evidence and for the most part unproven disciplinary theories. Agent-Based Modelling within the policy context is predominantly used to design contingency plans and early warning indicators. This allows the researcher to identify which data should be collected and suggest efficiencies based on the dynamics within the model.

2.1.1 Tools and protocols for Agent-Based Modelling

As mentioned before a computational representation of Agent-Based Models is build from the bottom up. This is done using a simulation platform which provides the underlying infrastructure most ABMs use. These platforms use general all-purpose languages such as Java, C++ or Python. There are a multitude of platforms available [27], popular examples are Netlogo, Swarm and Repast [13]. Depending on the computational complexity of the eventual model a choice must be made on which platform will be used.

To describe Agent-Based Models Grimm et. al [28] developed a standard protocol named “ODD”. This protocol consists of three sections: Overview, Design Concepts, and Details. These are in turn subdivided into seven elements: Purpose, State variables and scales, Process overview and scheduling, Design concepts, Initialization, Input, and Submodels. This protocol is used to facilitate the communication and replication of ABMs. If everyone uses the same method to describe their model and this information is always found in the same part of the model description it significantly reduces the effort needed to understand or reproduce the model by peers, developers or reviewers [29]. We will use the ODD protocol to describe our Agent-Based Segmentation Model (section 4).

2.1.2 Model validation and verification

No matter how good the model appears to be we need to keep in mind that it is still a simulation, an abstraction of the real world. By verifying and validating the model during its development we ensure that it is accurate and credible [30]. Thereby ensuring that it achieves its intended purpose.

Verification

When verifying an ABM one ensures that the model correctly implements specifications and assumptions defined beforehand. This predominantly involves the debugging of the model such that it works correctly and that the algorithms are correctly implemented i.e. that it correctly represents a model of the phenomena.

Validation

Validation on the other hands ensures that the right model has been built. In other words, it is used to determine whether the model is a reasonably accurate representation of the real world with regards to its intended purpose. Thus, it determines whether the correct algorithms were used and whether the output corresponds with our expectation about the real world output.
This process includes verifying calculations and adjusting parameters. The calibration of the ABM ensures its accuracy is acceptable. The acceptability can be determined in conjunction with experts to prevent confirmation biases.
There are multiple validation techniques, we will give an overview of those discussed in [31, 32].

- *Face validity:* This implies asking a domain expert whether the model behaves reasonably and whether the model is sufficiently accurate. The ways the model is presented to the expert can be either through an animation or a graphical representation, by showing the overall dynamic or by tracking a certain individual within the model.
- *Internal variability:* The variability of the model should be within reasonable bounds. If several replications of the model, results in a large variability then the model's results become questionable.
- *Multistage Validation:* Was first proposed in [32] and consists of a multistage process:
    1. Model assumptions must be based on theory, observations and general knowledge;
    2. The assumptions should be empirically tested;
    3. The input-output relationship should be consistent with the real world;
- *Parameter variability - Sensitivity analysis:* This consists of altering the values of the parameters and the initial conditions of the model to determine the effect upon the model dynamic. The parameters which turn out to be sensitive should be accurately defined.
- *Traces:* The trace is the behaviour of a specific agent. This should be followed through the model to determine if the model is accurate and whether the behaviour is reasonable.

In short, to test the validity, we must perform a combination of different validity checks. Once the validity of the ABM is determined, we can evaluate whether the model fulfils its initial purpose.

2.1.3 Agent-Based Model structure

To create an ABM one must identify the goal of the model, define the learning and decision algorithms, and implement these within a programming platform.
A typical Agent-Based Model consists of: an environment, decision-making heuristics, behavioural algorithms, a time step mechanism, and a set of agents [33].

The agent

The model is used to simulate the interactions of agents or groups of agents [34] which are assumed to have access to only local information. This means that the information available to an agent is defined within a subset of the environment wherein it exists.
Agents are defined to be autonomous, heterogeneous, self-directed, self-contained and uniquely identifiable [19]. Furthermore, agents have internal states and are capable of making decisions, performing actions and interacting with other agents within the model.
The model is designed using a bottom-up approach [20], wherein rules are constructed that specify the behaviour of each individual agent, and no specification is defined for the overall behaviour of the entire simulation [35]. Agents make decisions according to these predefined decision-making heuristics, they also interact with the other agents within the environment and adapt their behaviour according to predefined learning rules.

The agent is defined within the model using three elements: the decision-making heuristics/rules, the actions, and the properties/attributes. We will give a specification of each of these elements.

- *Properties:* are the characteristics of individual agents, such as age, sex, income, and the type of car they own. These are predefined but can change over time. They can also be made partially observable or completely unobservable to other agents. All of these properties must have well-defined conditions for initialisation and for change through time [33].
- *Actions:* define the behaviours that agents can perform within the simulation. These include their movement within the environment, their interaction with other agents, exchanging or gaining information and buying a product. All of the actions must have predefined conditions that trigger the action and their consequences. Which in turn can change the agents own properties but also the properties of others, the environment, and the agent's own rules [33].
- *Rules:* define how agents interact with the environment and each other, how they choose an action and update properties. These rules have as input the agent's properties, they can be time-dependent and are capable of creating or removing agents.

Time

Time is the unit in which rules, actions and their consequences are executed. Time is usually divided into time steps. In each time step certain actions are triggered according to their hierarchy within the computer model.

Environment

The environment provides the context for the agents and their interactions in the model and can change over time either due to the agent's activity or external stimuli. It contains the agents together with their properties, actions and rules.

2.2 Agent frameworks

The model we are trying to build must simulate human behaviour. The agent within the model must mimic human decision making, which is very complex. There are many ways in which human decision making can be modelled, and depending on one's goal, different frameworks can be used. These frameworks are developed in order to help the modeller design an agent, how it makes decisions and interacts with its environment and other agents.
Decision frameworks need to be complex enough to realistically capture someone's decision-making process while being simple enough to be computationally feasible and understandable. Decision frameworks are distinguished by five main dimensions, described in [36]: learning, affective, social, norm consideration and cognitive. Examples of such frameworks are the simple rule-based agent frameworks, the BDI (beliefs desires and intentions) architecture, the social agent framework, CLARION, PECS, Consumat, SOAR, among others [37]. In this chapter, we will discuss the most commonly used framework, the BDI architecture, and the consumat architecture which will be used within our Agent-Based Segmentation Model.

2.2.1 Beliefs-Desires-Intentions architecture

The Beliefs-Desires-Intentions (BDI) architecture [38] is one of the most commonly used frameworks to simulate the agents' decision-making process. It is mostly used within MAS. Agents, constructed using the BDI architecture, have a "mental state" consisting of beliefs, desires, and intentions.
Beliefs represent the information that the agent possesses about itself, its environment and the other agents. The beliefs do not need to correspond to reality. Desires are the states of affairs an agent would like to accomplish, they represent options that might have an influence on the agents' actions. Intentions are the desires to which the agent has in some way committed itself. Goals are the states the agent is actively trying to achieve which may eventually lead an agent to fulfil its intentions. Desires and goals differ in the fact that desires do not have to be mutually exclusive. At each time step, the agent updates its beliefs based on its perceptions. Agents are able to modify their own beliefs, intentions, and desires.

The BDI framework is a simple framework in which the agents' decision-making process is modelled within the "mental state" of the agent. This mental state determines the actions the agent will perform. It has been argued that the three components of the model are too simplistic in order to capture the entirety of the human deliberation process. A further downside to this model is that agents are unable to learn from past experiences and emotions are not taken into account. Moreover, it is hard to explicitly define peoples' goals. The Beliefs-Desires-Intentions framework is based on logic and philosophy [39] rather than psychological theories of human behaviour. It is therefore not the most suitable framework for our research.

Other architectures have been proposed including the Consumat model [40] which we will discuss in the next section.

2.2.2 Consumat architecture

The Consumat architecture [41] was developed in order to model the behaviours of consumers and market dynamics. The conceptual model of consumer behaviour is presented in Figure 3. It represents key processes that capture human decision making in different situations. It provides a simple structure that models which type of decision strategy is used under which conditions. Th Consumat framework is based on empirical evidence. And has the advantage of capturing high-level mental concepts while avoiding overly complicated processes and unnecessary details.
The environment is determined by the macro and micro level [40]. The macro-level consists of

technical, institutional, cultural, economical, and demographic developments. The micro-level consists of the agents own properties, their needs, the opportunities they have to consume and the ways in which they can do this as well as their degree of uncertainty. The agents' degree of uncertainty and level of need satisfaction, in turn, determines how they behave and act.

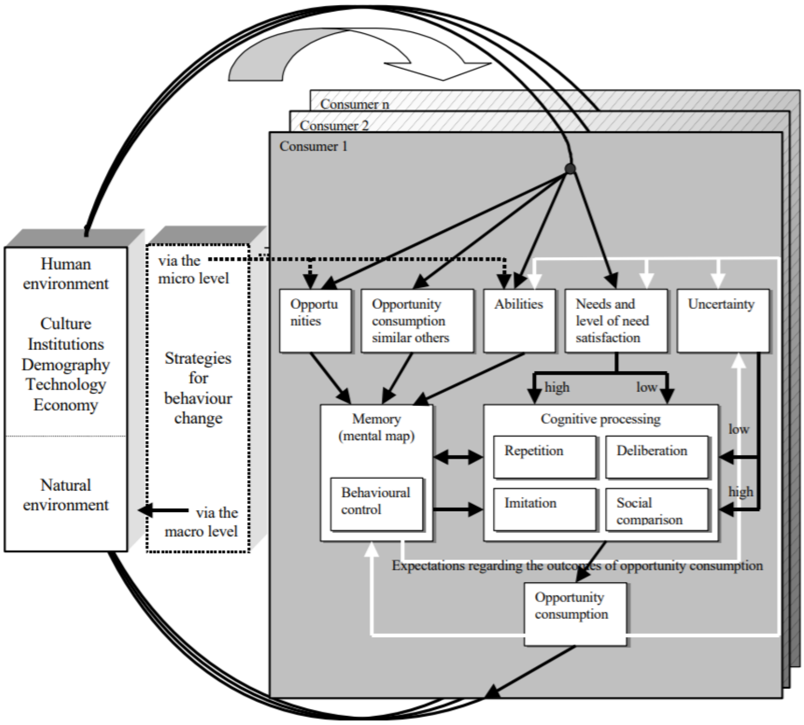


Figure 3: Consumat meta-model of behaviour [40]

The amount of time an agent spends on deliberation varies. When items are frequently bought and the satisfaction level is high virtually no cognitive resources are needed to decide to buy the product again. However, when someone is confronted with a decision with large consequences more cognitive resources will be used in the agents deliberation.

As said before, agents are defined by their needs which are satisfied by performing behaviours. These needs can be subdivided into three main groups [42]: the *social needs*, the *existence needs*, and the *personal needs* which can conflict with one another. These needs align with the three behavioural motives from the Goal Frame Theory [43]: hedonic, gain and normative goal frames. The *social needs* correspond to the interactions an agent has with others, their social status, whether they belonging to a group, conform to the norm by imitating others or anti-conform by seeking out different options through deliberation. When an agent anti-conforms it drives satisfaction from the fact of being different. Satisfying ones *personal needs* can be seen as a form of hedonism. Which involves engaging in activities that gives one pleasure. The more a certain activity aligns with ones taste the higher their satisfaction will be. *Existence needs* correspond to the economic dimensions of the agents, the need for food, income, housing, among others.

When an agent performs an action the degree to which this action satisfies the three needs discussed previously determines the agents level of satisfaction. Furthermore, the cognitive resources, as well as time resources available for decision making, are considered to be limited. This imposes a limit on the number of possibilities an agent can reason about at a certain given point in time. The agents' decision making is done under uncertainty which is considered to be the difference between expected outcomes and actual outcomes. According to [40] the more uncertain an agent is about a decision the more likely it will be to use social cues to influence its decision making.

The Consumat model includes a memory component wherein the agents' possible actions, their properties, and possibilities are stored. This memory component is updated every time the agent performs one of the cognitive processes discussed below. When an agent is dissatisfied it will want to change its course of action. To do so the agent will perform an extensive deliberation about alternatives and the amount in which they will increase its level of satisfaction. Depending on the agents level of uncertainty and level of need satisfaction there are four possible decision-making heuristics for cognitive processing, represented in Figure 4, the heuristics include:

- *Repetition or habit:* The agent will simply continue to repeat its previous behaviour. This occurs when one has a high degree of satisfaction and a low level of uncertainty.
- *Imitation:* This happens when there is a high level of satisfaction, but there is an uncertainty about the outcome. The agent either imitates the successful behaviour of the majority or it follows the behaviour of a select group of very successful peers not in line with the majority;
- *Social comparison:* Low levels of satisfaction and high levels of uncertainty makes one compare to others, their level of interest in certain products, and their preferences;
- *Deliberation:* This happens when an agent has very low levels of satisfaction with low levels of uncertainty. It consists of an homo-economicus kind of behaviour [42], wherein someone is forced to consider the alternatives courses of action. The agent can acquire this information either by consulting other agents, visiting websites, consulting the media or governmental instances;

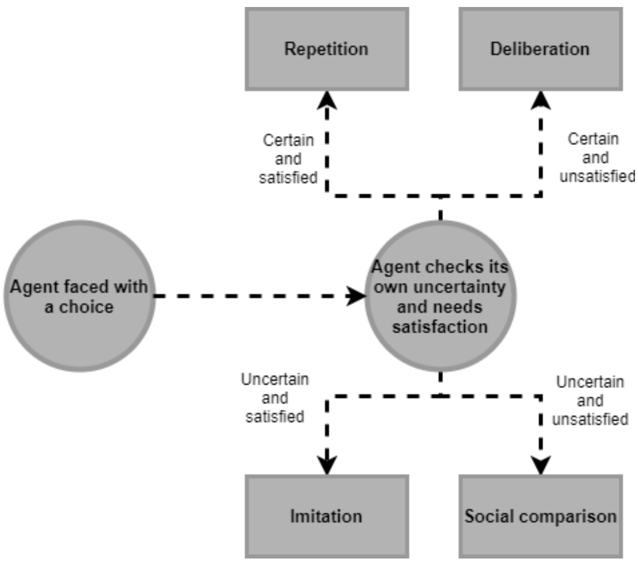


Figure 4: Deliberation schema of the four strategies [40]

The more unsatisfied an agent is the more it will engage in information-seeking strategies. When an agent is satisfied and thus engages in imitation and repetition, it will not update its cognition. This implies that even though there might be better options available to the agent it will not be aware of them and will continue its habitual behaviour. The strategy used by the agent does not solemnly depend on its level of need satisfaction and uncertainty, the agents' personality also plays a role. The agents personality is determined by the following four aspects:

- *Ambition Level:* Represents the level of need at which an agent is satisfied;
- *Uncertainty tolerance:* Represents the level of uncertainty tolerance at which the agents will start looking at other agents' behaviours;
- *Abilities:* Whether an agent is indeed capable of performing certain actions i.e. whether it can use certain behavioral options, this depends on for example income, cognitive capacity, et cetera;
- *Cognition:* An agents cognition stores information on behavioural opportunities such as: general information (media, advertisement), information about others experiences and information about ones own experiences;
- *Social interaction and Network:* Similar agents will interact more often [44]. By similar we mean demographic similarities. This similarity criteria can be used in order to construct a social network;

These aspects can differ from agent to agent. After the agent has performed one of the cognitive processes its level of need satisfaction will change as well as its abilities and opportunities. The social and physical environment in which they operate will also change. This, in turn, will influence the agents cognitive processing. A schema of the agents decision process is represented in Figure 3.

2.2.3 Applicability of the consumat approach

Models which implement this architecture rely on assumptions of which it is not clear whether they can be empirically tested. To formalise the consumat approach more effort and deliberation is necessary than with a standard rational actor. When one decides to include behavioural dynamics the need-satisfying capacities and resource demands of many different opportunities may have to be assessed. This requires a lot of effort. It is, therefore, possible to use a simplified version of the consumat approach wherein only certain elements of the consumat approach are included in the model. Applying the consumat approach in this fashion also has the added benefit of simplifying and making the outcomes more transparent and interpretable. Thereby giving a better insight into the behavioural processes underlying the outcomes. However, by using a simplified version of the consumat approach one must take into account the level at which the resulting model is representative of the actual system. Validity becomes an issue, there needs to be a reevaluation of the applicability of the model by reexamining how relevant and realistic it is.

Due to the lack of empirical data, it is difficult to validate the results from simulation experiments. To validate the model one must convince peers in the scientific community that the model adequately represents the processes that underlay real-world developments [40].

2.3 Overview of segmentation practices

Segmentation first originated within biology to provide taxonomies of animals and plants. The technique is now applied within multiple research fields including medicine, mathematics, computer science, business economics, marketing and sociology.
Segmentation is used to group objects, described by a set of variables, such that the objects within each segment are similar while objects across segments are different. Defining what we mean when we say “similar” or “different” is a key part of segmentation. To group objects into segments often requires a lot of contextual knowledge and insight. Furthermore, within computer science and mathematics, it is assumed that all variables and their respective values are known. In reality, this is rarely the case.
In this section, we will give an overview of the definition of segmentation within different field, including computer science, social sciences and marketing. We will also discuss the discrepancies and similarities between the different segmentation practices (section 2.3.4).

2.3.1 Computer science

Segmentation within computer science is treated as a clustering problem. Clustering is the process of using machine learning and algorithms to identify how different types of data are related and creating new segments based on those relationships. To construct segments the following approaches are typically used: supervised learning, through classification based on features, and unsupervised learning based on interdependencies in the population. Unsupervised clustering algorithms can be split into three main categories: hierarchical clustering, k-means clustering, and two-step clustering. Hierarchical clustering is used for smaller samples usually less than 300 items. To use this method the following properties need to be defined:

- How distance or similarity is measured;
- How clusters are aggregated;
- How many clusters are needed;

K-means clustering uses the Euclidean distance in order to maximise the variance between clusters and minimise the variance within clusters. This method also requires the researcher to predefine the number of clusters needed. The two-step clustering method is used for very large sample sizes. The method consists of two steps, first, the items in the data are grouped into pre-clusters then hierarchical clustering is used wherein each precluster is treated as a single item.
The methods we discussed here require that the type and number of segments are determined in advance. The segments are then established by using readily available, pre-existing characteristics.

2.3.2 Social sciences

The social segmentation practice generally involves breaking down a group of people into segments based on some logic and intended purpose. These segments commonly hold the same political, cultural, social, economic or lifestyle traits. The goal of the segmentation plays a vital role when defining the segments, it specifies the variable which must be forecast. When determining the segments, the stimuli that affect the variable to be forecast plays an important role as well. When the segments are exposed to the stimuli, small differences in behavioural response should exist within segments and large differences should occur between segments. Segmentation is especially desirable when the same stimuli, produces radically different effects on different segments of the population. Several issues must be addressed concerning segmentation:

- The level at which segmentation is applied;
- The specification of segments;
- To what extent the segmentation can be generalised;
- The prerequisites to belonging to each segmentation and the intersectional mobility;

Sociology is primarily used to design more effective marketing strategies by characterising and profiling target groups. This type of segmentation is most commonly used to develop targeted policies.

2.3.3 Market segmentation

To construct an Agent-Based Segmentation Model we must have a clear definition of what segmentation actually entails. The segmentation practice most applicable within our case is the market segmentation. In this section, we will give an overview of the requirements of this type of segmentation.
Targeted market strategies are used to maximise profit by getting a better fit between costumers and products. To achieve this a population is divided into segments based on their difference in needs, characteristics, or behaviours [45]. There are a few requirements for segments [46], these include:

- ***Identifiable:*** You should be able to identify individuals in each segment and measure their characteristics. These characteristics include: *demographic, geographic,* and *psycographic* characteristics. Individuals can also be identified based on their behavioural activities, technical knowledge, and the benefits they seek from a certain product [47].
- ***Differentiable:*** There needs to be a distinction between segments. This implies that each segment should be relatively unique. The individuals within each segment should have similar characteristics which are clearly different from those individuals belonging to other segments.
- ***Accessible:*** The individuals within the segment can be influenced in a cost effective way.
- ***Substantial:*** The segments sizes need to be large enough such that the success rate is significant.
- ***Actionable:*** You need to be able to target the individual segments.
- ***Stable and responsive:*** In order for the target policy effort to be successful, a segment should be stable enough for a long enough period of time such that the policy-mix can be applied successfully. This means that the individuals within a segment show a greater differential response when exposed to targeted policies compared to more general policies. We require that agents within a segment exhibit common reactions, or a similar and somewhat predictable response to the intervention.

The key to a good segmentation is its projectability onto the population to which we are marketing. The segments developed must be easily translated from the reported research to the actual competitive market. In [48] a literature overview is given of a wide array of possible segment evaluation criteria.

2.3.4 Similarities and discrepancies

We discussed two types of segmentation methods, the post hoc segmentation and the a priori segmentation. With the a priori segmentation method, the type and number of segments is determined in advance. The segments are established by using readily available, pre-existing characteristics which are considered to be most relevant. This type of segmentation is not based on any empirical research. The a priori approach provides broad behavioural insights about a population, but it rarely explains why people make particular decisions or engage in specific behaviours. Due to the instability of many segments, this type of segmentation can quickly become obsolete.

The post hoc type of segmentation is also known as cluster analysis and can be divided into the three types of clustering methods, discussed in section 2.3.1. This type of clustering is based on empirical research conducted specifically for outlining segments. Cluster analysis is used to discover structures in data without explaining why they exist. This method is more likely to produce accurate results though it is more costly since it requires the collection of large amounts of data.

Within the marketing domain characteristics such as needs, preferences, and attitudes are used to obtain segments. These characteristics are obtained from primary research regarding people's activities, interests, and beliefs. Segments emerge from this approach because of similarities in participants' responses across multiple variables rather than "a priori" intuition for specific, predetermined variables. Because the post hoc method is based on underlying motivations, it provides a very rich description for explaining behaviours and developing more powerful marketing programs.

Both the clustering and segmentation methods attempt to obtain a compact representation of the dataset using some model of similarity. However, segmentation and clustering differ in the way in which they are applied. Segmenting is the process of putting objects into groups based on similarities, and clustering is the process of finding similarities between objects so that they can be grouped.
Hence clustering can be seen as a way to find the borders between groups/clusters, while segmentation can be seen as a way to use borders to form groups. Different segment solutions are found by using different definitions for similarity and differences. Furthermore, segmentation is always possible even when the data is extremely homogeneous seeing as the researcher can decide exactly what parameters to use to segment the data.
From this section, we can conclude that the marketing segmentation practice is the most useful for the formalisation of the segment requirements within our model.

2.4 The battery electric vehicle (BEV)

In this section we will discuss the main characteristics of the battery electric vehicle, as well as some general information about electric vehicles in the Netherlands. This information will later be used in our model.

2.4.1 Total cost of ownership

Although the average purchase cost of a BEV is significantly higher than the average purchase cost of a conventional vehicle, the total cost of ownership of a BEV is lower. This is due to the fact that a BEV requires less maintenance, it has fewer fluids to change and far fewer moving parts. On average its maintenance cost is 30% lower than that of a conventional ICEV. Furthermore car insurance, tax benefits, subsidies, and consumption costs all contribute to a lower total cost of ownership. BEVs differ from conventional cars in their fuel costs. Depending on where someone charges their BEV, the charging price can differ significantly. Table 1 gives an overview of the fuel costs of the different types of vehicles.

Diesel vehicle		€1,19/liter
Gasoline vehicle		€1,69/liter
Electric vehicle	At home:	€0,22/kWh
	At a public charging station:	€0,35/kWh
	At a fast charging station:	€0,59/kWh

Table 1: Overview of the costs of driving electric, diesel or gasoline vehicles

2.4.2 Battery life

Batteries deteriorate over time, how fast this deterioration happens depends on the battery type and factors such as usage, high temperatures, high electrical current (such as with fast chargers), and whether the battery is operating at high or low states of charge. However, because electric vehicles use primarily lithium batteries their deterioration is homogeneous across the different car brands and models. One significant difference does exist between vehicles that use a liquid cooling system and those that use a passive air cooling system. More precisely, battery degradation is significantly lower in BEVs with a liquid cooling system [49]. According to [50] a standard BEV battery has a life expectancy of 8 to 20 years or 150.000 to 200.000 kilometres. Studies have shown that this decrease is minimal and happens at a moderate pace over time, a loss of 26 km of accessible range after 5 years is unlikely to impact ones day-to-day needs.

2.4.3 The battery electric vehicle in the Netherlands

The Dutch governments' ambition is that in 2030 all new-sold passenger vehicles will be zero-emission vehicles. In this chapter, we will give a quick overview of the state of affairs in the Netherlands with regards to electric vehicles and the corresponding necessary facilities.
According to [51] and [52], in December of 2019, there were 107.536 registered fully electric passenger vehicles, in the Netherlands, from a total of 8.530.584 vehicles. Table 2 gives an overview of the most popular brands of BEVs, their range, price, and the amount sold within the Netherlands.

Model	Amount	Electric range	Price
Tesla Model 3	29.937	280-395 km	€49.998
Tesla Model S	12.950	440-600 km	€88.818
Nissan Leaf	9.131	185-250 km	€36.990
Volkswagen Golf	6.963	160-220 km	€34.295
BMW i3	6.395	200-275 km	€41.994
Hyundai Kona	6.258	330-455 km	€41.595
RenaultZoe	6.068	270-370 km	€33.590
Tesla ModelX	5.120	390-520 km	€94.618
Jaguar I-Pace	4,327	320-415 km	€81.810
Hyundai Ioniq	3.979	215-300 km	€36.995

Table 2: Overview different starting prices of the top 10 registered passenger BEV models in the Netherlands until December of 2019, [53]

In December of 2019, 42,636 passenger cars were sold, 22.978 of those were BEVs which amounts to 53.9%. In the Netherlands there are 27.773 public charging stations, 21.747 regular semi-public charging stations, and 1.252 fast charging stations. The amount of private charging stations is unknown, [51] provides us with an estimate of 100.000 for the month December of 2018. This information will be used in order to build our model.

2.5 Overview of the Ministry's measures

While talking to policy-makers four main strategies for behavioural change were identified: (1) regulating and enforcing, (2) financial stimulation, (3) social stimulation, (4) providing easily accessible alternatives. Agent-Based Models can be used to simulate the effects of each of these strategies and offers insights into complex social processes.
Many measures have been developed to accelerate the adoption of BEVs by the Dutch population. Some of these measures directly benefit owners of BEVs and others have a deterring effect on non-BEV owners. These measures were developed by researching the hindrances experienced by people keeping them from buying or leasing a BEV. These include the higher purchase costs, limited charging infrastructure and longer charging time, range anxiety due to a limited action radius, no possibility to tow a trailer, uncertainty about the resale value of the vehicle, and ambiguity about the vehicle's battery life. These are some examples of possible perceived drawbacks of BEVs. Policy-makers aim to influence someone's decision process by altering behavioural processes through nudging practices to persuade people to make the right decision. An overview of the different measures is given in table 3. We made a distinction between the financial incentives (Fiscal measures) and the non financial incentives (Flanking measures). The measures are grouped according to the population segment they target.

Fiscal measures	**Flanking measures**
General: • Fuel tax increase 1 cent/liter; • BPM and MRB exemption for BEVs; • Subsidy on charging stations (differs per municipality); *New car* • Subsidy of €4000; • Scrapping premium; *Lease*: • Tax addition;	*General*: • Making people aware of the maintenance costs of a BEV vs. a conventional ICEV; • Parking discount for BEVs; • Free access everywhere in the city; • Facilitate home charging; • Increase visibility of charging stations and of the BEVs itself; • Always and everywhere free charging spots and accessibility to fast chargers; • Making charging stations exclusive to BEVs; • Introduce BEV practice in driving training;
Second hand: • Subsidy of €2000; • Charging credit (€1000);	*Second hand:* • Provide the population with reliable information; • Offer reliable battery check services; *Non-car owners*: • Car sharing with BEV option;

Table 3: Current and proposed measures

2.6 Data

We want to extract agent characteristics, attributes, and behaviours from data. The data must, therefore, be sufficiently detailed and be of sufficient size.
We must determine the kind of data that is required for building the model. This is primarily dictated by the scope and level of detail that is required to achieve the model objectives.
As described earlier our objective is to construct an ABM wherein segmentations are incorporated. These are groups of agents which share certain characteristics considered to be relevant.

2.6.1 Dataset collection process

During our search for data we obtained four datasets: LISS ([54]), OVIN ([55]), MPN ([56]) and RVO ([57]). Of the four datasets available to us in this project, only the RVO dataset is sufficiently detailed and contains the most relevant information in order to initialise our agents, implement our target segments, and provide a foundation to our behavioural rules.

> ”The LISS panel is a representative sample of Dutch individuals who participate in monthly Internet surveys. The panel is based on a true probability sample of households drawn from the population register. A longitudinal survey is fielded in the panel every year, covering a large variety of domains including work, education, income, housing, time use, political views, values and personality. The LISS panel data were collected by CentERdata (Tilburg University, The Netherlands) through its MESS project funded by the Netherlands Organization for Scientific Research.”

The LISS dataset was not suitable for our model because it contained little personal information and no information about ones current mode of transportation or knowledge about electric driving. The OVIN dataset consists of data wherein people keep track of their mobility during three days. This was not suitable for our research either because most of the data did not concern vehicle mobility but other modes of transport such as the bike, public transport, walking etc.

> ”The MPN is a household panel, in which the main objectives are to establish short-run and long-run dynamics in the travel behaviour of individuals and households, and to determine how changes in personal and household characteristics and in other travel-related factors (e.g. economic crisis, reduced taxes on sustainable transport, changes in land-use or increased availability and use of ICT) correlate with changes in travel behaviour (see [58] for more details)”.

The RVO dataset contained more specific information about the respondent’s knowledge and usage of BEVs. We, therefore, chose to use the RVO dataset for our research.
The RVO dataset was collected to conduct a study on electric car owners, it consists of 3887 respondents. From those individuals 3128 have a gasoline-powered vehicle, 445 have a diesel-powered vehicle, 197 have a hybrid vehicle, 19 have a PHEV vehicle, 30 have a BEV and none have a hydrogen vehicle. Furthermore, the RVO dataset contains information about:

- Both the person itself such as age, gender and address as well as their financial and professional situation;
- Someones general driving activity and mobility such as their commute distance and what someones parking situation is at home or at work.
- Someones mode of transportation:
  - Whether it is leased or not. This is needed in order to achieve our initial segmentation;

  - The weight of the car which is needed in order to estimate the cost of the persons displacement;
  - The age of the car which will be used in order to estimate whether it is second hand or not. The age of the vehicle also gives an indication of when it will need to be replaced;

- Ones awareness of certain environmental friendly actions and ones participation in them. Whether they are encouraged by their employer to choose environmentally friendly modes of transport. All these aspects can be used to tentatively form a picture of someones values and intentions.
- Whether someone is familiar with the electric vehicle and whether they have ever used one themselves.
- The people that own a BEV. Such as what positively and negatively surprised them about driving a BEV.

All these factors give us an indication of whether or not someone is likely to buy a BEV in the near future. The data provides us with the necessary building blocks in order to develop our model.

2.6.2 Disadvantages of the RVO dataset

The data contains no information about interactions between agents. In order to develop a more realistic model, the interactions should come from data. Due to the fact that this information is lacking in the dataset we must build an approximation of the kind of interactions that could have occurred. Both between electric car owners and non-electric car owners as well as the role of family, friends and colleagues. The data also contains no information on whether the respondent owns an occasion vehicle or new-bought vehicle. We are however able to estimate this property by using other characteristics, section 3.1.

2.7 Domain knowledge obtained from Policy-makers

During the initial stages of the development of our model, multiple workshops were conducted to determine the factors that hinder or encourage individuals to acquire a BEV. A survey was then conducted among four domain experts to determine which factors are considered to be most influential and which policy-measures target those factors. A follow-up interview was conducted to clarify inconsistencies among respondents and determine the expected effect of each of the target policy measures. The information obtained from the workshops, the survey, and the interview were vital in determining which factors to include in our model and in obtaining the assumptions underlying the behaviour of our agents.
In this section we will discuss the insights obtained from the workshops (section 2.7.1), the survey (section 2.7.2), and the interview and presentation (section 7.1). We discussed some of the resulting assumptions in section 3.4.

2.7.1 Workshops

During the initial stages of our model development, multiple workshops were conducted by Alexander Melchior in which domain experts of multiple different fields participated. These include domain experts from the travellers' association in the Netherlands (ANWB), Association of electric drivers (VER). During these workshops, domain experts indicated the factors that hinder or encourage individuals to acquire a BEV. The relation between the factors and their influence on individuals was also highlighted. The importance of the factors within the individual's decision making was then ordered according to importance.
Domain experts were further asked to highlight the goals and insecurities of individuals. The contribution of personal insecurities and the different factors to the achievement of the individual's goals was also discussed. This gives an indication of peoples' thought process and their expected behaviour. Some of the most important factors indicated by domain experts were the following:

- Fiscal and subsidy measures;
- Own experience with BEV;
- Driving schools;
- Politics;
- Social Media influencers;
- Media reporting of BEVs;
- Practical aspect (charging, range, etc);
- Car dealers (BOVAG, ANWB, etc);
- The opinions of friends, family and colleagues;
- Scientist and environmental organisations;

Some of the personal goals highlighted by domain experts include the following:

- *Mobility:* their future vehicle should be able to satisfy the individuals' mobility requirements, i.e. it should have a large enough range.
- *Status:* the desire for status is a fundamental human motive. The vehicle is a status symbol, people, therefore, want to acquire a vehicle which is liked by others.
- *Risk aversion:* new technologies which are uncommon are often seen as risky, most people will not acquire new technologies until they become more socially acceptable or until they have gained some experience with the technology itself.
- *Conformity:* the opinions of family, friends and colleagues have a great influence on an individuals behaviour more than the media or politics.
- *Gain, enjoyment and convenience* (*"Gewin Gemak Genot; De Wet van Fred"*, [59]): people can only be persuaded to change their behaviour if the behavioural change is expected to benefit them, either financially, socially or psychologically.

The domain experts also highlighted that the BEV is still only affordable to a very small percentage of the population. Fiscal incentives are, therefore, the most influential in the BEV adoption process. Furthermore, battery checks for occasion BEVs are essential to promote the large scale adoption of BEVs, seeing as the majority of the Dutch population buys occasion vehicles instead of new vehicles.

2.7.2 Survey

At the beginning of our modelling process, we required more information about the interaction between the policy-mix and the target segments. A survey was conducted to determine which policy measures are most important, how they are applied, which segment they target and what their expected effect is. We included the survey in Appendix A.1.
To determine the estimated effect of policies, we needed to determine the reasons why someone would be more or less inclined to acquire a BEV and which factors and activities are most influential. Four domain experts completed the survey, a follow-up interview was conducted to expand on the answers and clarify inconsistencies among respondents. We will briefly discuss the results of this survey here. The most important policy measures were those that reassure potential occasion BEV buyers, facilitate charging, and discourage the usage of ICEVs. Measures which promote the usage of BEVs and increase individuals acquaintance with the BEVs were also deemed important.
The respondents were asked to order factors according to the estimated importance within an individuals thought process. The following four factors were deemed most influential:

- The individuals' financial resources;
- The individuals' employment;
- The charging possibilities at their disposal;
- The influence of family and friends;

These factors are in agreement with the factors highlighted in the workshops.
Among policy-makers, some disagreements were present about the exact ordering of the factors and their motivation for this ordering. An interview was, therefore, conducted to determine why this disagreement existed. We will briefly discuss the argumentation behind each of the four factors:

- *The financial resources:* The BEV is unaffordable to the majority of the Dutch population, financial incentives such as tax brakes and subsidies make the BEV more accessible and is, therefore, deemed as the most important factor by all respondents;
- *Someones employment:* was a vital factor as well, if someone is unemployed they are far less likely to make a big investment, such as acquiring a BEV;
- *The charging possibilities at their disposal:* Owning a BEV should not provide extra challenges, the ease of charging is, therefore, a very determining factor. Having the possibility to charge at home is estimated to vastly increase someone's probability of acquiring a BEV. The placement of charging stations within neighbourhoods is also a measure which is estimated to improve individuals' disposition towards the BEVs;
- *The influence of family and friends:* is deemed as very important, negative publicity and false information is very detrimental to the perception of BEVs;

The ordering of the factors is subjective and therefore differs between respondents.

During the interviews a more in-dept discussion took part, about each of the surveys questions, we will briefly discuss our obtained insights:

- Range anxiety is no longer an influential factor amongst new buyers, most commute distances lie well within the range of the average BEV. For occasion buyers, there is still substantial anxiety about the battery life of the occasion BEV and its corresponding range. Trustworthy battery checks are, therefore, a necessity for those who buy an occasion BEV.
- The importance of import and export was highlighted, subsidies will be put in place to deter the export of occasion BEVs;
- Some disagreement existed about the accelerated placement of charging stations. Some of the respondents deemed this as a necessary and vital measure because it makes charging easier for BEV owners. Other respondents argued that the increase in charging stations increases the parking pressure, BEVs would then be considered to be a nuisance and their status would decrease. One suggested solution to this problem would be to make parking spots with charging stations exclusive to those who need to charge. Anyone who parks in a spot with a charging station that does not need to charge will be fined. Less charging station would then be needed which would decrease the parking pressure. However, making the charging station spots exclusive to those who need to charge makes charging more cumbersome for BEV owners. Whenever a BEV would be fully charged the owners would need to move their vehicle to a different stop, or risk a fine. No consensus was reached on this matter;

From this survey we concluded that the following five measures would be the most appropriate to include in our model:

- MRB tax and BPM tax exemptions;
- Increase in Gasoline fuel tax;
- Making charging spots exclusive to those who need to charge;
- Increasing the rate at which charging stations are added;
- Providing subsidies to BEV buyers;

These policies were estimated to have the biggest effect on the factors mentioned previously. Furthermore, we also include social interactions between agents to account for the influence of family and friends. The conducted workshops, survey and corresponding interview were vital in determining which factors to include in our model and in modelling the agents' behaviour.

3 Modelling Choices

In this section we describe our modelling choices regarding segmentation (section 3.1) and agent frameworks (section 3.2) as well as all the assumptions (section 3.4) we made during the development phase of the model together with the theoretical basis on which they were based on (section 3.3). Some assumptions were based on expert opinion whilst others were based on scientific research.

3.1 Segmentation implementation

In our model, we divide the entire population of agents into target segments. In section 2.3 we introduced four different segmentation practices, due to the nature of our research and the goals of our stakeholders we applied the market segmentation practice (section 2.3.3). Although the model is an approximation of market dynamics it does not reflect them accurately enough, nevertheless, there are some overlaps. Both try to influence the population to act in a certain way. Policy-makers aim to alter behaviour while market strategists aim to sell their product. In our particular case, we aim to model the influence that policy measures have on the adoption rate of BEVs. The policies try to maximise the adoption rate by creating a better fit between the individual/segment and the product. Market segmentation can therefore be used.
Just like in our use case, the agents were segmented according to their consumer behaviour. We divided the population into 3 segments, the agents who: own an occasion, own a new-bought vehicle (new buyers) and agents who leased their vehicle. This was done to comply with the goals of our stakeholders. We want to test the effects of policy measures on the agent population, these measures target the three target segments. It was, therefore, the sensible choice of segmentation. As mentioned in section 2.3.3 the segments we use need to satisfy certain requirements: *differential*, *identifiable*, *accessible*, *substantial*, *actionable*, *stable and responsive*. We will argue that our segmentation does indeed meet these requirements.

Identifiable

The segments are identifiable because we have data about their characteristics as discussed in section 2.6. From the available data we know whether the respondent leases their vehicle or owns their vehicle. We do not have any information about whether or not someone owns an occasion or new-bought vehicle. In order to obtain our 3 segments we, therefore, by our own criteria assumed that if the respondent has a vehicle which is older than 10 years and an annual income below 54 000 that they own an occasion vehicle, this makes the segments differential.

Accessible The agents within the model were design in such a way that they are influenced by the policies. This ensures that when the policies are implemented within the model that it has an effect on the agents deliberation, internal values and behaviour.

Actionable We know that the policy measures, given in section 2.5, were developed such that they target each of our segments. The behaviour of the agents within the model was designed to ensure that agents belonging to different segments show differential response when exposed to the same policy-mix. Therefore, the agent segments are actionable. The behavioural rules of the agents will be discussed in section 3.4 and 4.

Stable

Our segments are relatively stable, agents who lease will continue to do so, agents who own an occasion will also acquire an occasion in the future. Agents who have a new-bought vehicle can choose to buy a new vehicle or lease their new vehicle, only a small percentage will choose to do so.

Substantial

Our population size is quite small, it consists of 200 agents of which 168 own an occasion vehicle, 8 agents own a lease and 24 own a new-bought vehicle. Because the simulation spans 20 years in which almost all our agents replace their old vehicle, we can observe the effects of the policies on each segment, this allows us to observe the success rate. We, therefore, argue that the segments are also substantial.

3.2 Choice of agents framework

In section 2.2 we discussed the Consumat and the BDI framework which are used to simulate the decision-making process of agents. The architecture of the agents within our model consists of a conjunction of these two architectures.
The BDI framework (section 2.2.1) is too simplistic for our model. It does not allow us to integrate the complex need assessment and uncertainty deliberation involved in the acquisition of a new vehicle. However, we do use its components to describe our agents "mental states". The agents have *Beliefs* which consist of parameters taken from data, knowledge about its environment (such as policy measures), and information collected from other agents. We will discuss the agents in more depth in section 4.2.3.
The agents' goals and intentions are more related to the Consumat framework (section 2.2.2). It was important to incorporate the Consumat framework because it gives our agents more complexity, making their actions have a closer resemblance to actual consumer behaviour.
We were unable to implement the Consumat framework fully because we did not have enough personal information about the respondents to attribute our agents with an uncertainty tolerance, ambition level or a social network. To construct our model we needed to alter the Consumat framework. We will discuss these alteration below.

Decision strategies

When faced with the decision to replace their vehicle, agents have three decision strategies: deliberation, repetition and social comparison. Figure 5a gives an overview of the decision process of the agents within the Agent-Based Segmentation Model.
We have no information about social interactions from the respondents within the available data. We, therefore, did not include the social comparison strategy, as defined within the Consumat framework, within our model. Instead, we altered the deliberation strategy to include social comparison. When deliberating the agents are influences by the values and experiences of other agents. Furthermore, the only information available about the respondent previous consumer activities were obtained from the respondents' current vehicle. Repetition, therefore, entailed continuing to acquire a BEV or ICEV.
The first strategy is always deliberation. Here the agent will check its possibilities, i.e. whether it has enough money to acquire a BEV, and whether a BEV could cover its daily commute distance. If the BEV does not lie within its possibilities the agent will choose the repetition strategy, i.e. it will again acquire an ICEV. If the BEV lies within the agents' possibilities, the agent will either choose to acquire a BEV or an ICEV dependent on which one better fulfils their needs.

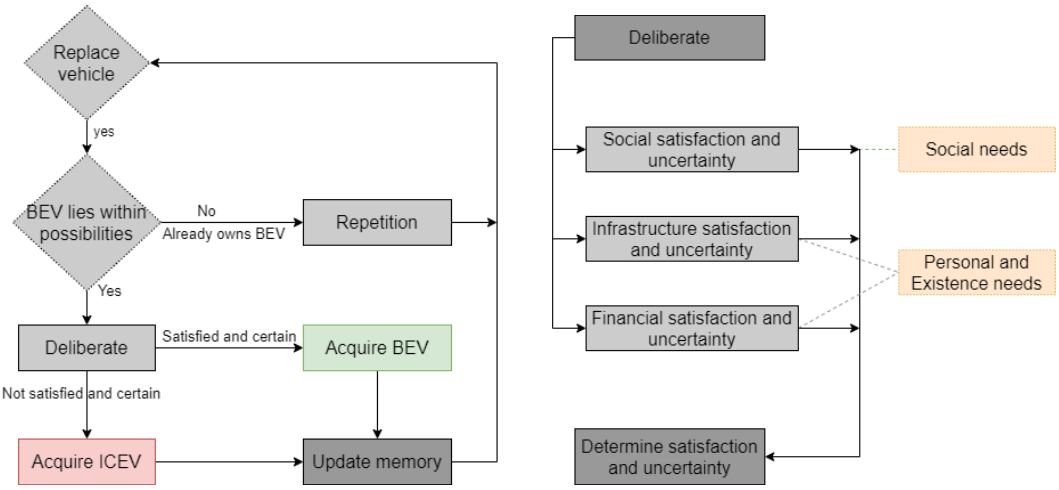
Needs

Unlike in the Consumat framework, the agent will not decide on one decision strategy but rather apply several at the same time to select the action which best fulfils its needs. The needs of the agent correspond to those described in the Consumat framework: *social needs*, *existence needs* and *personal needs*, which will be described in more detail in section 4.2.3.
To determine whether the BEV satisfies the agents' needs, the agent will deliberate about the

perceived satisfaction and uncertainty the BEV will bring them. Social comparison is part of the deliberation process. Therefore, the role of the agents' satisfaction and uncertainty play a different role within our altered framework. The satisfaction and uncertainty of the agents can subdivided into three subparts: financial, infrastructural and social. These parts represent the agents' needs, as indicated in figure 5b.

Memory component

Just like in the Consumat framework agents have a memory component which stores their values, possible actions, and properties. This memory component is updated every time the agent is faced with the decision to replace its vehicle.
As described in section 2.2.2 the agents have limited cognitive capacity, this implies that the agents instead of reasoning about all available vehicles they will only reason about a subgroup of vehicles, which lie within their price range (section 4.2.3). Thus, the agent selects a group of BEVs and a group of ICEVs and compares their characteristics to determine its satisfaction and uncertainty concerning the BEV.
If after deliberation the agent determines that the BEV does not fulfil its needs adequately it will choose to buy an ICEV (which corresponds to the repetition strategy in the Consumat framework). Imitation is not part of the agents' decision framework. Figure 5b gives and overview of the agents' deliberation process.



(a) Schema of the agents' decision process, including the strategies involved

(b) Schema of the deliberation process of the agents including need assessment

Figure 5: Schema of the deliberation an decision process of the agent within the Agent-Based Segmentation Model

3.3 Theoretical basis

In this section, we give an overview of some of the theoretical assumptions we used to construct our model as well as validate it. Not all assumptions discussed here are included in our model, some assumptions where included to show that they often contradict each other. The assumptions used to construct the model will be referred to later on in this thesis.

	Assumption	**Reference**
1.	BEV-drivers are more often: men between 25 and 45 years old, highly educated with a technological or commercial oriented job living in urban areas.	Profiel EV-rijders landelijk Reizigersonderzoek M&E-team DGMo (RVO)
2.	Attitude, personal norm, social norm and perceived control matter the most for BEV adoption.	[60]
3.	Psychological characteristics should be taken into account. Males with above-average income and willingness to pay for new technologies are usually the early adopters of BEV's.	[61]
4.	From a purely economic perspective: people with full-time jobs living in medium-sized cities with driving habits which suit the mobility profile of BEVs are the most likely to adopt a BEV.	[62]
5.	Living in big cities is a barrier to BEV adoption, since private parking is less common and charging locations are not readily available. Public transport is also used more often and incomes are lower which implies that for most a vehicle isn't affordable. Most young adults live in cities, and car ownership in this group is low.	[63]
6.	Socioeconomic characteristics should be taken into account. Namely that middle-aged men with technical professions living in the suburbs and rural areas with multi-person households are more likely to adopt BEV's.	[63]
7.	Well-educated, middle-aged small families that are trying to save money on their travel expenses are more likely to choose a BEV.	[64]
8.	Young and environmentally aware people are more likely to consider buying a BEV.	[65]
9.	The stated preference should be taken into account. Respondents capitalise about 5 years of fuel-saving into the purchase price of an electric vehicle.	[64]
10.	Social impact and less range anxiety are major contributors to BEV adoption.	[61]
11.	Electric cars are usually purchased as an additional vehicle.	[66]
12.	People who identify as pro-environmental have positive perceptions about BEV attributes.	[67]
13.	The vehicle purchase decision is heavily influenced by members of the household.	[60]
14.	Pro-environmental lifestyle, awareness and concern about environmental problems are factors that influence the adoption of BEV's.	[68]
15.	The more a consumer perceives a behaviour to be a social norm, the more likely it will be to adopt such behaviour.	[69]

16.	The decision-making process for private car purchases is predominantly driven by financial and performance considerations including price, fuel consumption, comfort, size, practicality and reliability. Environmental issues play little part in the process and are among the least important considerations for new car buyers.	[68][70]
17.	Happiness with one's vehicle decreases the further the usual parking spot is from ones home.	Own assumption
18.	36% of the Dutch population is interested in BEV's, 28% is not interested, the rest of the population is indifferent. Of the potential car buyers in the Netherlands, 56% considers buying a BEV, 27% is not considering buying a BEV.	[70]
19.	Only 32% of the Dutch population is aware of the policy measures concerning BEV's. 30% is aware of the purchase subsidy, 25% is aware of the lower tax addition, 22% is aware of the BPM exemption, 18% is aware of the MRB exemption	[70]
20.	Purchase subsidy has the most effect on the younger demographic (age between 18 and 30) and families with a modal income.	[70]
21.	After 250.000 km almost all Teslas had 90% of the original battery capacity left. It was shown that after five years almost all models of the electric vehicle still had 80% to 97% of the original battery capacity left (the vast majority has 90% battery capacity).	[50]
22.	The function for the percentage of battery degradation dependent on km is approximately represented by: $(-1.97 \times 10^{-4} \times millage^2 - 4.35 \times 10^{-2} \times millage + 99.64)/100$	[71]
23.	The total number of occasions sold in 2019 was 670000. There were also 446114 new vehicles registered in 2019 (more than half of these is owned by companies)	[72]
24.	In total there are 2.1 million private car buyers each year, 1.7 of those buy occasions, which is 80.9%. In 2019 there were 44678 privately bought occasion BEVs in the Netherlands and 2366 company bought BEVs.	CBS, RVO, RDW
25.	One of the main obstacles to adoption of BEV is the high initial investment. Charging uncertainty is also one of the principal hurdles experienced by people preventing them from acquiring a BEV	[70]
26.	People are influenced by the opinion of the people close to them. Being familiar with the BEV increases someone's probability of acquiring a BEV in the future.	[70]

3.4 Basic assumptions regarding consumers

In this section we will discuss some of the assumptions made during the development of the Agent-Based Segmentation Model, these assumptions concern primarily consumer behaviours. We will also discuss the assumptions made with regards to the difference in need evaluation between agents of different segments. The following assumptions were made concerning consumers:

1. Consumers are social beings. The opinions of people like them and of people whom they like have a greater influence on their behaviour than objective information from experts. This influence can also be subconscious, [73].
   This phenomena is represented in our model within the social uncertainty and satisfaction (section 4.3.1). Where the influence of other agents is included in the agent deliberation process. However, in the model all agents influence each other in the same way, there is no influence hierarchy.

2. Consumers are not good at processing numbers when trying to calculate the costs and benefits. They are subject to biases. This is exemplified in the fact that people are more averse to risk than motivated by possible gains, [74]. This implies that they are more sensitive to losses than to gains of the same magnitude. If a product is made more expensive this is perceived as a bigger loss than if the product would have been made the same amount cheaper.
   We captured this property in our model by making the agent's satisfaction and uncertainty weights differ. Agents are therefore like real people, they are biased towards negative influences. The fact that the initial investment for BEV is considerably higher than the initial investment for ICEVs will have a greater influence than the fact that the tax rate for BEVs is lower than for ICEVs.

3. Immediate financial benefit is perceived as more valuable than the same amount or a larger amount obtained later on [75], [76].
   This is captured within our model by making the initial investment and tax benefits weigh more than the overall lower cost of owning a BEV compared to an ICEV;

4. Consumers are not rational actors as defined by the economic theory. They do not treat money as interchangeable but rather attach labels to it, such as "grocery money", "rent money" to aid in their mental accounting [77].
   This is captured in our model by dividing the financial uncertainty and satisfaction into three main parts: initial investment, weekly expenses on commute costs, and tax benefits.

5. The majority of consumers are change-averse and will treat every new product sceptically. If change is not urgent then they will remain the same. They do not operate in the traditionally thought way of maximising benefits and minimising costs [78]. A small portion of consumers are considered to be risk-takers and are not deterred by change.
   This is included in our model in the following way: if almost no agent owns a BEV then agents will be less likely to acquire a BEV. If however owning a BEV is quite common in the simulation agents will be more likely to acquire a BEV. Also, if the agent does not have to replace its vehicle it will not engage in any kind of deliberation about possible future vehicles.

6. Consumers have limited cognitive capacity. When faced with an elaborate decision the consumer will oftentimes compare only a small number of options on a small number of features using simple rules (bounded rationality) [79].
   The agents within our model only consider, from the two power train sets, a small subset of vehicles which lie within their price range. They will then compare them to each other and select the power train that best suits there needs. The comparison of vehicles only happens on a small set of characteristics, such as range, price, age and brand status.

7. Agents will set aside 10% of their monthly income for fuel costs (this is an estimation).

A more extensive overview of studies and results focusing on consumer adoption of BEVs' can be found in [68].

3.4.1 Behaviour assumptions for our segmentations

To implement our segmentation and model the agents' attitudes and purchasing behaviour, we consulted with domain experts to determine the difference in need evaluation between agents of different segments. We will highlight theses assumptions below:

- For leasers, the initial investment difference between BEVs and ICEVs does not play a role in their decision making. They only take into account the monthly price difference between the two power trains and the tax and fuel cost difference.
- It is expected that the percentage of leasers of BEVs in the Dutch car market will increase considerably in the near future.
- The financial aspect is the most important aspect for people who lease their vehicle, the social and infrastructure aspect have little influence on their decision making.
- The people who consider acquiring an occasion BEV are most concerned with the battery degradation of that vehicle and the difference in initial investment.
- Because no official system is of yet in place that is able to accurately test the battery degradation of BEVs, people take into consideration the mileage and age of the vehicle and make a rough estimation on how much range loss it is expected to have.
- The financial aspect is the most influential aspect independent on which segment someone belongs to.
- The difference in initial investment between the BEVs and ICEs is largest for the new-buyer's segment, they are therefore the hardest to influence.
- People who consider acquiring an occasion BEV are the most unsure, social influences will therefore have a greater effect.
- People who are able to acquire a new BEV are most often also able to charge at home, for leasers and occasion buyers this is not the case. Availability of the necessary infrastructure has a higher effect on these segments.
- Because the initial investment for BEVs is considerable for new buyers, they are more unsure. The social influences therefore has a greater influence.

Further assumptions about the interaction between policies and peoples' behaviours were obtained from [80].

4 Model description using the ODD protocol

In this section, we will use the ODD protocol 2.1.1 to describe our model. We will start by stating the purpose of our model, how it should be used and the patterns it tries to simulate, section 4.1. Then we will describe the entities, variables and scales within our model, section 4.2. We will give a high-level process overview and scheduling in section 4.3 followed by a description of the design concepts in section 4.4. In section 4.5 we describe the model initialisation, followed by the description of the input data in section 4.6. We end this section with a description of the models' submodels, section 4.7.

4.1 Purpose and patterns

The choice of purchasing a BEV is influenced by many factors, each contributing in certain degrees to this choice. Our simulation is designed as a tool for understanding and communicating about people's behaviour in deciding to acquire a BEV. The conjunctive behaviour of all agents is called population dynamics.
The Agent-Based Segmentation Model was constructed to be able to observe and study the dynamics of a population. It allows us to interactively test the effects certain factors have on the dynamics of a population. This is done by using the sliders and buttons of the Repast GUI and observing the effects directly using the graphs, histograms and plots of the interface. Using these features it is possible to observe whether the number of agents that acquire a battery-electric vehicle (BEV) per year increases or not and how much. Using the model we aim to create an extensive exploration of the population dynamics to obtain a general idea of the outcome of behaviour.

4.1.1 Purpose within the policy context

The model can further be used to investigate the effects certain perturbations/policy-measures have on different segments of the population. Our model allows for the interactive testing of policy-measures on the artificial population. Whereby the effects of the different policies on the population dynamics can be observed, as well as the effects of the interaction of the different policies. This allows us to observe their overlapping effect and determine, by consulting experts, whether the models' behaviour is accepted or rejected. If it is rejected this would imply that the underlying behavioural rules of our system are either incomplete or wrong in some way. If it turns out that the underlying assumptions are wrong then because they are based on the factors given by the experts this would either imply that some factors are missing, that the causality is wrong or that some core assumptions about cause and effect of behaviour made by policy-makers are incomplete. The model, therefore, allows us to highlight some core uncertainties and discover potential intended or unintended consequences of policies as well as discern unexpected impacts. What is defined as expected and unexpected will be determined by the domain experts during the validation process of the model. Potential links and interactions between multiple policies can also be discovered. By observing the interactions of policies within our domain we are also able to suggest efficiencies based on the observed dynamics and explain why these efficiencies are relevant and what they would be able to offer within our context.
It is not our ambition to create a model that is realistic to a high degree. The simulation remains an imagined scenario and does only reflect a small part of reality. Lack of data, computational power and behavioural knowledge inhibit us from constructing a model that can reflect the real world accurately enough. Our model is in part an explanatory model as it explains why or how people proceed when deliberating about acquiring a BEV. The model incorporates a probabilistic causal chain with or without the acquisition of a BEV as its consequence.

4.1.2 Patterns

We modelled the agent's behaviour in such a way that it corresponds to what the policy-makers expect to see when single policy-measures are enforced. During the development phase, multiple interviews and workshops were conducted with policy-makers and other stakeholders to determine which factors might play a role in the BEV adoption process, this was discussed in section 2.7. During these interviews, we also determined what the expected effects are of each of the policy measures. For example, the higher initial investment cost for BEVs is known to be an important factor in the BEV adoption process because it is one of the main hurdles experienced by potential BEV buyers. One way of influencing the adoption process is therefore lowering the initial investment cost by implementing a subsidy on new battery-electric vehicles (BEVs). Lowering the initial investment cost is expected to increase the amount of BEVs in circulation. Both the initial investment cost as well as the subsidy was therefore included in the model. To test the effects of this policy measure the user is able to increase and decrease the value of the subsidy and observe the degree in which this affects the BEV adoption rate within the simulation. This same reasoning process was used to include multiple factors and measures within the model and approximate their estimated effects.
We were not able to include all factors within our model and we had to do a lot of estimations of how much a certain measure would influence an agents thought process. We also needed to bind the outcomes to plausible ranges by consulting experts.
Each year between approximately 5% of the agents will consider acquiring a new vehicle. BEV-owners will always acquire a BEV, whilst ICEV-owners will have to choose between a BEV or an ICEV. This choice is determined by their satisfaction and uncertainty values concerning BEVs, we will elaborate on this in 4.3.1. Agents are restricted in their abilities by the amount of money at their disposal.

4.2 Entities, state variables and scales

The model consists of a set of agents (section 4.2.3) which own a personal vehicle (section 4.2.1), which is another entity included in our model. The agent's exit within a neighbourhood (section 4.2.2) wherein they have parking spaces and a fixed home location. Each tick of the simulation represents one week in the agent's world, a year consists of 52 ticks.

Every tick in the model the agents will try to park their vehicle within the neighbourhood grid, they will also go to work which implies that they will cover their indicated daily distance. If an agent has the possibility to park at home it won't need to search for a parking space.
The agents first decide whether they want to replace their old vehicle or not, this is a simple process of assessing the age of their vehicle and the need to replace their current vehicle, we will explain this further in section 4.2.3. Once they have decided to replace their old vehicle they will reason about whether to acquire a BEV or an ICEV. When deciding between a BEV and ICEV, the agents will engage in information-seeking strategies. Information seeking involves determining how much satisfaction and uncertainty a BEV will bring. This involves reasoning about the financial aspect as well as the infrastructural and social aspect of owning a BEV, section 4.3.1. If an agent is certain and satisfied it will decide to acquire a BEV if not it will choose to acquire an ICEV. The agent can choose from a variety of vehicles as long as they are within its price range. Furthermore, if the agent does not have the means to acquire a new vehicle it will choose to lease a vehicle instead. We will discuss each of our model entities more in-depth in the following sections.

4.2.1 Vehicles

Each vehicle is either a BEV or a gasoline-powered vehicle (ICEV). Vehicles can either be new or second hand (occasion) vehicles. Vehicles differ in their price, power train, emissions, brand and model. The brand gives the brand of the vehicle (ex: Tesla, BMW(i3), etc), the model indicates whether the vehicle is small, medium, large, luxury or executive. In case the vehicle is a BEV they have a range, charging time and zero emissions. Occasions vehicles have two extra parameters which indicate the year in which the car was produced and the mileage of the vehicle. Each of the vehicle parameters were constructed using actual data gathered from car dealer websites[1]. We will discuss some of the vehicle parameters below.

Price: Each vehicle available to the agent has a price, this price includes eventual subsidy measures. At the beginning of the simulation, the user can alter the subsidy values for both the occasion BEVs as well as the new BEVs. During the simulation, the subsidy value does not change and is the same for all agents.

Range and millage: All BEVs available to the agent have a range. If the vehicle is an occasion BEV the agent will take into account the age and the mileage of the vehicles to estimate the vehicles' current battery capacity:

$$\%\text{-}battery\text{-}capacity = (-1.96825 \times 10^{-4} \times millage^2 - 4.35238 \times 10^{-2} \times millage + 99.6429)/100$$

This function is an approximation of the rate at which the battery capacity of BEVs decreases. It is estimated that the battery capacity of an average BEV drops about 5% per 75000 kilometres driven, assumption 22 section 3.3. The rate at which the battery degrades increases gradually as can be seen in figure 6. Once the agents have computed the estimated current battery capacity they will determine the current range of the occasion vehicle, which is done using the function:

$$Current\_range = Initial\_range\_vehicle \; * \; Battery\_capacity$$

The current range of the occasion BEV will be included in the agents' deliberation process. The lower the current range is compared to its initial range the less favourable that occasion will be.

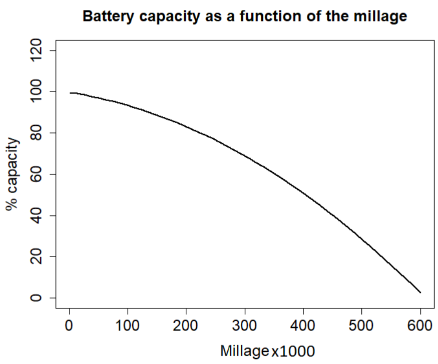


Figure 6: Battery degradation function according to [71]

Emissions: Each vehicle has a fixed emissions variable. BEVs have zero emissions and depending on the model of the ICEV the emissions might be higher or lower. Emissions influence the BPM tax category the vehicle falls into. The higher the emissions of the ICEV the higher the BPM-tax will be. The BPM tax is not fixed, the user is able to alter these values at the beginning of the simulation.

Brand: Each vehicle, available to the agent, has a brand. The BEV vehicles in the simulation have one of the brands given in Table 2. The ICEVs have brands correspondent to one of the top 10 sold gasoline vehicle brands of 2019. Occasion ICEVs equally have brands correspondent to one of the top 10 sold occasion vehicles in the Netherlands in 2019[2].

[1] The following websites were consulted: `https://www.autoscout24.nl/`, `https://www.autokopen.nl/aankooptips/best-verkochte-occasions-2019-2020-976` , and `https://www.anwb.nl/auto/kopen/zoeken/`

[2] According to `https://www.autokopen.nl/aankooptips/best-verkochte-occasions-2019-2020-976` and `https://www.viabovag.nl/blog/populaire-occasions-79snEI86OG8ybmn3TL7MlE`

Year: If the available vehicle is new the year parameter will be zero. If the vehicle is an occasion than the year parameter will correspond to the year in which the car was produced. This will influence how the agent will consider the vehicle. The older the vehicle the less favourable it will seem to the agent. This influence was included in our model to account for the fact that the battery capacity of BEVs will decrease the older the vehicle is.

4.2.2 Neighbourhood

The agents exist within a neighbourhood. The neighbourhood contains the parking spaces, the agents and their respective homes. The parking spaces surround the homes and the homes are distributed randomly across the grid. Each agent has a home location, if the agent does not have private parking they will try to park as close to their home as possible. There are some restrictions on parking. If the agent has a BEV and needs charging then it will try to park in a parking space that has charging facilities. If the agent does not need to charge they will try to avoid parking spaces with charging facilities, seeing as wrong parking results in a ticket.

4.2.3 Agent

All agents in the model own a vehicle. Agents distinguish themselves from one another by the characteristics of the vehicle they own, the location of their home as well as their parameters. The agent parameters are initially based on data. The data will be described in section 4.6. Some of the agent parameters will be updated during the simulation depending on the choices the agent makes. Once an agent replaces its old vehicle the agent parameters describing their vehicle will be updated. Agents can perform actions and reason about which action to take.
The agents' architecture consists of a conjunction of two architectures, the BDI (Section 2.2.1) and the consumat framework (Section 2.2.2), as discussed in section 3.2. Agents have beliefs, these include their income, the age of their vehicle, its type of power train, their knowledge of BEVs and their associated subsidies and tax benefits. They also have knowledge about other agents such as the type of vehicle they own, their ability to park, their satisfaction about BEVs and their uncertainty.
Agents also have desires and intentions these are more closely related to the needs described in the consumat architecture, section 2.2.2. The action the agent performs is in line with its needs. As described in section 2.2.2 agents have social, existence, and personal needs. We will quickly highlight these needs here:

- *Social needs:* The agents will observe the average parking success of the agents with different power trains and take this into account. Their social need is translated in the influence other agents have on them i.e. their need to conform. If almost no agent owns a BEV then agents will be less likely to acquire a BEV. If, however, owning a BEV is quite common in the simulation agents will be more likely to acquire a BEV. The social need is also observed in the brand of the vehicle they will consider. A more prestigious brand, i.e with higher ranking, will be considered more favourable. Agents will try and maximise their status by selecting a better brand of vehicle.

- *Existence needs:* The agents' existence needs consist of those needs necessary for the agent to survive. In our case, this only concerns owning a vehicle that they can afford, which can cover their daily commute distance, and which they are able to park close enough to their home.

- *Personal needs:* Corresponds to the overall enjoyment of life such as for example avoiding having to park too far from home, saving money by not overspending on a new vehicle as well as saving on fuel cost and taxes, and adhering to one's environmental conscientiousness.

Agents will perform certain actions in order to fulfil their needs. These actions include: parking their vehicle, deciding to replace their old vehicle with a BEV or ICEV, and deciding on which of the available vehicle to acquire.

Agent decision making

The agents' decision making is done under uncertainty, the outcome of their decision has to satisfy a certain satisfaction and uncertainty threshold. The agents' decision making revolves around the choice between a BEV and an ICEV.
The agents have an uncertainty and a satisfaction about the BEV which is updated when they decide to replace their old vehicle. The satisfaction and uncertainty of the agent reflect the degree to which the BEV satisfies their three needs: existence, personal, and social. We will further elaborate on the satisfaction and uncertainty of the agents in section 4.3.1.
Unlike in the Consumat framework agents do not have to decide between the four cognitive processes: *repetition*, *imitation*, *social comparison*, *deliberation* (section 2.2.2). Instead, agents always engage in deliberation once they decide to replace their old vehicle. The deliberation involves an assessment of the satisfaction and uncertainty the BEV will give them. The social comparison is part of the deliberation process. Once the agent has determined its satisfaction and uncertainty it will either choose to repeat its previous consumer action, by acquiring an ICEV, or acquire a BEV instead. The agent will only choose to acquire a BEV if it is satisfied and certain.
We do not have enough information about the respondent to attribute them with an uncertainty tolerance or ambition level, we will elaborate on this in section 4.3.1.
The agents within the Agent-Based Segmentation Model are able to perform three actions: *park, commute to work, and replace their current vehicle.* We will discuss each these action below and describe how we implemented them in our model in section 4.3.

Parking: Agents aim to fulfil their parking needs by parking their vehicle as close to their home as possible whilst adhering to their power train needs. Depending on their type of power train there are some imposed restrictions on parking.
Agents which own a BEV need to charge their vehicles, this is done by parking their vehicle in a parking spot which has charging facilities. If the agent is able to park at home we assume it is also able to charge at home. Agents which are not able to park at home will need to park as close to their home as possible.
The distance they will park from their home influences their happiness value. Agents with BEVs which are not able to charge at home will try to park their vehicles as close to their home as possible in parking spaces which have a charging station.
If the agent has an ICEV it will either park at home, if possible, or try to park as close to their home as possible on a parking space with no charging facilities. If an ICEV owner parks in a parking space with charging facilities its happiness will decrease. Likewise if a BEV owner parks in a parking space with no charging facilities its happiness will also decrease. This will further be described in section 4.3.

Going to work: Each agent will cover its weekly commute distance, which is obtained from the data. In order to do so, it will leave the parking spot it acquired in the previous tick, and search for a new parking spot adhering to the restriction discussed previously. If the agent owns a BEV it will need to charge after it has covered its commute distance. The agent will also reason about the cost of commuting using the two different power trains, section 4.3.

Replacing current vehicle: Agents are initialised by having some propensity to replace their current vehicle. This ensures that approximately between 5 and 14% of the agents will replace their current vehicle. The older the vehicle the higher the agents' propensity to replace it.

Agents aim to replace their vehicle with one which satisfies their satisfaction and uncertainty needs/thresholds. Depending on the agents' current vehicle it will choose to lease, buy an occasion, or buy a new vehicle. Furthermore, if the agent currently owns a new-bought vehicle it will either choose to lease or buy a new vehicle depending on the agents' income and age. We represented a schema of the agents' decision process in Figure 7. This decision process was developed such that our model follows current trends within the Dutch car market, which will be discussed in section 7. Once the agent has decided how it will replace its current vehicle it will only reason about new vehicles, leased vehicles or occasion vehicles.

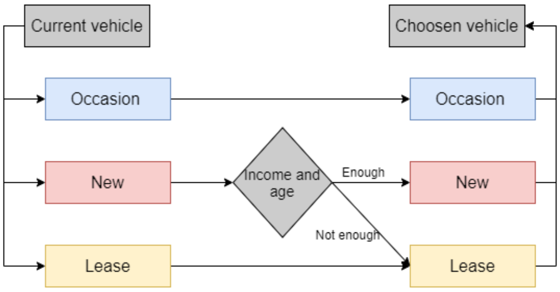


Figure 7: Schema of the vehicle ownership selection

The agent will further decide whether to acquire a BEV or an ICEV. We mentioned before that the agents have limited cognitive capacity, it therefore only compares a small number of vehicles on a small number of characteristics.
The agents' will compare a subset of the BEV vehicles to a subset of the ICEVs. The vehicles within those subsets lie within the price range of the agent. Once these subsets are obtained the agent will compare the vehicles by determining in which measure each of the vehicles would satisfy or bring uncertainty. The agent will select one vehicle which brings maximum satisfaction and minimum uncertainty. The uncertainty and satisfaction of new and occasions BEV's is determined differently because their properties are different.
The agents' selected BEV must surpass the agents' satisfaction threshold and not surpass its uncertainty threshold in order for the agent to decide to acquire this vehicle. Otherwise, the agent will acquire an ICEV within its price range. Figure 8 gives an overview of the factors taken into account during the selection process of the agents. In section 4.3 we give the agents' decision algorithms which describe the before mentioned processes in detail.

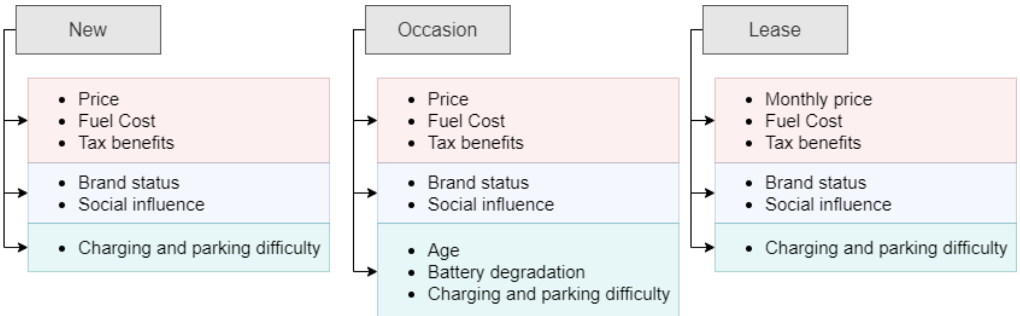


Figure 8: Schema of the factors taken into account during the power train selection process of the agents.

4.3 Process overview and scheduling

As discussed in section 3, our model will use a version of the Consumat framework [40] and BDI-framework in order to define the decision process of the agents. In our model, about 5 to 14% of the agents will replace their current vehicle each year. Agents that own an ICEV and want to replace their current vehicle will further decide on whether to acquire a BEV or an ICEV. This deliberation depends on their uncertainty about BEVs and the perceived satisfaction a BEV will bring them. Each agent will have a different uncertainty and satisfaction. The uncertainty and satisfaction are subdivided into a financial, social and infrastructure component. We describe each of these factors in section 4.3.1.
We know that the charging uncertainty, range anxiety and the higher initial investment for BEVs are some of the major hurdles preventing the widespread adoption of BEV's (section 3.3 assumption 25). We incorporated these aspects in the model. The financial considerations involved in buying a BEV are one of the most influential in the deliberation process (stated in section 3.3 assumption 16). These financial considerations include the initial investment, the commute cost differences (section 3.3 assumption 9), the financial benefits provided by subsidies as well as the fact that owning a BEV offers tax benefits and is cheaper to drive in general. This deliberation is taken up in both the financial uncertainty and the financial satisfaction. The higher initial investment contributes to the agents' uncertainty and decreases the agents perceived satisfaction of BEVs. By considering the uncertainty and satisfaction we try to emulate the complex thought process involved in the decision-making process.
Furthermore aspects like environmental awareness, social pressure and status are incorporated in the social uncertainty and satisfaction. Dependent on the agents' norms concerning environmental awareness they will be more or less influenced by others within their community. Agents will also observe BEV owners within their community and compare their happiness to the ICEV owner group. The agents' happiness concerns parking only, thus whether BEV owners experience stress due to limited charging stations or the walking distance to the nearest charging spot.
The agents charging anxiety is also incorporated within the infrastructure uncertainty component. If the agent is not able to charge at home, they will experience some uncertainty. The ease in which they will be able to charge near their residence will influence their infrastructure uncertainty. Furthermore, their range anxiety will be dependent on their daily commute distance and the range of the BEV they can afford. Their knowledge of the electric vehicle and their technological affinity will also be taken into account (section 3.3 assumption 1) when determining their infrastructure uncertainty. If an agent with an ICEV is able to park at home its perceived satisfaction about BEVs will increase seeing as the ability to charge at home lowers its commute cost considerably and nullifies its parking anxiety.

Financial	Social	Infrastructure
• Investment price • Subsidies • Commute costs • Tax benefits	• Social pressure • Status • Environment friendliness	• Walking distance • Charging/parking difficulty • Range anxiety • Battery degradation • Technological knowledge

Figure 9: Factors included in the satisfaction and uncertainty components

We give an overview of each of the satisfaction and uncertainty components in figure 9. These components will be discussed in more depth in this section.

4.3.1 Uncertainty and satisfaction

We are primarily interested in the factors involved in the adoption process of BEVs. Therefore, only ICEV owners will reason about whether to acquire a BEV or not. Agents which currently own a BEV will always acquire a BEV in the future. As mentioned before, ICEV owners will have a certain perceived satisfaction and uncertainty concerning BEVs. The calculation of the uncertainty and satisfaction involves a multitude of factors which take into account the properties of BEVs as well as their comparison to ICEVs. The reasoning process of new buyers and occasion buyers differs slightly, the factors, as well as the weights given to the factors, might differ (assumption 2 section 3.4).

Both the agents' satisfaction and the uncertainty are composed of three aspects: social, infrastructure and financial. It is necessary to keep in mind that although the uncertainty and satisfaction consist of the same components they are determined very differently. It is possible for an agent to be easily uncertain yet very hard to satisfy. The uncertainty and satisfaction have values between 0 and 1. If an agent has a satisfaction of 1 this implies that it is very favourable towards BEV. An uncertainty of 0 means the agent considers BEVs to be very trustworthy. An uncertainty of 1 and satisfaction of 0 is the most unfavourable situation for BEV's.

We were unable to obtain a satisfaction threshold or uncertainty tolerance from our data. We thus assume that both the uncertainty tolerance as well as the satisfaction threshold is equal to 0.5 for all agents, this implies that the agent will only acquire a BEV if their uncertainty is below 0.5 and their satisfaction higher than 0.5. Otherwise, the agent will acquire an ICEV. We will give a description of each of the three aspects included in the satisfaction and uncertainty calculation below.

Financial uncertainty and satisfaction

The financial uncertainty and satisfaction, about BEVs, is determined by comparing BEVs and ICEVs based on three aspects:

- *The initial investment* (assumption 16 and 25 section 3.3): Whereby the agent compares the initial investment needed to acquire a BEV and an ICEV. The price differs for the different segments: the initial investment is higher for new vehicles than for occasions, while the initial investment for leasing a vehicle consists of the monthly lease cost. The more expensive a BEV is compared to an ICEV the more uncertain the agent will be and the less perceived satisfaction the BEV will bring;
- *The fuel costs:* the agent will compare the commute cost of using both power trains. If the commute cost using a BEV is lower than the commute cost using an ICEV, the agents' satisfaction will increase and its uncertainty will decrease.
- *The tax costs:* the agent will take into account the tax benefits of owning a BEV instead of an ICEV;

The agents' knowledge of the subsidies and tax benefits concerning BEVs is also taken into account when determining the financial uncertainty and satisfaction, algorithm 7 shows this process in more detail.

Infrastructure uncertainty and satisfaction

The infrastructure uncertainty and satisfaction about BEVs is determined by comparing BEVs and ICEVs based on the following aspects:

- *The agents parking success:* if few charging stations are available and the pressure on existing charging stations is high, the agent will perceive BEVs as being less favourable, i.e. the agents' satisfaction will decrease and uncertainty will increase, assumption 5 section 3.3.

If however the amount of charging stations in the neighbourhood is high, then the agents that own an ICEV will have a hard time finding a parking spot and the agents satisfaction concerning BEVs will therefore increase and the uncertainty will decrease.
The parking success also takes into account the charging options available to the agent, which is either private, or in their neighbourhood. In case the agent is not able to charge at home, the distance it has to walk to the nearest charging station and the ease in which surrounding BEV owners are able to access this charging station is taken into account.

- *The occasions millage and age.* If the agent considers acquiring an occasion then it will take the millage and age of the occasion into consideration. The higher the agents commute distance the more influence the occasions battery degradation will have on the agents' uncertainty. This means that, in general, the agents' infrastructure uncertainty is higher for occasions than for new vehicles.
- *The agents' technical knowledge.* From our data we know someone's profession. From assumption 1 and 6 of section 3.3 we can conclude that one's profession has an influence on their propensity to acquire a BEV. Therefore, agents with a more technical profession, such is the case with jobs in construction/industry or commercial services, have a lower uncertainty and higher satisfaction than agents without a technical profession.
The agents also determine their range-anxiety which takes into account their commute distance. If the agents' commute distance is close to the range of the vehicle their infrastructure uncertainty, about owning a BEV, increases and the infrastructure satisfaction decreases.
- *The agents' knowledge of BEVs.* If the agent has ever driven a BEV or knows someone with a BEV then according to [70] this has a large influence on the agents' perception of the BEV. The uncertainty of the agent, therefore, decreases and its satisfaction increases.

Social uncertainty and satisfaction

The agents exist within a neighbourhood since we don't have data on the agents' interactions and the agent population is quite small we assume that all agents influence each other. Agents take into account the satisfaction and uncertainty of the other agents within their community, as well as their happiness with parking facilities. If, for example, parking becomes more difficult for BEV owners, then their parking happiness will decrease. Other agents will take this into account by lowering their social satisfaction and increasing their social uncertainty. If on the other hand parking for ICEVs will become more difficult then the social satisfaction of the agents will increase and the uncertainty will decrease.
The amount of BEVs owners in the population also influences the agents' social satisfaction and uncertainty. According to assumption 15 of section 3.3 the more someone perceives a behaviour to be a social norm, the more likely it will be to adopt such behaviour. We included this in our model. If more agents own a BEV then the social satisfaction of the agents will increase and its social uncertainty will decrease which implies that the probability of that agent adopting a BEV increases.
From the data, we have some information about the respondent's environmental involvement. The environmental involvement of the agent contributes to their social uncertainty and satisfaction.
The brand of the occasion vehicle the agent is considering acquiring also contributes to the social satisfaction and uncertainty of the agents. The higher the brand is ranked, on the top 10 (figure 2.4) most popular vehicles, the higher the agents' social satisfaction will be and the lower its social uncertainty.
The way in which the social, financial and infrastructure are determined is given in algorithms 7, 8 and 9 in appendix C.

4.4 Design concepts

In this section, we will describe the design concepts used to construct the Agent-Based Segmentation Model. We will discuss the basic principles used to construct the model in section 4.4.1. In section 4.4.2 we will give a summary of the emergent phenomena from the interaction of the agents. In section 4.4.3 we will describe how agents adapt their behaviour to the behaviour of other agents and the environments current state. In section 4.4.4 we give a summary of the agents' goals, in sections 4.4.5 and 4.4.6 we describe the learning process and how agents predict the outcome of their behaviour. In section 4.4.7 we describe the environmental variables perceived by the agents, the interactions of the agents is described in 4.4.8. In section 4.4.9 we describe the stochasticity of our model i.e. the introduced randomness. We will end this section by discussing the collectives/segmentations in our model 4.4.10 as well as how data is gathered from our model 4.4.11.

4.4.1 Basic principles

The hypothesis and theories used to construct the model are described in section 3.3 and 2.7. The general concepts, modelling approaches and assumptions where described in section 3.4. The hypothesis determine the factors included in the model. The assumptions and modelling choices determine how we have implemented these factors within the model.

4.4.2 Emergence

In section 5 we can see that in most cases the majority of agents eventually switch to a BEV, but there are some that will never make the switch. The degree to which and how fast agents switch depends on the parameters. Certain parameters have a greater influence than others. The price of vehicles being one of the most influential.
The rate at which BEVs are adopted in each population segment is different. A fluctuation of the age of the vehicles can be observed within the simulation whenever the agents replace their vehicles. Almost all agents will remain in the same segment, i.e. if an agent belongs to the lease segment it will remain in the lease segment, however if the agent owns a new bought vehicle it is able to lease a vehicle instead.

4.4.3 Adaptation

In this model, agents are not explicitly programmed to increase their utility, happiness or some other measure of individual success. They do however try to adhere to status, hedonism and environmental awareness norms by acquiring a vehicle which satisfies these norms to the highest degree. The agents within our model are restricted by their financial means. The user is able to alter the subsidy values within the simulation. Altering the subsidy values could change the type of vehicles which lie within the price range of the agent.
The agents in the simulation will attempt to get the best possible parking space given their requirements for it. Only when they fail to satisfy these requirements will they go for alternatives.

4.4.4 Objectives

Referring to the previous paragraph, our agents do not have explicit goals or objectives, apart from obtaining the best possible parking spot and acquiring the vehicle best suitable to them. The success criteria consist of the parking distance from their home location and the acquisition of an adequate parking space. Whether they succeed in this process affects their happiness.

4.4.5 Learning

Experience is not included in our model. Agents do not learn from previous actions. We believe it to be of little relevance, in this case, seeing as our main goals is to study the factors involved in acquiring a BEV and agents who consider acquiring a BEV have not done so before.

4.4.6 Prediction

The agents do not predict future conditions or the consequences of their decisions. During the decision process, the agent does keep in mind the cost of commuting with a different power train. This can be seen as a form of prediction.

4.4.7 Sensing

Agents can sense the parking pressure within their neighbourhood. The agents are aware of how many other agents with BEVs are dependent on a certain charging facility spot. The agents are also able to sense the happiness, satisfaction and uncertainty of other agents. Sensing the values of other agents influences their probability of purchasing a BEV.

4.4.8 Interaction

Agents interact with the environment by occupying and departing the available parking spots. Interaction between agents is limited: agents do not directly interact with each other. Agents can, however, observe whether another agent has occupied a certain parking space or not.

4.4.9 Stochasticity

The distribution of homes and respective parking spaces within the grid is done randomly. Preferably this distribution would be based on an actual neighbourhood. However, within our model, this is not the case.
The agents choice to replace their current vehicle is decided by the age of their current vehicle as well as some randomness. This is done in order to ensure that only 5 to 14% of agents replace their vehicle each year. Which ICEV an agent will decide to buy is also subject to some randomness. The agent will choose one random vehicle from a set of ICEVs that lie within its price range.

4.4.10 Collectives

Agents belong to either the: occasion, new or lease collectives. These collectives are also called segments. The collective an agent belongs to determines their needs and choice probabilities (section 4.3.1). The need assessment and choice probabilities have a direct effect on the agents' decision making. In general new owners have more income than those who own an occasion. These collectives are defined as a separate kind of entity within our model with their own state variables. We discussed the differences between agents belonging to different collectives in section 3.1, 3.4, and 4.3.

4.4.11 Observation

There are numerous graphs and displays which can be used to extract data from our simulation. Within the repast interface, we have a representation of the neighbourhood grid wherein we can observe the 3 collections of agents which are represented by different colours. Within this grid, we can directly observe whether or not they are successful at parking. We further have two types of charts: histograms and graphs. There are eight histograms available from which we can extract the following information:

- The amount of parking spaces with charging facilities and without charging facilities within the neighbourhood;
- The amount of agents with a BEV and ICEV which have parked successfully or unsuccessfully at each tick;
- The amount of occasion ICEVs of each brand bought by agents.
- The amount of occasion BEVs of each brand bought by agents.
- The amount of new ICEVs of each brand bought by agents.
- The amount of new BEVVs of each brand bought by agents.
- The amount of agents who have: not replaced their current vehicle, have replaced their vehicle with an occasion BEV, new BEV, occasion ICEV or new ICEV.
- The ages of the cars in the simulation. Each bar of the histogram represents the amount of agents who own a vehicle of that age;

The histograms containing the number of vehicles bought of each brand will reset at the end of each year such that the data observed only concerns that particular year.
The simulation contains 9 graphs:

- Three graphs representing the uncertainty and satisfaction of the occasion, lease and new agents decomposed into each of their three sub-parts.
- A graph which represent the average parking happiness of BEV and ICEV owners.
- Three graphs which represent:
  - the number of new-bought BEVS and new-bought ICEVs.
  - the number of occasion-bought BEVS and occasion-bought ICEVs.
  - the number of leased BEVs and leased ICEVs.
- A graph which represents the total number of agents which own a BEV or ICEV in the simulation.
- The percentage of agents that buy or lease a vehicle BEV/ICEV.

Data can extracted, from the model, by using the text sinks available within the Repast interface.

4.5 Initialisation

Initially, the simulation starts with a grid containing a neighbourhood with 200 agents and their 200 respective home locations. Each agent occupies a unique home location. Our Repast implementation contains a parking grid which illustrates where each agent has parked its vehicle. To simulate the real-world situation in the Netherlands, approximately 6.5% of the agents own an electric vehicle. The rest owns a gasoline ICEV. We did not include diesel, ICEVs, PHEVs, Hydrogen or LPG powered vehicles. Seeing as these type of ICEVs were of no particular interest to our research.

All agents start with a happiness of 0.5 and satisfaction and uncertainty of 0.5. Governmental subsidies were implemented in the model. Their initial value is 4000 for new BEVs and 2000 for occasion BEVs. The subsidy value is retracted from the actual price of the BEV the agent is considering to acquire. MRB and BPM tax values correspond to those in actual effect in 2019. The MRB and BPM value differs per province and according to the weight of the vehicle.
The MRB and BPM values can be increased by using the sliders in the Repast GUI. Other parameters can also be altered including the gasoline fuel-tax and the rate at which charging facilities are added to existing parking spaces. The grid representing the neighbourhood together with the sliders can be seen in figure 10.

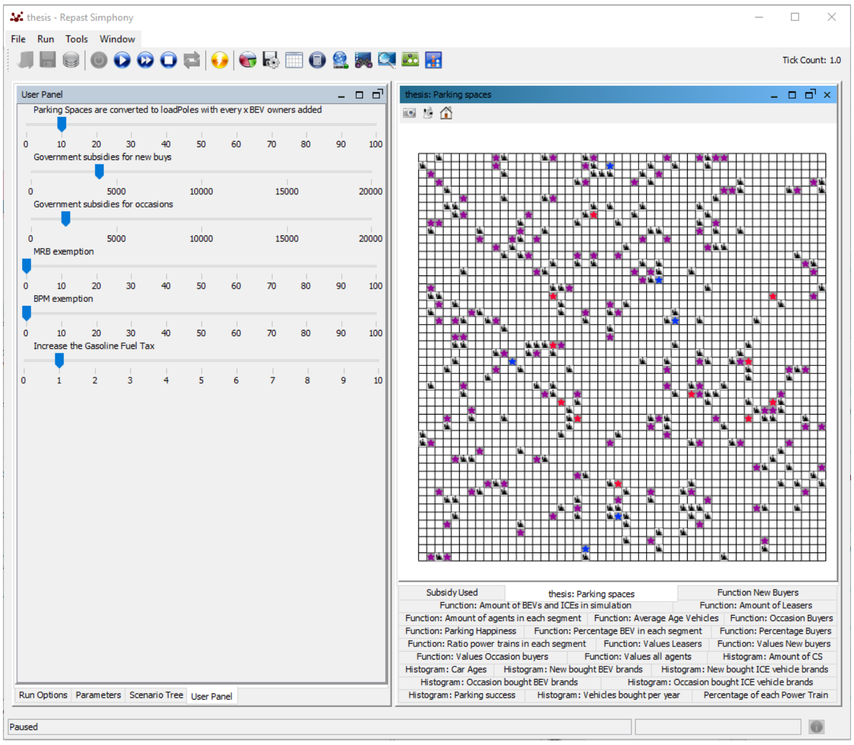
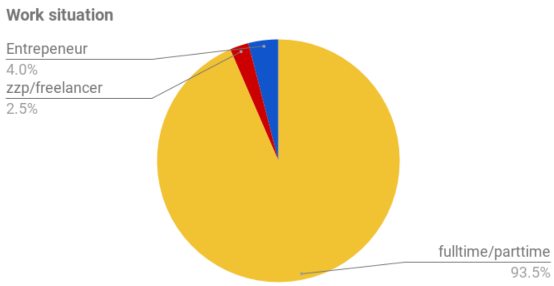


Figure 10: Image of the neighbourhood grid and User Panel

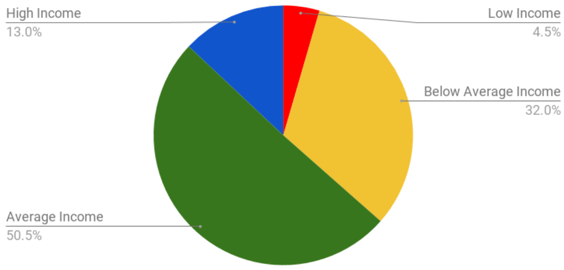
4.6 Input data

We used the RVO dataset [57] to initialise our agents. The demographic parameters obtained from the dataset are the following: age, sex, income, household composition, education, the providence

in which the respondent lives, whether they have a private parking space or they have to park in the neighbourhood (paid or not).
From the data we also have information about the respondents professional occupation, the number of days the respondent works outside of their home, their daily commute distance, and the availability of parking at work.
Furthermore, the data also contains information about the vehicle the respondent owns, such as: the car weight class, age, CO2 emissions per km, combustion type (ICEV or BEV). From the data, we know whether someone owns or leases their vehicle.



(a) Work situation of the agents



(b) Income of the Agents

Figure 11: Work and Income overview of the Agents

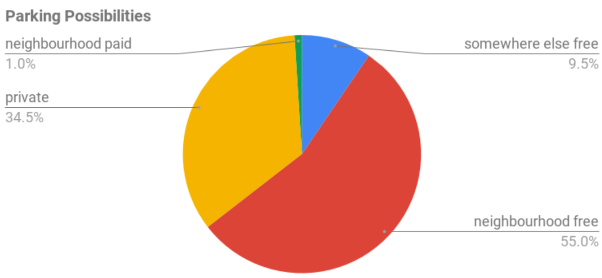


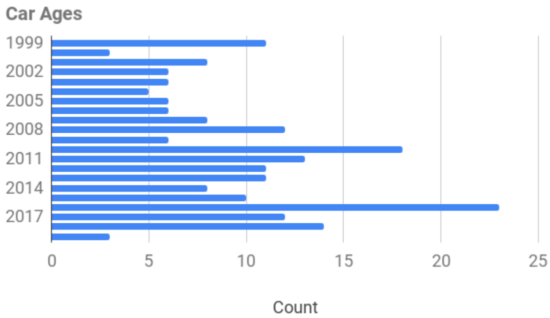
Figure 12: Parking possibilities of the agents

The available data also contains information on whether the respondent is satisfied with their commute distance, why they prefer to use a car, whether they are familiar with BEVs, as well as the respondents' knowledge of environmental actions and their participation in them.
Approximately half of our agent population is female (49%) and the other half is male (51%), the agents have a relatively average income, as can be seen in figure 11b, and the vast majority has a full or partime job, figure 11a. An overview of the age of the agents and their respective vehicles is given in figure 13.
Further information about the education level and household composition of the agent population can be found in figure 49 and 48 in appendix D. Figure 12 gives an overview of the parking possibilities of our agent population.
We used data from car dealer websites[3] to construct a dataset of cars from which the agent can pick a vehicle to buy. The characteristics of the vehicles in the dataset correspond to the characteristics of actual vehicles for sale on those websites. We only added those vehicles which were of the top 10 most sold brands in the Netherlands in 2019, [81, 51].

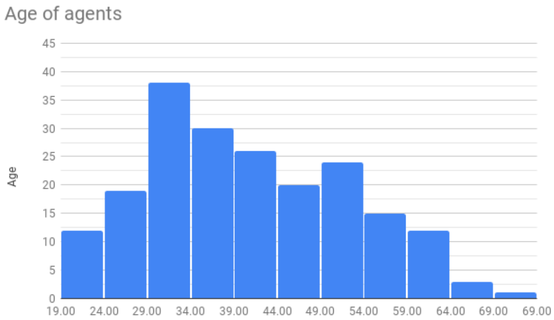
4.7 Submodels

The submodels are represented in the algorithms 1, 2, 3, 4, 5, 6, 7, 8, and 9 in appendix C.

[3]The following websites were consulted: `https://www.autoscout24.nl/`, `https://www.autokopen.nl/aankooptips/best-verkochte-occasions-2019-2020-976`, and `https://www.anwb.nl/auto/kopen/zoeken/`



(a) Age of agent vehicles at the beginning of our simulations



(b) Age of the agents in our simulation

Figure 13: Age of the agents and their respective vehicles in our simulation

5 Results of single measures

Now that we have constructed the model using a theoretically founded framework, we are able to run certain scenarios. These scenarios allow us to observe the effect different policy-measures have on the number of agents who buy a BEV. The scenarios implemented within the model were determined to be the most relevant for the domain experts. The results obtained from these scenarios were used to determine the usefulness of the Agent-Based Segmentation Model.
In section 6.3, we will reflect on the results obtained from the single and combination-scenarios, and attempt to answer some of the questions posed by the domain experts.
In this section, we will describe the scenarios which implement a single adjustment to our initial scenario and analyse/describe their effects on the perception and adoption rate of BEVs. The single-measure scenarios in this chapter are divided into two themes: the policy-scenarios (section 5.1) and the development-scenarios (section 5.2).

The policy-scenarios include the following:

- Subsidy variation for BEV vehicles (section 5.1.1)
- Fuel tax increase for Gasoline vehicles, (section 5.1.2)

The development-scenarios include the following:

- Range of BEV's increases gradually over the years (section 5.2.1)
- Price of BEV's decreases gradually over the years (section 5.2.2)
- Increase in the rate of charging station placement (section 5.1.2)

In section 6 we will discuss the results of more complex-scenarios, which result from the combination of multiple single-measure scenarios. All simulations start in 2019 which corresponds to year 0 in the graphs.

5.1 The policy-scenarios

In section 2.5 we discussed the targeted policy measures that aim to accelerate the adoption of BEVs by the Dutch population.
By conducting interviews with policy-makers we determined several future policy scenarios which can be simulated using our model. The included measures were discussed in section 2.7, they include:

- Varying the amount of subsidies for BEVs (section 5.1.1);
- Implementing a limited subsidy supply (section 5.1.1);
- Increasing the Gasoline fuel taxes (section 5.1.2);

In this section we will show the results of each of these scenarios.

5.1.1 Subsidy variation for BEVs

In this section we will compare the original simulation, in which the subsidy for BEVs stays the same, to simulations in which subsidies are decreased or limited.

Gradual decrease of subsidies

Table 4: Changes in subsidy values during the gradual decrease of subsidy scenario.

Tick	**Year**	**Subsidy new**	**Subsidy Occasion**
312	2024	4000	2000
364	2025	4000	2000
416	2026	3200	1600
468	2027	2400	1200
520	2028	1600	800
572	2029	800	400
624	2030	0	0

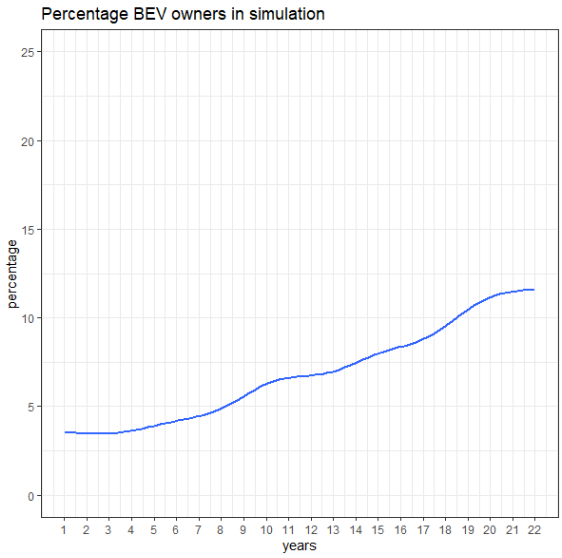
One of the scenarios, proposed by policy-makers, is the decrease of subsidies. Starting in 2025 subsidies will gradually decrease until they are abolished in 2030. This scenario was integrated within our simulation according to table 4.
In figure 14 we can observe the percentage of BEV owners, within our agent population, over a 22 year time-span. Both the original scenario (figure 14a) and the scenario in which we decrease subsidies (figure 14b) is represented.

From figure 14a and 14b we observe that the amount of BEV-owners decreases drastically when subsidies for BEVs are decreased. At the beginning of our original simulation 3.5% of agents owned a BEV, at the end of our original simulation 11.5% of agents own a BEV. In the scenario wherein we implement a gradual decrease of the amount of subsidy for BEVs', only 4.5% of agents own a BEV after 22 years. In the gradual decrease scenario, we only see a minimal increase in the amount of occasion BEV owners. Table 5 gives an overview of the results of our simulations. The results obtained in this section are the average of 5 consecutive simulation runs.

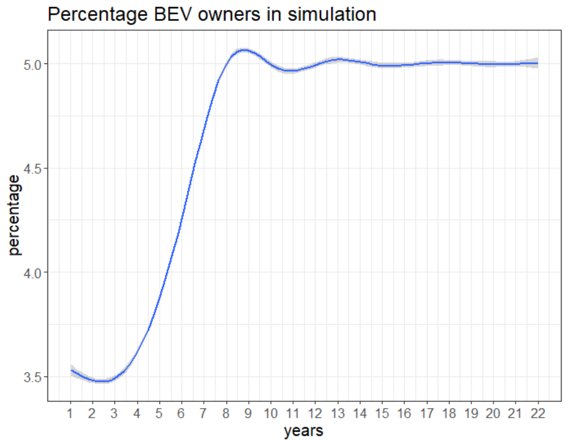
Table 5: Percentage BEV-owners in the population as a whole and within each segment, at the end of the original-scenario and the scenario wherein we gradually decrease the subsidies.

	New	Occasion	Lease	Total
Original	11.1%	10.7%	21.4%	11.5%
Decrease of subsidies	11.1%	4.4%	0.0%	4.7%

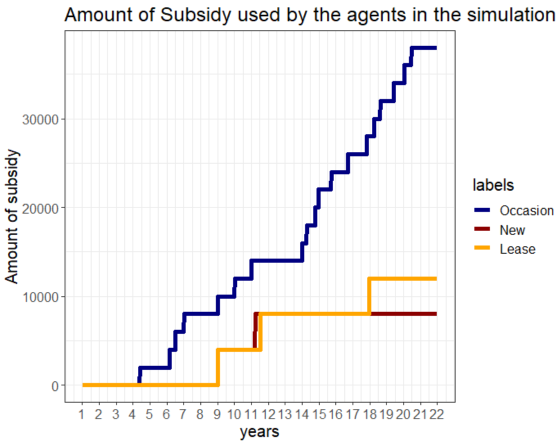
To explain the simulation behaviour dynamics we use the agents' internal values. Figure 15 represents the average internal values of the agents belonging to the occasion segment. When we compare the average values of the agents in the original scenario (figure 19a) to the average values of the agents in the scenario where we decrease the subsidy (figure 15b), we can observe a significant increase in the financial uncertainty (dark red) and decrease in financial satisfaction (light red).
Furthermore, we observe that whilst the social satisfaction in the original scenario starts out lower it increases until it becomes higher than the social uncertainty, this happens around year 11. The increase in social contempt is due to the increased number of BEV-owners, which directly affects the agents' social satisfaction and uncertainty values (assumption 15 of section 3.3).
In the scenario wherein we gradually decrease the subsidy we do not observe this drastic increase and decrease in social satisfaction and uncertainty, these values stay relatively stable, which reenforces the agents' discontentment with the BEV.



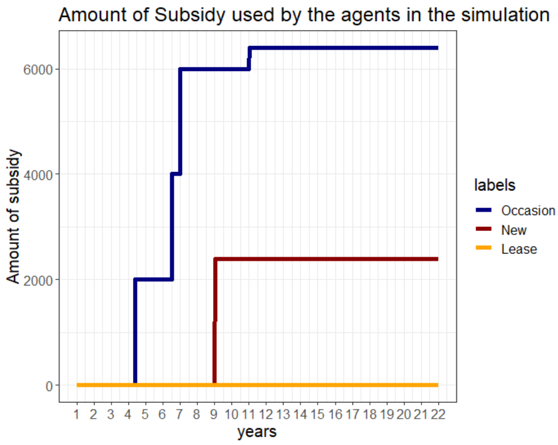
(a) Percentage of BEV's in the original scenario



(b) Percentage of BEV's when we apply the decrease subsidy scenario



(c) Subsidy used when we apply the original scenario

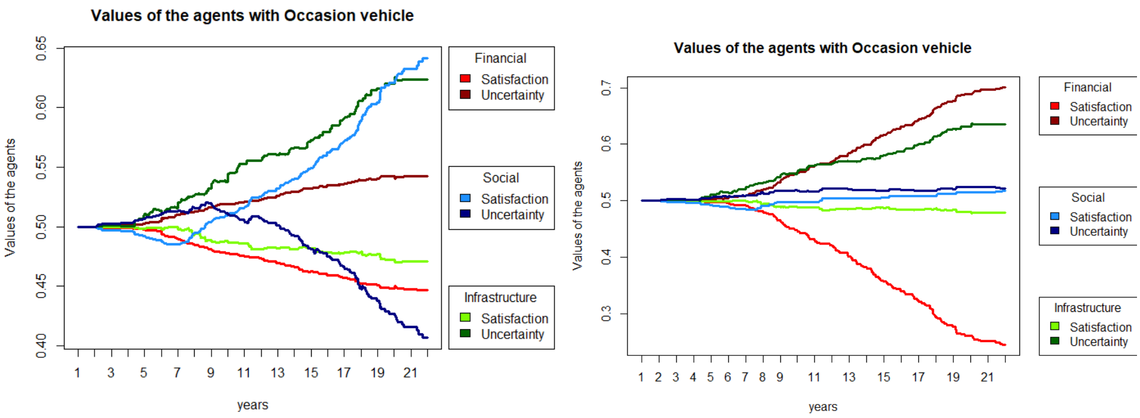


(d) Subsidy used when we apply the decrease subsidy scenario

Figure 14: Comparison between the original scenario and the scenario in which we gradually decrease the subsidy

The behaviour observed within figure 15 is in line with our initial assumptions that the financial aspect is an important driver of behaviour, discussed in section 3.4. Interestingly enough, although the decrease in subsidy starts in year 5 in our simulation we only observe a large effect after year 9, when subsidies are completely abolished. At the very least we would expect less BEV vehicles being bought due to the lower subsidy value. This is however not the case, the reason for this delay is likely the slow onset of the financial uncertainty and social uncertainty.
The satisfaction decrease and uncertainty increase occur gradually, its effects therefore only get noticeable later on in our simulation.

In the original scenario, we observe that within the occasion segment the amount of BEV owners



(a) Values of the occasion agents in the original scenario (b) Values of the agents when the decrease scenario is applied

Figure 15: Comparison between the values of the agents in the original scenario and the scenario in which we gradually decrease the amount of subsidy for BEVs

increased by 7.72% and the amount of lease owners increases by 21.4%, table 5. When we implement a gradual decrease in subsidy we can observe, that the amount of BEV owners increases only in the occasion segment by just 1.42%. This is in line with our assumption that the financial aspect is an important driver of behaviour especially for agents in the lease and new-buyers segment (section 3.4).

Statistical analysis

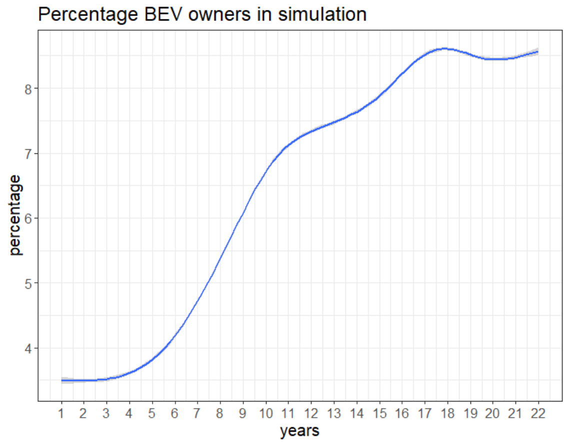
A t-test for independent variables was performed with the increase in the percentage of electric vehicles as the dependent variable and the subsidy value as the independent variable. This was performed to compare the mean increase of BEV owners in the simulation wherein subsidies are decreased against the simulation in which subsidies remains stable. The result implies that there is a difference in the increase of electric cars after 22 years; Decreasing the subsidy for BEVs' has a significant effect on the number of electric cars that are bought (p-value $<2.2e-16$; t $= -29.396$). We tested for homogeneity of variances and for normality of our dataset beforehand.

Limited available subsidy

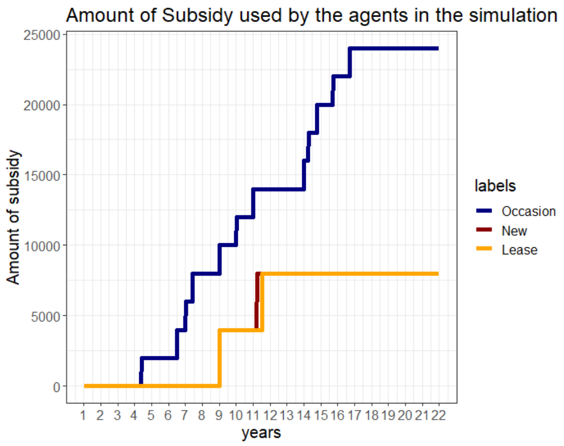
The amount of subsidy for BEVs granted by the Dutch government amounts to 10 million euros, which can be accessed by those who acquire a new-BEV in the form of a 4000 euro subsidy and by those who acquire an occasion-BEV in the form of a 2000 euro subsidy.
In 2020 there were 13 000 new electric car sold in the Netherlands, of which the vast majority are company-owned. Our simulation only consists of 200 agents we, therefore, roughly estimate that our agents will have access to 40 000 euros in the form of subsidies. We will now compare the original scenario to the scenario in which we implement a limit on the amount of available subsidy.

In our original simulation a total of 48 000 euros of subsidy is used by the agents, figure 14c, when we implement a limit on the amount of available subsidy this limit is achieved at year 15 in our simulation. The effect of this measure, therefore, only becomes noticeable later on in our simulation. At the end of the simulation, only 8.5% of agents own a BEV compared to the 11.2% in the original scenario.

The lack of subsidy in the last few years of the simulation forces the agents to reason about the BEV at its full price, which will decrease their financial contentment with the BEV, this can be observed in figure 17b.

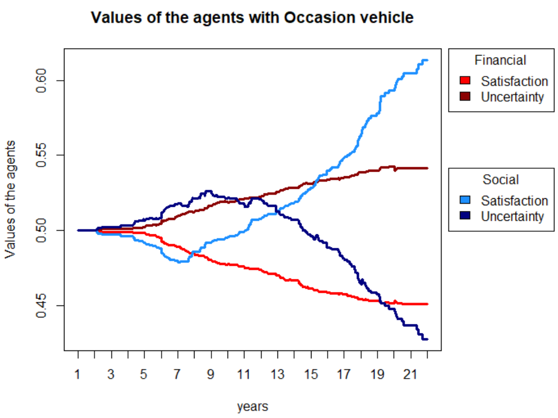


(a) Percentage of BEV owners when the limit scenario is applied

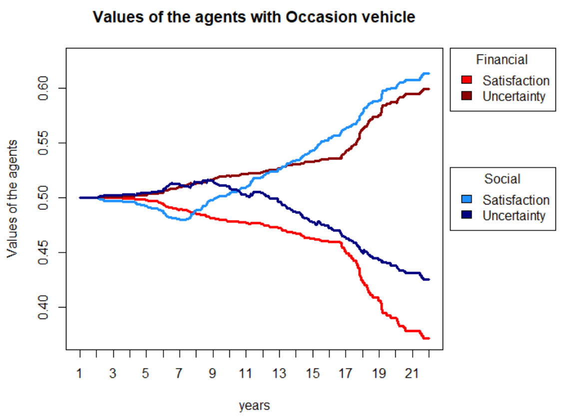


(b) Amount of subsidy used when we apply the limit scenario

Figure 16: Results when we apply the limit scenario



(a) Values of the occasion agents in the original scenario

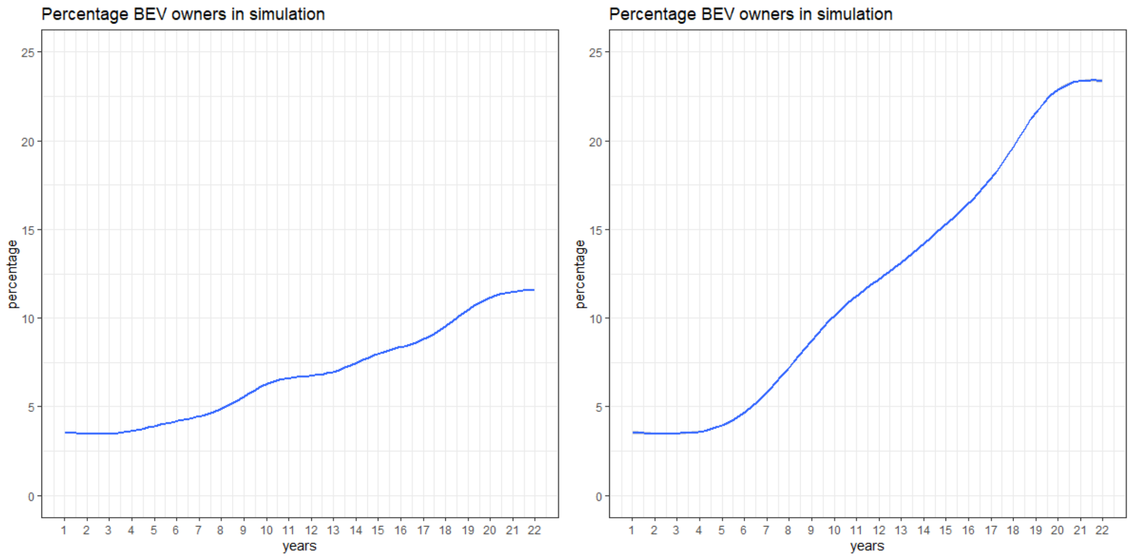


(b) Financial and social Values of the agents when the Limit scenario is applied

Figure 17: Comparison between the values of the occasion-agents in the original scenario and the scenario in which we apply a limit on the amount of subsidy for BEVs

5.1.2 Increase of the Gasoline fuel tax

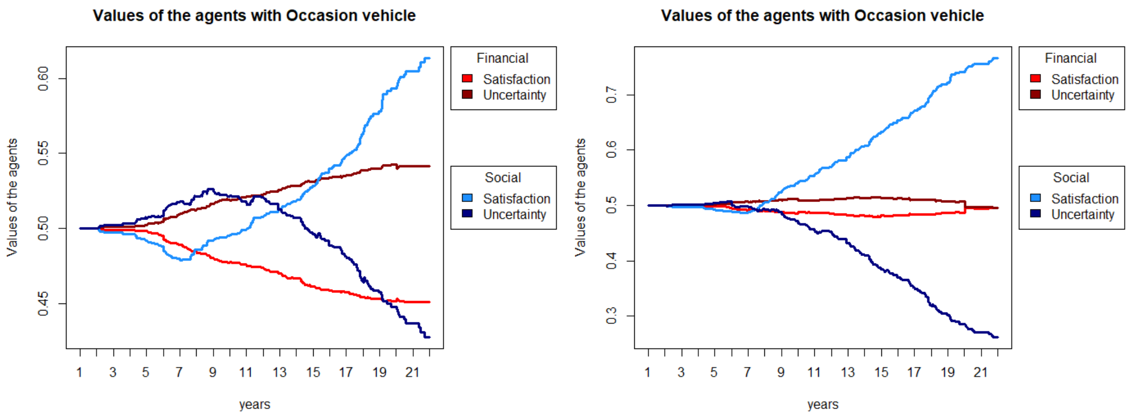
Policy-makers estimate that increasing the Gasoline fuel tax would greatly increase the number of BEV owners. We, therefore, implemented a scenario in which the gasoline fuel tax increases 10 cents each year starting in 2019. From table 6 we can observe that when we increase the fuel tax 23.4% of the agents own a BEV at the end of the simulation, which is more than double the number of BEV-owners at the end of the original scenario.
In figure 18 we can observe the increase in the number of BEV owners when the fuel tax is increased. At the beginning of our simulation the gasoline costs €1.69 per litre, at the end of our simulation gasoline costs €5.69 per litre, which amounts to a cost of 35 cents per km driven. When we compare this price to the 3 cents per km for the electric vehicle, we would expect a higher increase in the amount of BEV owners.



(a) Percentage of BEV's in the original scenario (b) Percentage of BEV's when we increase gasoline fuel tax

Figure 18: The BEV percentage in the original scenario and in the scenario wherein we increase the fuel tax

To explain the behaviour of the agents we will consult the agents' internal values, more specifically the agents financial and social values, figure 19. With an increase in the amount of BEV owners, we observe an increase in the agents social satisfaction and a decrease in the agents' social uncertainty. Hence, the social contentment of the agents concerning BEVs increases, this leads to an increase in the probability of other agents acquiring a BEV.
However, the financial aspect still remains the most influential, we assumed in section 3.2 that agents have limited cognitive capacity, agents therefore only compare their weekly commute costs of using a BEV to the weekly commute costs of using a Gasoline vehicle. We can observe in figure 19 that in the scenario wherein we increase fuel taxes the agents' financial satisfaction and uncertainty converge around year 20. In the original scenario, the financial-values do not converge.



(a) Average values of the occasion agent in the original scenario

(b) Average values of the occasion agents when we increase gasoline fuel tax

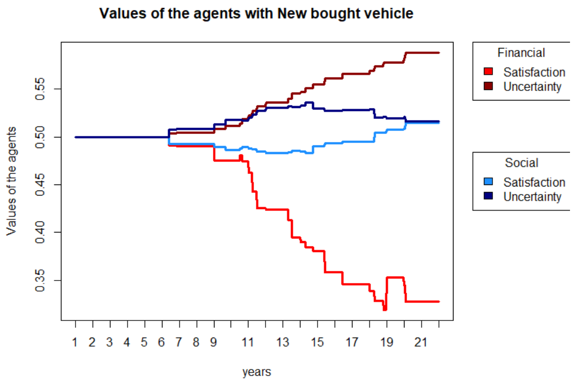
Figure 19: The average values of the occasion agents in the original scenario and in the scenario wherein we increase the fuel tax.

We also observe that the agents' financial values are less divergent than in the original scenario, which explains the higher number of BEV owners. However, for the initial 19 years of our simulation, the agents' financial satisfaction remains lower than their uncertainty leading to a slower adoption of BEVs than would be expected. The high initial investment cost is the culprit for the agents lower financial satisfaction and higher financial uncertainty.

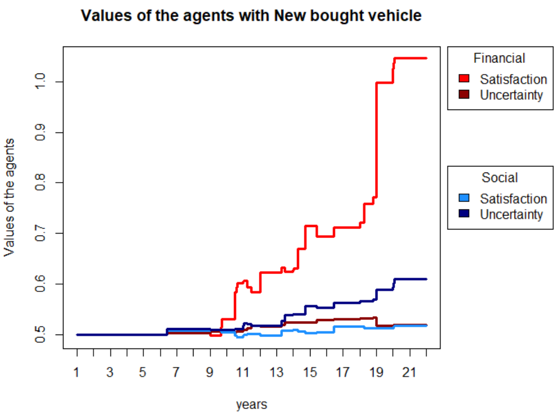
Table 6: Percentage of BEV owners within each segment and the populations as a whole, at the end of the original simulation and the simulation in which Gasoline fuel taxes are increased.

		BEV's in Original Scenario		BEV's in fuel tax scenario	
	Total	Beginning	End	Beginning	End
Occasion	168	2.98%	10.7%	2.98%	21.9%
New	24	11.1%	11.1%	11.1%	38.9%
Lease	8	0%	21.4%	0%	21.4%
Total	200	3.5%	11.5%	3.5%	23.4%

Interestingly, the tax-increase scenario also affects the target segments. In table 6, we can observe that increasing the Gasoline fuel tax has the biggest effect on the agents belonging to the new-buyers segment. In the original scenario, none of the agents in the new-buyers segment acquire a BEV whilst in the scenario wherein the fuel tax is increased 27.8% of the new-buyers switch to a BEV, table 6. No effect is observed within the lease segment, at both the end of the original scenario and the end of the increase in the fuel tax scenario we observe that 21.4% of the lease agents are BEV-owners. In the occasion segment, the amount of BEV-owners increases by 11.2%, which is only slightly lower than in the new-buyers segment.



(a) Values of the agents belonging to the new buyers segment in the original scenario



(b) Values of the agents belonging to the new buyers segment when we increase gasoline fuel tax

Figure 20: Values of the agents belonging to the new buyers segment in the original scenario and in the scenario wherein we increase the fuel tax.

For new-buyers, the initial investment lies considerably higher than for occasion-buyers. By increasing the fuel tax for gasoline owners, the cost of owning a BEV becomes considerably cheaper which then has a higher effect on the agents financial contentment, figure 20, and consequently the agents' decision-making.

Statistical analysis

A t-test for independent variables was performed with the increase in the percentage of electric vehicles as the dependent variable and the Gasoline fuel cost as the independent variable. This was performed to compare the percentage increase of BEV owners in the simulation wherein Gasoline fuel taxes are increased by 10 cents against the simulation in which gasoline fuel costs only increase 1 cent each year. The result implies that there is a difference in the increase of electric cars after 22 years.
Increasing the Gasoline fuel tax has a significant effect on the number of electric cars that are bought (p-value $<2.2e-16$; t $= 23.495$). We tested for homogeneity of variances and for normality of our dataset beforehand.

5.2 Development scenarios

Technology is subject to continuous evolution, becoming better and cheaper. It is, therefore, essential that our model accounts for certain developmental scenarios. We will discuss three developmental scenarios: the increase in range of BEVs (section 5.2.1), the price decrease of BEVs (section 5.2.2), and the acceleration of the placement of charging stations (section 5.2.3).

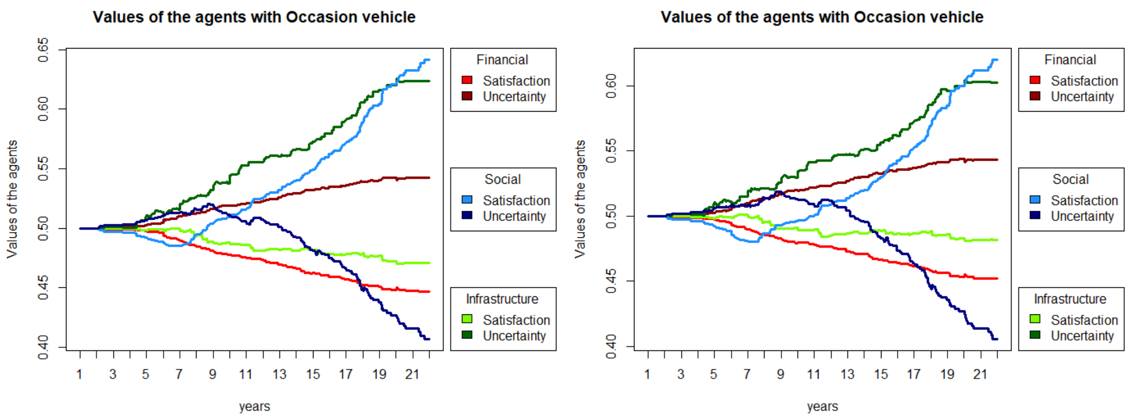
5.2.1 Range of BEVs increases over the years

The range of BEVs has increased considerably in recent years. In 2004 the Tesla Roadster had the largest range of all BEVs, travelling more than 320 km per charge. In 2020 the Tesla Roadster travels more than 965 km per charge, this is an increase of approximately 7% in range per year, we implemented this same increase within our model. In the increased range scenario, each year the available vehicles will have a 7% higher range than the year before. If we take the Renault(Zoe) vehicle, for example, in 2019 its range was 320 km, at the end of our simulation in 2040 the range equals 1238 km.
The average weekly distance travelled by the agents in our simulation is 160 km which is approximately 32 km a day, the highest distance travelled is 347 km in a day. Seeing as the average daily commute distance is well within the range of the cheapest vehicle (which has the lowest range of 218 km), we would predict that the increase in range does not affect the purchase rate of BEVs.
We compare the results of our original scenario to those of the increased range scenario. We can observe the amount of BEV-owners at the end of each scenario in table 7.

Table 7: Percentage BEV owners in the population as a whole and within each segment, when we run the original scenario and the scenario wherein the range of BEVs increases.

	New	Occasion	Lease	Total
Original	11.1%	10.7%	21.4%	11.5%
Range increase	11.1%	10.8%	21.4%	11.6%

As predicted, there is no difference between the original scenario and the scenario in which the range increases for the lease and new segment.



(a) Values of the occasion agents in the original scenario (b) Values of the occasion agents in the range increase scenario

Figure 21: Values of the occasion agents in the original and range increase scenario

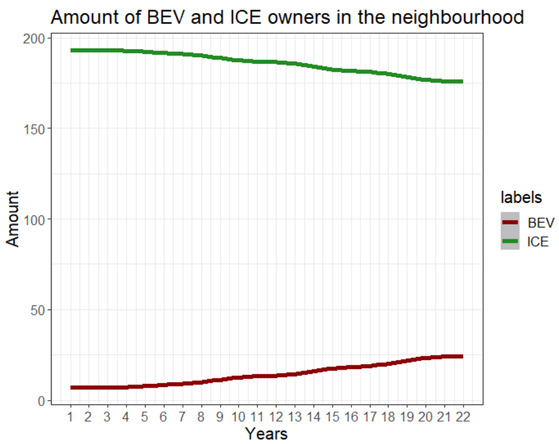
We do see an increase in the infrastructure satisfaction in the agents. For the agents in the occasion segment, the values for infrastructure in the increased range scenario are slightly better than their values in the original scenario (figure 21). However, the difference in infrastructure values is not big enough and does therefore not change the agents' behaviour.
The occasion agents, besides reasoning about range, also reason about the age of the vehicle, the status of the brand, among other factors (section 4.3). Most of the agents' commute distance lies within the range of the occasion BEVs, hence the occasion-buyers do not experience any major range-anxiety. Increasing the range, therefore, does not have a major effect on the agents.

Statistical analysis

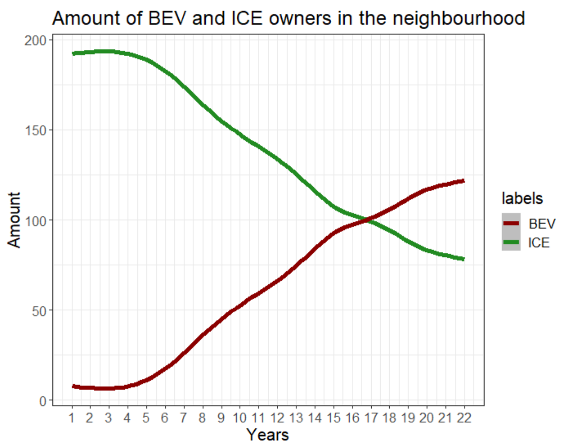
A t-test for independent variables was performed with the increase in percentage of electric vehicles as the dependent variable and the range of the BEVs' as the independent variable. This was performed to compare the mean increase of BEV owners in the simulation wherein the range of BEVs' is increased against the simulation in which range of BEVs' remains stable. The result implies that there is no significant difference in the increase of electric cars after 22 years; Increasing the range of electric vehicles has no significant effect on the number of electric cars that are bought (p-value = 0.7643; t = 0.29985). We tested for homogeneity of variances and for normality of our dataset beforehand.

5.2.2 Price of BEVs decreases over the years

On average BEVs are 30% to 40% more expensive than conventional ICEVs. This is estimated to change in the near future, therefore, we implement a scenario wherein the price of new BEVs decreases 30% over a 21-year time span and the price of occasion BEVs decreases 20%. In this scenario, the price of new BEV's drops by 3% and the price for occasion BEVs drops by 1.5% each year. We will compare the results of the scenario wherein the price of BEVs decreases to our original scenario.
At the beginning of the decreased price scenario, some agents still acquire an ICEV, as the simulation progresses almost all agents choose to acquire a BEV. In figure 22, we can see the increase of BEV-owners. After 16 years the number of BEV-owners exceeds the number of ICEV owners.



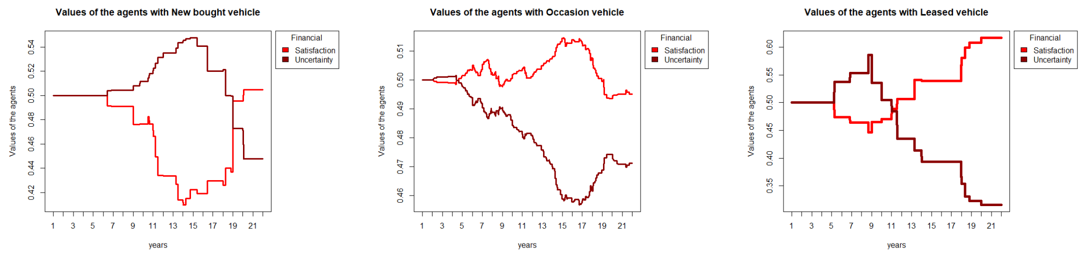
(a) Ratio of BEV and ICEVs in the original scenario



(b) Ratio BEV and ICEVs in the scenario wherein the price of BEVs decreases

Figure 22: Values of the agents belonging to the new buyers segment in the original scenario and in the scenario wherein the price of BEVs decreases.

In figure 23, we can observe the effect of the decrease in BEV price on the agents' financial values.



(a) Financial values of the new-buyers in the decreased price scenario

(b) Financial values of the occasion-buyers in the decreased price scenario

(c) Financial values of the leasers in the decreased price scenario

Figure 23: Values of the agents in the scenario wherein the price of BEVs decreases.

In table 8, we observe the effect of the gradual decrease of BEV prices on each of the segments. The biggest effect can be observed in the lease-segment with a 77.1% increase in the number of BEV-owners. In the occasion-segment, we see an increase of 59.52% and for the new segment, we see an increase of 22.2%. We assumed in section 3.4 that the financial aspect was the most influential factors for lease-owners, decreasing the price of BEVs, therefore, has the biggest effect on this segment.

Table 8: Percentage of agents that own a BEV at the beginning and end in the original and the scenario in which the price of BEVs decreased gradually decreases.

	Amount of Agents		Original Scenario		Decreased BEV price scenario	
	Beginning	End	Beginning	End	Beginning	End
Occasion	168	168	2.98%	10.12%	2.98%	62.5%
New	24	18	11.1%	11.1%	11.1%	33.3%
Lease	8	14	0.0%	21.4%	0.0%	77.1%
Total	200	200	3.5%	11.5%	3.5%	60.9%

On average our occasion agents have an income of €41 000, which is not particularly high. Decreasing the price of occasion BEVs has a large effect on this segment because these agents are less able to make a large investment.

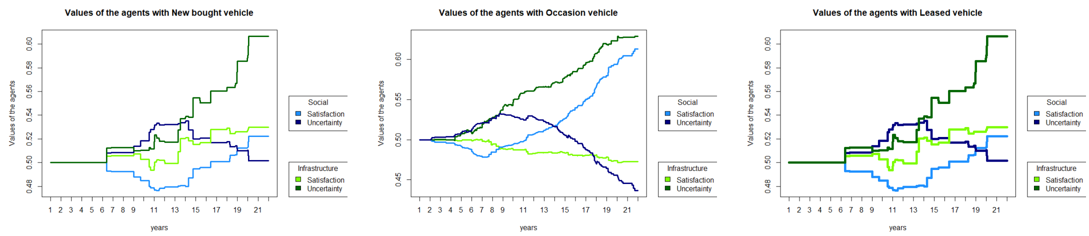
The segment least affected by the decrease in BEV-price is the new-buyers segment. The initial investment for a new BEV is still considerably higher the first few years of the simulation, after 19 years the price of BEVs has decreased enough that all agents belonging to the new buyers' segment will also acquire a BEV.

Statistical analysis

A t-test for independent variables was performed with the increase in the percentage of electric vehicles as the dependent variable and the decrease of the vehicle price as the independent variable. This was performed to compare the mean increase of BEV-owners in the simulation wherein the price of BEVs' gradually decreases against the simulation in which the price of BEVs' remains stable. The result implies that there is a significant difference in the increase of electric vehicles after 22 years; Gradually decreasing the price of BEVs has a significant effect on the number of electric cars that are bought (p-value $<2.2e-16$; t = 39.496). It also has a significant effect on each of the segments, when we test the effect the gradual decrease in BEV price has on the segments we get a p-value <0.05. We tested for homogeneity of variances and for normality of our dataset beforehand.

5.2.3 Increase in the rate of charging station placement

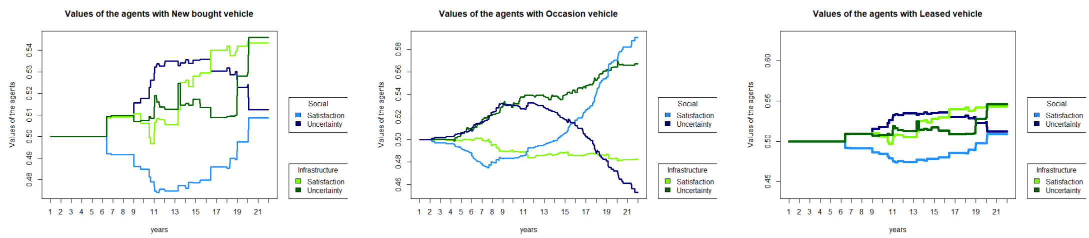
In the original scenario with every 10 additional BEV-owners, one charging station (CS) is added to the neighbourhood. We included a scenario in which a charging station is added with every three additional BEV-owners. We observe, in figure 24, a slight difference between agents' values in the original scenario and the scenario wherein we increase the rate at which charging stations are added.



(a) Values of the new-buyer agents in the original scenario

(b) Values of the occasion-agents in the original scenario

(c) Values of the lease agents in the original scenario



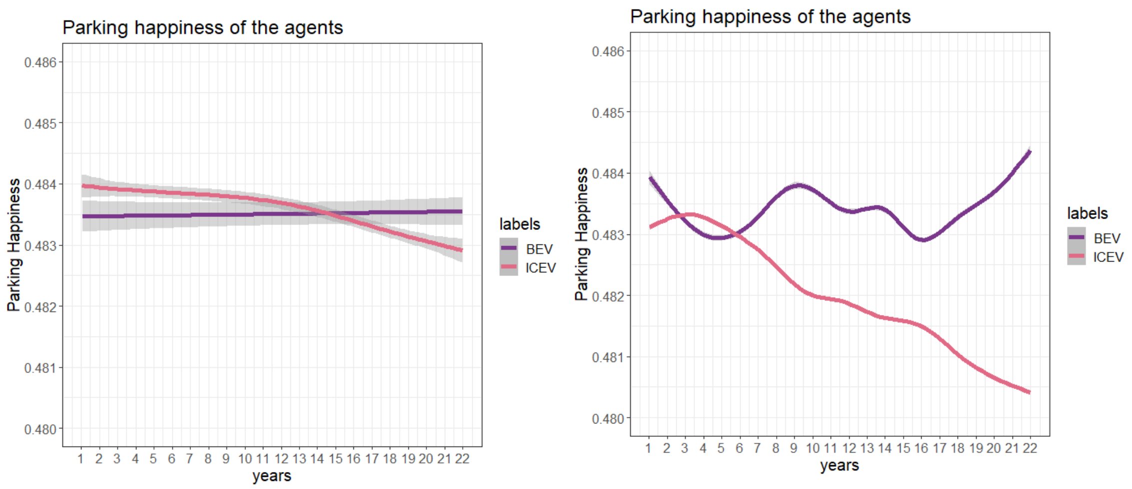
(d) Values of the new-buyer agents in the scenario in which the rate at which CSs are added is increased

(e) Values of the occasion-agents in the scenario in which the rate at which CSs are added is increased

(f) Values of the lease agents in the scenario in which the rate at which CSs are added is increased

Figure 24: Values of the agents in the original scenario and the scenario in which the rate at which CSs are added is increased.

One big difference in the values of the agents between the two scenarios is the increase of the infrastructure satisfaction and the decrease of the infrastructure uncertainty. The increase in the agents' infrastructure contentment is due to the increase in parking satisfaction (figure 25). Although the amount of CSs influences the happiness of the agents, which does affect the agents values, the increase in contentment is not large enough to change the agents behaviour. We also observe, in figure 24 a slight increase in the agents' social satisfaction and a decrease of the agents' social uncertainty.



(a) Parking happiness of the agents in the original scenario

(b) Parking happiness of the agents in the scenario in which the rate at which CSs are added is increased

Figure 25: Parking happiness of the agents in the original scenario and in the scenario in which the rate at which CSs are added increases

The contentment of the agents does not increase enough we only observe a slight increase in the agents' parking happiness, figure 25b, the social and financial contentment of the agents' does not change.
The financial aspect remains the most important factor in the agents' decision making we, therefore, did not expect the increase in CS placement to have a significant effect. Implementing this scenario will be more interesting when the rate at which BEV are bought increases, we will discuss this in section 6.

Table 9: Percentage BEVs in the original scenario and the scenario in which more charging stations are added.

	New	Occasion	Lease	Total
Original	11.1%	10.7%	21.4%	11.5%
Increasing rate of CS placement	11.1%	10.7%	21.4%	11.5%

Statistical analysis

A t-test for independent variables was performed with the increase in the percentage of electric vehicles as the dependent variable and the addition of charging stations as the independent variable. This was performed to compare the mean increase of BEV owners in the simulation wherein every three new BEV owners one CS is added against the simulation in which every ten new BEV owners one CS is added. The result implies that there is no difference in the increase of electric cars after 22 years; Increasing the rate at which charging stations are added has no significant effect on the number of electric cars that are bought (p-value = 0.7845; t = -0.27348). We tested for homogeneity of variances and for normality of our dataset beforehand.
Increasing the rate at which charging stations are added does have a significant effect on the average happiness of both the BEV owners as well as the owners of vehicles with an ICEV (the p-values are respectively $3.59e-11$ and $2.2e-16$).

6 Results combination scenarios

In this section, we will describe the effect of the combination of multiple of the previously discussed scenarios. The combination scenarios in this chapter are divided into two themes: the development scenarios (section 6.1), and the development and policy scenarios (section 6.2).

The development scenarios include all the development scenarios:

- Range increase of BEVs, price decrease of BEVs, and increased rate of CS placement.

The development and policy scenarios include the following:

- The conjunction of all the development scenarios including the increase in fuel-tax.
- The conjunction of all the development scenarios including implementing limited BEV-subsidy.
- The conjunction of all the development scenarios including decreasing the BEV-subsidy.
- The conjunction of all the development scenarios and policy scenarios.

At the end of this section, we will reflect on the effect of each of these scenarios on the BEV adoption rate (Section 6.3).

6.1 All development scenarios

In this section we will show the results of our simulation when we apply the following alterations to our original scenarios:

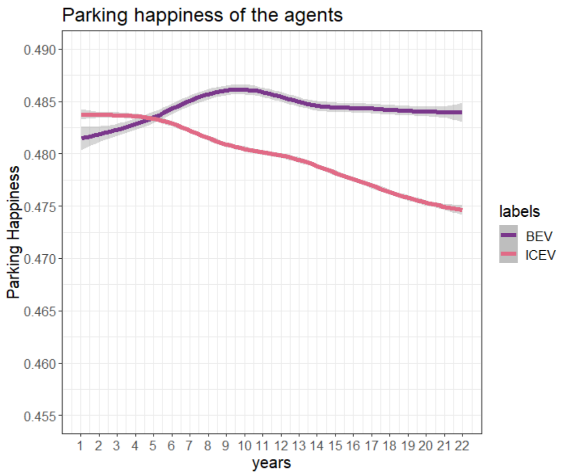
- The range of electric vehicles increases with 7% each year;
- The price of BEVs decreases with 3% each year;
- The rate of CS placement is increased;

We know, from section 5.2.1, that increasing the range of vehicles does not have a significant effect on the agent population. In section 5.2.2 we observed a considerable increase in the amount of BEV owners when the price of BEVs' gradually decreases.
When the number of BEV owners increases so does the need for charging. If the charging need is not met, it has a negative effect on the agents' perception of BEVs. Therefore, if we meet the BEV owners parking needs by increasing the number of CSs in the neighbourhood, we expect to see a positive effect on the agents' perception of BEVs and an increase in the number BEV owners.
We will compare the scenario in which we increase the range and decrease the price of BEVs to the scenario in which we also increase the rate at which charging stations are added to the neighbourhood. Table 10, represents the results for both scenarios.

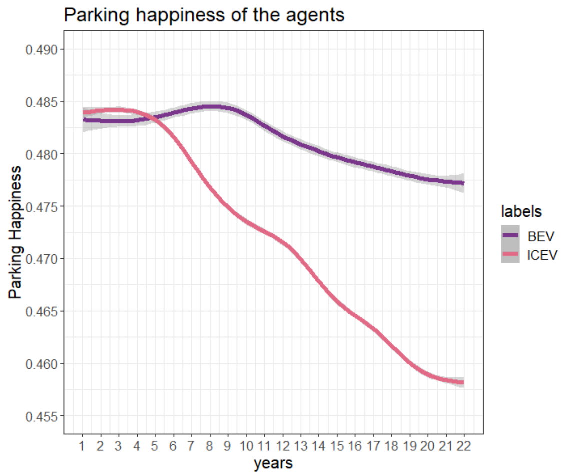
Table 10: Percentage of BEV owners at the end of the price decrease and range increase scenario and at the end of the price decrease, range increase and acceleration of the CS placement scenario.

Scenario	Occasion	New	Lease	Total
Price and Range scenario	63.1%	33.3%	77.1%	61.4%
Price, Range and CS scenario	62.4%	33.3%	77.1%	60.8%

From table 10, we can see that increasing the rate at which CSs are added does not increase the amount of BEV owners. This is unexpected, to explain this behaviour we will consult the agents parking happiness which is directly affected by their ability to park and charge.



(a) Parking happiness of the agents in the scenario wherein we increase range and decrease price of BEVs



(b) Parking happiness of the agents in the scenario wherein we increase range decrease price of BEVs and increase rate at which CS are added

Figure 26: Parking happiness of the agents in the scenario wherein we increase range decrease price of BEVs and the scenario wherein we also increase the rate at which CS are added

From figure 26, we see a clear difference between the two scenarios. When we increase the rate at which CSs are added, we see that the agents' happiness increases compared to the scenario in which we do not increase the rate of CS placement. However, once 24% of agents have a BEV and 15% of parking spaces have a CS we see a decrease in the agents' happiness, this is due to the penalty BEV-owners receive when they are parked in a CS while they do not need to charge. At the end of the simulation, 44% of the parking spaces have a CS and 61% of agents own a BEV. We also see a drastic decrease of the parking happiness of the ICEV owners, compared to the original scenario.

Statistical analysis

A t-test for independent variables was performed with the increase in the percentage of electric vehicles as the dependent variable and the addition of charging stations as the independent variable. This was performed to compare the mean increase of BEV owners in the simulation wherein we only account for technological improvements against the simulation in we account for technological developments and the increased rate at which charging stations are added. The result implies that there is no difference in the increase of electric cars after 22 years; Increasing the rate at which charging stations are added has no significant effect on the number of electric cars that are bought (p-value = 0.9805; $t = -0.024466$) when we account for technological developments. We tested for homogeneity of variances and for normality of our dataset beforehand.

6.2 Development and policy scenarios

In this section, we compare scenarios wherein we implement a combination of technological and policy-scenarios. We will show the effects of the policies on each of our segments and compare them to each other.

6.2.1 Technological and policy

In this section, we compare scenarios in which the technological assumptions are included and one of the following policy measures is included: gasoline fuel tax increase, a decrease of subsidies for BEVs, and a limited amount of available subsidy. We can observe our results in table 11.

Table 11: Percentage of agents that own a BEV at the end of the scenarios wherein technological developments are accounted for as well as the increase in fuel tax, the decrease in BEV subsidy, and the limited available subsidies.

	Original	Fuel Tax	Subsidy Decrease	Limited Subsidy
Occasion	63.1%	70.9%	17.1%	15.1%
New	33.3%	55.6%	11.1%	11.1%
Lease	77.1%	77.1%	50.0%	42.9%
Total	61.4%	70.0%	18.9%	16.7%

In all the scenarios listed in table 11, we accounted for technological developments, meaning that the range of BEVs' increases by 7% each year and price of BEVs' decreases with 3% each year, as described in section 5.2.1 and section 5.2.2. The policy measures are implemented as described in section 5.1.1 and 5.1.2.
In order for our model to be more realistic we altered the limit policy scenario, instead of having only €40 000 available subsidy during the entire simulation, the agents will have a total of €20.000 at their disposal each year.

Technological development and fuel taxes

From table 11, we observe that the scenario with the highest amount of BEV-owners is the scenario in which we increase the gasoline fuel taxes. This result was expected seeing as it is the only scenario in which the TCO of the BEV decreases. In the other scenarios the subsidy is decreased or limited, this has a negative effect on the agents' financial perception of BEVs.
Imposing gasoline fuel taxes has a positive effect on the BEV adoption rate. There are approximately 8.6% more BEV-owners when fuel taxes are increased compared to the original scenario in which no fuel taxes are included.
Increasing the gasoline fuel tax has the largest effect on the new buyers' segment, with an increase of approximately 22.3% compared to the original scenario. The least effect is observed in the lease segment. When lease prices drop considerably it has a far greater effect than the drop in commute cost. Changes in commute costs, therefore, become negligible for the lease segment.

Technological development and subsidy decrease

When we implement a decrease of the amount of subsidies, we see a 42.5% drop in the amount of BEV-owners compared to the original scenario, with the most noticeable effect on the occasion segment. The agents in the occasion segment have less capital compared to the other agents, any increase in BEV price has a negative effect on this segment. Furthermore, occasion agents have a

relatively high infrastructure uncertainty compared to the other agents. The occasion infrastructure uncertainty concerns the battery uncertainty of occasion BEVs and their millage. The low income and high infrastructure uncertainty, of occasion agents, explains why we see a larger effect on the occasion segment.
The lease-segment is the least affected by the decrease in BEV subsidy. If prices of BEV vehicles drop then the lease price of BEVs becomes more favourable than the ICEV counterparts, agents belonging to the lease segment will, therefore, continue acquiring BEVs. The subsidy decrease has little influence on this process.

Technological development and limited subsidy availability

The decrease of subsidies and the limited availability of subsidies have approximately the same effect on our agent segments. We see a 44.7% drop in the amount of BEV-owners compared to the original scenario. The biggest change occurs within the lease segment, this can be explained by the timing of the lease agents. The moment the lease agents, decide to replace their vehicle likely occurs before the price of BEVs drops sufficiently enough, or after the available subsidy has been used up. The unfavourable lease price then causes the lease agents to acquire an ICEV instead.

Statistical analysis

A t-test for independent variables was performed with the increase in the percentage of electric vehicles as the dependent variable and each of the different policy interventions as the independent variable. For each of the conducted tests, the p-values were smaller than 0.05 which leads us to conclude that the interventions have a significant effect on the number of electric cars that are bought, we give an overview of our results for each segment in table 12.

Table 12: Statistical analysis for each segment, as well as for the population as a whole.

		p-value	t-value
Decreased subsidy	New-buyers	22e-16	-17.198
	Occasion-buyers	22e-16	-29.567
	Leasers	22e-16	27.833
	Total	22e-16	-28.243
Fuel Tax Increase	New-buyers	22e-16	18.424
	Occasion-buyers	0.01721	2.3841
	Leasers	22e-16	32.18
	Total	0.003	3.012
Limited Subsidy	New-buyers	22e-16	-17.198
	Occasion-buyers	22e-16	-31.881
	Leasers	22e-16	21.543
	Total	22e-16	-30.844

6.2.2 Technological and multiple policy scenarios combined

In this section, we will compare scenarios in which we combine a multitude of technological assumptions and policy measures. Table 13 shows our results, we accounted for technological developments in all of the scenarios.

Table 13: Percentage of agents that own a BEV in each segment and the total population when we run the seven different scenarios. In all scenarios we account for technological developments. The scenarios are further divided into two groups depending on whether the gasoline fuel tax is increased or not. Within those two groups we have have four scenarios: the original scenario (in which we only account for technological developments), the scenarios in which we gradually decrease subsidies, the scenario in which we limit subsidies, and the scenario in which we both limit and decrease the subsidies (we called this scenario the L&D scenario).

	Excluding Fuel Tax				Including Fuel Tax			
	Original	Limited	Decrease	L&D	Original	Limited	Decrease	L&D
Occasion	63.1%	15.1%	17.1%	14.3%	70.9%	18.7%	21.1%	17.9%
New	33.3%	11.1%	11.1%	11.1%	55.6%	38.9%	38.9%	38.8%
Lease	77.1%	42.9%	50%	42.9%	77.1%	44.3%	50.0%	42.9%
Total	61.4%	16.7%	18.9%	16.0%	70.0%	22.3%	24.7%	21.6%

We observe in table 13, that including Gasoline fuel taxes has a positive effect on the amount of BEVs in the simulation. Whenever we implement a measure which restricts or decreases the amount of available subsidy we see a decrease in the amount of BEV-owners at the end of the simulation. The most positive effect on the adoption rate of BEVs is obtained in the scenario in which we increase the Gasoline fuel tax and account for technological developments. Furthermore, combining two unfavourable measures has a more negative effect on the adoption rate of BEVs than applying just one unfavourable measure, this result was as expected. In order to determine how significant our results are we will perform a statistical test.

Statistical analysis

A t-test for independent variables was performed with the increase in the percentage of electric vehicles as the dependent variable and each of the different policy interventions as the independent variable. From section 6.2.1 we know that including fuel tax, decreasing subsidy and limiting subsidies all have a significant effect (with p-values <0.05).

We used the ANOVA-test to determine whether there was any significant difference between the percentage of BEV-owners in the three previously mentioned scenarios. To determine whether combining policy measures has a significant effect compared the scenarios in which we apply only one policy measure, we will use the Tukey Post Hoc test, our results can be observed in table 14.

Table 14: Statistical significance of the combination of the measures in each segment and the population as a whole.

	Segment	Limited * Decrease	Decrease * L&D	Limited * L&D
Without increase in fuel tax	Occasion	**significant**	**significant**	**significant**
	New	not significant	not significant	not significant
	Lease	**significant**	**significant**	not significant
	Total	**significant**	**significant**	not significant
With increase in fuel tax	Occasion	**significant**	**significant**	not significant
	New	not significant	not significant	not significant
	Lease	**significant**	**significant**	not significant
	Total	**significant**	**significant**	not significant

From our analysis, we can conclude that decreasing and limiting subsidies only has a statistical effect within the occasion segment when gasoline fuel taxes are not increased. In general limiting subsidies and decreasing subsidies has the same effect as only limiting the available subsidies.
Furthermore, limiting subsidies has a greater detrimental effect on the number of BEV-owners than gradually decreasing subsidies. Both policy measures have no significant effect on the new-buyers. We can, therefore, conclude that the least favourable scenario is the one in which we do not increase gasoline fuel taxes and limit the available subsidy. The most favourable scenario the one in which we increase gasoline fuel taxes.

6.3 Reflection

In this section, we will reflect on the results of our model, its expected and unexpected behaviour and its limitations as well as its explainability.
The previously discussed results were shown to policy-makers to determine whether the Agent-Based Segmentation Model could provide new insights. Three main questions were posed:

- Which measures are least effective in stimulating the adoption of BEVs?
- Given favourable circumstances, within what time frame is full diffusion of electric cars possible, within the simulation?
- How does the infrastructure improvement influence the diffusion of BEVs within the simulation?

We will attempt to answer these questions. Table 15 gives an overview of the percentage of BEV-owners at the end of all our previously discussed scenarios, our scenarios end in 2040.

Table 15: Percentage of BEVs in all previously discussed scenarios

	Scenario	New	Occasion	Lease	Total
Without technological development	Original	11.1%	10.7%	21.4%	11.5%
	CS	11.1%	10.7%	21.4%	11.5%
	Subsidy Decrease	11.1%	4.4%	0.0%	4.7%
	Increased Fuel Tax	38.9%	21.9%	21.4%	23.4%
	Limited Subsidy	11.1%	10.5%	21.4%	11.3%
	Price decrease	33.3%	62.5%	77.1%	60.9%
	Range increase	11.1%	10.8%	21.4%	11.6%
With technological development	Original	33.3%	63.1%	77.1%	61.4%
	CS	33.3%	62.4%	77.1%	60.8%
	Subsidy decrease (D)	11.1%	17.1%	50.0%	18.9%
	Limited Subsidy (L)	11.1%	15.1%	42.9%	16.7%
	Increased Fuel Tax (F)	55.6%	70.9%	77.1%	70.0%
	L and D	11.1%	14.3%	42.9%	16.0%
	F and D	38.9%	21.1%	50.0%	24.7%
	F and L	38.9%	18.7%	44.3%	22.3%
	F and D and L	38.8%	17.9%	42.9%	21.6%

Which measures are least effective in stimulating the adoption of BEVs?

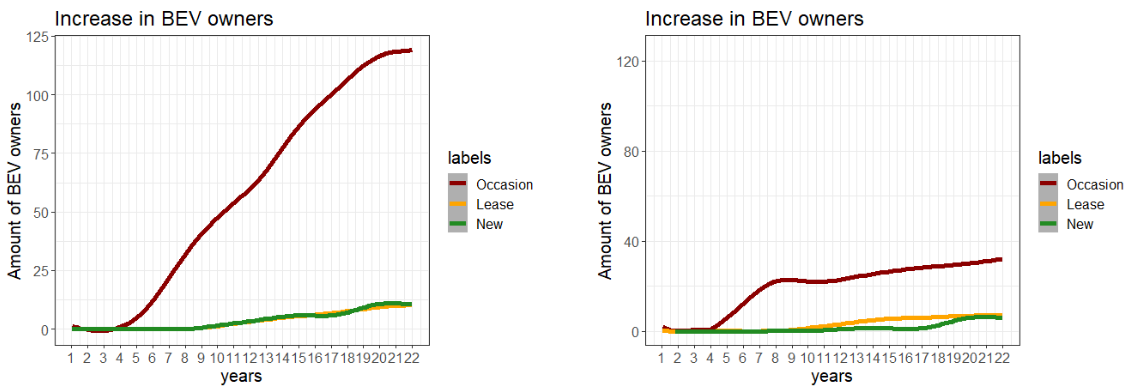
When we do not account for technological developments we observed that decreasing the subsidies has the worst effect on the adoption rate of BEVs.
At the end of the decreased subsidy scenario, there are only two additional BEV owners within our population. When we compare this result to the scenario in which we do not decrease subsidies, we observe the largest difference in the percentage of BEV owners in the lease segment. No effect is observed within the new-buyers segment.
We concluded that this result is to be expected, the monthly investment price is the most influential for the agents belonging to the lease segment. If the BEV is considerably more expensive than the ICEV, due to the decreasing the BEV subsidies, then the agents who lease their vehicle will not acquire a BEV. The decrease of subsidy has no significant effect on the new-buyers because the difference in initial investment is too large even when subsidies are applied.

In section 5, we discussed a policy-measure wherein a limit is imposed on the amount of available subsidy. Although this provides us with some interesting results, it is not very realistic. In section 6.2.1 we altered this scenario to resemble reality more closely. Instead of providing only 40 000 euros during the entirety of our simulation, we provide our agents with 20 000 euros of subsidy each year. However, when we do not account for technological developments, the number of agents that acquire a BEV is not sufficient to exhaust the available subsidy. The limited subsidy scenario is, therefore, comparable to the initial scenario.

When we do account for technological developments, we observe that the least favourable scenario is that in which we both decrease subsidy and impose a limit on the available subsidy. The simultaneous effect of the combination of two detrimental policies has a stronger influence on the occasion-segment than the effects when these measures are applied separately. For the lease and new-buyers segment limiting the subsidies has the same effect as limiting and decreasing subsidies. Within our simulation, the majority of agents own an occasion vehicle. When the agents have limited subsidies, the bulk of the available subsidy will go towards the occasion agents, this explains why decreasing and limiting subsidies has the same effect on lease and new-buyer agents. The lease and new-buyer agents will have limited to no subsidy available, decreasing the subsidy, therefore, does not affect these segments.

Given favourable circumstances, within what time frame is the goal of the Ministry achieved, within the simulation?

If we consider the Ministries goal, that approximately 30% of vehicles will be electric by 2030, we can see that this goal is achieved within our model when we do not limit or decrease subsidies and account for technological improvements. If we also increase fuel taxes, a measure which we proved to be very beneficial, we see that this goal is achieved within our hypothetical simulation, two years earlier in 2028.
Of course, these scenarios are not realistic. When limited-subsidy is included we observe that in 2030 only 14.2% of agents own a BEV, if we then also include fuel taxes we see that by 2030, 15.8% of agents own a BEV.



(a) Scenario wherein technological progress as well as an increase in gasoline fuel tax are applied

(b) Scenario wherein technological progress as well as limited subsidies and increase in gasoline fuel tax are applied

Figure 27: Increase in amount of BEV owners within each segment, in a 22 year time span.

How does the infrastructure improvement influence the diffusion of BEVs within the simulation?

When we increase the rate at which CSs are added to our simulation we see a significant difference in both the parking happiness of the BEV-owners as well as the parking happiness of the ICEV-owners. However, in table 16 we see that the difference in happiness between the two groups is quite small. The inconsequential difference in happiness between BEV and ICEV owners, explains why increasing the rate at which charging stations are added to the neighbourhood does not affect the percentage of BEV-owners.

	Min	Max	Median	Mean
Parking happiness of BEV owners	0.3861	0.4985	0.4891	0.4835
Parking happiness of ICEV owners	0.4667	0.4820	0.4756	0.4754

Table 16: Statistical summary of the BEV owners parking happiness and the ICEV owners happiness.

The reason why the happiness of BEV-owners does not increase with the increase in available charging stations is that there is a penalty for parking in a spot with a CS when one does not have to charge. We can, therefore, conclude that adding more charging stations does not have the desired effect when penalties are put in place for unnecessary use of charging station parking spots.

7 Validation

Our simulations show hypothetical developments envisioned until 2040. We validate our model by determining whether the observed behaviour is within reasonable bounds. This is determined in two ways: by consulting with domain experts (section 7.1) and by comparing the behaviour of the simulation to predictions obtained from the extrapolation of trends observed in the current Dutch car market (section 7.2).
In this section we will also argue that our model is *multistage valid*, *internally valid*, and that it satisfies *face validity* as discussed in section 2.1.2.
We will end this section with a discussion about the validity of the abstract properties of our agents in section 7.3. A conclusion of the model validation will be given in section 7.4.

7.1 Interview

Two interviews were conducted during the development of our model. In section, 2.7 we discussed the survey and the preceding interview conducted at the beginning of our model's development. In this section, we will discuss the interview conducted at the end of our modelling process. This interview was conducted to determine whether the behaviour of our model is in accordance with the expectations of domain experts (i.e. whether it satisfies *face validiy*) and whether the model and its simulation are perceived as useful.

In appendix A.2 we included a document send to the three interviewed domain-experts prior to the interview. This document was intended as a preparation for the actual interview. In this document, we briefly explain what our model entails and its underlying mechanisms and assumptions.
Three domain experts were interviewed. The interviews were conducted through Webex, this imposed some restrictions. The simulations were shown to the domain experts through the graphs and plots of the Repast GUI, the interviewees were unable to use the GUI themselves. Nevertheless, we were able to show multiple simulations by using the scenario list and the sliders to adjust parameters.

During the interviews, the domain experts were asked whether the shown behaviour was in accordance with their expectations and whether the influence of the different factors (infrastructure, social and financial) on the agents' internal values was within reasonable bounds.
The observed behaviour was largely in accordance with their expectations. Some criticisms were expressed about the effect of certain policies, we adjusted the model's parameter weights to adhere to the described expected behaviour.
The domain experts were unable to estimate whether the effect of the different factors on the agents' internal values was accurate. However, the resulting behaviour was deemed to be reasonable, it largely represented the expected behaviour. Since the agents' behaviour was in accordance with the behavioural expectations of the domain experts, no new behavioural insights were obtained by observing the model dynamics.

Most modelling techniques commonly used within the policy-development process are black-box modelling approaches which do not allow policy-makers to test their own proposed scenarios. These modelling techniques offer no insight into the human decision process.
Black-box modelling approaches to consumer behaviour ignore what goes on within the human mind and focus on discovering which stimuli produce the desired outcome. The Agent-Based Segmentation Model does the opposite, it focuses on how consumers are affected by stimuli. The model allows policy-makers to observe the effects, in real-time, of different interventions on the internal values of the agents and their consumer behaviour.

Policy-makers develop policies to influence behaviour, having a model which allows them to observe the effect of their interventions on behaviour is therefore very valuable. The effect the internal values had on the dynamic of the system were also deemed interesting and valuable. Furthermore, our model offered an intuitive representation of the simulation output and the possibility to test out multiple scenarios and alter the agents' parameters. This provided policy-makers with a certain autonomy that is absent in many other modelling techniques. Being able to autonomously alter parameters and observe effects in real-time was a very valuable trait according to policy-makers. This autonomy could not only be used to improve ones understanding of the policy-problem but also be used to communicate the problem to others.
Interest in extending our model was also expressed by the interviewees, some of the proposed extensions to our simulations were:

- Addition of competing technologies such as the hydrogen vehicle;
- Adding export and import dynamics to our simulations;
- Increasing the agent population size;
- Including Diesel vehicles and other ICEVs to our simulations;
- Including scenarios in which wrong parking is not penalised;

This shows that the interviewees were interested in the capabilities of our model and would like to test out more scenarios. A discussion about the models' applicability within different contexts was also conducted. Some misunderstanding about the usage of Agent-Based Models occurred during the presentation of our model. The domain experts wanted to estimate whether the population dynamics and the effect of policy measures could be estimated by using Agent-Based Models. We explained that this is not how Agent-Based Models should be used. We cautioned against using this simulation, or any of its kind, as a predictive tool. The competency of our model instead lies in visualising the effects of stimuli and their interaction in a complex social system. It should be seen as a tool through which population dynamics can be inspected in a relatively effortless way.

During the model's construction policy-makers were asked to revisit and discuss the implicit mental models behind their decision-process. Their assumptions and expectations were then compared and discussed. Although our model did not offer new insights into population dynamics it was still perceived as useful by policy-makers. Our model presented policy-makers with a modelling option in which they were provided with the autonomy to test out their assumptions, play out multiple scenarios and observe the effect of their measures on different target segments in real-time.

7.2 Extrapolation of market trends

In this section, we will compare our simulation results to trends in the Dutch car market. This is done with regards to market stability (Section 7.2.1), ownership aspects (Section 7.2.4) and predicted adoption rate of electric vehicles (Section 7.2.2).
The survey data, used to initialise the agents, was collected in October of 2019, six months before the actual development of our model. The behaviour of the model consists of hypothetical scenarios obtained by extrapolating current trends.

7.2.1 Vehicle market

The vehicle market in the Netherlands is relatively stable, every year there is a slight growth in the number of registered vehicles. Because this is only a slight increase we did not include it in our model.
In 2019 there were 8.530.584 registered vehicles in the Netherlands. Of the 8.530.584 registered vehicles in the Netherlands, 6.804.125 are Gasoline vehicles and 107.536 are BEVs. Which implies that 79.8% of vehicles were Gasoline powered and 1.3% was fully electrically powered. The rest of the vehicles are PHEV, Diesel, LPG, CNG and LPG powered vehicles, figure 28. Our model only accounts for BEVs and Gasoline vehicles we, therefore, altered these values to 3.5% BEVs and 96.5% Gasoline vehicles.

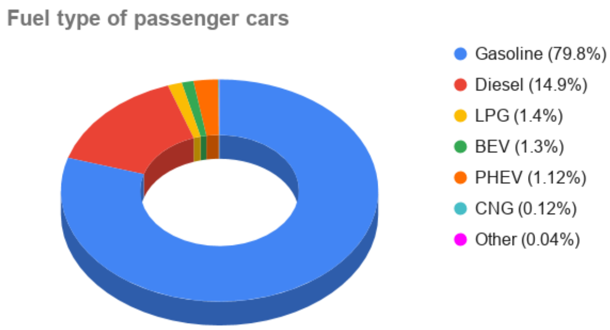


Figure 28: Fuel type of passenger cars in the Netherlands [82]

According to data from Statistics Netherlands (CBS) approximately 2.288 million vehicles are acquired each year, of which 2.1 million are bought and 188.000 are leased [83]. Of the 2.1 million vehicles bought, 1.7 million are occasions and 400.000 acquire a new vehicle. In table 17, we give an overview of the data used to implement the population segments within our model and to estimate the number of agents that replace their vehicle each year.

Private new buyers:	400.000	17.4%	BEV:	4.686	1.2%
Occasion buyers:	1.700.000	74.3%	BEV:	2.366	0.14%
Total buyers:	2.100.000	23.9%	BEV:	7.052	0.33%
Leasers:	188.000	8.1%	BEV:	unknown	unknown
Total amount of vehicles acquired:	2.288.000	36%	BEV:	unknown	unknown

Table 17: Approximate number of vehicles buyers each year in the Netherlands [83], [82], [53]
.

These statistics include company-owned vehicles and company leased vehicles. We only account for privately-owned vehicles in our simulation. We estimate that between 5% and 14% of agents replace their old vehicle each year.
Within our model we assume market stability, this implies that agents will repeat their consumer behaviour. For example, if an agent owns an occasion vehicle it will replace this vehicle with another occasion vehicle, likewise for those who lease their vehicle. A small portion of new-buyers will choose to lease their vehicle.
From table 17, we observe that approximately 8.1% of newly acquired vehicles are leased, 74.3% are bought occasions and 17.4% are new. At the beginning of our simulation, 84% of agents own an occasion vehicle, 12% own a new-bought vehicle and 4% leases their vehicle. Due to our assumption of market stability, the majority of our agents will acquire occasion vehicles. Therefore, the model approximates the actual market sales in the Netherlands.

Available vehicles

All the car models available to the agents in the simulation are based on actual data. Their specifications are based on freely available information from the Royal Dutch Touring Club (ANWB) and dealers' websites. Only certain brands of BEVs are available to the agents, these correspond to the top 10 most sold brands of BEVs (figure 2). The prices of the available BEVs were selected to ensure that they would be slightly more expensive than their gasoline counterparts.
We assumed that in the foreseeable future these same top 10 brands will continue to be sold. The price of the vehicles is static in the basic scenario. In the scenario wherein technological developments are accounted for the price of BEVs decreases. Gasoline vehicles remain static they consist of a set of hypothetical standard brands with standard prices.

7.2.2 Trends in the Dutch car market

The trends discussed in this section are obtained by observing data. The number of occasions sold each year in the Netherlands has been steadily increasing over the past three years as can be seen in figure 30. Because this increase is not very significant we choose to not include it in our model.

Figure 29: Number of lease contract per year

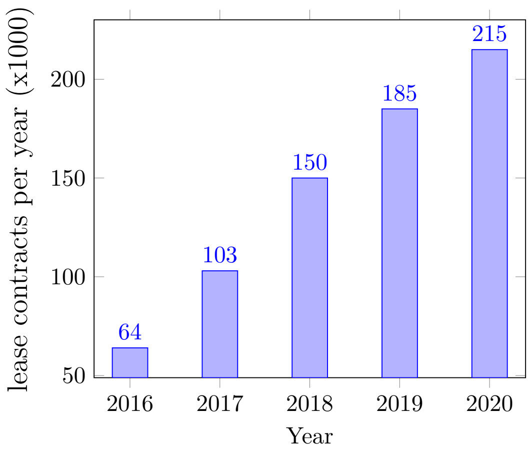
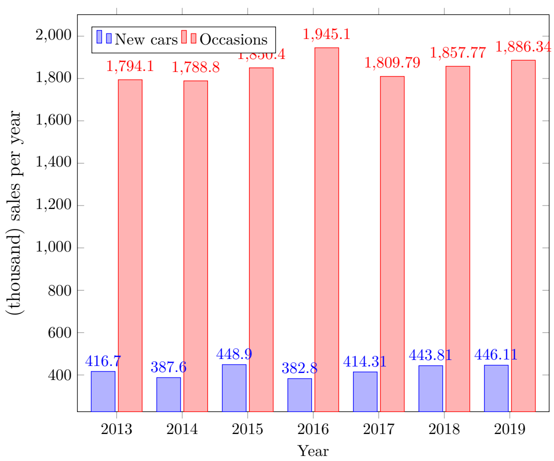


Figure 30: Yearly sales figures for both new cars and occasions (CBS, BOVAG)



In figure 29 we can observe that the amount of private leasers increases each year. We included this trend within our model, this can be observed in figure 31. The agents in our model are only allowed to acquire a lease instead of a new vehicle.

Figure 31: Observation of the increase in the amount of lease-owners and decrease of the amount of new-buyers in the original simulation

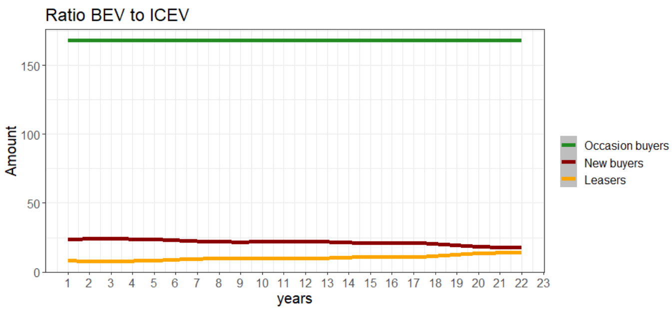
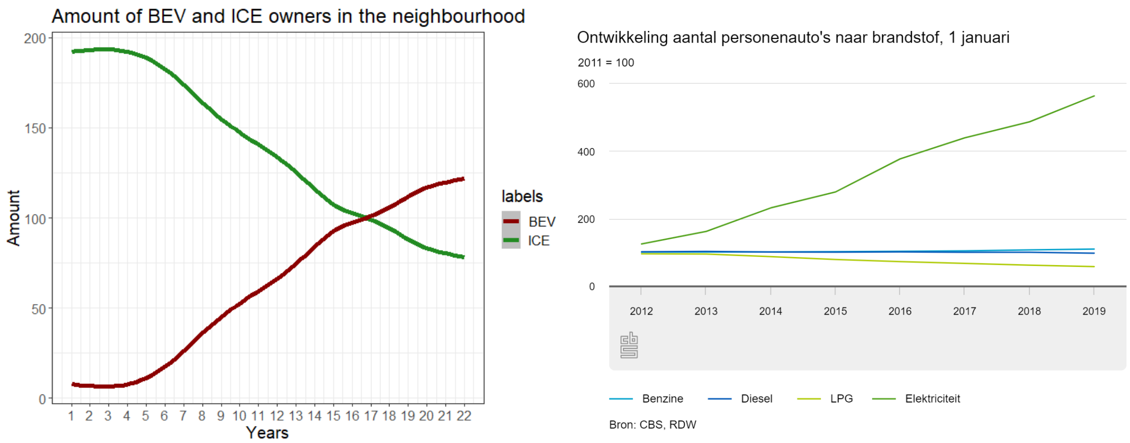


Figure 32: Amount of agents that own a BEV at the beginning and end of the original scenario

	Beginning		End	
	Total	BEV	Total	BEV
Occasion	168	5	168	18
New	24	2	18	2
Lease	8	0	14	3

In January of 2020, 107.000 BEVs were registered in the Netherlands which is 104% more than in 2018 (CBS). In June 2020 there were 122.195 registered BEVs in the Netherlands (RVO) which is an increase of 12.4%. This indicates that the amount of BEV-owners will keep increasing, as can be seen in figure 33b. The initial scenario of our model, without parameter alterations, follows this trend, figure 33a.



(a) Adoption rate of BEVs within our simulation when we account for technological developments

(b) Amount of private passenger cars per fuel type

Figure 33: Development of the Dutch car market according to Statistics Netherlands and our model

7.2.3 BEV adoption rate

There are only a small number of fully electric vehicles currently registered in the Netherlands, an even smaller percentage of those belong to private owners. Since our sample is quite small, validating the rate of BEV adoption is quite difficult. The trends in section 7.2.2 do indicate that the rate of BEV adoption is likely to increase in the upcoming year. In figure 33a we can see that this trend is also observable within our model when we account for technological development, i.e.

when the price of BEVs decreases over time.
As mentioned before the number of BEVs in the Netherlands only constitutes 1.3% of the total number of registered passenger cars. At the start of our simulation, 3.7% of agents own a BEV, this is considerably higher than the actual percentage of BEV owners in the Netherlands. This is important to keep in mind when interpreting the results of the simulation.
With this model we do not aim to replicate the actual adoption rate of BEVs, instead, we test the effects of policies measures on the segmentations and show the resulting trends and dynamics.

Availability of charging stations

At the beginning of the simulation, there are only 2 charging stations available to the agents. The number of charging stations increases steadily the more agents acquire a BEV. This corresponds to the actual municipal approach for placing charging stations. According to the municipal protocol, if someone owns a BEV they have the right to access a charging station within 300 meters of their residence. The rate at which charging stations are added to our simulations can be increased by using the sliders of the Repast GUI.

7.2.4 Ownership Aspects

When validating our model we will take into account two aspects of vehicle ownership: the average vehicle age, and the financial aspect which includes the average price set aside for vehicle acquisition as well as maintenance and usage. We will discuss each of these aspects and substantiate them using our assumptions from section 3.4 and real world data.

Average vehicle age

The average age of vehicles in the Netherlands has increased considerably over the past years. At the beginning of 2020, the average age of passenger vehicles was 11 years whilst this was only 9 years at the beginning of 2010. The average age of vehicles within our model also increases, at the beginning of our simulation the average age of vehicles is 10.06 which increases to 10.215 after 25 years. The agents have vehicles which are between 0 to 21 years old. Furthermore, agents only have a limited selection of occasion vehicles to choose from. The occasion vehicles have ages ranging from 0 to 11 years of age. Older vehicles were not included in the simulation. This explains why the average age of vehicles within the simulation only increases slightly.
The age of the agents' current vehicle also influences its probability to replace it, the older their vehicle is the more likely they are to replace it, this probability is modelled according to the function in figure 34.

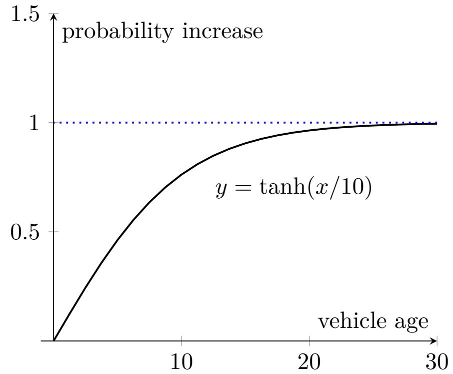


Figure 34: Probability increase according to the age of vehicle

Financial aspects

We assume that whenever an individual is deciding between a BEV and an ICEV, it will compare the difference in initial investment costs, the difference in tax costs as well as the difference between electricity and gasoline commute costs (consumer assumptions 4 and 6 section 3.4). We will discuss each of these aspects below.
Agents view initial investment, the commute cost and the price they pay for taxes differently (assumption 4, section 3.4), this will be further explained in section 7.3.

- **Initial investment:** According to assumption 6, consumers have limited cognitive-capacity they only compare a small number of options. Our agents, therefore, only consider those vehicles which lie within their price range. They will select two subgroups of vehicles from each power train. They will then compute the average price difference between the two power trains and normalise it: $\frac{diffence\ in\ price - min\_price}{max\_price - min\_price}$. Where *min_price* is 10% of the agents yearly income and *max_price* is 30% or 45% of yearly income depending on whether the vehicles is a BEV or an ICEV. Their satisfaction and uncertainty about the price difference are then calculated according to the functions shown figure 35.

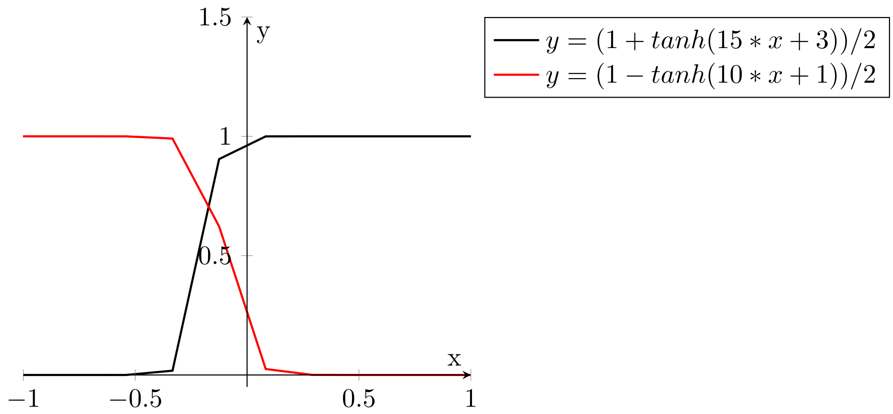


Figure 35: Uncertainty and satisfaction dependent on normalised price difference

- **Fuel cost:**
At the beginning of the simulation, the fuel cost for each power train corresponds to the actual fuel cost in 2019 (table 1). In the standard scenario, each year that passes in the simulation the cost of gasoline increases with 0.01, which represents the actual standard increase in fuel tax. The price of electric charging remains the same. As mentioned before the agents keep in mind the price difference between driving a BEV and driving an ICEV. They do this by calculating how much it would cost to cover their commute distance using the two different power trains, they then determine the discrepancy between the two commute costs and compare it to their monthly income (assumption 7, section 3.4).

- **Taxes:**
The agents are taxed according to the actual regulations in place. Depending on the weight of their vehicle and its carbon emissions the MRB and BPM tax rate differ. BEV-owners are exempt from BPM and MRB taxes until 2025. After 2025 BEV owners will pay 360 euros BPM and pay 25% of the MRB after 2026 they will pay 100% of the MRB tax.
Agents in the simulation will compare the difference in taxes they will have to pay for the two types of power trains. Because the price of taxes for BEVs is always lower than the price of taxes for ICEVs, the tax factor always contributes positively to the agents' values.

7.3 Perception

Both the satisfaction and uncertainty are abstract properties of our agents, we are not able to validate these properties using data. However, their development over time provides insight into the behaviour of the simulation. The satisfaction and uncertainty of the agents' only concern BEVs, as discussed in section 4.3.1. At each tick, the agents that want to replace their old vehicle will determine its uncertainty and satisfaction.
In this section we will discuss not only the agents' satisfaction and uncertainty (section 7.3.2) but also the agents' parking happiness (section 7.3.1).

7.3.1 Parking happiness

As discussed in section 4.2.3, we know that agents park their vehicle. When the number of BEV-owners increases, in our simulation, more charging stations are added. This implies that parking for BEV owners becomes easier, the happiness of BEV owners will therefore go up. The increase in happiness can be observed in figure 36. The happiness of ICEV owners will go down because the new charging stations will take up their available parking spots.

Figure 36: Increase in parking happiness of BEV owners

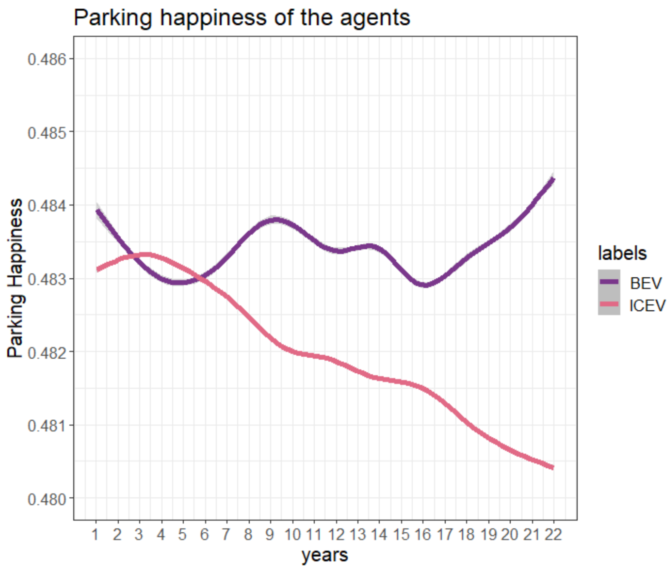


Figure 37: Statistical analysis of the agents' parking happiness within each segment

		Happiness
Mean	Lease	0.487
	Occasion	0.481
	New	0.471
St. Dev	Lease	0.046
	Occasion	0.061
	New	0.068

This increase is however not very significant. This is due to the fact that parking at charging spots is reserved for those who need to charge. We discussed in section 5 that both the BEV owners as well as the ICEV owners are negatively affected by this measure.

7.3.2 Satisfaction and uncertainty

In this section, we will discuss the agents' satisfaction and uncertainty values. We will give motivation for the value dynamics, and conduct a statistical analysis. Figures 39a and 39b show the development of the estimated decomposed satisfaction and uncertainty of the agent that owns a BEV and an ICEV.
We know that subsidies and tax breaks have a big effect on consumer behaviour because starting in 2020 the tax addition for business drivers increased from 4% to 8%. This caused a spike in electric vehicle sales in the last month of 2019, as can be seen in figure 38. We can thus conclude that financial incentives are an important driving factor in the BEV adoption process it, therefore, has a considerable effect on the agents' satisfaction and uncertainty.

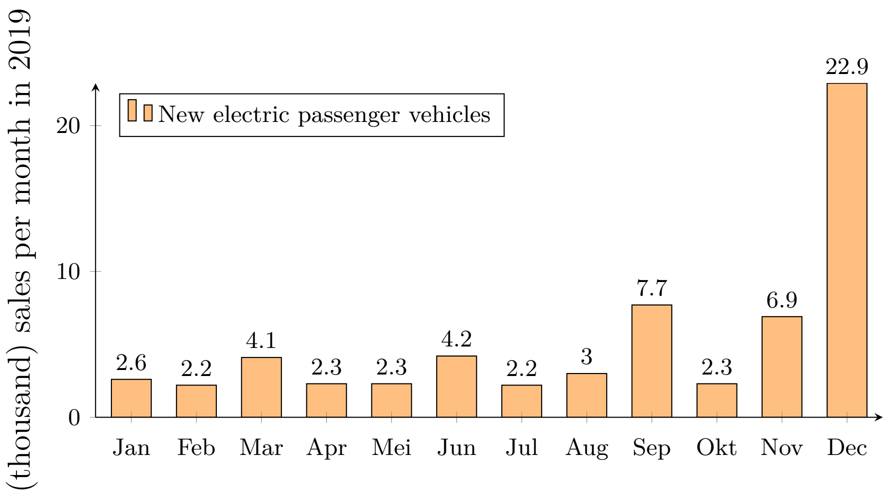
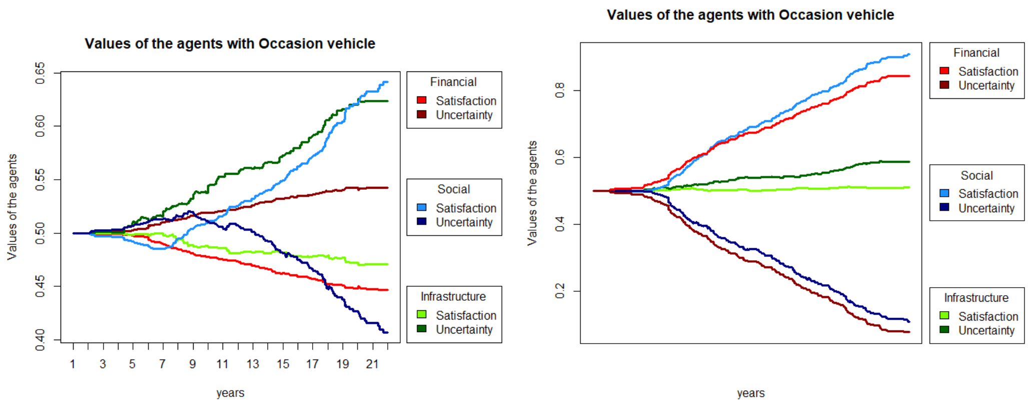


Figure 38: Number of new sold BEV per month in 2019

If we decrease the amount of subsidy the agents receive, using the sliders of the Repast GUI, to 8000 for new buyers and 5000 for occasion buyers we can see a drastic increase in the amount of BEV owners, figure 40. This behaviour is caused by the increase in the agents financial and social satisfaction and decrease of the agents financial and social uncertainty, figures 39a and 39b. From our simulation results, discussed in section 5 and 6, we can observe that decreasing the subsidies or restricting them has a big effect on the outcome of our model. This shows that within our model changes in subsidy values have a direct effect on the financial satisfaction of the agents and, therefore also, on the agents' consumer behaviour.

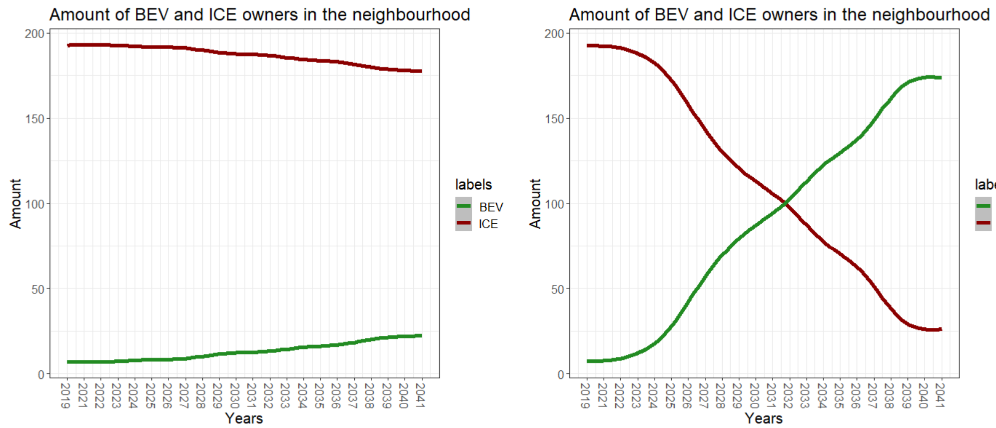
From figure 40 we can observe that the social satisfaction of the agents is directly affected by the amount of BEVs in circulation, if more agents own a BEV it will become more socially acceptable and the social satisfaction and uncertainty will then increase and decrease respectively. The social values of the agents are, therefore, in accordance with assumption 26 of section 3.3.
When the amount of charging stations in the neighbourhood increases we observe a decrease in the agents' infrastructure uncertainty. However, because of the penalty for wrong-parking, the agents' satisfaction does not increase significantly, this behaviour was also expected.



(a) Values of Occasion agents in the original scenario

(b) Values of the Occasion agents when subsidies are increased

Figure 39: Values of the Occasion agents in the original scenario and the scenario in which subsidies are increased



(a) Ratio BEV and ICEV in the original scenario over a 22 year time span

(b) Ratio BEV and ICEV in the scenario wherein subsidies are increased over a 22 year time span

Figure 40: Ratio of BEV and ICEVs in the original scenario and the scenario in which subsidies are increased

We conducted a statistical analysis of the values of our agents, observable in table 18. From this table, we observe that increasing subsidies does indeed have a positive effect on the average financial and social satisfaction values of the agents over time. Increasing the subsidies also has a positive effect on the financial and social uncertainty in the sense that it decreases the uncertainty. The biggest effect can be observed on the occasion and lease segment. We do not see any big increase or decrease in the agents' values when we increase subsidies, we do observe a decrease in the standard deviation for the occasion and lease segment and an increase for the new segment.

Table 18: Statistical analysis of the agents' values per segment in both the original scenario and the scenario in which we account for an increase in subsidies.

			Mean			Standard deviation		
			Lease	Occasion	New	Lease	Occasion	New
Original simulation	Financial	Satisfaction	0.433	0.476	0.376	0.147	0.041	0.182
		Uncertainty	0.531	0.521	0.625	0.044	0.041	0.281
	Infrastructure	Satisfaction	0.542	0.506	0.516	0.075	0.092	0.039
		Uncertainty	0.509	0.525	0.493	0.087	0.141	0.059
	Social	Satisfaction	0.500	0.507	0.481	0.052	0.105	0.069
		Uncertainty	0.507	0.508	0.523	0.059	0.111	0.073
Increase in subsidies	Financial	Satisfaction	0.447	0.667	0.571	0.137	0.085	0.183
		Uncertainty	0.530	0.296	0.368	0.042	0.183	0.223
	Infrastructure	Satisfaction	0.538	0.505	0.520	0.073	0.051	0.092
		Uncertainty	0.506	0.540	0.492	0.083	0.055	0.150
	Social	Satisfaction	0.596	0.684	0.551	0.132	0.102	0.208
		Uncertainty	0.360	0.329	0.434	0.194	0.140	0.241

7.4 Conclusion of our model validation

In section 2.1.2 we discussed multiple validation techniques for Agent-Based Modelling. In section 3.3 and 3.4 we discussed the theoretical assumptions and other basic assumption made during the development of our model. The previous sections show that the parameterisation of our model results in a model which is validated against real-world data. Purchase behaviour approximate actual sales figures, the ownership duration, average vehicle age and BEV adoption rate reflects current Dutch market trends. We can therefore conclude that our model is *Multistage valid*.
Furthermore, when several replications of the simulation are preformed, no significant variability of the model results occur. Our model is, therefore, also *internally valid*.
We conducted a *sensitivity analysis* on our model by altering the subsidy values, the rate at which charging stations are added, and the subsidy and tax values. From these alterations, we can clearly observe an effect on the outcome of our model.
During the development phase of our model, we consulted with experts to ensure that the behaviour of our model is sensible, i.e. that the simulated behaviour lies within reasonable estimates. We can, therefore, conclude that our model satisfies *face validity*.

Furthermore, we do note that whilst validating consumer behaviour is possible, up to a certain extent, the validation of the adoption rate of BEVs is quite troublesome. Many of the assumptions made, during the development of the model, about consumer behaviour and the consumer's thought processes are not based on empirical evidence but on extrapolations of trends, estimations and expert opinions. This makes it nearly impossible to validate. Nevertheless, all assumptions made are well substantiated (section 3) and can be altered if in the future they are proven to be unfit. We can, therefore, conclude that our model is *Multistage valid*, *internally valid* and satisfies *face validity*.

8 Answer to research question and discussion

To conclude this work, it is important to reflect on our initial research questions, given in the introduction (section 8.1). In this section, we will discuss each of our research sub-question as well as our main research question (section 8.1). We will discuss our research process and the limitations of our model in section 8.2. We end this section with a discussion of the models' possible future extensions and improvements as well as the necessary data to achieve this, in section 8.3.

8.1 Answer to research questions

In section 1.2.2 we defined our main research question and divided it into several sub-questions. We will discuss each of our research questions separately. We start by discussing the research questions within our problem investigation, followed by the questions in our treatment design and validation. Finally, we will discuss our main research question.

1. Problem investigation

In this section, we will discuss the questions described in our problem investigation (section 1.2.2). We begin by explaining what we mean by a target segmentation, within our context, and what the interplay is between policies and segmentations. We will then discuss the two decision frameworks used within our model and whether they provide a suitable cognitive framework for our research.

1.1 What is meant with a target segmentation in our context?

Segmentation is the act of dividing a large population into distinct groups. The people within the segments have similar characteristics, needs, or behaviours.
Target segments consist of individuals which are considered to be more susceptible to certain incentives. These individuals share certain characteristics which make them more likely to comply with certain targeted policy directives.
Within our case study, target segmentation is applied to achieve the main goal: increase the amount of BEV-owners. The population is segmented according to their consumer behaviour. Hence, target segmentation within this particular policy context has many commonalities with targeted market segmentation which is discussed in section 2.3.3.

1.2 What is the interplay between policies and segmentations?

Policy measures are developed to achieve certain policy goals by changing people's behaviour. Behavioural change is achieved by enabling or coercing people to do things they would otherwise not do. Not all people will be susceptible and influenced by the same incentives, some incentives might work better than others. It is therefore not possible to develop one policy which achieves the same behavioural change in all individuals.
To design an effective policy-mix, policy-makers segment the population according to their needs, characteristics, or behaviours. Such a segmentation gives a better understanding of the population, their differences as well as their susceptibility to certain incentives. A policy-mix can then be developed which directs incentives and applies measures directly towards the designated target segment in a cost-effective way and in a manner consistent with that segment's characteristics. The application of such a policy-mix is expected to increases the likelihood of people adopting the behaviour needed to achieve the policy goal.
Once the policies are implemented, an evaluation is done to determine whether the estimated effect

on the segments was indeed achieved. Policy development is an iterative process in which target segments and policy measures are subjected to continuous improvement. If it is observed that a certain policy did not have the intended effect, the segmentation or the policy-mix will be revised.

1.3 What state of the art decision frameworks are available and to what degree are they applicable within our context?

Decision frameworks are used to model the reasoning underlying an agents' choices and behaviours. We were particularly interested in decision frameworks which could capture consumer behaviour. In section 2.2, we discussed two decision frameworks: the BDI-architecture (section 2.2.1), and the Consumat architecture (section 2.2.2). The BDI-architecture is a common method to design expressive and realistic agents capable of deliberation. However, intentions, desires and beliefs are not able to capture the entirety of the human deliberation process. The BDI-architecture is not well suited for building systems that must adapt their behaviour. Moreover, the BDI-architecture gives no consideration to multi-agent aspects of behaviour.
The Consumat architecture was specifically developed to model the behaviour of consumers and market dynamics. To fully implement this framework, data about respondents' needs, attitudes, and personal characteristics need to be available. The data necessary to implement the Consumat architecture is not always readily available.

In this research project, we use agents to model the interaction between policy-measures and different segments of the population. To be able to model the effect of policy-measures on different segments of an agent population, the agents' behaviour must be modelled. Agents of different segments have distinct behaviours and different ways of evaluating their needs. Agents can also influence each other, independent of which segment they belong to. Having a cognitive architecture that covers all segments, enables us to define exactly where the specifications of the segment types differ allowing for easy comparison and plausibility assessment. Cognitive frameworks are, therefore, invaluable to the validation of the output of social simulations.
While the Consumat framework was the most appropriate framework for our project, lack of data meant that we were unable to fully implement the Consumat approach. Although the BDI-architecture allows us to design expressive and realistic agents capable of deliberation, it was not well suited to model adaptive consumer behaviour. However, the Consumat architecture is adjustable, extensions, and alterations to the framework are easily made. It is, therefore, possible to combine the two decision frameworks, as was discussed in section 4.2.3 and 3.2. We use the BDI-framework as the basis of our agent architecture. The agents' desires and intentions are more closely related to the needs described in the Consumat architecture, section 2.2.2.
By combining the architectures we require less specified data and our agents will have a higher level of complexity, making their actions have a closer resemblance to actual consumer behaviour.

2. Treatment Design

In this section we will discuss our questions concerning the treatment design (section 1.2.2). We will discuss how we used the available data to build the Agent-Based Segmentation Model and how we formalised the segmentation requirements within the model.

2.1 How do we formalise the segmentation requirements within our model?

In section 2.3.3 we formalised five requirements for segmentations:

- *Identifiable:* Based on the characteristics of the agent we should be able to determine the target segment it belongs to.
- *Differentiable:* The individuals within each segment should have similar characteristics which are clearly different from those individuals belonging to other segments.
- *Actionable:* The agents within the different segments should possess those characteristics which can be influenced by target incentives. Therefore, agents within a segment exhibit a common reaction, or a similar and somewhat predictable response to the target intervention.
- *Accessible:* Agents within a segment show a greater differential response when exposed to targeted policies compared to more general policies.
- *Stable:* A target segment should be stable enough for a long enough period of time such that the interventions can be applied successfully.

These segmentation requirements ensure that the implemented policy-mix targets the appropriate segments and that the individuals within those segments are susceptible and influenced by those policies.
To assure that the target segments were implemented correctly within our model, we constructed our segmentations in such a way that they satisfied each of the previously mentioned requirements. In section 3.1 we briefly discuss why we think our segmentation satisfies each requirement.
The initial segmentations were obtained from data by determining the respondents consumer type. Three segments were established: the people that lease their vehicle, the people that buy occasion vehicles, and the people that buy new vehicles. We also ensured that the segment sizes were large enough for the policy effect to be significant. Agents belonging to different segments have different ways of evaluating their needs. The difference in agent needs between segments was based on subjective information obtained by interviewing domain experts (section 3.4.1), no empirical evidence was found on this subject. This difference ensures that agents belonging to different segments are affected differently by the same policy mix. By observing the behaviour of our model we were able to determine whether the implemented target segmentations were indeed affected by the policy mix and whether the agents behaviour differed, section 5 and 6.

2.2 How can we use available data to build Agent-Based Segmentation Models?

To construct an Agent-Based Segmentation Model, the agents and their corresponding segmentation should be established. Agents should be initialised using the available data. To establish the initial segmentation, data that contains information about the respondent's behaviours and demographic characteristics should be available. The link between the target segments and the segmentation objective gives us an indication of which aspects and agent behaviours are relevant to include in our model. The agents' choices and behaviours are modelled using a cognitive framework. The necessary data to implement the relevant behaviours and cognitive processes within the cognitive framework should be available. This data should include information on the respondent's

behaviour patterns as well as their characteristics.
Depending on the goal of the segmentation, and the cognitive framework used to implement the agent's behaviours, different data is needed.
Once the model is constructed it could be validated by comparing the outcome of the model to actual real-world data.

In our use case, the goal of our model is to study the dynamic interaction between population segments and the policy-mix given in section 2.7.2. The goal of the target segmentation is to increase the likelihood of people buying a BEV. The behaviour of the agents within our model should, therefore, represent consumer behaviour.
In section 4.6, we discussed the available data. We used the available data to initialise our agents, help segment our agent population and aid in the modelling of the agent behaviours.
The available data was not sufficient to fully implement our cognitive architecture and fully develop the agents' behaviour rules. We resorted to empirical evidence and expert knowledge to develop criteria and make assumptions which complemented the available data and allowed us to construct the Agent-Based Segmentation Model.

We will briefly discuss how we used the available data to: initialise the target segment and establish the agents' behaviours. We will also discuss what was missing from our data and how we used the criteria and assumptions to complement it.

Target segments

Within our model, the target segments were obtained by segmenting the agents based on their consumer type. No information was available about the consumer intention of the agents, i.e. how they wanted to acquire their future vehicle. We, therefore, assumed that agents who owned an occasion would substitute their old vehicle by an occasion vehicle. We also assumed that agents who leased their vehicles would also lease their future vehicles. Agents who own a new-bought vehicle are allowed to lease their future vehicles, provided they are under a certain age an have a lower income. This was done to adhere to a current trend within the Dutch car market in which the number of people choosing to lease a vehicle increases every year, discussed in section 7.

Agent behaviours

The difference in need assessment between agents of different segments was established by consulting experts. We determined which needs and behaviours are targeted by policies giving us an indication of how agents might react to certain stimuli. We discussed each of our assumptions in section 3.4. The proportions of our three segments roughly represented the population of Dutch car owners (section 7.2).
The agent's attitudes, needs and values were modelled using a cognitive framework. As mentioned earlier, most information necessary to fully incorporate the Consumat architecture was missing. Most notably the absence of information about the respondents' attitudes, general life values and need for conformity, among others. However, some information was provided about the respondent's knowledge of BEVs, allowing us to estimate how familiar the agents were with the BEV and how much the policy measures might affect their internal values. The data also contained information about the respondents driving activities, which allowed for a rough estimation of the agents' driving needs.
Any model is always an abstraction and simplification of reality, the data provided to us might not have been the most suitable. By incorporating assumptions and certain predefined criteria that were established by consulting domain experts, we were able to instantiate a diverse and representative range of agents.

3. Validation

In this section we will discuss our research questions concerning the validation of our model (section 1.2.2). We will discuss whether the behaviour of our Agent-Based Segmentation Model can be explained by policy-makers, whether our model was able to bring new insights and if it is considered to be useful by policy-makers.

3.1 Does the ABM show behaviour that can be explained by a policy-makers?

The model was constructed to study the dynamic interaction between policy-measures and the segments of a population. Our model allows us to interactively test the effects certain policies have on the dynamics of a population. The user can alter parameters and activate policy scenarios by using the sliders and buttons of the Repast GUI, represented in figure 41. The GUI is user-friendly, it can easily be used to test out different scenarios and adjust parameters.

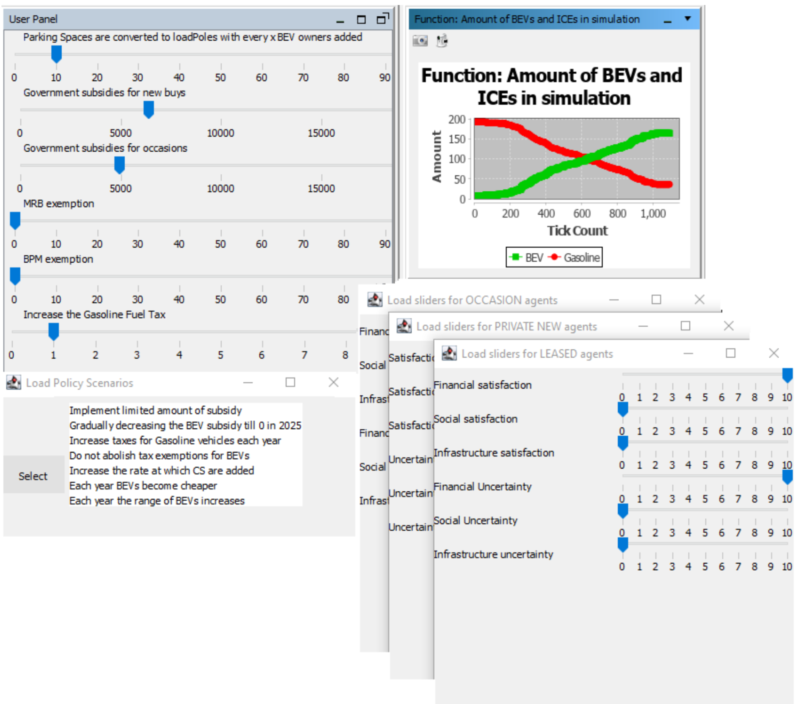


Figure 41: Representation of the Repast GUI containing the sliders and buttons

The simulation results and the effects, of the alterations, can be observed directly by using the graphs, histograms, and plots of the interface. The graphical representations are intuitive to understand. At the end of our models' development phase, an interview with policy-makers was conducted, we discussed this interview in section 7.1. During this interview, policy-makers were able to alter parameters, activate policy scenarios, and observe the model's results using the Repast graphical interface. During the interview, policy-makers were able to provide feedback on the simulation results. This feedback was used to revise our model such that it adheres to the policy-makers behavioural expectations. The statistical significance of our results was not of particular interest to the domain experts. They were predominantly interested in the overall behaviour of the model. They wanted to know how certain alterations would affect the simulation outcomes and which parameters needed to be altered to obtain a certain result. The interpretation of the graphs and other interfaces sometimes required an explanation beforehand to be interpretable by policy-makers. The population dynamics and simulation results are largely in accordance with the expectations of policy-makers and can be explained by them.

3.2 Does the ABM bring new insights, do the domain experts find it useful?

Our model was generally well-received. Contrary to black-box modelling approaches, commonly used within the policy domain, our model offered an intuitive representation of the simulation output and the possibility to directly observe the effects of different interventions on the behaviour of the model itself. The possibility to test multiple scenarios and alter the parameters of the different interventions provided policy-makers with a certain autonomy that is absent in many other modelling techniques. This autonomy could not only be used to improve ones understanding of the policy-problem but also to communicate the problem to others. Policy-makers develop policies to influence behaviour, having a model which allows them to observe the effect of their interventions on behaviour is therefore very valuable. The effect the internal values had on the dynamic of the system were also deemed interesting and valuable.
The user-friendly GUI of our model allows policy-makers to test out multiple scenarios and observe their effects in real-time. Being able to autonomously alter parameters and observe effects in real-time is a very valuable trait according to policy-makers.
Interest in extending the model, to include multiple other scenarios, was also expressed, one example of such extensions is the addition of competing technologies such as hydrogen cars.
New insights into population dynamics were unfortunately not obtained. However, the observation of population dynamics in our model did provide new insights into the flexibility of Agent-Based Models and the descriptive possibilities of the system.
The construction process of our model allowed policy-makers to revisit and discuss the implicit mental models driving their decision process. Incorporating the policy-makers implicit mental models in an explicit model, such as Agent-Based Models, allows us to compare assumptions and check for inconsistencies.
Although the agent-based segmentation model did not provide new insights into population dynamics, this does not imply that it is not seen as useful. The model provided policy-makers with new insights into Agent-Based Modelling techniques. Such insights are useful because it provides policy-makers with an alternative modelling technique in which they are able to include more detail and context than other modelling approaches.

Main Question: How can population segmentation be applied in a useful way within ABM?

We subdivided our main question into various sub-questions, through answering each of the sub-questions we obtained an answer to our main question.
In our problem investigation, we begin by evaluating what is meant with a target segmentation and why such segmentation is necessary within our context. The link between the target segments and the segmentation objective gives us an indication of which aspects and behaviours are relevant to include in the Agent-Based Segmentation Model. The initial goal with which the target segments were obtained also provide us with valuable insights into the expected behavioural differences between people belonging to different target segments. The established behavioural differences and their related causes can be translated to needs and behavioural rules. A decision framework is then used to integrate these needs and behavioural rules within an Agent-Based segmentation Model.
Multiple decision frameworks are available, the decision framework best suited for the study case must be selected. The decision frameworks are compared based on their applicability within the context, i.e. whether it allows for the integration and modelling of the necessary cognitive processes and behavioural rules. Once a framework is selected, the segmentation requirements must be formalised. These requirements ensure that the target segments within the Agent-Based Segmentation Model are implemented correctly.
Behavioural differences between people belonging to different target segments can be caused by differences in their demographic, geographic or psychographic characteristics as well as differences in their norms, values, behavioural activities, and technical knowledge. Domain experts can be consulted to establish a link between behavioural differences and personal characteristics. These characteristics can often be obtained from data.
Data on such characteristics is necessary to initialise the agents within the segments and implement their behavioural rules within the cognitive framework.
Once the Agent-Based segmentation Model is constructed an evaluation must be made of the model's behaviour. The phenomena represented in the model results should be easy to interpret. The factors which influence the agent population should be adjustable and their effect on the different target segments observable within the model results. The GUI of the model should allow the user to autonomously alter parameters, test out multiple scenarios and observe their effect in real-time. The behaviour shown by the model must lie within reasonable bounds and resemble the behaviour expected by domain experts.
Once the model behaviour lies within reasonable bounds, the model can be used to compare the behaviour of the agents belonging to different target segments across a number of potentially relevant scenarios. Domain experts and stakeholders can be consulted to determine which scenarios are relevant.
During the construction phase of the model different scales of decision-making and decision, priorities can be made explicit as well as the factors involved in those decisions. The information elicited from domain experts during the construction of the model can also be compared, this allows for the detection of previously unknown inconsistencies among domain expert assumptions. Hence, the modelling process can help structure ones understanding of the problem as well as clarify and communicate that understanding.
The repercussions and ramifications of certain perturbation on the different agent population segments can provide valuable insights. These insights and the modelling process itself determine whether the model is useful.

8.2 Discussion

The primary goal of our research was to determine how population segmentation can be applied in a useful way within ABM. To do so we conducted literature research, build an Agent-Based Segmentation Model, validated the model, and determined whether the model provided policy-makers with new insights and whether they found it useful.
The model needed to be able to show consumer behaviour, up to a certain extent. Our goal was not to replicate reality but rather to have a model that shows behaviour which is interpretable and expected. A study of segmentation practices was conducted to incorporate segmentations within our model. Lack of data meant that cognitive architectures needed to be altered and that criteria needed to be devised to represent expected behaviour.
We were interested in what this kind of model would be able to show us, and how useful it would be for policy-makers. Furthermore, the process of incorporating segmentations was also one of the main focuses of our research. How agents in different segments would compare and on which levels they would differ.

Issues arose during the development of our model, not only with available data but also with the use of cognitive frameworks. The use of cognitive frameworks allows for a combination of interdisciplinary insights, as well as promoting scientific discourse by making the models' underlying assumptions more transparent. In our case, the framework was used to facilitate the interpretation of the model's results, by showing how different measures affect the need evaluations of agents within different segments.
The data used in our research was not the most suitable, data from surveys which focus more on behaviour-specific beliefs would have likely provided a more valid input. Lack of data meant that sub-optimal modelling decisions had to be made, the insights we gained and discussed may be able to help the field of Agent-Based Modelling further. For future projects, we advise the use of input data which is tailored for the purposes of the Agent-Based Model.

We discussed how multiple measures and scenarios influence the rate of BEV adoption, observations on the effect of their combined interaction were also made. The use of the different graphical representations allowed us to understand the effect certain macro and micro-developments had on the different population segments.

Validation of the simulation is an important aspect of Agent-Based Modelling. We compared our model results to trends in the Dutch car market. These trends were obtained from data on sales figures, ownership duration, and readily available information about the Dutch car market. How legitimate the observed behaviour is within our simulations is determined by using domain experts. This was necessary because data that can be used to validate our model results is not yet available. Feedback received from domain experts are subjective and did sometimes conflict. Nevertheless, we constructed an Agent-Based Segmentation Model which intuitively and comprehensibly represents the complexities involved in the consumer adoption process of BEVs. By applying the Agent-Based Segmentation Model within our use case, we were able to determine whether its application was considered to be useful.

8.3 Future research directions

In this section, we will give some suggestions for improvements to the model, including extensions that could lead to additional insights. The data necessary to achieve these improvements and extensions will also be discussed. These insights allow for an improvement of future models.

8.3.1 Model extensions and improvements

In this section, we will discuss some ways in which the model can be improved upon and suggest some extensions to the current model which would provide interesting insights.

Improvements

In our current model, our agents are reactive, they do not take into account future developments. The agents within the segmentation model do not make predictions or take into account future occurrences, section 4.4.6. By allowing agents to react proactively we would increase the validity and accuracy of our results. Proactive agents represent human behaviour more accurately. For example, they can reason about future policy changes, fluctuations in fuel prices/charging-costs, and technological improvements, and alter their behaviour accordingly. The proactive behaviour of the agent should be based on solid-theory of how proactive behaviour influences consumer decision-making.

Another improvement to our model would be revising the current neighbourhood grid. The residences in the neighbourhood wherein the agents reside are distributed randomly across the grid, parking spaces are then added near these residences. Within the Repast domain, it is possible to represent actual Dutch neighbourhoods with realistic plans for the addition of charging stations. Adding a realistic neighbourhood grid would increase the validity of our model.

In section 7 we discussed several trends in the Dutch car market, one of which indicates an increase in the number of people who will opt to lease their vehicle instead of buying it. This dynamic is not completely included in our model and could bring valuable insights. Currently, only new-buyers can choose to lease their vehicle, our model could also include this possibility for occasion-buyers. The higher initial investment cost of BEVs is made irrelevant when an agent chooses to lease their vehicle, this adds a new dynamic to our model.

Social influences are included within our model, however, no distinction is made between individuals. All agents influence each other the same way. Social networks could be included within our model if the necessary data would be available. The social networks would allow some agents to be more influential and allow us to include family dynamics as well as the influence of friends and colleagues (assumption 26 of section 3.3). The influence of family and friends is an important factor in ones inclination to buy a BEV, including such a network within our model would, therefore, increase the accuracy of our results.

Extensions

It is possible to extend our model. We will discuss some of these extensions here.

We can expand the car market of the agent-segmentation model by including the limited availability of certain brands and import-export dynamics. Expanding the car market within our model would allow us to simulate how an increase of new-bought BEV vehicles affects the occasion-BEV vehicle market. The scrappage costs and trade-in values of BEV and ICEV could also be added to our model. Including export and import dynamics within our model would allow us to model the effect the import and export of BEV vehicles have on the vehicle market. However, to do so accurate data should be collected on the import and export of BEV vehicles in the Netherlands, and the size of our agent population should be increased considerably.

Our model can further be extended by including multi-car households. Currently, our model only includes single-car households, by including multi-car households we account for the fact that most BEVs are purchased as additional vehicles (assumption 11 section 3.3). By introducing multi-car households new dynamics could be observed that could alter the BEV adoption rate. For example, single-car households might not acquire a BEV because it does not satisfy their needs, however, having a BEV in a multi-car household could be considered to be useful because it diversifies one's car fleet.

The simulations within our model could also be extended by including a universal battery health-check. This new technology would be able to accurately test the battery degradation of an occasion-BEV. The uncertainty about battery life in BEVs is one of the main hurdles keeping people from acquiring an occasion-BEV. Having a way to accurately test the battery degradation is expected to increase the number of people who acquire an occasion-BEV. We would be able to include this within our model, by decreasing the battery uncertainty of the occasion agents.

Another extension to our simulations would be to include the possibility of the agents charging outside of their home. Our model could be extended to include a nationwide fast-charge network.

Incorporating other algorithms within our existing model could also be feasible. Examples of such algorithms are:

- Prediction algorithms on how financial incentives affect the rate of BEV adoption (Carbon Tax Model [84], commissioned by PBL: Dutch Environmental Assessment Agency);
- Algorithms on social influences, such as the CODEC model [85], which models how social influences affect the perception and adoption rate of BEVs;

Part of these algorithms could be integrated within our existing model to make it more realistic. Other extensions to our simulations include an increase in governmental subsidies, the addition of carbon taxes or the emergence of new technologies such as the hydrogen car.

8.3.2 Necessary data

We discussed earlier that using input data that is specifically tailored to the purposes of the ABM and corresponding cognitive framework ensures the construction of a model well fitted to reality. During our modelling process, we identified the kind of data needed to model necessary intrinsic factors.
Data which focuses on attitudes, values, personal characteristics, conformity values and social status needs to be available. This information could be translated to needs, need weights and abilities/personality, which would allow us to implement the Consumat architecture completely. Data on patterns of behaviour and corresponding needs should also be available. Often a person's car history gives an indication of their preferences, their vehicle standards and what they might find important. This also gives us an indication of how the individuals might react to certain stimuli. Further information on what a respondent looks for in a future vehicle would allow us to estimate which values should be more influential.
With regards to our segmentation, the majority of the demographic data was available. However, data on what consumer behaviour the agent was likely to adopt in the future was not. We had no information on whether the respondent was going to lease or buy a new/occasion vehicle, this

should also be included in the data.
Someone's disposition towards electric vehicles and their familiarity with the BEVs was also missing from our data, these are important determining factors in one's probability to acquire a BEV (assumption 28 section).
The factors and misconceptions keeping someone from acquiring a BEV, and the negative BEV stereotypes could also be obtained from data. Having data on these aspects would allow us to more accurately estimate how different measures would influence those individuals.
Multiple scenarios could be given to respondents to test their personality type and estimate the influence policies might have on them. Once the reaction pattern of the respondents is obtained we would be able to simulate them within an ABM.

If a social network were to be included within our model, accurate information would need to be collected on how someones social network influences their probability of acquiring a BEV. How the BEV is perceived by people in the respondent's direct environment, should therefore be determined. If we are able to include a social network we would be able to use Rogers diffusion of innovation model, [86]. This model delineates the process by which an innovation spreads via certain communication channels among members of a social system [86]. If the necessary data would be available, it would be possible for us to estimate in which consumer category an individual would lie. There are five consumer categories: early adopters, innovators, early majority, late majority, or laggards. Data could be collected on how early BEV adopters differ in ambition levels, uncertainty tolerances and general life values from owners of traditional ICEVs. The consumer category indicates how much societal change would need to happen before a certain individual would decide to change power trains.
Furthermore, if data could be collected on the same respondents to determine whether they purchased a BEV in actuality, we would have a way to validate our model using this data. We would also be able to track the changes in their behaviours, opinions and preferences, this information could then be used to compare our model to a regression-analysis and possibly adjust our parameters to increase the models' goodness of fit.

8.3.3 Internship reflection

My nine-month internship at the Ministry of Infrastructure and Water Works was a worthwhile experience as it helped me gain considerable professional knowledge about policy-making, the modelling behind it and the way in which stakeholders and domain experts are consulted.
During my internship I gained insight into how different ministerial tasks are carried out and the way work is done in the Ministry. My internship was at the Behavioural Insights Team (BIT). The internship allowed me to attend several meetings, workshops and seminars. I learned about how behavioural theories are used to achieve behavioural change and how these theories are applied to learn from failed policies. I learned how nudging is used to influence behaviour. These behavioural insights were also a vital part in the construction of the Agent-Based Segmentation Model. Not only did my internship allow me to gain valuable experience and knowledge, but it also allowed me to interview multiple domain experts as well as policy-makers. Building my model would not have been possible without the support of my supervisor Gert-Jan de maagd and my colleagues at the Ministry. Their support and willingness to help was crucial in the construction of the model. Their dedication to their jobs and their fellow employees is something I will never forget.
The data used within this project was also provided by the Ministry. During my internship I gained experience in analysing this data and integrating it within a working model.
The domain knowledge and behavioural insights as well as the theories behind the domain knowledge were the building blocks on which the model rests.
My experience at the Ministry helped me understand the complexity and uncertainty involved in the making of policies, and the vast reach those policies can have.

9 Conclusion

The goal of this research was to determine how a population segmentation can be applied within Agent-Based Modelling in a useful way. To do this we conducted a case study in which we build an Agent-Based Segmentation Model. This model artificially simulates the effect government policies have on the diffusion rate of BEVs among Dutch consumers.
To construct the model, the interplay between target segments and government policies needed to be determined. The goal of the initial segmentation gives an indication of which aspect and behaviours should be included in the model.
We evaluated multiple segmentations practices and compared them to the segmentation implemented within our policy-context. The agent population, within the model, was segmented according to their vehicle consumer behaviour. We established requirements for our target segments which ensure that the segments within the Agent-Based Segmentation Model were implemented correctly. The knowledge of domain experts was used to determine how to implement the target segments using the available data.
A decision framework was used to model the decision processes of the agents within the model. A lack of data restricted our choice of framework. We opted to implement a hybrid framework to attribute agents with a higher level of complexity.
The behaviour rules by which we modelled the agent's vehicle purchasing behaviour and need assessments were established based on theoretical and consumer assumptions as well as our subjective intuition.
Domain experts were interviewed to determine which measures and developments would be most useful to simulate. Using this information we constructed multiple scenarios, in which we determine the influence of multiple measures on the adoption rate of BEVs. The interaction of those measures was also described.
Our model allows one to observe how technological advancements of BEVs and policies can influence each other over a twenty-year time span. However, caution must be applied when interpreting the result of our model. The model should not be used as a predictive tool, it is not a final version that can be used to guide the policy process. Its competency lies in the visualisation of behaviour and dynamics in a complex social system.
The behaviour of the system was validated by consulting with domain experts and comparing the results to trends in the Dutch car market.

Once our model was constructed interviews were conducted with domain experts to determine whether our model provides them with new insights. We discussed how the behaviour of our model was in line with expectations of domain experts, and could therefore be explained by them. Regrettably, no new insights into population dynamics were obtained, this does not imply that our model is not perceived as useful. The intuitive representation of the model output and the behavioural insights it provided was deemed to be very useful. The autonomy given within our model to alter the agents' parameters, test ones assumptions, and apply different interventions in real-time is a valuable trait of our model, often absent in many other modelling techniques. Interest in extending the model was also expressed. The observation of emergent phenomena in our model provided policy-makers with new insights into the flexibility of Agent-Based Models and the descriptive possibilities of the system.

With regards to the original purpose of our model we believe it is fulfilled. Through the construction and application of our Agent-Based Segmentation Model, we gave an example of how segmentation could be applied in a useful way within ABM. This allowed us to generalise our findings and construct a roadmap for applying population segmentation in a useful way within ABM, thereby answering our main research question.

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A Survey and interview

A.1 Enquête

De vogende personen hebben deelgenomen aan deze enquête: Gert-Jan de Maagd, Koos Tamin, Richard Hovinga, Sibolt Mulder.

Doelen van het interview:

- Weten welke van de flankerende maatregelen het meest van belang zijn, hoe deze kunnen worden uitgevoerd en de te verwachte effecten. Deze zullen dan vervolgens worden opgenomen in het model;
- Inzicht krijgen in de belangrijkste motivaties die iemand kan hebben voor de aanschaf van een elektrische auto;
- Weten waarom iemand meer/minder geneigd zou zijn om een elektrische auto te kopen, welke factoren en activiteiten zijn hierbij van belang en welke zouden moeten worden opgenomen in het model.

Inleiding

Op dit moment ben ik bezig met de ontwikkeling van een agent-based model (ABM) waarbij ik de effecten van de klimaatmaatregelen op verschillende doelgroepen simuleer. Hiermee onderzoek ik de interactie tussen personen en de verschillende maatregelen. Dit model moet beleidsmakers meer inzicht geven in het gedrag van mensen met betrekking tot het kopen van een elektrische auto. Met name m.b.t. de factoren die hierop invloed kunnen hebben.

Het doel van deze enquête is om uw inzicht en kennis te benutten voor het verder ontwikkelen van mijn model. Er zijn meerdere maatregelen. Ik wil weten welke van deze het meest van belang zijn, hoe deze kunnen worden uitgevoerd en wat hun te verwachte effecten zijn. Ook wil ik uw kennis van het menselijk gedrag inzetten om gebruikmakend van uw expert judgement de belangrijkste factoren te bepalen die een indicatie kunnen geven wanneer iemand meer/minder geneigd is een elektrische auto te kopen.

Na deze enquête vindt enige tijd later een interview plaats waarin ik aan de hand van uw gegeven antwoorden meer verdieping en verduidelijking vraag. Uiteraard is hier ruimte voor opmerkingen of vragen.

Vragen:

Naam: ____________________________

Vraag 1: Prioriteer de volgende flankerende maatregelen naar welke in uw mening het meeste van belang zijn voor het stimuleren van de koop van een elektrische auto. Prioriteer deze van 1 (minst belangrijk) naar 9 (meest belangrijk).

___ Consumenten van betrouwbare feiten voorzien zoals bijvoorbeeld over de kosten van een EV vs. traditionele benzine/diesel auto;

___ EV-occasion zekerheid bieden (universele batterij check);

___ Zichtbaarheid EV-rijders vergroten (bv door gebruik van groene kentekens);

___ Laadpaalkleven bestrijden;

___ Versneld plaatsen van laadpalen (commercieel en in openbare ruimten);

___ Thuis opladen vergemakkelijken door subsidie op privé laadpalen of wallboxen of door aanbieden van lagere tarieven;

___ Toegang van benzine/diesel beperken in binnensteden en milieuzones;

___ Deelautos uitbreiden met EV-modellen en laadplekken;

___ EV-zakelijk verplichten.

Vraag 2: Geef voor de 4 belangrijkste maatregelen, die u hebt aangegeven bij de vorige vraag, aan hoe deze in de praktijk zouden kunnen worden uitgevoerd, zodanig dat het de transitie naar elektrische auto's versnelt.

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Vraag 3: Kruis elk van de onderstaande verklaringen aan als u het er mee oneens bent. Deze verklaringen specificeren wat de te verwachte effecten zijn van de bovenstaande benoemde maatregelen op de koop van elektrische auto's.

___ Het verlenen van betere en duidelijke informatie aan de consument heeft minder effect dan informatie afkomstig van iemands sociale omgeving;

___ EV-zakelijk verplichten zou niet alleen de verkoop van elektrische auto's aan de zakelijke markt verhogen maar ook de verkoop aan consumenten.

___ Door de toegang van benzine- en dieselauto's te beperken in binnensteden creëer je sociale onrust. Dit kan een negatief effect hebben op het imago van de elektrische auto wat vervolgens een nadelig effect kan hebben op de verkoop hiervan;

___ Door het versneld plaatsten van laadpalen zal er sociale onrust ontstaan doordat deze plekken de normale parkeerplekken zullen innemen en hierdoor de parkeerdruk voor niet-elektrische auto's verhogen.

Vraag 4: Geef voor elk van de bovenstaande aangekruiste verklaringen aan waarom u het er niet mee eens bent.

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Vraag 5: In ons onderzoek focussen we ons op verschillende doelgroepen. We onderzoeken wat voor invloed bepaalde maatregelen hebben op deze doelgroepen. Prioriteer de onderstaande doelgroepen volgens uw eigen inzicht van 1 (minst beinvloedbaar) naar 6 (meest beinvloedbaar). Afhankelijk van hoe beinvloedbaar de doelgroepen zijn door elk van de maatregelen. Een voorbeeld wordt gegeven in de eerste alinea van de tabel.

MAATREGELEN	DOELGROEPEN					
	Privé nieuw geleasde auto	Nieuwe auto in privébezit	Leaseauto van de zaak	Bedrijfsauto	Deelauto	Privé tweedehandsauto
Subsidie voor de aanschaf van een occasion (voorbeeld)	1	1	1	1	1	6
Consumenten van betrouwbare feiten voorzien zoals bijvoorbeeld over de kosten van een EV vs. traditionele benzine/diesel auto; Zichtbaarheid EV-rijders vergroten (bv door gebruik van groene kentekens);						
Laadpaalkleven bestrijden;						
Versneld plaatsen van laadpalen (commercieel en in openbare ruimten);						
Thuis opladen vergemakkelijken door subsidie op privé laadpalen of wallboxen of door aanbieden van lagere tarieven;						
Toegang van benzine/diesel beperken in binnensteden en milieuzones;						
Deelautos uitbreiden met EV-modellen en laadplekken;						

Vraag 6: Wat zijn naar uw mening de belangrijkste motiverende factoren bij het aanschaffen van een nieuwe auto? Prioriteer deze van 1 (minst belangrijk) naar 8 (meest belangrijk).

___ Mobiliteit moet: snel, makkelijk en goedkoop zijn;

___ Status;

___ Imago;

___ Passen binnen iemands gewoontes;

___ Goede voorbeeld geven;

___ Geen schuldgevoel hebben;

___ Bij de groep horen (of juist niet);

___ Milieuvriendelijk zijn.

Vraag 7: Gedragsinzichten: Welk van de volgende factoren leiden, naar uw mening, ertoe dat iemand meer geneigd is om een elektrische auto te kopen. Prioriteer deze van 1 (minst belangrijk) naar 7 (meest belangrijk).

___ Iemands werkweek: de hoeveelheid dagen dat iemand werkt;

___ De afstand die iemand moet aflegen naar het werk;

___ Of de werkgever de reiskosten vergoedt;

___ De flexibiliteit die iemand heeft om thuis te werken en zijn werktijden zelf te bepalen;

___ Hoeveel mensen er werken bij de organisatie waar iemand werkzaam is;

___ Of iemand een eigen OV kaart heeft;

___ Of iemand ooit gebruik heeft gemaakt van een deelauto;

Vraag 8: Prioriteer de volgende factoren wat naar uw mening het meeste invloed heeft op iemands keus om een elektrische auto te kopen. Prioriteer deze van 1 (minst belangrijk) tot 8 (meest belangrijk).

___ Financiële ruimte;

___ Werksituatie: zzp'er, ondernemer, in loondienst (fulltime/parttime), werkzoekend, niet werkzoekend;

___ Of iemand kinderen heeft jonger dan 12 jaar;

___ Auto oplaad mogelijkheden (gratis opladen op het werk, genoeg oplaadpalen in de buurt, eigen oprijrit);

___ Iemands werkgever voert een actief beleid op het gebied van duurzame mobiliteit;

___ Ervaringen en meningen van vrienden, familie en collega's;

___ Berichtgeving uit sociale media en/of gewone media;

___ Influencers met een elektrische auto.

Vraag 9: Motiveer voor elk van de drie belangrijkste factoren waarom deze van belang zijn en hoe dit inzicht geeft in iemands keuzeproces bij het wel of niet aanschaffen van een elektrische auto.

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A.2 Agent-based modelling voor beleidsmakers

Op basis van Europese normen is er reeds een stimulans om een deel van het wagenpark te elektrificeren, dit gebeurt onder meer door het stimuleren van (tweedehands) elektrische auto's voor particulieren. Om dit nationaal te versnellen wordt er een pakket aan maatregelen ingezet ter stimulering van de aanschaf en het gebruik van elektrische auto's. Deze maatregelen bestaan onder andere uit: het versnellen van de uitrol van laadinfrastructuur, het vergemakkelijken en financieel aantrekkelijker maken van elektrische voertuigen (BEVs), het beboeten van verkeerd parkeren bij laadpalen.

Wanneer we kijken naar de gehele populatie, kan men zien dat de voorheen genoemde maatregelen niet altijd evengoed werken. Om betere maatregelen te vinden heeft het ministerie van I&W de totale populatie verdeeld in doelgroepen; hierdoor kunnen de maatregelen doelgericht worden toegepast. De totale populatie is verdeeld in drie groepen: de eerste doelgroep bestaat uit personen met een occasion auto, de tweede doelgroep bevat personen met een nieuwe particuliere auto en de derde doelgroep bestaat uit personen met een particulier geleasede auto.

In het door ons ontwikkelde agent-based model, zijn de aannames van beleidsmakers verwerkt. Voor ons model kijken wij vooral naar aannames die gaan over het elektrisch rijden. In dit model wordt tot op zekere hoogte de realiteit vertegenwoordigd en kan gebruikt worden om een simulatie uit te uitvoeren. Hierin bestaat een populatie genaamd 'agents' die ieder karakteristieken hebben van echte personen. Zo hebben ze allen een leeftijd, beroep, inkomen, een auto en leggen ze dagelijks een bepaalde afstand af naar hun werk en behoren tot een van de drie hiervoor genoemde doelgroepen. In ons model zijn wij geïntereseerd naar het koopgedrag van de agent. Wij willen te weten komen wat voor type auto onze agents zullen aanschaffen na verloop van de simulatie.

In de grafieken en histogrammen van de simulatie kunnen we zien hoeveel agents een elektrische auto kopen. Ook is te zien welke merken elektrische auto's er worden gekocht. Met de informatie die wij uit onze grafieken en histogrammen halen is het mogelijk om het indivueel effect en het gezamenlijke effect van de toegepaste maatregelen te observeren. Verder kunnen wij met onze resultaten ook het mogelijk effect van de maatregelen op elke doelgroep specifiek observeren.

Om het effect van maatregelen te laten zien in onze simulatie zijn er veel voorafgaande aannames nodig zodat we het gedrag kunnen simuleren. Aannames die gedaan zijn in ons model gaan vooral over het gedrag van de agent, welke factoren dit gedrag beinvloeden en in welke mate deze factoren het gedrag beinvloeden.

De agents gedragen zich volgens onze aannames. Enkele voorbeelden van onze aannames zijn:

- Financiële prikkels hebben de meeste invloed op iemands koopgedrag.
- De toegankelijkheid van de benodigde laadinfrastructuur heeft een grote invloed op iemands keuze tussen een elektrische auto of niet.
- Mensen beinvloeden elkaar door ervaringen en informatie te delen.

De aannames verwerkt in ons model komen overeen met de aannames van beleidsmakers.

We kunnen de invloed van elk van de factoren veranderen met het wijzigen van schuifregelaars (sectie 3.3). Door hiermee te spelen en de effecten direct te observeren in de grafieken en histogrammen, is het mogelijk voor beleidsmakers om interactief hun gedragsaannames en bijbehorende invloeden te testen.

We zullen eerst beginnen met een korte beschrijving van de data die is gebruikt voor het bouwen van ons model, daarna is er een beschrijving van het model zelf. Verder geven wij een uitleg over de beschikbare visualisatie in onze simulatie. Tenslotte behandelen wij, aan de hand van ons model, enkele scenarios die interresant zouden kunnen zijn voor beleidsmakers.

1. Data

De data die gebruikt wordt om de agents te initialiseren, is afkomstig uit het landelijke reizigersonderzoek. Het onderzoek is uitgevoerd in opdracht van het RVO. De vragenlijst bestaat uit de volgende type vragen:

- (Woon-)werksituatie: de woon-werk afstand en de provincie waarin iemand woont
- Parkeren: of de respondent over een prive parkeerplek bezit of gratis/betaald parkeert in de nabijheid van hun woning
- Thuiswerken: aantal dagen dat iemand buitenshuis werkt
- Specificatie Auto: gewicht, leeftijd
- (beleids)maatregelen: of de respondent bekend is met de maatregelen verwerkt in ons model
- Elektrische auto: of de respondent ooit een elektrische auto(BEV) heeft gereden of iemand kent met een BEV
- Achtergrond: leeftijd, geslacht, gezinssamenstelling en beroep

In ons onderzoek gebruiken wij enkel een subgedeelte van de bovengenoemde data; deze bestaat uit respondenten die een auto bezitten en behoren tot de werkzame beroepsbevolking. De auto's van respondenten zijn of een occasion of een nieuw gekochte particuliere auto of een particulier geleasede auto.

2. Model

De door beleidsmakers als relevant aangegeven factoren zijn verwerkt in dit model. De factoren waar de agent rekening mee houdt zijn opgesplitst in drie hoofdfactoren:

- Het sociale aspect van de BEV
- • Het financiële aspect van de BEV
- De benodigde laadinfrastructuur voor het hebben van een BEV

Deze factoren hebben invloed op de agents' voldoening (*satisfaction*) en hun onzekerheid (*uncertainty*). De uiteindelijke voldoening en onzekerheid van de agents bepaalt of ze een BEV of Benzineauto kopen. Elk van deze hoofdfactoren is onderverdeeld in subfactoren. We zullen hieronder een kort overzicht geven.

- **LaadInfrastructuur factor**
  - De technische bekwaamheid van de agent
  - De agents' kennis over elektrische auto's
  - De beschikbaarheid van laadpalen in de wijk waarin de agent woont

  - Als een agent overweegt een occasion te kopen dan houdt hij rekening met de kilometerstand en het bouwjaar van die auto.
- **Financieel factor**
  - Het verschil in initiële investering voor een BEV en een traditionele benzine auto
  - Het verschil in reiskosten tussen een BEV en een traditionele benzine auto
  - De belastingvoordelen voor BEVs
- **Sociale factor**
  - Agents beïnvloeden elkaar door informatie te delen over de parkeerdruk en de beschikbaarheid van laadpalen
  - Ook het aantal BEVs in de wijk beinvloedt de onzekerheid van de agents, hoe minder BEVs hoe onzekerder de agents zijn
  - Ook het merk van de beschikbare auto's heeft invoed op het keuzeproces van de agents

3. Visualisatie

Zoals eerder aangegeven worden de resultaten van het model weergegeven door gebruik van grafieken, histogrammen en een kaart. We geven hieronder een kort overzicht van onze visualisatie mogelijkheden.

3.1 Kaart

In figuur 42 zien we een kaart van de wijk waarin de agents zich bevinden. Iedere agent heeft een huis en een auto. Als de agents niet op hun privé terrein kunnen parkeren dan proberen zij zo dicht mogelijk bij hun huis te parkeren. Als de agents een elektrische auto hebben dan proberen ze een parkeerplek te vinden met een laadpaal. Als de agents een benzine auto hebben, zoeken ze juist naar een parkeerplek zonder laadpaal. Elke dag in het model, wat ook wel een tick wordt genoemd, verlaten de agents de parkeerplek waarop ze geparkeerd stonden en proberen ze een nieuwe parkeerplek te vinden. De volgorde waarin de agents hun parkeerplek zoeken verschilt per tick. Een blokje op de kaart vertegenwoordigt 10 meter. De agents proberen binnen 300 meter van hun huis te parkeren. Als dit niet lukt melden ze dit aan andere agents om hun ongenoegen te delen.

3.2 Grafieken en histogrammen

Door gebruik te maken van de grafieken en histogrammen kunnen we observeren hoeveel agents een elektrische auto kopen. In figuur 44 zien we enkele van deze grafieken en histogrammen.

3.3 Schuifregelaars

In onze simulatie is het mogelijk om bepaalde maatregelen wel of niet toe te passen door middel van het gebruik van schuifregelaars en knopjes. De volgende maatregelen kunnen worden toegepast:

- Subsidie voor occasions kan verhoogd of verlaagd worden
- Subsidie voor particulier nieuw en lease kan verhoogd of verlaagd worden

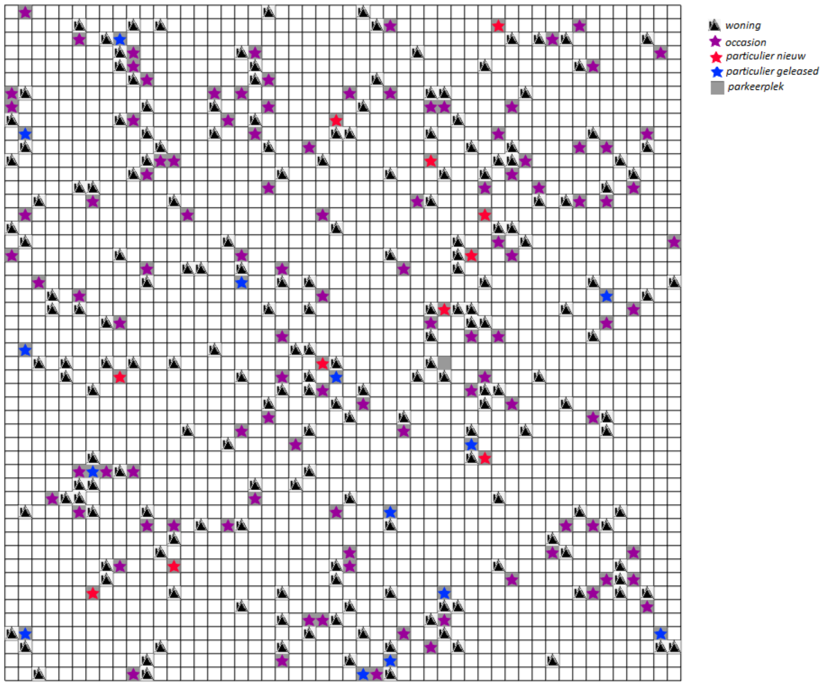

Figure 42: Kaart visualisatie in de interface

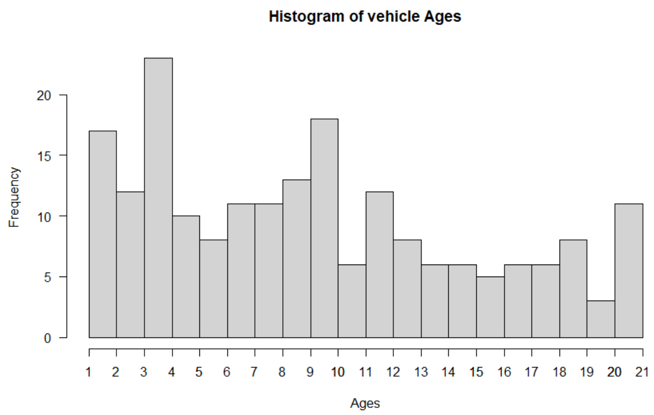

Figure 43: Visualisaties in de interface

- De snelheid waarin nieuwe laadpalen worden aangemaakt kan verhoogd of verlaagd worden
- De belasting op brandstof kan verhoogd of verlaagd worden

De invloed van bepaalde factoren op de voldoening en onzekerheid van de agents kan ook worden aangepast. De schuifregelaars zijn te zien in fig.45

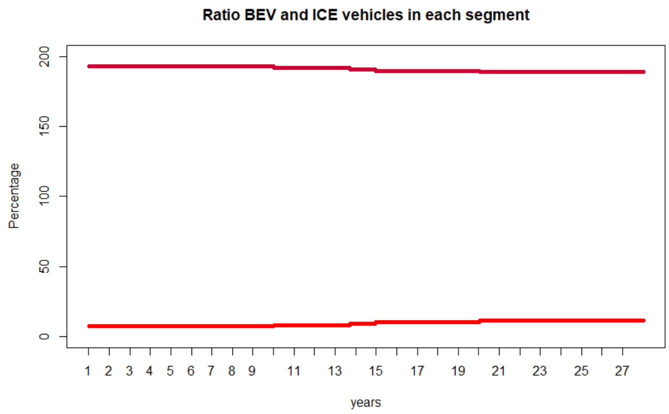

Figure 44: Visualisaties in de interface

4. Scenarios

Om de toepasselijkheid van het model te bestuderen, behandelen wij enkele scenarios die relevant zijn voor beleidsmakers. De scenario's die wij behandelen zijn:

1. De subsidie voor elektrische autos wordt langzaam afgebouwd tot 0 vanaf 2025
2. Het aantal laadpalen wordt aanzienlijk verhoogd
3. De belastingvoordelen voor elektrische autos wordt opgeheven

Sommige voor beleidsmakers relevante vragen zijn:

- In hoeverre kunnen wij onze parameters beïnvloeden zodat in 2030 alle verkochte autos BEV's zijn. Hiermee kunnen wij kijken of het doel van het IenW in ons model te behalen is.
- Wat voor invloed hebben onze parameters op de verkoop van occasions?
- Welke factoren moeten invloedrijk zijn op het gedrag van de agents en welke factoren niet?
- Hoe zouden nieuwe technologieën zoals de waterstof auto in het model kunnen worden geïmplementeerd?

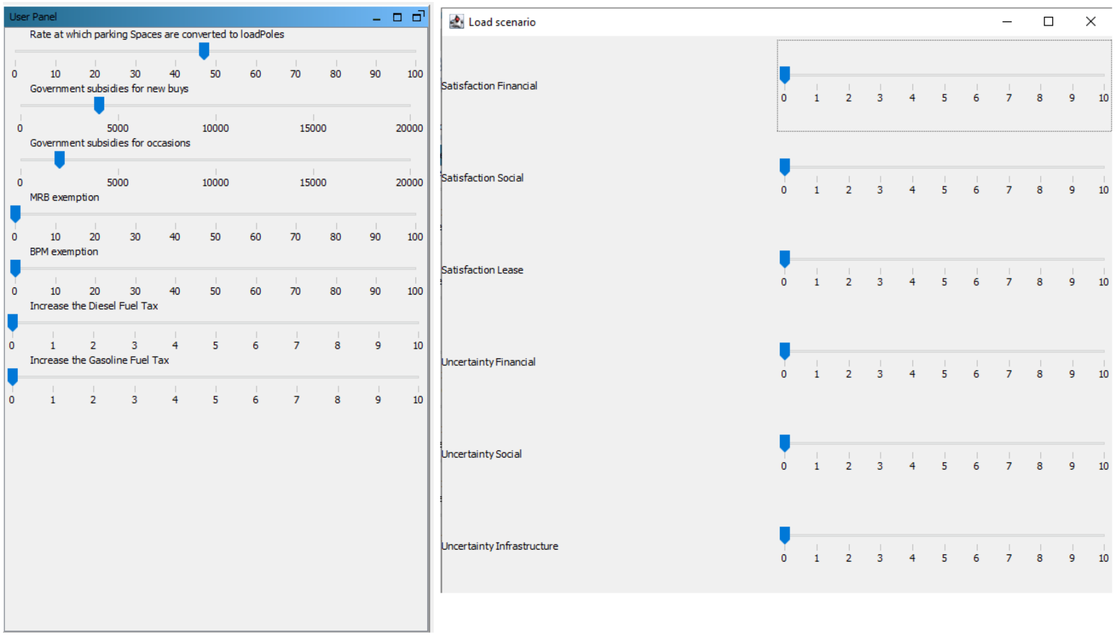

Figure 45: Sliders in de interface

Doel van het interview

Hoewel het onze eerste intuïtie zou zijn om dit model te gebruiken als voorspellingsmethode, door het gedrag van de agents in het model te extrapoleren naar de realiteit, is dit niet de bedoeling.
Het model vertegenwoordigt de realiteit tot op zekere hoogte. Gebrek aan data, rekenkracht en gedragskennis verhinderen ons er van om een model te bouwen dat de werkelijkheid nauwkeurig genoeg kan weergeven. Het is daarom niet mogelijk om het model te gebruiken om te voorspellen.

Binnen de beleidscontext zijn er meerdere doeleinden waarvoor dit model wél kan worden gebruikt. Zoals bijvoorbeeld als test of simulatie, als een manier om ideeën uit te werken. Ons model is gebouwd door al onze aannames, belangrijke factoren, interacties en mogelijke consequenties concreet te maken. We hebben dus functies gemaakt die simuleren hoe een agent wordt beïnvloed. Het gedrag van de agents is dus zo gemodelleerd dat het overeenkomt met de aannames van beleidsmakers. Als we dan vervolgens onze maatregelen toepassen, zoals bijvoorbeeld de subsidie, kunnen we direct het effect hiervan zien. We kunnen ook meerdere maatregelen tegelijk toepassen en ze op elkaar laten inwerken. Zo kunnen we hun overlappende werking observeren en bekijken of dit overeenkomt met onze verwachtingen. Bovendien kunnen we observeren of er bepaalde interessante gebeurtenissen plaatsvinden. Het model stelt ons daarom in staat om enkele kernonzekerheden in onze aannames te benadrukken en om mogelijke bedoelde of onbedoelde gevolgen van beleid te ontdekken.

Het model is niet het eindproduct, maar moet gezien worden als een basis waarop kan worden voortgebouwd. Dit is een evolutionair proces, waarin we constante aanpassingen kunnen maken door invloeden toe te voegen of juist weg te laten. Net zoals in het werkelijke leven, veranderen ook de factoren die we willen bestuderen. Als bijvoorbeeld de elektrische accu goedkoper wordt en de prijs van elektrische auto's daalt dan zal het effect van subsidies minder worden. We zouden dit dan kunnen testen door de prijs van de voor de agent beschikbare auto's te verlagen en het effect van de subsidies te bestuderen.

Het doel van dit interview is uw mening verkrijgen over de visualisatie van het gedrag evenals het gedrag zelf. Verder zou ik ook graag willen weten of u iets ziet wat niet intuïtief is. Ook zou ik graag van u willen weten of u nog andere scenario´s of vragen kunt geven die u interessant zou vinden om te testen. Als u verder nog algemene opmerkingen heeft over het model binnen de beleidscontext, dan zou ik dat ook graag van uw willen horen.

B Overview BEV brands

Brand/Model	Electric range	Price	Available since
Audi e-tron 55 quattro	315 - 415 km	€ 84,100	December 2019
Renault Zoe ZE50 R110	270 - 370 km	€ 33,590	November 2019
MG ZS EV	195 - 260 km	€ 29,900	November 2019
Hyundai Kona Electric 64 kWh	330 - 455 km	€ 41,595	November 2019
Renault Zoe ZE50 R135	265 - 365 km	€ 35,190	November 2019
Audi e-tron 50 quattro	240 - 315 km	€ 71,900	November 2019
Hyundai IONIQ Electric	215 - 300 km	€ 36,995	October 2019
Mercedes EQC 400 4MATIC	305 - 405 km	€ 80,995	September 2019
Tesla Model S Performance	430 - 585 km	€ 105,718	July 2019
Tesla Model X Performance	380 - 505 km	€ 110,818	July 2019
Nissan LEAF e+	275 - 375 km	€ 45,850	June 2019
Tesla Model S Long Range	440 - 600 km	€ 88,818	June 2019
Tesla Model X Long Range	390 - 520 km	€ 94,618	June 2019
Tesla Model 3 Standard Range Plus	280 - 395 km	€ 49,998	April 2019
Tesla Model 3 Long Range Dual Motor	395 - 550 km	€ 59,998	February 2019
Tesla Model 3 Long Range Performance	380 - 520 km	€ 65,598	February 2019
Kia e-Niro 64 kWh	320 - 435 km	€ 42,510	December 2018
BMW i3 120 Ah	200 - 275 km	€ 41,994	October 2018
BMW i3s 120 Ah	195 - 265 km	€ 45,693	October 2018
Jaguar I-Pace	320 - 415 km	€ 81,810	June 2018
Nissan e-NV200 Evalia	160 - 215 km	€ 44,689	April 2018
Nissan LEAF	185 - 250 km	€ 36,990	February 2018
Opel Ampera-e	290 - 395 km	€ 46,699	September 2017
Peugeot Partner Tepee Electric	95 - 125 km	€ 30,470	August 2017
Renault Kangoo Maxi ZE 33	140 - 190 km	€ 37,985	July 2017
Volkswagen e-Golf	160 - 220 km	€ 34,295	May 2017
Citroen C-Zero	75 - 100 km	€ 22,360	April 2016
Peugeot iOn	75 - 100 km	€ 22,360	April 2016

Figure 46: Overview BEVs' [87]

Brand/Model	Electric range	Price	To be available in
DS 3 Crossback E-Tense	235 - 320 km	€ 43,190	January 2020
Kia e-Soul 64 kWh	315 - 425 km	€ 42,995	January 2020
Volkswagen e-Up!	165 - 230 km	€ 23,475	January 2020
Skoda CITIGOe iV	170 - 230 km	€ 23,290	January 2020
Porsche Taycan Turbo	350 - 475 km	€ 157,100	January 2020
Porsche Taycan Turbo S	330 - 440 km	€ 191,000	January 2020
Porsche Taycan 4S	310 - 415 km	€ 109,900	January 2020
Porsche Taycan 4S Plus	360 - 485 km	€ 116,786	January 2020
Kia e-Niro 64 kWh	320 - 435 km	€ 44,995	January 2020
SEAT Mii Electric	170 - 230 km	€ 23,400	February 2020
Mini Electric	150 - 210 km	€ 34,900	March 2020
Lightyear One	460 - 695 km	€ 149,990	March 2020
Opel Corsa-e	245 - 335 km	€ 30,999	March 2020
Peugeot e-208	250 - 345 km	€ 36,250	March 2020
Peugeot e-2008 SUV	235 - 315 km	€ 40,930	March 2020
Audi e-tron Sportback 50 quattro	250 - 330 km	€ 74,000	March 2020
Audi e-tron Sportback 55 quattro	330 - 430 km	€ 86,000	March 2020
Hyundai Kona Electric 39 kWh	210 – 290 km	€ 36,795	May 2020
Tesla Model 3 Standard Range	260 - 370 km	€ 43,500	June 2020
Lexus UX 300e Electric	245 - 330 km	€ 50,000	June 2020
Polestar 2	375 - 515 km	€ 59,800	June 2020
Volkswagen ID.3 Mid Range	290 - 400 km	€ 40,000	June 2020
Honda e	165 - 230 km	€ 35,330	September 2020
Honda e Advance	165 - 230 km	€ 38,330	September 2020
Volvo XC40 P8 AWD Recharge	N.A.	€ 59,900	September 2020
Volkswagen ID.3 Standard Range	230 - 315 km	€ 30,000	September 2020
Volkswagen ID.3 Long Range	380 - 515 km	€ 47,500	September 2020
Mazda MX-30	N.A.	€ 33,990	September 2020
Ford Mustang Mach-E SR RWD	N.A.	€ 49,925	November 2020
Ford Mustang Mach-E ER RWD	N.A.	€ 58,075	November 2020
Ford Mustang Mach-E SR AWD	N.A.	€ 57,665	November 2020
Ford Mustang Mach-E ER AWD	N.A.	€ 67,140	November 2020

Figure 47: Overview BEVs' [87]

Fueltype	**2019**
Benzine	6 804 125
BEV	314 563
Type of ownership	
Total	8 530 584
Company owned	994 721
Private totaal	7 535 863

Table 19: Overview different car types and ownership [82]

C Algorithms

Algorithm 1 Go to work function

```
procedure GO TO WORK(Agent)
    if one tick passes then
        leave parking space the agent currently occupies;
        find new parking space nearest to home location which satisfies the agents power train;
```

Algorithm 2 Decide whether to replace current vehicle

```
procedure DECIDE-TO-REPLACE-CURRENT-VEHICLE(Agent)
    if agent wants to replace vehicle then
        update-internal-values
        determine-affordable-vehicles
        if agent owns a PRIVATE LEASE then
            decide-between-lease-BEV-and-lease-CI
        if agent owns a OCCASION then
            decide-between-occasion-BEV-and-occasion-CI
            determine-chosen-occasion-vehicle
        if agent owns a PRIVATE NEW then
            decide-between-new-BEV-and-new-CI
            determine-chosen-new-vehicle
```

Algorithm 3 Update Internal values

```
procedure UPDATE-INTERNAL-VALUES(Agent)
    if Agent owns a PRIVATE NEW vehicle then
        Update the agents uncertainty and satisfaction about private new BEVs algorithm 8, 7 and 9
    if Agent owns an OCCASION vehicle then
        Update the agents uncertainty and satisfaction about occasion BEVs algorithm 8, 7 and 9
    if Agent owns a PRIVATE LEASE vehicle then
        Update the agents uncertainty and satisfaction about lease BEVs algorithm 8, 7 and 9
```

Algorithm 4 Determine affordable vehicles

```
procedure DETERMINE AFFORDABLE VEHICLES(yearly_income_agent)
    min_price_affordable_vehicle = 10 % of yearly_income_agent
    max_price_affordable_vehicle = 30 % of yearly_income_agent
    max_price_affordable_BEV_vehicle = 45 % of yearly_income_agent
    Select vehicles of each group: OCCASION_CI, OCCASION_BEV, NEW_BEV, NEW_CI which have a price that lies within previously defined max and min range.
```

Algorithm 5 Parking function for both power trains

```
procedure PARK(BEV)
    if needsCharging then
        if There exist empty parking spaces with lp then        ▷ lp = load poles
            park in the space closest to the agents home location;
            value = 0.1;
            agent.hasParked = true;
        else if there are no empty parking spaces with a lp then
            park in parking spot without a lp which is closest to ones home location;
            value = - 0.1;
            Hippie.hasParked = true;
        else
            unable to park
            value = - 0.1;
    else
        if there exist empty parking spaces without lp then        ▷ lp = load poles
            park in the space closest to the agents home location;
            value = 0.1;
            Agent.hasParked = true;
        else if there are no empty parking spaces without a lp then
            park in parking spot without a lp which is closest to ones home location;
            value = - 0.1;
            Agent.hasParked = true;
        else
            unable to park
            value = - 0.1;

procedure PARK(CI vehicle)
    if there exists empty parking spaces without lp then
        park in space closest to the agents home location
        value = 0.1;
        Agent.hasParked = true;
    else if there are no empty parking spaces without a lp then
        park in parking spot without a lp which is closest to ones home location;
        value = - 0.1;
        Agent.hasParked = true;
    else
        unable to park
        value = - 0.1;

happiness = 0.5*sin(π/maxdistance*[parkdistance +(maxdistance/2)]) + value;
                ▷ The value parameter is determined by the user in the Repast simphony interface
```

Algorithm 6 Decide between a BEV and a CI

procedure DECIDE-BETWEEN-LEASE-BEV-AND-LEASE-CI(*Agent*)
  satisfaction = n_social_satisfaction + l_financial_satisfaction + n_infrastructure_satisfaction
  uncertainty = n_social_uncertainty + l_financial_uncertainty + n_infrastructure_uncertainty
▷ n = private new, l = private lease
  if satisfaction > 0.5 and uncertainty < 0.5 **then**
    Acquire a BEV private lease
  else
    Acquire a CI private lease

procedure DECIDE-BETWEEN-OCCASION-BEV-AND-OCCASION-CI(*Agent*)
  satisfaction = o_social_satisfaction + o_financial_satisfaction + o_infrastructure_satisfaction
  uncertainty = o_social_uncertainty + o_financial_uncertainty + o_infrastructure_uncertainty
▷ o = occasion
  if satisfaction > 0.5 and uncertainty < 0.5 **then**
    Acquire a BEV occasion
  else
    Acquire a CI occasion

procedure DECIDE-BETWEEN-NEW-BEV-AND-NEW-CI(*Agent*)
  satisfaction = n_social_satisfaction + n_financial_satisfaction + n_infrastructure_satisfaction
  uncertainty = n_social_uncertainty + n_financial_uncertainty + n_infrastructure_uncertainty
▷ n = private new
  if Satisfaction > 0.5 and uncertainty < 0.5 **then**
    Acquire a BEV private new
  else
    Acquire a CI private new

Algorithm 7 Update the agents financial satisfaction and uncertainty values

commute_cost_difference = cost_of_commute_using_CI - cost_of_commute_using_BEV
tax_difference = taxes_for_CI - taxes_for_BEV
knowledge_of_financial_incentives = the knowledge the agent has about tax the BPM and MRB exemption as well as the subsidy
procedure UPDATE LEASE_FINANCIAL_SATISFACTION(*Agent*)
  ▷ BEV price includes subsidy
  monthly_price_difference = monthly cost of owning a BEV - monthly cost of owning a CI
  S = lf_{11}∗monthly_price_difference +lf_{12}∗commute_cost_difference +lf_{13}∗tax_difference
  U = lf_{21}∗monthly_price_difference +lf_{22}∗commute_cost_difference +lf_{23}∗tax_difference
procedure UPDATE OCCASION_FINANCIAL_UNCERTAINTY(*Agent*)
  ▷ BEV price includes subsidy
  initial_investment_diff = investment cost for a occ BEV - investment cost for a occ CI
  S = of_{11}∗initial_investment_diff +of_{12}∗commute_cost_difference +of_{13}∗tax_difference
  U = of_{21}∗initial_investment_diff+of_{22}∗knowledge_of_financial_incentives
procedure UPDATE PRIVATE NEW_FINANCIAL_UNCERTAINTY(*Agent*)
  ▷ BEV price includes subsidy
  initial_investment_diff = investment cost for a BEV - investment cost for a CI
  S = nf_{11}∗initial_investment_diff +nf_{12}∗commute_cost_difference +nf_{13}∗tax_difference
  U = nf_{21}∗initial_investment_diff+nf_{22}∗knowledge_of_financial_incentives

Algorithm 8 Update the agents social satisfaction and uncertainty values

social_satisfaction_others = average_satisfaction_of_others
social_uncertainty_others = average_uncertainty_of_others
difference_happiness = happiness_of_BEV_owers - happiness_of_CI_owners

procedure UPDATE OCCASION_SOCIAL_SATISFACTION(*Agent*)
    acceptance_based_of_BEVs = tanh(percentage_of_BEV/10)
    status_vehicle = the ranking of the vehicle from 1 to 10
    income_acceptance = tanh(income_agent/90000)

    S = (os_{11}∗difference_happiness + os_{12}∗acceptance_based_of_%BEVs + os_{13}∗income_acceptance + os_{14}∗status_vehicle + social_satisfaction_others)/2 ▷ o = occasion
    U = (-ou_{21}∗difference_happiness + (1-ou_{22}∗acceptance_based_of_%BEVs) + (1-ou_{23}∗income_acceptance)+social_uncertainty_others)/2

procedure UPDATE PRIVATE NEW_SOCIAL_SATISFACTION(*Agent*)
    difference_happiness = happiness_of_BEV_owners - happiness_of_CI_owners
    acceptance_based_of_%BEVs = tanh(percentage_of_occasion_BEV*10)
    environmental_concern = the agents knowledge and participation in environmental measures

    S = ns_{11}∗difference_happiness + ns_{12}∗acceptance_based_of_%BEVs + ns_{13}∗n_environmental_concern + ns_{14}∗social_satisfaction_others ▷ n = new
    U = (-nu_{21}∗difference_happiness + (1-nu_{22}∗acceptance_based_of_%BEVs) + (1-nu_{23}∗income_acceptance + nu_{24}∗social_uncertainty_others)/2

Algorithm 9 Update the agents infrastructure satisfaction and uncertainty values

procedure UPDATE OCCASION_INFRASTRUCTURE_VALUES(*Agent*)
  battery_satisfaction = determines the satisfaction of the loss of range compared to the daily commute distance: $1/(e^{km\_of\_commute\_loss/500})$
  battery_uncertainty = $1 - 1/(e^{km\_of\_commute\_loss/500})$
  age_satisfaction = $(1/(e^{age\_vehicle}) - 1)/500$
  age_uncertainty = $1 - (1/(e^{age\_vehicle}) - 1)/500$
  standard_satisfaction = satisfaction the agent would have about a private new BEV
  S = os_{11}∗battery_satisfaction + os_{12}∗age_satisfaction + os_{13}∗standard_satisfaction
  U = ou_{11}∗battery_uncertainty + ou_{12}∗age_uncertainty + ou_{13}∗standard_uncertainty
procedure UPDATE PRIVATE NEW_INFRASTRUCTURE_VALUES(*Agent*)
  technological_uncertainty = average_range_of_affordable_bev_vehicles + range_anxiety + technological_knowledge
  knowledge_knowledge = If the agent knows someone with a BEV or has ever driven a BEV
  charging_uncertainty = the sort of parking the agent has at its disposal as well as the distance to the nearest
  charging_satisfaction = the sort of parking the agent has at its disposal as well as the distance to the nearest charging station and the pressure on that charging station

  U = -nu_{11}∗technological_knowledge - nu_{12}∗knowledge_uncertainty + nu_{13}∗charging_uncertainty
  S = ns_{21}∗technological_knowledge + ns_{22}∗knowledge_uncertainty + ns_{23}∗charging_satisfaction

D Tables

Table 20: Statistical summary

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
New.Financial.Satisfaction	1,092	0.4	0.1	0.3	0.4	0.5	0.5
New.Financial.Uncertainty	1,092	0.5	0.03	0.5	0.5	0.6	0.6
New.Social.Satisfaction	1,092	0.5	0.03	0.4	0.4	0.5	0.5
New.Social.Uncertainty	1,092	0.5	0.04	0.5	0.5	0.6	0.6
New.Infrastructure.Satisfaction	1,092	0.5	0.04	0.5	0.5	0.6	0.6
New.Infrastructure.Uncertainty	1,092	0.5	0.01	0.5	0.5	0.5	0.5
Occasion.Financial.Satisfaction	1,092	0.4	0.1	0.2	0.3	0.5	0.5
Occasion.Financial.Uncertainty	1,092	0.6	0.1	0.5	0.5	0.6	0.7
Occasion.Social.Satisfaction	1,092	0.5	0.00	0.5	0.5	0.5	0.5
Occasion.Social.Uncertainty	1,092	0.5	0.01	0.5	0.5	0.5	0.5
Occasion.Infrastructure.Satisfaction	1,092	0.5	0.01	0.5	0.5	0.5	0.5
Occasion.Infrastructure.Uncertainty	1,092	0.5	0.01	0.5	0.5	0.5	0.5
Lease.Financial.Satisfaction	1,092	0.3	0.1	0.2	0.2	0.5	0.5
Lease.Financial.Uncertainty	1,092	0.7	0.1	0.5	0.5	0.8	0.9
New.Social.Satisfaction.1	1,092	0.5	0.03	0.4	0.4	0.5	0.5
New.Social.Uncertainty.1	1,092	0.5	0.04	0.5	0.5	0.6	0.6
New.Infrastructure.Satisfaction.1	1,092	0.5	0.04	0.5	0.5	0.6	0.6
New.Infrastructure.Uncertainty.1	1,092	0.5	0.01	0.5	0.5	0.5	0.5

Table 21: Statistical analysis of the agents' values

		Mean			St. Dev			Min			Max		
Category	Values	Lease	Occasion	New	Lease	Occasion	New	Lease	Occasion	New	Lease	Occasion	New
Financial	Satisfaction	0.433	0.476	0.376	0.147	0.041	0.182	0.044	0.371	0.103	1.145	0.829	0.754
	Uncertainty	0.531	0.521	0.625	0.044	0.041	0.281	0.500	0.077	0.067	0.618	0.605	0.987
Infrastructure	Satisfaction	0.542	0.506	0.516	0.075	0.092	0.039	0.500	0.000	0.500	0.767	0.625	0.741
	Uncertainty	0.509	0.525	0.493	0.087	0.141	0.059	0.402	0.195	0.402	0.722	1.396	0.731
Social	Satisfaction	0.500	0.507	0.481	0.052	0.105	0.069	0.336	0.333	0.325	0.673	1.000	0.648
	Uncertainty	0.507	0.508	0.523	0.059	0.111	0.073	0.335	0.128	0.368	0.680	1.000	0.692
	parking_happinness	0.487	0.485	0.483	0.046	0.055	0.060	-0.194	-0.266	-0.296	0.501	0.501	0.501

Table 22: Statistical analysis when price of BEVs decreases

		Mean			Standard deviation			Minimum			Maximum		
		Lease	Occasion	New	Lease	Occasion	New	Lease	Occasion	New	Lease	Occasion	New
Financial	Satisfaction	0.470	0.504	0.528	0.153	0.081	0.147	0.128	0.091	0.275	1.619	0.785	0.841
	Uncertainty	0.508	0.482	0.431	0.093	0.084	0.251	-0.013	0.202	0.0001	0.606	0.814	0.834
Infrastructure	Satisfaction	0.535	0.519	0.519	0.062	0.039	0.050	0.500	0.282	0.500	0.784	0.634	0.804
	Uncertainty	0.510	0.521	0.492	0.090	0.133	0.056	0.402	0.165	0.402	0.731	1.428	0.712
Social	Satisfaction	0.604	0.676	0.535	0.145	0.218	0.081	0.500	0.325	0.500	0.884	0.986	0.797
	Uncertainty	0.355	0.325	0.456	0.203	0.220	0.115	-0.044	-0.052	0.060	0.500	0.794	0.500
	parking_happinness	0.486	0.482	0.470	0.053	0.058	0.060	-0.283	-0.366	-0.106	0.501	0.501	0.501

Table 23: Statistical analysis of the agents values per segment in both the original scenario and the scenario in which we account for technological developments

			Mean			Standard deviation		
			Lease	Occasion	New	Lease	Occasion	New
Original simulation	Financial	Satisfaction	0.433	0.476	0.376	0.147	0.041	0.182
		Uncertainty	0.531	0.521	0.625	0.044	0.041	0.281
	Infrastructure	Satisfaction	0.542	0.506	0.516	0.075	0.092	0.039
		Uncertainty	0.509	0.525	0.493	0.087	0.141	0.059
	Social	Satisfaction	0.500	0.507	0.481	0.052	0.105	0.069
		Uncertainty	0.507	0.508	0.523	0.059	0.111	0.073
Technological development simulation	Financial	Satisfaction	0.470	0.504	0.528	0.153	0.081	0.147
		Uncertainty	0.508	0.482	0.431	0.093	0.084	0.251
	Infrastructure	Satisfaction	0.535	0.519	0.519	0.062	0.039	0.050
		Uncertainty	0.510	0.521	0.492	0.090	0.133	0.056
	Social	Satisfaction	0.604	0.676	0.535	0.145	0.218	0.081
		Uncertainty	0.355	0.325	0.456	0.203	0.220	0.115

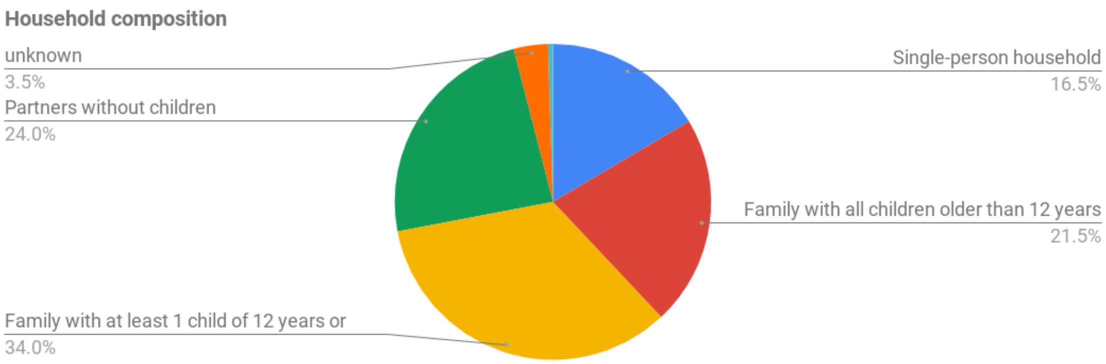

Figure 48: Household composition of our agent population

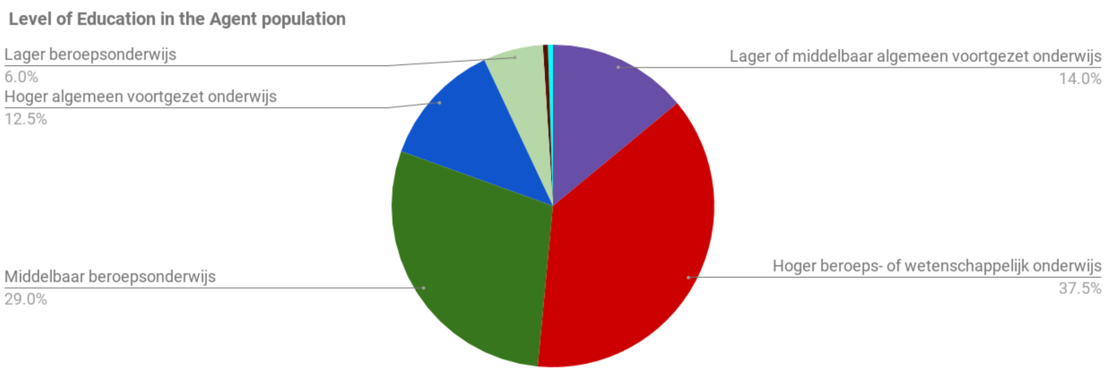

Figure 49: Level of education of the agents