Tampere University

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A MODEL-BASED STUDY ON FINNISH ELECTRIFIED VEHICLE MARKET

Faculty of Engineering and Natural Sciences

Master's Thesis

February 2019

ABSTRACT

Roope Vesa: A model-based study on Finnish electrified vehicle market
Master’s Thesis
Tampere University
Degree Programme in Information and Knowledge Management, MSc (Tech)
February 2019

Electrified vehicles are facing challenges in diffusion as they are not just being introduced to the vehicle market as a new alternative, but instead they are trying to replace a market incumbent with the same purpose, excellent performance, and a lower cost. This implies that there is a zero-sum-game where one can only benefit at the expense of the other(s). In the field of system dynamics, such a problem is also referred as a success to successful or relative achievement problem archetype. Therein, a possible closed-loop solution is to introduce an external balancing force that can bring the system to a new equilibrium. Such an external force is often applied in the form of policies and legislative actions, which in turn can be studied and developed by means of system dynamics modelling.

On this basis, the goal of the thesis was to study the Finnish electrified vehicle market by means of system dynamics modelling and thereby to increase understanding of the effectiveness of different policies in the national context and the effects of external factors on electrified vehicle diffusion. In order to do this, relevant theoretical background and existing body of research were studied, and a dynamic hypothesis of the problematic behaviour was formulated. Then, using stock-and-flow maps the hypothesis was translated into a simulation model with the help of which effectiveness and impacts of current policy measures and external factors could be studied.

The analysis showed that while policy measures are needed, and they seem to benefit especially battery electric vehicles, differences in policy effectiveness are generally small and it seems that it is the system conditions that ultimately determine the diffusion speed of electrified vehicles. Purchase subsidies can induce battery electric vehicle adoption in the short term, but investments in charging infrastructure seem to more effective in the long term. Similar observations were done in the other categories as well. Further, model results were found to be sensitive to development of cost of kWh, weight put on usage costs versus purchase price, technological development rate of battery electric vehicles, and marketing efforts of electrified vehicle platform. While these introduce factors of uncertainty to the model results, they also highlight the meaning of these variables to market development and the role of system conditions in vehicle stock development.

This study concludes that the two key drivers of electrified vehicle diffusion are social exposure and relative attractiveness of electrified vehicles. The former induces word of mouth marketing, which has found to be a strong reinforcing causal structure. Through social exposure and word of mouth consumers become more willing to consider the market entrant as a realistic option. At the same time, however, the relative performance of that alternative has to be sufficiently high in comparison to their reference point, so that those consumers will actually make a purchase.

Keywords: electrified vehicle, policy analysis, system dynamics modelling, simulation study

The originality of this thesis has been checked using the Turnitin OriginalityCheck service.

TIIVISTELMÄ

Roope Vesa: Mallinnukseen perustuva tutkimus Suomen sähkö- ja hybridiautomarkkinasta
Diplomityö
Tampereen Yliopisto
Tietojohtamisen DI-tutkinto-ohjelma
Helmikuu 2019

Sähkö- ja hybridiautojen yleistymisen keskeinen haaste on, että ne pyrkivät syrjäyttämään olemassa olevan teknologian, jolla on sama käyttötarkoitus, hyvä suorituskyky ja halvempi hinta. Sähkö- ja hybridiautot voivat täten yleistyä vain olemassa olevan teknologian kustannuksella, mikä tarkoittaa, että markkinoilla vallitsee nollasummapeli. Systeemidynamiikan saralla tällaista ongelmaa kutsutaan myös suhteellisen hyödyn arkkityypiksi (engl. relative achievement archetype), jonka ratkaisuna on käyttää ulkoisia tekijöitä systeemin saattamiseksi kohti uutta tasapainotilaa. Vastaavissa ongelmissa ulkoinen tekijä viittaa usein lainsäädännöllisiin ja hallinnollisiin ohjauskeinoihin, joiden tutkimisessa ja kehittämisessä systeemidynamiikka taas on toimiva keino.

Työn tavoitteena oli täten hyödyntää systeemidynaamista mallinnusta ja lisätä ymmärrystä Suomen sähkö- ja hybridiautomarkkinasta ja tällä tavoin edesauttaa tehokkaiden ohjauskeinojen laatimisessa. Tutkimuksen pohjana on käytetty olemassa olevia mallinnustutkimuksia sekä diffuusioteoreettista taustaa, joita vasten simulaatiomalli on rakennettu. Mallin avulla toteutettiin useita herkkyysanalyysejä ja testattiin mallin käyttäytymistä erilaisissa skenaarioissa.

Tutkimuksen perusteella näyttäisi siltä, että vaikka nykyiset ohjauskeinot ovatkin hyödyllisiä erityisesti täyssähköautoille, erot ohjauskeinojen tehokkuudessa ovat pieniä. Lisäksi, analyysien tulokset viittaisivat siihen, että suurempi vaikutus sähkö- ja hybridiautojen leviämiseen on systeemin vallitsevilla olosuhteilla sekä ulkoisilla tekijöillä, kuten yhden sähköauton akussa käytettävän kilowattitunnin hinnalla. Nämä tekijät osaltaan lisäävät mallin tuloksiin liittyviä epävarmuuksia, mutta osaltaan myös korostavat näiden muuttujien merkitystä sähkö- ja hybridiautokannan kehityksessä.

Tutkimus tunnistaa kaksi keskeistä ajuria sähkö- ja hybridiautojen yleistymiselle. Ensimmäinen oli altistuminen uudelle teknologialle (engl. social exposure) ja sitä kautta tietoisuuden leviäminen kuluttajien keskuudessa, minkä on huomattu olevan voimakas ”noidankehämäinen” ilmiö. Altistuminen uudelle teknologialle ja muilta kuluttajilta kuultu palaute lisäävät luottamusta uutta teknologiaa kohtaan, jolloin kuluttajat oat valmiimpia harkitsemaan niitä realistisena vaihtoehtona. Toinen keskeinen ajuri sen sijaan ajuri on sähkö- ja hybridiautojen suhteellinen viehättävyys verrattuna polttomoottoriautoihin, joihin taas suurimmalla osalla ohjauskeinoja voidaan vaikuttaa. Kun kuluttajat ovat valmiita harkitsemaan sähkö- ja hybridiautoja, niiden suhteellisen hinnan ja suorituskyvyn on oltava sellaisia, että ne houkuttelevat kuluttajia siirtymään pois polttomoottoriautoista.

Avainsanat: sähkö- ja hybridiautot, ohjauskeino, systeemidynamiikka, simulaatiotutkimus

Tämän julkaisun alkuperäisyys on tarkastettu Turnitin OriginalityCheck –ohjelmalla.

PREFACE

Now that the thesis project has come to an end, I would like to thank a number of people who have helped me in this project. First and foremost, I would like to thank Jarkko Vesa and Not Innovated Here for providing me with an interesting and challenging thesis project. I got a chance to develop my skills in analytical decision making and quantitative analysis, while also gaining new competences. The project was not a walk in the park, but it taught me a lot. Secondly, I would like to thank professor Hannu Kärkkäinen and professor Juho Kanniainen for guiding my thesis. Especially in the beginning, when the direction of the study was not yet very clear, your guidance was very helpful. Thank you also for your insightful comments on the work as the project progressed. Thirdly, I would like to thank Heikki Ahdekivi and Kesko for providing me with a report on your customer survey. Finally, I would like to thank all my great friends and family for the supporting me during the project and all those years at the Tampere University of Technology/Tampere University.

In Tampere, Finland, on 12 February 2019

Roope Vesa

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SYMBOLS AND ABBREVIATIONS

AFV	Alternative Fuel Vehicle
EFV	Electrified Vehicle
EU	European Union
EV	Electric Vehicle
FCEV	Fuel Cell Electric Vehicle
HEV	Hybrid Electric Vehicle
ICEV	Internal Combustion Engine Vehicle
PHEV	Plug-in Hybrid Vehicle
REEV	Range Extended Electric Vehicle
SD	System Dynamics
WtC	Willingness to Consider

1. INTRODUCTION

1.1 Background

Global warming is an issue that concerns policy makers around the globe. Numerous nations have presented roadmaps and strategies with the target of reducing greenhouse gases. The European Union (EU) presented its own low-carbon economy roadmap in 2011, the goal of which is to reduce greenhouse gases progressively through a selection of actions by 80 percent by the year 2050 (European Commission 2011). The target has been recently revisited, and it now presents a vision that by 2050 the EU would be climate neutral (European Commission 2018).

One of the most important sectors in this roadmap is transport whose emissions could be, according the EU calculations, reduced by as much as 60 percent from the 1990s' levels (European Commission 2011, 2018). The plan builds upon three components; in the short term, most progress can be made by further reducing the emissions of diesel and petrol vehicles and improving their fuel-efficiency. In the mid- to long-term, the plan is to encourage transition to plug-in hybrid (PHEV) and battery electric vehicles (BEV), which are notably more fuel-efficient and less pollutant (European Commission 2011, 2018). Plug-in hybrid vehicles differ from traditional internal combustion engine vehicles (ICEV) in that they have an electric battery which can be used together with the combustion engine, or separately (EEA 2016). As for battery electric vehicles, they do not have a combustion engine, but run solely on electricity provided by vehicle batteries (EEA 2016). The third component of the roadmap is to introduce more biofuels to aviation and road haulage, as it is likely that all heavier goods vehicles will not run on electricity in the future. (European Commission 2011, 2018)

Norway is not a member of the European Union and is therefore not compliant with the union-wide targets, but it has excelled in its policy making. According to Hertzke et al. (2018), Norway is the only country to date that has reached the point where electric-drive disruption is inevitable. The country laid out its first low-emission policies already around the millennium and in 2016 over 20 percent of new cars sold were electric vehicles (Testa 2017).

The Finnish government also has presented its long-term strategy for reducing emissions. In 2008, the Ministry of Employment and the Economy presented its report on the national Energy- and Environment Strategy and stated that in the long-term, vehicle fleet should build upon alternative fuels and more efficient solutions (Ministry of Employment and Economy 2008). Unlike the more recent EU roadmap, this also included hybrid electric vehicles (HEV) that do have an electric battery but can only run shorter distances on electricity and cannot be charged on park (Ministry of Employment and Economy 2008; EEA 2016). More recently, the Ministry updated this strategy and defined its targets for low-emission vehicles more closely. In 2030, there should be 250,000 electric vehicles; electric vehicle being either BEV, PHEV, or fuel cell electric vehicle (FCEV) (Ministry of Employment and Economy 2017). The latter is also a fully electric vehicle but differs from a BEV in that electricity is stored in a stack of hydrogen cells instead of a battery (EEA 2016). The Ministry stated that policies and incentives should be introduced to the market in order to guarantee that alternative technologies are a viable option in the market. The Ministry also concluded, however, that the general development of those technologies and related infrastructure should still be mostly market-determined. (Ministry of Employment and Economy 2017)

Since the two countries differ from each other in many terms, it might not be appropriate or even realistic for Finland to just copy the Norwegian policy portfolio. Therefore, it is in the interest of this thesis to study how the Finnish electrified vehicle market works and to increase the understanding of how different policies might contribute to the aforementioned goal.

System dynamics (SD) modelling is a branch of computer-aided simulation modelling and is a powerful tool for gaining insight into situations of dynamic complexity and possible policy resistance (Sterman 2000, p. 39). It is a method for building flight simulators for managers and policy makers, and it can increase their understanding of the complex systems they operate within (Sterman 2000, p. 4). SD modelling has been applied increasingly in public policy settings and in companies alike (Sterman 2000, p. 39; see chapter 2.2), but it appears that SD has not been applied the context of Finnish electric vehicle market. Hence, this study has also theoretical relevance.

The present study is conducted by order of a consulting company called Not Innovated Here (NIH). NIH consults public and private organizations in the fields of circular economy and electric vehicles in Finland, and it is in the interest of NIH to conduct a study that will not only be beneficial for the company itself, but also its customers.

1.2 Research problem

Despite their evident environmental benefits, electric vehicles are facing challenges in diffusion. The most prominent issue is that electric vehicles, and other alternative drivetrain technologies, are not just being introduced to the market, but they are trying to replace an existing technology with the same purpose, excellent performance, and a lower price (Bosshardt et al. 2007; Testa 2017). This implies that the competition between ICEVs and electric vehicles is a zero-sum-game where success is gained at the expense of the other. This is also what system dynamicists regard as a *relative achievement* (Wolstenholme 2003, 2004; Kwon 2012) or *Success to successful* problem archetype (Senge 1990, p. 307-312). Archetypes are general descriptions that capture the essence of a problem and present it by means of various combinations of causal loops (see chapter 2.2)

(Wolstenholme 2003, 2004). In particular, they consist of an intended consequence feedback loop, which results from an action taken within an organizational sector, and an unintended consequences feedback loop, which results from a reaction within another sector or outside the organization (Wolstenholme 2003, 2004). Archetypes are characterized by delays that occur before the unintended consequence manifests itself and organizational boundaries that hide the unintended consequence from the party initiating an action (Wolstenholme 2003, 2004). Further, for every problem archetype, there is a solution feedback loop that can bring the system to a new equilibrium (Wolstenholme 2003). These are illustrated below in Figure 1.

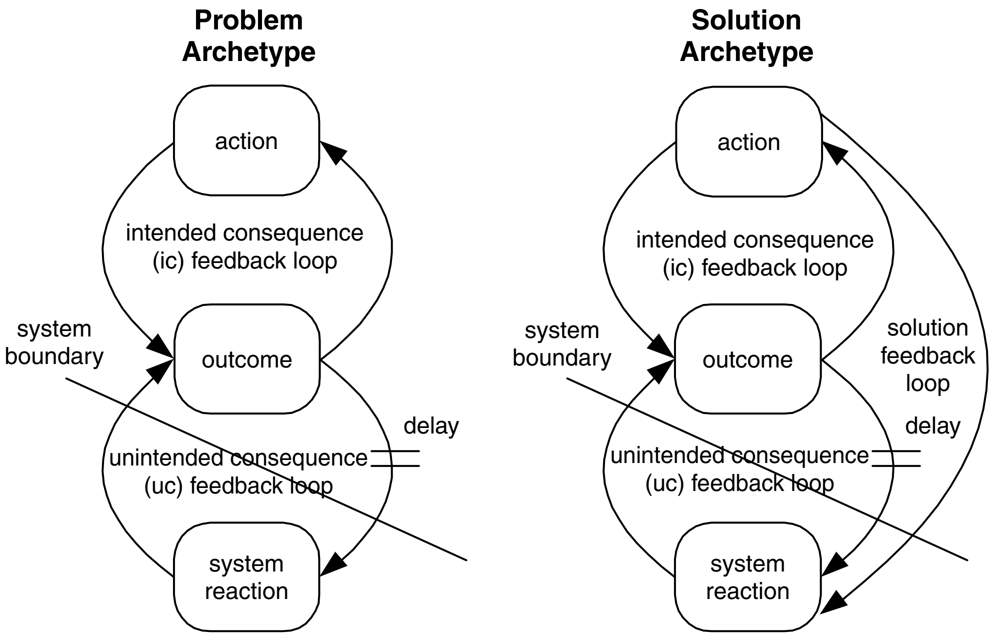

Figure 1. Generic system archetypes (adapted from Wolstenholme (2003, p. 10))

In a relative achievement problem, a possible closed-loop solution to the archetype is a balancing loop by which transition to a new state can be controlled (Wolstenholme 2003). In an organizational setting this can be done by means of external regulation (Wolstenholme 2003), which is also the logical solution in the ICEV-EV competition (Kwon 2012).

Evidently the role of policies, incentives, and other regulatory actions is crucial in the endeavour to make electric drive-train the dominant design (Utterback & Abernathy 1975) of vehicle market. But in order to lay out effective regulatory actions, policy makers need to be able to see the "big picture" and understand how the system works. One of the major obstacles inhibiting such understanding is, as stated by Wolstenholme (2003), '[…] the presence of time factors before unintended consequences show themselves'. This highlights the applicability on system dynamic simulation as a method to study the behaviour of a system, and in the case of Finnish electric vehicle market, the relevance of this study.

Another aspect that underlines the relevance of this study is that, as stated by Harrison & Thiel (2016), whether a policy will work or not is always dependent on the national context it is applied into. As there are no similar studies conducted in the Finnish context to date and to the knowledge of the writer, this study can contribute to more efficient policy making in Finland.

1.3 Research questions

In order to increase understanding of the Finnish electrified vehicle (EFV) market, this study answers the following question:

What are the key drivers of EFV diffusion in Finland?

In order to achieve this, dynamic characteristics of the EFV market are studied and modelled into the Finnish context. More specifically, underlying causal structures, delays, and accumulations need to be recognized and possible counterintuitive effects of decisions and policies need to be studied. This further necessitates that the Finnish policy portfolio and possible new alternatives are studied. Furthermore, in order to increase credibility of the model presented herein, existing body of modelling research in the field must be reviewed. Thus, as a means for answering the main research question, the following sub-questions are to be answered:

Q1: What kind of dynamic features (causal structures, accumulations, delays, counterintuitive effects) are causing the problematic behaviour of the system, i.e. the EFV market?

Q2: What kind of (SD) models have been presented to study those features?

Q3: What kind of policies have been implemented in the EFV market?

Q4: Are those policies effective in inducing EFV adoption?

Q5: Are there other central factors that affect the diffusion of EFVs in Finland?

1.4 Research context and definitions

The focus of this study is in the Finnish electric vehicle market, and the aforementioned Norwegian market is studied only briefly. The purpose of the study is not to compare policy portfolios per se, but rather to find alternatives that might complement the current portfolio of the Finnish government.

This thesis adopts the approach of e.g. Struben (2006), Struben & Sterman (2008), Shepherd et al. (2012), and Testa (2017), and considers only light-duty vehicles. Further, this study is limited to *privately* owned vehicles; even though a majority of electric vehicles sales in Finland still go to corporate customers (Finnish government HE 156/2017), leasing cars only constitute roughly a third of the whole vehicle market (Autoalan tiedotuskeskus 2016), thus, it is in the interest of this study to increase understanding towards the majority of the light-duty market.

Unlike many recent model-based studies (e.g. Shepherd et al. 2012, Testa 2017), this thesis considers HEVs separately from ICEVs, in addition to BEVs and PHEVs. HEVs are not included in the most recent Finnish emission strategy, but they have been growing rapidly (see chapter 7.1) and are currently the dominant alternative drive-train in Finland. Studies have also found that HEVs may act as gateways for more sceptic consumers to move towards greener options in the vehicle market (Walther et al. 2010; Kieckhäfer et al. 2017), hence, their role in the electrified vehicle market should be noted.

This thesis does, however, aggregate mild-hybrid vehicles (MHEV) (Küpper et al. 2018) and HEVs, range-extended electric vehicles (REEV) (EEA 2016) and PHEVs, and BEVs and FCEVs together, respectively. Further, in this study, these are collectively referred as electrified vehicles (EFV). This study also does adopt the approach of Testa (2017) and uses ICEV as an umbrella for a number of vehicle types; all vehicles except BEVs, HEVs, and PHEVs (i.e. EFVs) are aggregated under the term. This is a simplifying procedure and the writer acknowledges that such demarcation may hide some interesting features of the dynamic nature of the vehicle market, but it is considered appropriate as the interest of this thesis lies within the *electrified* vehicle market instead of alternative drive-trains as a whole.

Lastly, this thesis studies the market behaviour and dynamics in a timeframe of 2000-2050. This is in line with studies of e.g. Struben & Sterman (2008), Shepherd et al. (2012), and Testa (2017), and is considered to be long enough to capture the essential behaviour of the vehicle market (see chapter 5.1 for further discussion). It is also adequate for assessing long-term effects of policies, as well as for capturing plausible effects of exogenous factors that may influence the Finnish electrified vehicle market in the long run.

1.5 Content

The present study is structured as follows. Research methodological choices and strategies are discussed in Chapter 2. The chapter starts with general descriptions on computer-aided simulation and system dynamics as research methods, which are then followed by more detailed description on how the present study conducted, what kind of data has been used, and how those data have been collected. The chapter concludes with discussion on existing body on modelling research and thereby contributes to answering to the research question Q2.

Chapter 3 provides a theoretical background for the study. Theories on technological diffusion and adoption and consumer choice are presented, and the underlying factors guiding that choice in the context of EFVs are presented in more detail. Chapter 4, then, studies policies and incentives that have either been recognized by other studies, implemented in Finland to date or have been applied elsewhere. The chapter answers in part to the research question Q3.

Chapter 5 describes the existing body system dynamics modelling studies in more details and establishes the groundings on which the present study builds upon. Not only is this important regarding the empirical part of the study, i.e. the model itself, but it also answers to the Q2.

Closely relating to what is discussed in Chapter 5, the Chapter 6 then describes the model used in the present study. As implied, it draws on existing models, but complements them by extending them to consider HEVs and PHEVs as well and further by bringing it to the Finnish context. The model is then used in for a number of analyses in Chapter 7, results of which are then presented in Chapter 8 together with conclusions and recognized limitations and needs for further research. These chapters are the most important in answering questions Q4 and Q5, and especially the main research question of the present study.

Further, after the list of references used in the present study, model documentation, sources of parameters, along with additional details on model structure and validation process are provided in Appendices A-I.

2. RESEARCH METHODOLOGY

2.1 Simulation

Simulation modelling is computer enabled imitation of real-life phenomena (Harrison et al. 2007; Law 2015, p. 1). The entity of interest is usually called a *system* and it is translated into a virtual laboratory by means of formal modelling (Harrison et al. 2007). As defined by Harrison et al. (2007), a formal model is "a precise formulation of the relationships among variables, including the formulation of the processes through which the values of variables change over time, based on theoretical reasoning." (Harrison et al. 2007, p. 1232). In practice, this means that a modeller has to identify underlying processes that determine the behaviour of a system and formalize them as mathematical equations and transformation rules (Harrison et al. 2007).

If the relationships are simple enough, it may be possible to obtain an exact solution to the question of interest analytically; that is, using mathematical methods such as algebra or probability theory (Law 2015, p. 1). More often than not, however, the phenomenon under study is too complex to be evaluated analytically, but it can be simulated (Law 2015, p. 2015). In simulation a model is evaluated using numerical methods and data is gathered in order to estimate the characteristics of the model (Law 2015, p. 1). This is one underlying strengths of simulation research; it allows complex systems to studied quantitatively when those systems are intractable for analytical methods (Harrison et al. 2007).

Another distinctive strength of simulation is the theoretical rigor introduced by formal modelling (Harrison et al. 2007). As stated by Harrison et al. (2007), "a process may appear to be well understood, but an attempt to specify an equation for the operation of the process over time often exposes gaps in this understanding. (Harrison et al. 2007, p. 1233). Even at a minimum, the formalization process forces cloudy areas to be addressed, thereby promoting scientific advancement (Harrison et al. 2007).

Determining what processes are needed to replicate system behaviour, and how those processes interact, is a theoretical exercise. A modeller is informed by previous research and theories, but ultimately it is the modeller's intuition and objectives that guide the selection (Harrison et al. 2007). As stated by Harrison et al. (2007), prior research can rarely provide a formal specification to the system at hand, thus, development of new ideas is needed (Harrison et al. 2007). They further state that "[the] resulting model is not only the outcome of theoretical development but also *is* the theory in the sense that it embodies the theoretical ideas." (Harrison et al. 2007, p. 1233) The existing body of theories is thereby enriched with those ideas, forming an interactive process, which is illustrated below in Figure 2.

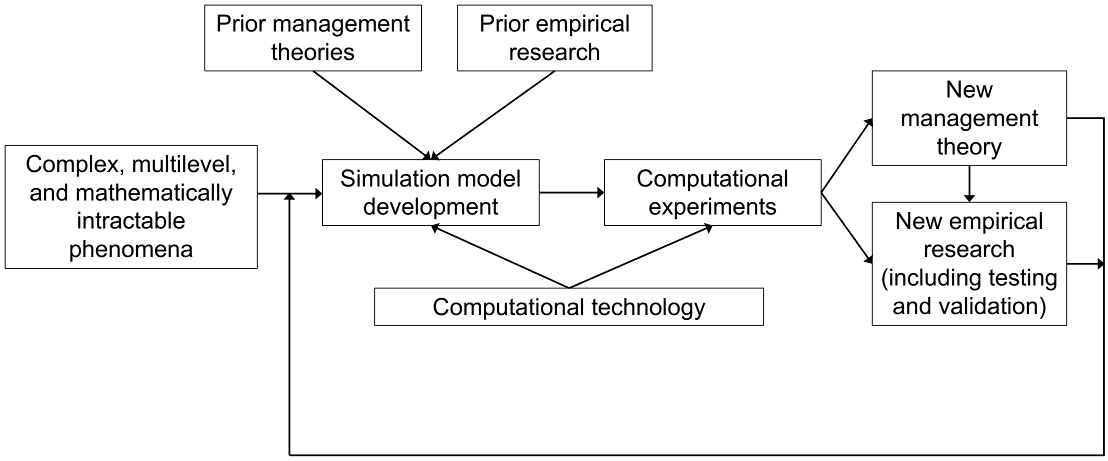

Figure 2. Simulation research process (Adapted from Harrison et al. 2007)

This study is conducted in a similar fashion. The thesis addresses a complex issue that is studied by means of simulation modelling. The theoretical development builds upon existing theories of technology diffusion as well as existing empirical research on EFVs. On this basis, a simulation model is built, and computational experiments can be carried out and new insights be found that may complement existing knowledge on the topic and possibly future studies.

2.2 System dynamic approach

System dynamics (SD) modelling is a branch of simulation modelling which was created by Jay W. Forrester at the Massachusetts Institute of Technology in the 1950s. SD is used for designing and improving policies and strategies in businesses, governments, and the military (Law 2015, p. 708). It is an application of the principles and techniques of control systems to organizational and socio-economic problems (Pryut 2013, p. 1).

SD models focus on modelling the behaviour of the system as whole and they simulate the processes that lead to changes in the system over time (Harrison et al. 2007; Law 2015, p. 708). They are simplified representations of complex information-feedback systems where all behavioural laws cannot be known (Forrester 1961, p. 124; Pryut 2013, p. 34). As such, they should **not** be regarded as a method for point prediction, but rather as mean to study the types of system behaviour (Forrester 1961, p. 125).

SD modelling builds upon the assumption that the behaviour of a system is largely caused by its own structure (Pryut 2013, p. 1, 33). SD includes a variety of tools that can be used to study a model structure, such as model boundary diagrams, subsystem diagrams, causal loop diagrams, and stock and flow maps (Sterman 2000, p. 97). Especially relevant for the present study are causal loop diagrams (CLDs) and stock-and-flow maps that are visualized in Figure 3 and Figure 4, respectively.

CLDs are an excellent tool for visualizing central feedbacks in a system (Sterman 2000, p. 137). In a CLD, key variables are connected with *causal links* that exhibit causal relationships between those variables (Pryut 2013, p. 35). When causal links start from one variable and eventually return to the first one, those variables form a *causal loop* (Pryut 2013, p. 35). A causal loop can be *reinforcing* or *balancing*, depending on the polarities of causal links between variables that form the loop. A reinforcing loop is such that the feedback effect reinforces the original change (Sterman 2000, p. 144). In isolation, they generate exponentially escalating behaviour which can be either highly positive or highly negative, depending on the initial momentum (Pryut 2013, p. 35). Such loops are also called *virtuous* and *vicious* cycles, respectively (Pryut 2013, p. 35). In a balancing loop, the feedback effect opposes the original change (Sterman 2000, p. 144), and (in isolation) it can generate balancing or goal-seeking behaviour (Pryut 2013, p. 35). Lastly, there may be *delays* in the causal loop when the cause and the effect of causal relationship are distant in time. In a CLD, these are marked with two crossing lines.

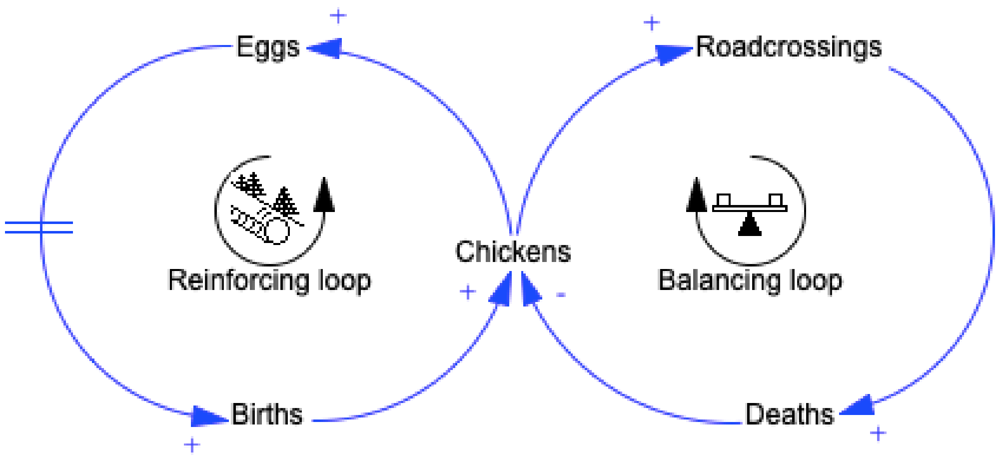

Figure 3. An example of a causal-loop diagram

"Stocks and flows, along with feedback, are the two central concepts dynamic systems theory" (Sterman 2000, p. 191). *Stocks* are accumulations that represent the state of a system at a given time. They give systems inertia and create delays, as they accumulate differences between *inflows* and *outflows* that alter the state of the system. The decoupling of rates of flow also mean that stocks are the source of disequilibrium in dynamic systems. (Sterman 2000, p. 192)

Mathematically speaking, stocks are integrals of their inflows and outflows; the net flow into a stock is the rate of change of the stock (Sterman 2000, p. 192). Thus,

$$Stock(t) = \int_{t_0}^{t} [Inflow(s) - Outflow(s)]ds + Stock(t_0), \qquad (1)$$

where s is a point of time between initial time t_0 and the current time t. (Sterman 2000, p. 192) However, as system dynamics is a method to study *complex* systems there might hundreds of equations that form the model. In this regard it is more convenient to visualize those equations in the form of stock-and-flow maps. An illustration is provided below, in Figure 4.

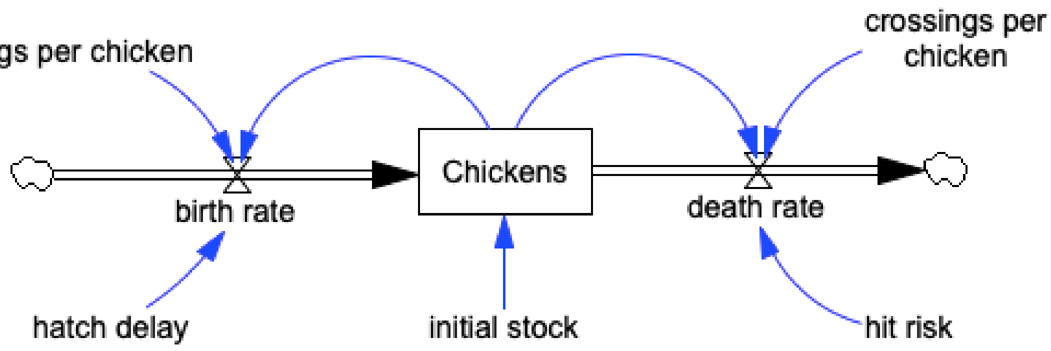

Figure 4. A stock-and-flow map representation of the example

There are four central elements in a stock-and-flow map: Stocks that are represented as rectangles, flows that are represented as pipes flowing into/out of a stock, valves that control flows, and clouds that are sources or sinks, depending on their location. Sources and sinks have unlimited capacity and they are merely used for sourcing material to inflows and draining material out of the system. (Sterman 2000, p. 192) Further, there may auxiliary variables and constants that affect the rate of change, and/or that initialize the stocks, but stock-and-flow maps can also be built without them (Sterman 2000, p. 202; Pryut 2013, p. 34).

The model presented herein, as well as the two examples above, are done using Vensim-DSS (www.vensim.com) simulation software. It is a flexible and easy to use system dynamics simulation software that can be used to model complex system in the aforementioned fashion.

2.3 Research approach

Similar to many other research strategies, simulation research can also have several types of purposes. Harrison et al. (2007) recognize seven uses for simulation studies, namely prediction, proof, discovery, explanation, critique, prescription, and empirical guidance. Most relevant to the present study are discovery and explanation. Firstly, according to Harrison et al. (2007), simulation modelling can be used to *discover* unexpected consequences that are caused by simple interactions. These can be, for instance, path dependent effects which are also characteristic to SD studies. Secondly, simulation models can be used in situations where certain behaviour is observed, but there is causal ambiguity. In such cases simulation can be used to *explore* plausible explanations for the type of behaviour. (Harrison et al. 2007)

The present study aims to identify endogenous factors that explain the dynamic behaviour and establishes causal relationships between them. Further, by modelling the system and putting it into the Finnish context, the study generates insights into why the market development has been such as it has. Thus, it is an *explanatory* research (Saunders et al. 2012, p. 140).

From the premise that simulation studies can develop new theories, their research approach is inductive (Saunders et al. 2012, p. 125-126). As discussed above, the present study also aims to imitate the behaviour of Finnish EFV market and make conclusions based on generated data.

However, simulation studies also closely resemble deduction in that simulation outcomes depend directly on the assumptions made; when a formal model is built, the modeller has to make a set of underlying assumptions of the model behaviour, which inevitably affect simulation outcomes (Harrison et al. 2007). Likewise, in deduction a set of hypotheses are deduced from a theory which are then tested against it (Saunders et al. 2012, p. 124-125). What follows in both cases is that, as stated by Harrison et al. (2007), "[the] results are only as good as the assumptions". To this end, simulation could also be seen as deductive.

Harrison et al. (2007) recognize simulation studies as a third way of doing science. There are clear similarities between simulation and induction, and simulation and deduction, but they also differ from each other. Deductive studies rely on mathematical techniques and analytical methods for which, as mentioned, complex systems may still be intractable (Harrison et al. 2007). Inductive studies again use empirical data that has been and be *gathered*, rather than data that has been generated for the extended time frame of interest (Harrison et al. 2007). Thus, it might be misleading to categorically declare simulation as being either of the two. The present study adopts this approach and recognizes that there are both, inductive and deductive, features in it.

2.4 Research strategy

The present study is a single case study that uses computer-aided SD simulation to study a phenomenon in a limited context. The research strategy is chosen on the grounds that it is highly concerned with the context it is applied in and it allows the use of secondary data as principal empirical material (Saunders et al. 2012, p. 146, 256-258).

The chosen technique indicates that the modelling approach is quantitative; a system dynamic model is built based on qualitative analysis of existing literature, which is then quantified and contextualized to the Finnish market. The modelling process follows the process presented above, in Figure 2, as well as the steps presented in Sterman (2000, p. 83-105):

1. Problem Articulation
2. Formulation of Dynamic Hypothesis
3. Formulation of a Simulation Model
4. Testing

5. Policy Analysis

In the first phase, the actual research problem is defined, and it is limited to certain context and time frame; in this case, the Finnish light-duty EFV market in 2000-2050. Thereafter, key variables that might explain the problematic behaviour of the system must be recognized and their historical behaviour needs to be studied. The historical behaviour of key variables is the *reference mode* of the simulation model, i.e. how the model should work (Sterman 2000, p. 86).

In this study, the knowledge base for identifying key variables builds upon a literary review that was conducted on to the existing studies on EFV diffusion. Reference modes, in turn, were retrieved from the Finnish Transport Safety Agency Trafi (see chapter 2.5).

On the basis of existing empirical studies and theories on technology diffusion, the relationships between recognized key variables are formalized into a *dynamic hypothesis* (Sterman 2000, p. 94). The dynamic hypothesis is an initial theory about the problematic behaviour. It is dynamic because it maps the underlying characteristics into a feedback structure and in terms of stocks and flows, but it is also a hypothesis as it is subject to revision and modifications (Sterman 2000, p. 94-95).

In chapters 4 and 5, a dynamic hypothesis is developed using the existing knowledge base, and later in Chapter 6 mapped into a conceptual causal loop diagram. By building upon existing theories and empirical research, the aim is to ensure that the model presented herein is consistent with other theories on the topic and structurally coherent.

Once the dynamic hypothesis is mapped into a stock and flow representation, it needs be formalized, as discussed in chapter 2.1. The formulation of an actual simulation model entails the empirical part of the study, as mathematical equations need to be formed to describe behavioural relationships, and parameters and initial conditions need to be estimated from real-world data.

The fourth phase of the process is model validation. This is a highly important process as the value of simulation results relies on the validity of the model (Harrison et al. 2007). There are numerous tests that serve this purpose, inter alia, behaviour reproduction, dimensional analysis, extreme conditions tests, and sensitivity analysis (Sterman 2000, p. 859-889). In chapter 7, simulation results are compared to the aforementioned reference modes. The sensitivity of simulation results to different variables is also discussed. A thorough documentation on model validation is provided in the Appendix B, where the model structure is tested for robustness in extreme conditions, and the sensitivity of error prone variables, dimensional consistency, and plausible effects of chosen integration method are tested. Lastly, a summary of model validation is provided in the conclusions.

In the actual policy analysis, the simulation model is used for analyses. For instance, the model can be used for what if -analyses, policy design, sensitivity analysis, and to test if there are synergies between policies (Sterman 2000, p. 86, 103-104). In the present study, the model is used for sensitivity analysis; to find out which policies seem to affect EFV diffusion the most, and further how much they might affect. The model is also used for what if -analyses and retrospectively, i.e. what would have happened if different policies were not implemented. These analyses are presented in chapter 7. The purpose of such analyses is to synthesize discussion about different policies and dynamic nature of the EFV market and thereby provide answers to main research questions.

2.5 Data collection

This study relies on secondary data (Saunders et al 2012, p. 256) that has been collected using content analysis (Duriau et al. 2007) from various public and governmental sources, books and academic journals. The model presented herein builds upon a number of theories and extends the existing body of modelling studies by bringing it to the Finnish context. Therefore, *qualitative* data is in the heart of model formation while *quantitative* data allows the model to be contextualized to the Finnish market.

For the most parts, the model is contextualized using compiled data (Saunders et al. 2012, p. 258) that has been retrieved from publications, annual and quarterly reports, governmental bills, and public information services, such as Trafi's Statistics Database (www.trafi.fi/en). In some cases, however, needed information was not readily available so raw data was used and the needed information were compiled manually.

Literature and academic publications not only provide theoretical groundings for the present study, but also serve as sources for parametrization. That is, some variables used in the model (see Chapter 6) are such that empirical data from the national context does not exist and/or the variable per se is such that it would be difficult to quantify. In such cases, values are retrieved from literature in order to ensure model's credibility. Examples of such sources are the studies of Struben & Sterman (2008) and Testa (2017).

The most important sources for national data are the Finnish Transport Safety Agency Trafi, Autotietokanta (Vehicle database), Tilastokeskus (Statistics Finland), Autoalan tiedotuskeskus, the Finnish Government (the Ministry of Employment and Economy and the Ministry of Transport and Communication), Energiavirasto (Energy Authority), the European Union and its organizations (e.g. www.eafo.eu), Petroleum & Biofuels Association Finland (www.oil.fi), and Tax Administration (www.vero.fi/en). These sources provide information about market development in all four categories, details on model diversity, gasoline and electricity consumer prices, vehicle taxation, charging infrastructure, and other factors that affect the performance of a vehicle platform (see Chapter 3).

Trafi's Information Services and archives are used in the present study primarily for constructing reference modes of market development. Trafi's open data is also used for estimating the number of EVs, HEVs, and PHEVs in 2000-2006, since these numbers cannot be retrieved from the statistics database. Further, information provided by Trafi are used indirectly as many organizations have compiled their own statistics and reports on this basis; for example, the average lifetime of a vehicle in Finland was retrieved from Autoalan tiedotuskeskus who, in turn, retrieved their data from Trafi and Statistics Finland (Autoalan tiedotuskeskus 2017). Similarly, the development of Finnish car parc as whole is based on Trafi's data but was retrieved from Autoalan tiedostuskeskus (Autoalan tiedotuskeskus 2018). Hence, Trafi is the single most important source for empirical data in this study.

2.6 Existing modelling studies

The number of studies modelling the diffusion of electric drive-trains is constantly growing. Studies have had their own aspects to the topic in terms of modelling method and locus. For instance, Sierzchula et al. (2014) carried out a regression analysis to study factors that affect PEV diffusion. They studied up to 30 countries ranging from China to Europe and further to the United States. Kangur et al. (2017) performed an agent-based simulation study in the Netherlands to forecast PHEV and BEV market shares. Eppstein et al. (2014) and Shafiei et al. (2012) also used agent-based modelling, but both of these studies were limited to plug-in hydrids and were carried out in the United States and Iceland, respectively.

A number of studies have also been presented to the topic that are particularly interesting for the present study in the sense that they have used system dynamics as a simulation method. Struben (2006) appears to be one of the first studies that have extensively modelled AFV adoption process. The paper consists of four essays that collectively form a solid theory about how a consumer becomes familiar with AFVs and takes them into their consideration set. The study also considers the effect of driving behaviour on AFV attractiveness in Californian context. (Struben 2006)

Building upon the previous study, Struben & Sterman (2008) extended the model into a version that appears to be highly relevant even today. Struben & Sterman (2008) introduced a concept called Willingness to Consider (see chapters 5 and 6) which has also been adopted by a number of later studies (e.g. Walther et al. 2010, Shepherd et al. 2012, Harrison et al. 2016). SD based models are studied in further detail in chapter 5.

The studies of Harrison et al. (2016) and Harrison & Thiel (2017) are interesting in the sense that they have studied the system on an EU aggregate level. Likewise, the study of Testa (2017) is highly relevant for the present study, as it studies PEV diffusion in Norway and Sweden. Such studies provide insights in relevant contexts and can thereby be used to triangulate model results.

Examples of other modelling studies are listed below, in Table 1. The listing is non-exhaustive and is constantly complemented, as more research is carried out on to the topic.

Table 1. Modelling studies on EFV and AFV diffusion

Authors	*Year*	*Modelling approach*	*Locus*
Al-Alawi & Bradley	2013	Review on HEV, PHEV, and EV market modelling studies	Theoretical
Benvenutti et al.	2017	SD-model based simulation	Brazil
Bosshardt et al.	2007	SD-model based simulation	Switzerland
Browstone et al.	2000	Mixed logit model	The United States
Eppstein et al.	2011	Agent-based model simulation	The United States
Harrison & Thiel	2017	SD-model based simulation	EU member countries
Harrison et al.	2016	SD-model based simulation	EU aggregate
Kangur et al.	2017	Agent-based model simulation	The Netherlands
Kieckhäfer et al.	2017	SD and Agent-based hybrid model simulation	Germany
Kwon	2012	SD-model based simulation	Theoretical
Langbroek et al.	2016	Survey study, Mixed logit model	Sweden
Mellinger et al.	2018	Monte Carlo simulation model	Finland, Switzerland
Müller et al.	2013	Theoretical, SD-model based simulation	Theoretical
Pasaoglu et al.	2016	SD-model based simulation	EU member countries
Shafiei et al.	2012	Agent-based model simulation	Iceland
Shepherd	2014	A review of system dynamics models applied in transportation	Theoretical
Shepherd et al.	2012	SD-model based simulation	Great Britain
Sierzchula et al.	2014	Regression analysis	30 countries
Struben	2006	SD-model based simulation	The United States
Struben & Sterman	2008	SD-model based simulation	The United States
Testa	2017	SD-model based simulation	Norway, Sweden
Ulli-Beer et al.	2010	Mathematical modelling, SD-model	Theoretical
Walther et al.	2010	SD-model based simulation	The United States

What can be noticed from the above is that there are, in fact, numerous SD based studies that can be referred in the present study. This is beneficial in the sense that relevant concepts, boundaries, assumptions, and so on, can be adopted from existing studies and thereby increase the credibility and validity of this study.

3. THEORETICAL BACKGROUND

3.1 Technological diffusion and adoption

Kemp & Volpi (2008) define technological diffusion as the adoption of technology by a group or population over time. Diffusion theory takes a macro perspective and is interested in the spread of innovation among potential adopters, rather than in explaining why a particular unit has adopted the innovation at a particular time (Straub 2009; Hagman et al. 2016). Adoption theory, again, takes a micro perspective and examine specifically the choices an individual makes before accepting or rejecting an innovation (Straub 2009). The two are, however, tightly connected as diffusion composes of individual adoptions and describes the adoption process across a population over time (Straub 2009).

A groundbreaking theory on innovation diffusion was presented by Everett Rogers in 1962. The *innovation diffusion theory* provides a comprehensive foundation for understanding the factors that affect the choices an individual makes about an innovation (Rogers 1962; Straub 2009). It binds adoption and diffusion closely together and explains how adoptions by individuals constitute diffusion over time. As stated by Straub (2009), "it is the basis for understanding innovation adoption", and it has had an impact on numerous other adoption and diffusion theories (Straub 2009).

Rogers's theory describes the adoption process through five phases; awareness, persuasion, decision, implementation, and confirmation (Straub 2009). *Awareness* refers to the phase when an individual becomes aware that an innovation exists. This is followed by *persuasion*, when the individual gains knowledge about the innovation and forms an opinion about it. Based on that judgement, the individual makes a *decision* to either adopt the innovation or reject it and then acts accordingly; i.e. *implements* the decision. Finally, the individual confirms the decision by reflecting on it and re-evaluating whether to continue with the adoption or not. (Straub 2009)

According to Rogers's theory, there are four key elements that, when combined, describe how individual adoptions represent a diffusion; namely, the innovation itself, communication channels, social system, and time. The innovation aspect holds that the innovation must have a relative advantage compared other similar ideas; it must be compatible with individuals current understanding and perceptions of similar ideas; it should not be difficult comprehend; it must available for experimentation; and it must be visible to the individual, so that the innovation will eventually diffuse. (Straub 2009)

Considering BEV adoption, all the aforementioned aspects of innovation diffusion are slightly alarming: BEV technology is hardly superior to the well-established technology used in ICEVs; the use of BEVs may require more planning from drivers than ICEVs due to shorter driving ranges and longer charging times, and this may cause the user anxiety;

BEVs are still few and far between and therefore difficult evaluate; and, especially considering the last two, it might be difficult for a consumer to grasp why she/he should adopt such a new technology. Having said that there are incentives and policies that can be used to mitigate these issues, and those discussed thoroughly in Chapter 4.

Another key element in the theory is communication channels, which refers to the means by which information about new innovations is shared among individuals (Straub 2009). According to Straub (2009), those can be direct communication, vicarious observations, or even mass and social media. Social system, in turn, refers to the context, culture, and environment wherein an individual is involved. (Straub 2009)

The fourth element, time, is the factor that separates adopters to different groups. Rogers defined five groups of adopters on the basis of how long it took for them to adopt an innovation (Bass 2004; Straub 2009). Those groups are innovators, early adopters, early majority, late majority, and laggards. These five groups represent the market share of an innovation as a function of time and form the plausibly best-known diffusion curve in the field of technology and innovation management. This is illustrated below, in Figure 5.

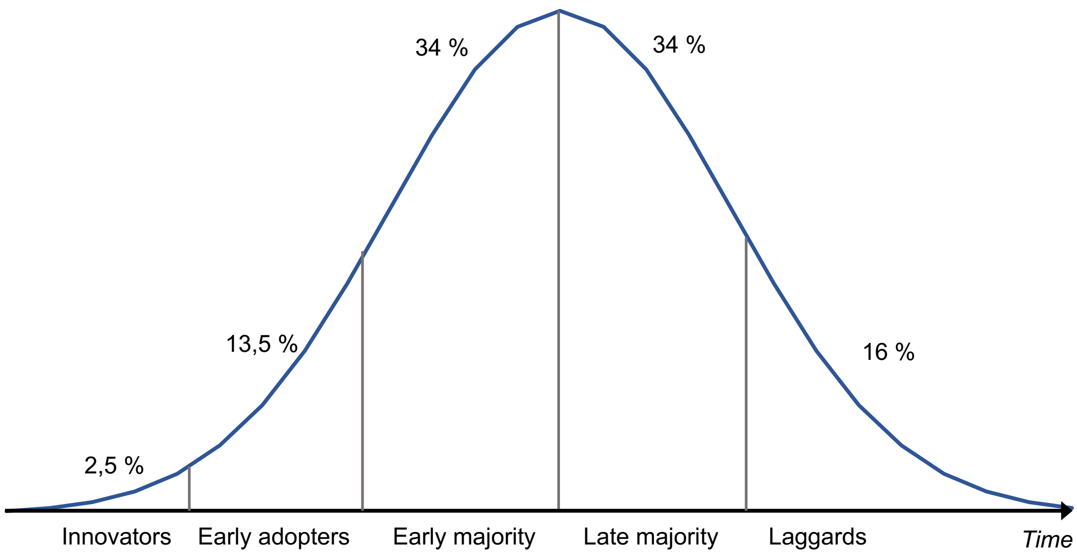

Figure 5. Rogers's diffusion curve

Each group on have their own characteristics. According to Rogers (1976, p. 283), Innovators have the highest social status, financial liquidity, they are literate and can tolerate the risks that are related to an innovation that may not ultimately take off. Early adopters also tend to be more risk tolerant, wealthy, and more educated than late adopters, and they are also the most prominent opinion leaders among the adopter groups. In comparison to innovators, however, they tend to be more discreet in their decision making. (Rogers 1976)

Adopters in the early majority have above-average social status but they do require more for adoption than adopters in the former two groups. They interact with early adopters and may occasionally act as opinion leader in the system. The late majority, in turn, are already notably more sceptic towards innovations and decide to adopt it only once a vast number of individuals have already adopted it. They have lower social status and little financial liquidity and, thus, are less risk tolerant. Lastly, laggards tend to be conservative and like to stick with traditions. They have the lowest social status and have low risk tolerance and, consequently, they are the last ones to adopt a new innovation. (Rogers 1976)

3.2 The Bass model

While Rogers's theory is the backbone of diffusion studies, the discussion is mostly literary and descriptive; the theory does not tell how to facilitate adoption but rather why it occurs (Bass 1969; Straub 2009). To address this, Frank Bass presented a mathematical model that would describe how products diffuse in a population (Bass 1969). Building upon Rogers's theory, the model lies on the premise that consumers can be classified as either *innovators* or *imitators*. Following Rogers's typology, Innovators make their decisions independently from other actors in the social system, while potential adopters in other groups are influenced in timing of the adoption by the pressure of the social system, which increases as the number of adopters increases (Bass 1969, 2004). In mathematical terms, what follows is that the likelihood of an adoption at time *T* is a linear function of the number former adoptions:

$$P(T) = p + \left(\frac{q}{m}\right) Y(T) \qquad (2),$$

where p and q are constants that are called the coefficients of innovation and imitation, respectively, *m* represents market potential, and the term $Y(T)$ is the number of adoptions at time *T* (Bass 1969, 2004). The coefficient of innovation represents the probability of the initial purchase or adoption (Bass 1969). The coefficient of imitation, in turn, is a term that is proportional to the number of adopters and captures the linear relationships between them (Bass 1969, 2004). These two coefficients have also been referred as external influence and internal influence, illustrating the different communication channels – i.e. media and word-of-mouth (Mahajan et al. 1990).

The model structure is such that it generates an S-shaped growth; if the coefficient of imitation is greater than the coefficient of innovation, adoption grow exponentially and then decay (Bass 2004). In this regard, internal influences, such as interpersonal communications and vicarious observations, are important in determining the speed and shape of the S-shaped pattern in a social system (Mahajan et al. 1995).

3.3 Purchase funnel

Struben (2006) studied the diffusion of AFVs in California using SD modelling. The model draws on the family of Bass diffusion models (e.g. Bass 1969; Mahajan et al. 1990) and their applications in the auto industry (e.g. Urban et al. 1990), but with significant extensions. That is, as stated by Struben (2006), the traditional models confound exposure, familiarity, and the purchase decision, which is not applicable in the context in question. Instead, more detailed descriptions of social exposure mechanisms are needed to capture the underlying dynamics of vehicle purchases and technology adoption (Struben 2006). To this end, Struben (2006) extends the Bass model so that in addition to internal word-of-mouth, diffusion is affected by marketing efforts and media attention; there is uncertainty in value of the innovation; and consumers can do repurchases. Further, he decouples internal influences into own variables; the adoption process of an AFV is modelled through exposure, familiarity and an adoption decision, word-of-mouth through non-users and a discrete choice replacement. (Struben 2006)

Struben's approach endorses Rogers's theory, as it separates different communication channels through which consumers can bring an alternative to their choice set (Struben 2006). As can be noted from the above, the adoption process is also for the most part in line with that of Rogers's. While doing so, however, it does highlight some dynamic features of the diffusion context; because there is competition between alternatives, consideration for the new innovation is gained slowly, i.e. it is delayed (Struben 2006). Or, if external and internal influences are too low, consideration can even degrade, and potential adopters can forget the innovation (Struben 2006).

Vehicles are complex products that involve many attributes that can only be determined through purchase, usage, or heavy exposure (Struben 2006). What's more, as discussed above, being able to comprehend the benefits of an innovation greatly contributes to the likelihood of adoption. In this regard, potential adopters need to be exposed to the new alternative so that they can learn about those attributes and seriously consider it as an option (Struben 2006). This can be lengthy process and requires numerous channels for information (Struben 2006) which, again, reasons the approach applied by Struben (2006).

Lastly, unlike many diffusion models, Struben's (2006) model considers the competition between technologies and integrates the diffusion concept with a discrete choice model that illustrates the *preference* of a consumer. This is extremely relevant for the present study as well, since the goal is not to model merely the adoption of a new alternative, but also *which one* of them.

Struben's approach has been adopted by other authors as well and it has been modified to a further extent. Especially, Struben & Sterman (2008) refined the model so that the gaining of consideration was not referred as simple familiarity, but instead they introduced the concept of Willingness to Consider (WtC). The authors define WtC as a concept that captures the cognitive, emotional, and social processes through which drivers gain enough information about, understanding of, and emotional attachment to a new alternative for it to enter their consideration set (Struben & Sterman 2008).

This study draws on the Rogers's theory, the family of Bass models, and the works of Struben and Sterman (2008), as it introduces the following purchase funnel through for EFV adoption:

Figure 6. EFV purchase funnel

Similar to Rogers's adoption process, the purchase funnel above begins with consumers becoming aware of a new alternative. They are then exposed to it through various internal and external influences and, through the WtC process described above, the new alternative enters their choice set. As the time comes that they want to buy or renew their vehicle, the alternative is in their choice set and they make a decision about which vehicle to purchase.

3.4 Consumer choice

Most models introduced in literature for vehicle choices use applications of utility theory (Mohammadian & Miller 2003; Struben 2006; Shafiei et al. 2012). They assume that consumers are fully rational in their decision making and choose an alternative with the highest utility (Mohammadian & Miller 2003). The utility of an alternative is assessed through a set of attributes that are weighted according to a decision rule (Shafiei et al. 2012). From the modeller's point of view, the decision rule is based on coefficients that are usually determined statistically on the basis of stated preference (SP) and revealed preference (RP) studies, as done in inter alia Brownstone et al. (2000), Mohammadian et al. (2003), and Batley et al. (2004).

However, as stated by Kahneman & Tversky (1979), consumers do not necessarily behave as rationally as the theory assumers; their decisions are biased and based on heuristics rather than analysis. They make decisions in isolation rather than comprehensively and react differently to *gains* and *losses*; when risking losses, consumer tend to be risk-seeking, but when facing prospective gains, they are often risk-averse. (1979) This is illustrated with a hypothetical value function, in Figure 7. Similar bounded rationality has been observed by Kampmann & Sterman (2014), who state that consumers often follow a social rather than individual utility.

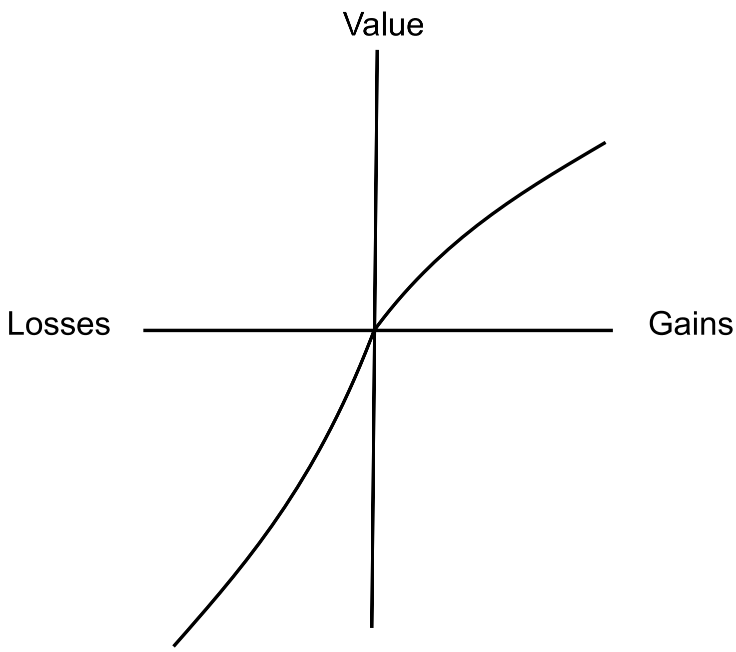

Figure 7. A hypothetical value function (adapted from Kahneman & Tversky 1979)

To address these issues, Kahneman & Tversky (1979) presented their own theory that would more accurately describe individual decision making under risk. *Prospect theory* distinguishes two phases in the choice process, namely editing and evaluation. The editing phase is a "preliminary analysis" of offered prospects which yields a simplified representation of the choice set. In the evaluation phase these are then assessed to determine the one with highest value. In particular, the following four operations are recognized:

- People perceive outcomes as gains and losses relative to a *reference point*, rather than as final states of wealth or welfare. Thus, the location of reference point and the consequent coding of gains and losses have to be determined.
- If the choice set contains similar prospects, they can be combined in order to simplify the decision making.
- Prospects can be segregated into riskless and risky components, so that the possible outcomes of the decision can be seen or estimated more clearly
- People tend to make decisions in isolation, which implies that they discard components that are shared by other offered prospects or constituents that are common to all alternatives; i.e. outcome-probability pairs. (Kahneman & Tversky 1979)

In addition to the four main operations, Kahneman & Tversky (1979) list simplification and detection of dominance as additional operations. The former holds that an individual can round values or probabilities or omit extremely unlikely outcomes from the decision making. The latter, in turn, holds that if there are clearly alternatives that are dominated by other prospects, they can be ruled out from the decision making without further evaluation. (Kahneman & Tversky 1979)

The theory has some clear strengths regarding the present study. First, given that EFVs are new entrants in the vehicle market, consumers are likely to compare their attributes and expenses to those ICEVs. Thus, the value of a prospect can be evaluated relative to a reference point. Second, having said that consumers are likely to compare EFVs and ICEVs, they do contain a lot of similarities, which can be ignored in light of the isolation effect described above. Thus, attributes that need be considered are reduced to a simpler set. Further, as prospect theory recognizes the differences in reactions when it comes to possible gains and losses, the model can capture the slight resistance consumers may put up towards moving to alternative drive-trains; e.g. loss in travel range can cause range anxiety as relative losses are more dramatic than relative gains (see Chapter 3.5.2 and Chapter 6.2.2). In this regard, the present study adopts the approach of Testa (2017) and applies prospect theory in modelling consumer choice.

The present study also adopts the approach of Sterman (2000, p. 349-406, 525-529) and Testa (2017), as it considers the *attractiveness* of a product. Attractiveness of a product is determined through a number of attributes, such as price, availability, quality and service (Sterman 2000, p. 365-367, 392-396). Each attribute has an effect on the attractiveness and those effects are then totalled to get a representative value (Sterman 2000, p. 392-396, 525-529). Here, the attractiveness of a vehicle type (BEV, HEV, ICEV, PHEV) will be determined as a product of the effect of price on attractiveness and the effect of performance on attractiveness (Sterman 2000, p. 392-396):

$$\text{Attractiveness of vehicle type} = \text{Effect of price on attractiveness} * \text{Effect of performance on attractiveness} \qquad (3)$$

A similar approach was also applied in Testa (2017). Values for these effects are determined by applying prospect theory and table functions (Sterman 2000, p. 552-563). These will be discussed in detail in Chapter 6.2.2. Further, variables that determine the performance of a vehicle type will be discussed in further detail in the next subchapter.

Performance of a vehicle type is modelled accordingly; it is a sum of effects of attributes on performance. Each attribute is normalized using its reference point and the ratio is then transformed into an effect using an applicable function. Here, the effect of each attribute X_l on attractiveness a is determined using a power function:

$$\text{Effect of } X_l \text{ on } a = \left(\frac{X_l}{X_l^*}\right)^b \qquad (4),$$

where X_l^* is the reference point of the attribute X_l and b is the sensitivity of attractiveness a to the attribute X_l. The attributes l will be discussed in Chapter 3.5.2. The sensitivity will be valued at 0.5, which implies that the function is a square root function. As stated by Testa (2017), the use of square root function is convenient in cases where the ratio is near unity, as values below unity are slightly raised towards and values above are slightly lowered towards unity. When these effects are totalled up, they form the representative value for vehicle type performance.

The effect of price on attractiveness is also modelled with reference points and in a similar fashion as in Testa (2017). The effect is determined through relative *costs* and relative *price*, which are then weighted accordingly to get the representative value. This approach was adopted from Testa (2017) and will be discussed in detail in Chapter 6.2.7. Furthermore, different cost elements of electric vehicles will be discussed in the next subchapter.

The market share of a vehicle type is modelled similarly as in Sterman (2000, p. 392-396) and using the attractiveness values of vehicle types. In the present study, market share of a vehicle type *i*=1, 2, 3, 4 (BEV, HEV, ICEV, PHEV) will be determined as:

$$\text{Market share of vehicle type } i = \frac{\text{Attractiveness of vehicle type } i}{\text{Total Attractiveness of all vehicle types}} \qquad (5).$$

This study also assumes that the choice of vehicle type is nested, as observed by Ben-Akiva (1973). This means that a consumer first decides between vehicle categories – here, between ICEVs and EFVs – and then between vehicle types. The selection of vehicle category builds in part on the discussion above and to the concept of willingness to consider. Denoted with W, willingness to consider is a dimensionless factor with an interval [0, 1], where unity implies that a consumer is fully willing to consider an alternative. Similar to Struben (2006) and Struben & Sterman (2008), it is assumed that all vehicle drivers are willing to consider an ICEV and all drivers that have already bought an EFV will consider it again. A simplifying assumption is made, however, so that the same rate of willingness is used for all EFV types: i.e. if a consumer is willing to consider a BEV, he/she is equally willing to consider a HEV or a PHEV. On this basis, the variable of interest is the willingness of ICEV drivers to consider an EFV, and

$$\boldsymbol{W} = \begin{bmatrix} 1 & W_{ICEV,EFV} \\ 1 & 1 \end{bmatrix} \qquad (6)$$

As discussed in Chapter 3.3, once consumers are sufficiently willing to consider an EFV, they make a choice based on their preferences. If we denote the attractiveness of vehicle type *i*=1, 2, 3, 4 (BEV, HEV, ICEV, PHEV) with a_i, willingness to consider platform *j*=1, 2 (ICEV, EFV) given the current platform *k*=1, 2 (ICEV, EFV), and combine (4), (5) and (6), we can model the indicated share of sales of a vehicle as

$$\text{Share of sales on } i = \frac{w_{j,k} a_i}{\sum_i w_{j,k} a_i} \qquad (7)$$

Thus, it is a kind of an integrated form of multinomial logit model (MNL) that includes the attractiveness of a vehicle type and the effects of social exposures, i.e. external influences (Struben & Sterman 2008; Shafiei et al. 2012). A similar approach has been adopted in, inter alia Shafiei et al. (2012), Shepherd et al. (2012), Pasaouglu et al. (2016) and Harrison & Thiel (2017).

The most distinctive difference between the present study and the majority of previous discrete choice models is that attractiveness of a vehicle is not determined by means of expected utility theory or a random utility model, but instead it uses reference points and relative values to determine a representative value to each vehicle type. Similar to Testa (2017), it is assumed that ICEV technology is already so matured that significant improvements in technology are difficult to achieve. Thus, by grounding the reference points of variables to those ICEVs', they would be relatively stable and allow the model to illustrate the advantages and shortcomings of EFV types relative to ICEV. Another benefit of this approach is that in the absence of RP/SP studies from Finland, this study would not draw on coefficients that are retrieved based on consumers in other countries. To this end, however, the following assumption is made:

Consumers will use the well-established technology as a reference point against which each EFV drive-train is compared individually.

As long as ICEVs will not "disappear" from the market and consumers minds' and remain as reference points, this assumption is applicable. Further, the IIA property of alternatives will be fulfilled: the ratio between any two attractiveness values will not change if a third one is removed from the choice set (Mohammadian & Miller 2003; Train 2009, p. 54). In other words, the present study assumes that there will still be internal combustion engine vehicles in the Finnish vehicle market in 2050.

3.5 EFV attractiveness

In this study, the attractiveness of an EFV is determined as a product of price and performance. These will be discussed separately in the following two subchapters.

3.5.1 Costs

The lifetime costs of a vehicle can differ greatly depending on the vehicle type and especially between BEVs and ICEVs. Operating costs of BEVs are notably lower than those of ICEVs as electricity is generally cheaper than gasoline (see Chapter 6), electric drive trains are more energy efficient than their conventional counterparts, they pay lower taxes (see Chapter 4), and they are cheaper to maintain (Energiateollisuus 2010; Knüpfer et al. 2017). In their study, Hagman et al. (2016) observed a difference in fuel costs for Volvo V40 D3 and BMW i3 of more than 3,000€ a year. Propfe et al. (2012) found that maintenance and repair costs are lower for BEVs and PHEVs than for HEVs and ICEVs; the difference was, at its highest, almost 2 cents per kilometre. (Propfe et al. 2012)

At the same, however, purchase price of an EFV can be considerably higher. For instance, a BEV with 30 kWh can cost even $10,000 more than a comparable ICEV (Sierzchula et al. 2014). According to Sierzcuhla et al. (2014), this is the most prominent barrier to EV adoption. The phenomenon can be observed in Finnish prices as well: Hyundai i30 Hatchback prices start from 19,790€, i30 Wagon from 21,190€, and Ioniq electric from 36,790€. Similar differences can be also be found in HEV and PHEV prices, as the list prices for

Ioniq Hybrids and Ioniq Plug-in hybrids start from 27,590€ and 32,990€, respectively. (www.hyundai.fi)

According to Knüpfer et al. (2017), this phenomenon has implications for both consumers and manufacturers: in order to make BEVs – and other EFVs – a profitable business, car manufacturers should shift their economic balances from purchase prices to total costs of ownership (TCO). To this end, they also have to establish business models that support this. When it comes to consumers, they should also consider the TCO of their vehicle during its service time, rather than being merely horrified by the high purchase price. (Knüpfer et al. 2017) Despite the high upfront investment, an EFV can be a cheaper option, if the annual vehicle mileage is high enough, there are purchase subsidies established, or if the service time of the vehicle is closer to ten years (Wu et al. 2015; Hagman et al. 2016; Liimatainen et al. 2018; Trafi 2018). Wu et al. (2015) conclude that the cost-efficiency depends on the annual mileage, but further state that the vehicle class has a notable effect. They use three vehicle classes: mini and small vehicles, such as VW Polo; lower medium and medium-sized vehicles, such as VW Golf; and sport utility vehicles, such as VW Tiguan. The authors found that with a low mileage, an ICEV is likely to remain most cost-efficient until 2025 in all vehicle categories. In the medium case, PHEVs and HEVs are likely to be most cost-efficient in the small vehicle, while in the bigger classes ICEVs and HEVs are likely to be most cost-efficient. For long distances, BEVs are likely to be most cost-efficient in all vehicle types, but as of 2020 the competition is between BEVs and HEVs. (Wu et al. 2015)

The biggest reason for the price differential in vehicle types is the powertrain – i.e. the battery (Nykvist & Nilsson 2015). While the absolute costs unrelated to powertrain are approximately equal in all vehicle types, according to Küpper et al. (2018) their relative share of total costs is 84 % for an ICEV, while the corresponding number for a BEV is 50 %. That is, the battery pack accounts for 35 % of the costs, and the rest goes to electric motor and power electronics. (Küpper et al. 2018)

A key variable here is the unit cost of kilowatt-hour (kWh). In 2010, the average cost of a kWh was approximately $1,000, but it has decreased exponentially thereafter (Nykvist & Nilsson 2015; Knüpfer et al. 2017). Nykvist & Nilsson (2015) carried out a systematic review on kWh cost development during 2007-2014 and concluded that the average price decline for the whole industry has by been 14 % a year, and 8 % for the largest manufacturers. Knüpfer et al. (2017) observed even steeper decline, stating that the cost of kWh dropped by approximately 80 % during 2010-2015. They further estimate that the cost of kWh in 2020 would be around $190/kWh. (Knüpfer et al. 2017) Similar development should continue so that BEVs could reach cost parity with ICEVs. According to Nykvist & Nilsson (2015), it is commonly understood that parity could be reached closer to 2030, when the cost of kWh drops below $150/kWh.

The cost of a battery depends on its size, and so does the travel range of the vehicle (Sierzchula et al. 2014). It is therefore a trade-off between price and travel range, both of which are great barriers for EFV adoption (Sierzchula et al. 2014). For PHEVs it is even more so since their batteries are more expensive than BEVs' due to a higher power requirement (Nykvist & Nilsson 2015). That is, according to Nykvist & Nilsson (2015), the difference in cost of kWh can be up 30-50 % for PHEVs than BEVs.

Struben (2006), Sierzchula et al. (2014), and Testa (2017) also recognize the value of time as cost item that separates plug-in vehicles (PEV) from those that use cannot be charged, i.e. ICEVs and HEVs. According to Sierzchula et al. (2014), the fact that an ICEV can be "charged" at a gas station in approximately 4 minutes, while a comparable BEV needs 30 minutes at a fast charging station or several hours if charged with slow charger, can form another barrier for adoption. Such losses can be mitigated through local policies (see Chapter 4) that allow BEVs to e.g. use bus lanes and cost-free ferry rides, as done in Norway (Testa 2017). The present study recognizes such measures as a way of mitigating functional risks of BEVs, but does not consider them thoroughly due to the fact that, at least to knowledge of the writer, no data can be found in the Finnish context that would quantify the value of time for Finnish people, nor have such policies widely implemented in Finland to date (see Chapter 4).

Sierschula et al. (2014) state that the price of gasoline and electricity is one of the most powerful predictors of EFV adoption. This is line with the findings of e.g. Wu et al. (2015), since the cost of gasoline has a direct influence on the operating costs of a vehicle. However, because the present study adopts a similar approach as in Testa (2017), where the ICEV is an umbrella term for numerous fuel types, this study also acknowledges the fact that the price development as well as relative use shares of different fuels, are highly uncertain and simplified.

3.5.2 Performance

There are numerous factors that can explain why some consumers have adopted the new technology already and others have not. Following the discussion above in Chapter 3.4, this study focuses on a simplified set of attributes that are notably different between ICEVs and EFVs, namely travel range, charging availability, model diversity, vehicle emissions, and vehicle lifetime. These attributes are also the basis of performance in Testa (2017), and they are recognized by Knüpfer et al. (2017) as criteria in which technological parity must be reached in order to move from Innovators to Early adopters.

According Clean technica (2016), the main reason for European first-movers to move to electric vehicles was their lower emissions. There are no exhaust emissions when using electric drive-train, which is why BEVs and PHEVs are considered green alternatives to ICEVs (EEA 2016). According to European Energy Agency (2016), the greatest effect on the environment is achieved when consumers drive BEVs and the electricity needed to charge EFVs is produced using renewable energy. But even if some of that electricity is produced using fossil fuels, BEVs are still more environmentally-friendly than ICEVs. However, if electricity is produced with fossil fuels only, BEVs can be the *worst* option for the environment. (EEA 2016) This is illustrated below, in Figure 8. The figure also illustrates why PHEVs are considered a valid option when it comes reducing transportation GHGs.

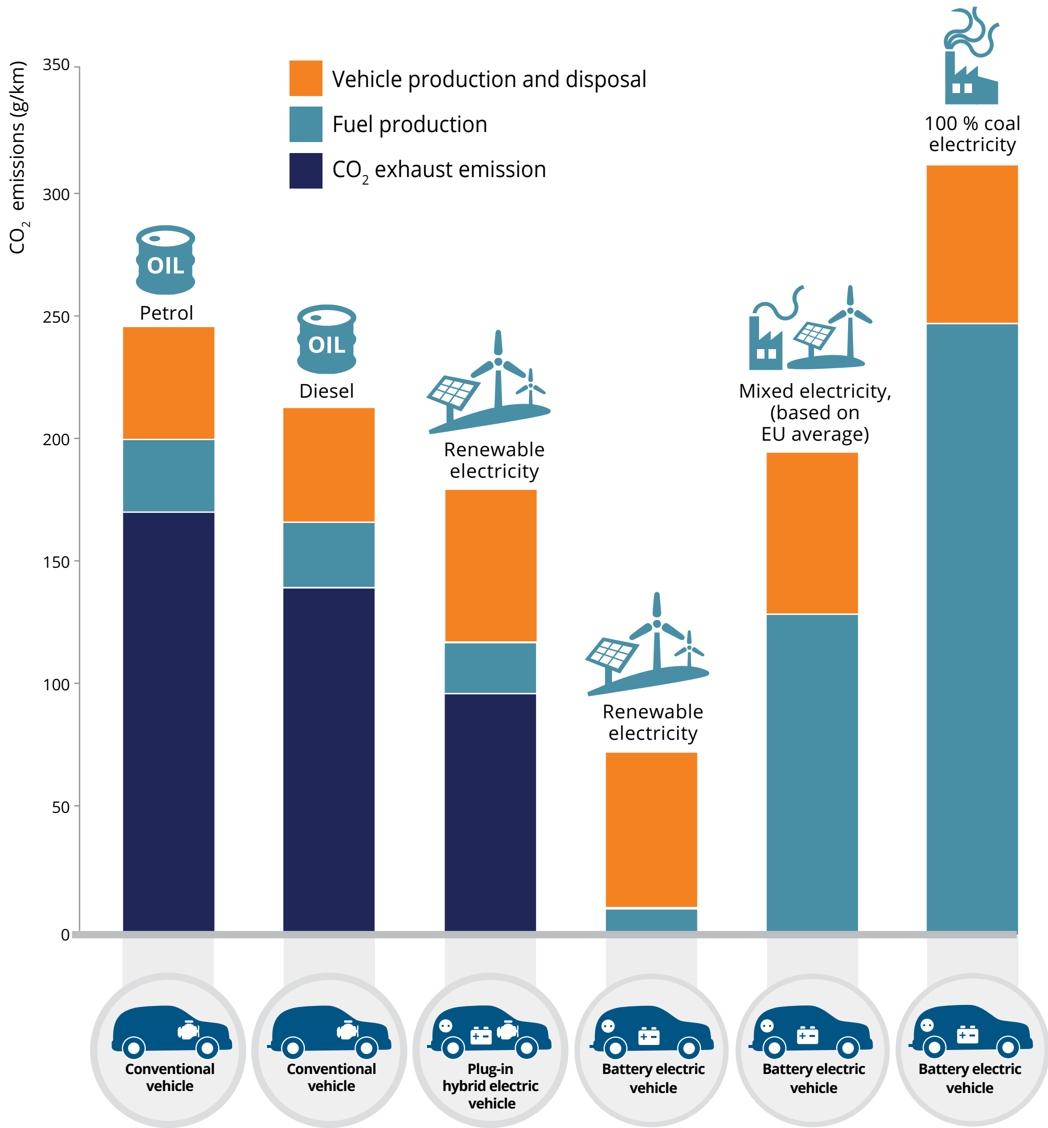

Figure 8. Environmental friendliness of vehicle types (Adapted from EEA 2016, p. 45)

Model diversity determines the likelihood of consumer finding a vehicle they desire. According to Knüpfer et al. (2017), one of the obstacles in wide-scale EFV diffusion, and EV in particular, has been the mismatch in supply and demand in EV models. Consumers are increasingly interested in more affordable and small electric vehicles, while the car manufacturers have been more interested in selling to less price-sensitive premium users instead. (Knüpfer et al. 2017) Pasaoglu et al. (2015) and Struben & Sterman (2008) have also concluded that market offering is one of the most important determinants of market entrant diffusion. Sierzchula et al. (2014) found also in their study that there is a positive correlation between the number of models offered to consumers and EV market share.

While the model diversity in ICEVs is abundant, EFV offering is not yet that well-established. Based on Trafi's open data, in 2010 there were 11 HEV models offered in market and 8 in BEV class. PHEV were not yet even introduced to the market. Thereafter the model offering has increased steadily in Finland in all vehicle classes, as can be seen from Figure 9 below.

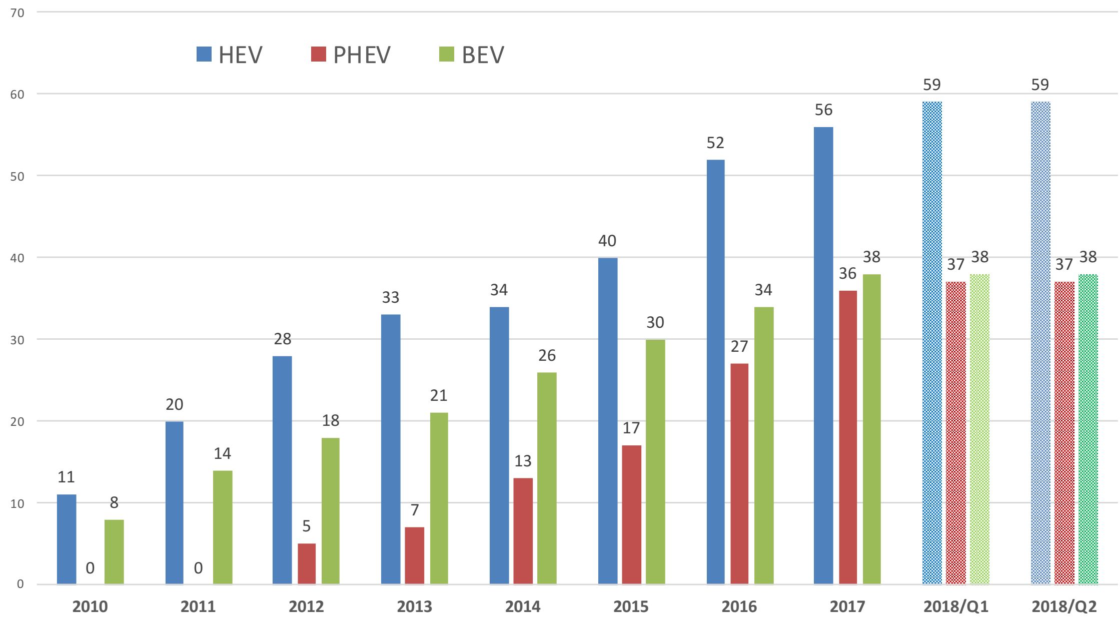

Figure 9. Development of model diversity in Finland

Modelling-wise, the present study adopts the approach of Testa (2017) and assumes that once there are more than fifty models offered in a vehicle category, the likelihood that a consumer will find the desired vehicle is boosted, and once the number closes to hundred, the likelihood will equal to unity. Regarding the development of model diversity in Finland, this seems reasonable and it could be expected that such a situation is reached before 2030.

Although technology used in electric powertrains is developing really quickly, it is still relatively poor compared to internal combustion engines (Knüpfer et al. 2017). Their lifetime is shorter, and they face issues that electric drive-trains experience while internal combustion engines do not, such as degradation of battery if it is charged with fast chargers too frequently (EEA 2016). Shorter lifetime can be slightly buyer-repellent, but according to Knüpfer et al. (2017), this gap is constantly closing, and in the future, it is possible that the lifetime of electric drive-trains even exceeds the lifetime of internal combustion engines.

One of the most prominent obstacles in EFV adoption is the lack of supplementary infrastructure (Struben 2006; Struben & Sterman 2008; Sierzchula et al. 2014; Harrison & Thiel 2017). Consumers are accustomed to a dense network of fuel stations and notably faster refuelling times, which tend to form a barrier to EFV adoption (Struben 2006). Combined with fact that travel range of a BEV is still at its best only roughly a half of ICEV's (Trafi 2018a), consumers can experience range anxiety.

Together with the price barrier, range anxiety with all of its factors are constantly regarded as the main reasons why BEVs have not yet taken off (e.g. Struben 2006; Struben & Sterman 2008; Sierzchula et al. 2014; Harrison & Thiel 2017). This has also been observed in the Finnish context: in Kesko's questionnaire to their Kylä -customer association (Kesko 2017, 2018a), three out of four biggest barriers the responders listed related to range anxiety. The biggest barrier for BEV purchase was their high price, second was travel range, third was charging availability, and fourth was the effect of winter conditions on electric drive (Kesko 2018a). In this regard, charging availability is considered as one the most important determinants of relative performance of an EFV.

Charging points can differ from each other in terms of location, charging power and current, price of charging, popularity, suitable battery types, and even the plug itself (Testa 2017; Ohmhomenow 2018; Trafi 2018a). *Slow charging points* provide less than 10 kW and are meant for home chargin points and park&charge stations (McKinsey 2014). They are cheaper to build and, according to European Energy Agency (2016), they should be the primary charger type for plug-in vehicles, as they do not harm the battery of a vehicle as badly as fast chargers do. They should also be preferred due to the fact that there are many BEVs and PHEVs that are not compatible with fast chargers at the time being (EEA 2016).

Fast charging points provide the near-equivalent to refuelling at traditional gas stations. They provide 50 kW (or higher) charging power and they can charge a vehicle in roughly half an hour to 80 % of the maximum (McKinsey 2014). They are usually located at gas stations as they serve a similar purpose (Trafi 2018a). Having said that slow charging points should be preferred, fast charging points could be used to mitigate range anxiety on longer travels, as it does not take several hours to charge a BEV or a PHEV. In that regard, driving behaviour can greatly affect the importance charging behaviour; as stated by Testa (2017), for urban settlers, who mainly drive between work and home and who can charge their vehicle at home, the importance of public charging points is low. However, for drivers living outside city areas and where distances are longer, the importance of charging points is also greater.

As mentioned above, travel range of electric vehicles is generally shorter than those of ICEVs. Depending on several aspects, the effective range of a mid-sized BEV can range from a couple of hundreds of kilometres to roughly 600 km (EEA 2016; Trafi 2018a). Similar to charging infrastructure, the importance of travel range is dependent on driving behaviour. The longer the usual journeys are, or the further outside city areas a consumer lives, the greater the importance of travel range. (Thiel et al. 2012; Testa 2017). If the daily travel consists of short travels to work and back, even a shorter travel range will probably suffice. However, as the distances grow, the need for a longer travel range grows as well.

Electric vehicles are also sensitive to weather conditions and drive terrain; under very low temperatures, the effective travel range can drop up to 30 % of the nominal value (Testa 2017; Trafi 2018a). This increases the importance of travel range for people who live rural areas and face extreme conditions more often (Thiel et al. 2012). In Finland, winter usually last 110-190 days (Ilmatieteenlaitos 2018) and cold weather is not uncommon. In this regard, the sensitivity of travel range to cold weather can be quite alarming for many consumers, and as mentioned it was in fact the fourth biggest barrier to BEV purchase in Kesko's questionnaire.

Lastly, what follows from the shorter travel range and novel charging possibilities is that the charging behaviour will be significantly different from what consumers are accustomed to (McKinsey 2014). It may take even several hours for an EFV driver to get a battery fully charged, but it can be done when the driver is at home or at work. This will naturally compensate the time loss that comes from vehicle charging (McKinsey 2014). On the other hand, however, this highlights the importance of having a charger at home; otherwise consumers might experience high range anxiety.

The other aspect to the changed charging behaviour is the frequency of charging (McKinsey 2014). Due to shorter travel ranges, electric vehicles need to be charged more frequently than conventional vehicles need refuelling (McKinsey 2014). This also calls for having those novel charging availabilities, and fast charging points, in place so that the barrier to adoption will not become insurmountable. This effect will, however, become less important over time, as the travel ranges of electric vehicles increase (McKinsey 2014).

4. EFV POLICIES AND MARKET INCENTIVES

4.1 Governmental policy instruments

In order to induce early adoption of EFVs, policies are needed to mitigate the financial and functional risks that are related to EFVs (Sierzchula et al. 2014, Knupfer et al. 2017). They can be implemented through incentives, investments, or sanctions; targeted at consumers, organizations, manufacturers or the fuel industry; and they can be applied locally in a specific city or more widely in a whole nation (Bosshardt et al. 2007; Walther 2010; Langbroek et al. 2016).

Laukkanen & Sahari (2018) list six policy instruments that are targeted primarily to consumers and can be used to assist EFV diffusion; vehicle taxation, fuel taxation, purchase subsidies, investments in infrastructure, use-based benefits, and information campaigns. Here, *vehicle taxation* refers to a vehicle tax that is based on greenhouse gas emissions, but the policy can also be targeted to the value added tax. Both taxes are paid at the time of purchase, so decreasing or removing them will lower the purchase price of an EFV. (Laukkanen & Sahari 2018) As defined by Langbroek et al. (2016), it is a purchase-based incentive that decreases the fixed cost of EV-use.

Fuel taxation is a policy instrument that not only affects the driving behaviour of ICEVs, but also encourages consumers to move towards low emitting vehicles (Laukkanen & Sahari 2018). The higher the tax in combustion engine fuels, the lower the relative cost of recharging appears to consumers, and the more attractive EFVs may appear. Contrary to vehicle taxation, fuel tax benefits are use-based incentives that decrease the marginal cost of EV usage (Langbroek et al. 2016).

Purchase subsidies refer to point of sale grant incentives that are given to consumers when they buy a vehicle (Sierzchula et al. 2014; Langbroek et al. 2016; Hardman et al. 2017). It can be either a monetary discount, according to Hardman et al. (2017) ranging from $2000 to $20 000; a right to deduct costs in taxation; or it can be a conditional discount that is given when scrapping an old vehicle (Laukkanen & Sahari 2018). Following the categorization above, purchase subsidies are purchase-based incentives, despite the form in which they are given.

Use-based benefits consist of incentives such as free parking in cities, exemption from congestion fees, and a right to use bus lanes (Testa 2017; Laukkanen & Sahari 2018). Their monetary benefit is indirect, but their total amount can add up to even thousands of euros a year (Laukkanen & Sahari 2018). They are premised on the fact that consumers value their time and do not want to sit in traffic or spend time searching a parking space (Testa 2017; Laukkanen & Sahari 2018). In this regard, use-based benefits may be highly efficient in cities where there are lots of traffic, but in sparsely populated areas they may not be as relevant.

The attractiveness of EFVs is closely connected to the availability of charging points (Laukkanen & Sahari 2018). As travel ranges of electric vehicles are still lower than those of conventional vehicles, consumers may be forced to change their driving behaviour and experience range anxiety (Melliger et al. 2018). It can be mitigated by investing in public charging infrastructure (Harrison & Thiel 2017). Investments can be used for building different kinds of stations; slow charging stations that can be used e.g. during night time or working hours, or fast chargers that require roughly half an hour to charge 80 % of the battery (McKinsey 2014) and are therefore more comparable to conventional gas stations.

In comparison the former four policy instruments, *infrastructure investments* do not necessarily deliver any financial benefits to consumers, but they do mitigate functional risks that are associated with EFVs. In this regard, they are neither purchase-based nor use-based incentives, and they mainly deliver functional value to a possibly wider audience.

Lastly, Laukkanen & Sahari (2018) recognize information campaigns as a policy instrument. They state that uncertainty and suspicions among consumers can form a barrier to EFV adoption. Further, as long as there are so few EFVs on the streets, consumers cannot compare, for instance, statistics of EFV performance or resale value to those ICEVs. (Laukkanen & Sahari 2018) By heavily educating consumers about EFVs, their attitudes towards the new technology can be changed (Liimatainen et al. 2018). This has also been noted by other studies, such as Hardman et al. (2017).

Similar to infrastructure investments, *information campaigns* do not provide financial benefits to consumers, but can mitigate perceived functional risks. For example, according to Green et al. (2014), the majority of travels done in New York could already be done solely on electric drive. Mellinger et al. (2018) also claim that over 90 percent of travels could be done on electric drive in Finland and in Switzerland, provided that home charging was available. But if the common perception is that electric travel ranges are short and consumers experience range anxiety, they are unlikely to purchase an electric vehicle. By educating consumers about the performance of electric vehicles, such a barrier could be removed.

The policy instruments listed above can be seen as *carrots*; they persuade consumers to move towards greener vehicles by providing financial or functional benefits, or by mitigating risks, at the very least. An alternative to such instruments is to use *stick*; in this context, to use sanctions or even prohibitions. According to Walther et al. (2010), the state of California has set strict regulations to increase the sales share low and zero emission vehicles (ZEV), and similar regulation has thereafter been adopted in 13 other states as well. Car manufacturers have to pay high penalties if they do not comply state's emission regulations. Compliance is assessed using credits in two categories; GHG credits that are compared annual GHG targets, and ZEV credits that follow compliance of ZEV sales targets. In both cases, failure to meet set targets results in negative credits that must be compensated in 5 or 3 three years, respectively. If no correction is done within that time period, the manufacturer will be sanctioned a civil penalty $5,000 for each remaining credit that are short from target. (Walther et al. 2010)

The necessity to sell a certain number of ZEVs annually means for a car manufacturer that they not only have to produce products consumers would like to buy, but also market them. In other words, sanctions set to manufacturers may appear to consumers as a more diverse model selection and/or as more intensive marketing efforts.

The most aggressive policy instrument a government can use is to set a ban for certain type products. Such plans have been reported by United Kingdom, France, and China, who are planning on banning internal combustion engine vehicles in the near future (Melliger et al. 2018). Evidently, this would mean that car manufacturers have to start investing in product development and prepare themselves for a radical shift in three big markets. For consumers, this would mean that they are forced to get acquainted with EFVs and other alternative drive-trains.

4.2 Commercial measures

While most policies and incentives are primarily introduced by the government, car manufacturers and the fuel industry can also take measures to support technological diffusion (Bosshardt et al. 2007). That is, apart from taxation and prohibiting actions, all measures discussed in the last chapter could be taken by the fuel industry or car manufacturers as well (Bosshardt et al. 2007). For instance, car manufacturers can give their own purchase subsidies to consumers when they buy an EFV and thereby support the EFV diffusion (Bosshardt et al. 2007), and they are already doing so in Finland (see chapter 4.5); in every purchase subsidy (paid at the time of writing), there is a governmental share and an industry share that are combined into one discount that is given to a consumer buying an EFV. Likewise, the fuel industry can encourage consumers to buy or convert their vehicle into a biogas car and then give them their own discounts. This is also an action already witnessed in Finland, as Gasum offered a fixed price campaign for biogas (Gasum 2018).

Commercial organizations can also invest in charging infrastructure, as it may evolve into a profitable business as the industry matures. Such behaviour has occurred in Finland, as grocery chains are investing in a building charging network in Finland (ABB 2018; Kesko 2018b). This is likely to be beneficial all parties; a wider charging network can relieve range anxiety, provide new business areas to commercial organizations, while also helping the government to achieve their environmental targets.

Car manufacturers and the fuel industry are also important in terms of marketing EFVs and other green alternatives (Bosshardt et al. 2007). That is, a government probably cannot market new vehicles that are introduced to the market, but the car manufacturers themselves can. In this regard, they can help in increasing awareness and exposure to

EFVs. In a similar fashion the fuel industry can educate consumers about new drive fuels. (Bosshardt et al. 2007)

4.3 Effectiveness of policies

According to Langbroek et al. (2016), incentives are efficient they considerably increase the likelihood of buying an EFV; otherwise they are merely redistribution of income. Generally, policies do contribute EFV diffusion and numerous studies have concluded that they are vital for EFV diffusion (e.g. Shafiei et al. 2012; Sierzchula et al. 2014; Pasaoglu et al. 2016), but it is not self-evident that all policies would work equally well in different situations and in different nations (Harrison et al. 2017). Further, as noted by Sierzchula et al. (2014) and Benvenutti et al. (2017), even with policies the growth of EFV shares can be slow and uncertain. In other words, policies cannot guarantee that the diffusion will be successful.

Hardman et al. (2017) studied the evidence of the effectiveness of financial incentives and found that purchase incentives are the most effective when they are applied upfront. Tax exemptions were found to be particularly effective, but even with them there is a risk of premature removal of policies, which can halt the diffusion. They state that once the diffusion has reached late majority of potential adopters, subsidies can be gradually removed, but premature removal can be harmful. Further, they recognize that financial policies are most effective when applied with high taxation on ICEVs and together with information campaigns. (Hardman et al. 2017)

Shepherd et al. (2012) and Pasaoglu et al. (2016) also recognize the importance of subsidy duration and state that premature removal of subsidies can make the share of PEVs crash, despite a promising start. Shepherd et al. (2012) also found that the target of purchase subsidies matter; if both PHEVs and BEVs are subsidized, PHEVs are likely gain more advantage. Kangur et al. (2017) also noticed this and further stated that if only BEVs are subsidized, their share will grow more while PHEVs will grow almost equally well; other benefits can compensate the removal of subsidies.

According to the Shepherd et al. (2012) and Pasaoglu et al. (2016), one of most important factors in determining EFV success is the marginal costs of ICEV usage; i.e. annual taxation and gasoline prices. This is line with the conclusion of Laukkanen & Sahari (2018) that taxation is an efficient policy instrument; as mentioned, it not only encourages consumers to move towards alternative drive-trains, but also affects the driving behaviour of ICEV drivers.

Sierzcula et al. (2014) studied the effects of different policies using data from 30 countries and regression analysis. They found that the number of charging points per thousand residents explained market share growth the best; its effect was twice the size of 1000€ purchase subsidy. However, a totally opposite opinion is presented by Green et al. (2014), how claim that range anxiety is one of the underlying market biases in the EFV market.

They claim that for example in the New York, virtually all travels could already be done using electric drive, provided that home charging is available. In this regard, they conclude that range anxiety is more psychological barrier than physical and, thus, using millions of dollars in infrastructure investments is a waste of capital. Such differences in opinions support the conclusion of Harrison et al. (2017) that there may be different kinds of needs in different countries.

Kangur et al. (2017) found that the effectiveness of policies is *path dependent*; if purchase subsidies are introduced before charging infrastructure is built, their effect is smaller than if the two implemented the other way around. Testa (2017) presents similar conclusions and notes that the effectiveness of policies is connected to the phase of adoption. When consumers are first introduced to EFVs information campaigns and marketing are highly important. Once consumers are aware of the option, they should be encouraged to consider them as relative alternative to ICEVs. The means for this can be purchase subsidies and/or tax exemptions. Simultaneously, practical barriers and risks still exist and those can be mitigated by investing in charging infrastructure. (Testa 2017)

As the discussion above illustrates, the effectiveness of policies is not self-evident and may differ between contexts. This complements to the importance of the present study. Further, the effectiveness may be affected by the order in which policies are implemented, thus, it may be path dependent. This, in turn, underlines the applicability of system dynamics as method to study system behaviour, since path dependency is one of the key characteristics of dynamic systems (Sterman 2000, p. 22).

4.4 Norwegian policy portfolio

As mentioned in Chapter 1, Norway is the only country to date that has been able to reach stable growth of the electric market. In 2016, roughly 20 of new vehicles sold were already electric vehicles (McKinsey & Company 2018). It is noteworthy, however, that this has taken more than two decades; in Norway, first policy measures were already taken in 1990, when the country removed purchase fees from electric vehicles (Government bill 156/2017). For an average priced car, say Volkswagen Golf, such discount would add up to 6 000€-9 000€ (Figenbaum 2017). Thereafter, the country has broadened its policy portfolio through numerous actions, such as free municipal parking, free road tolls, access to bus lanes, and additional tax exemptions (Figenbaum 2017; Testa 2017). According to Figenbaum (2017), financial benefits of these policies for a consumer could add up to a couple thousands of euros; for instance, road tolls in some parts of the nation can exceed 2,500€/year; annual license fee ranges for a BEV is around 50€ while 350-410€ for an ICEV; and a 25 % VAT exemption for the Volkswagen Golf would mean roughly 5,000€ (Figenbaum 2017). And, in addition to the financial advantages, the consumer can avoid traffics and find parking spaces more easily (Figenbaum 2017).

All market incentives and policies that have been introduced to the Norwegian market are listed below, in Table 2.

Table 2. Norwegian BEV policy history (adapted from Figenbaum 2017 & Testa 2017)

Year	**Incentive**
1990	Exemption from registration tax
1996/1997/2004	Reduced annual vehicle license fee
1997	Free road tolls
1999	Free municipal parking
2000	50 % reduction on company car tax
2001	25 % VAT on purchase
2003/2005	Access to bus lanes
2009	Reduced rates on ferries, Financial support for charging stations
2011	Financial support for fast charging stations
2015	Exemption from VAT on leasing contracts

As stated by Testa (2017), because of the tax exemption established in the beginning of this century, the choice of an electric vehicle may have halved the price paid for a vehicle. Evidently, these have been the most important financial policies in inducing EFV diffusion, as the country has not offered any direct purchase subsidies, unlike many other countries in the European Union (Testa 2017; Eafo 2018), and public infrastructure investments were not made until 2009.

Norway uses a polluter pays principle, or *bonus malus* (Melliger et al. 2018), in vehicle taxation, which has also, in part, enabled the lighter taxation on electric vehicles (Hardman et al. 2017; Testa 2017). The country supports also PHEVs and HEVs – plug-in hybrid vehicles are granted with a 26 % tax exemption on a mass- and power-based tax, while HEVs receive a similar discount but counting only 5 % (Government bill 156/2017) – while ICEV drivers pay higher taxes (Hardman et al. 2017; Testa 2017). The long-term strategy for transportation builds upon BEVs and PHEVs, HEVs, and biofuels are considered merely as a short- to mid-term transition means (Testa 2017). Having said that, according to Testa (2017), hydrogen vehicles can also be a valid option once the technology has matured enough.

While many countries in Europe have just introduced policies and market incentives, Norway is already planning on removing subsidies (Government bill 156/2017). By 2025, there should no longer be active subsidies and first measures are presumably taken already in 2018-2019 (Government bill 156/2017), as the decision making regarding local policies, i.e. access to bus lanes and municipal parking, is moved to local governments as of 2018 (Testa 2017).

Reflecting to the discussion in Chapter 4.3, the gradual removal of subsidies seems realistic, as the market growth is starting to stabilize. This might indicate that the early majority of adopters is reached and, thus, the removal of external factors would not result in boom-and-bust behaviour.

4.5 Current state in Finland

Prior to large-scale introduction of PHEVs and BEVs to the consumer market, and in the infancy of HEVs, the earliest measures taken were targeted to vehicle taxation. In the beginning of the century diesel and gasoline vehicles were the only ones in the market, thus, vehicle taxation was also grounded to those types of vehicles. Vehicle tax was determined using comparison tax percentages that, in turn, were based on the car brand and vehicle model (Tax Administration 2018). If no comparison tax for a particular model was determined, the tax would be based on fuel type (Tax Administration 2018). There were two tax percentages; one for diesel vehicles and one for all others (Tax Administration 2018), and the tax percentages were 30,0 and 29,0, respectively.

The law was in force until 2003, when the basis of comparison tax was reformed to include other drive-trains, power of the vehicle, and the body style of the vehicle (Tax Administration 2018). For an average sized, affordably priced vehicle this induced a slight decrease in taxation.

A new law came into effect at the same time the Finnish government introduced its strategy for reducing emissions (Tax Administration 2018). In the new law, vehicle tax was primarily determined based on CO2-emissions. From that time on, the Finnish vehicle taxation has started to resemble the bonus malus principle applied in Norway; taxation became cheaper for vehicles with lower emissions, while the tax pressure moved more directly towards high emitting vehicles. The exact percentages have evolved gradually, and by the time the Government updated its climate strategy, a clear distinction in vehicle taxation could already be seen (Tax Administration 2018).

The most recent reform in vehicle taxation came into effect in September 2018, when the measurement method of fuel consumption and CO2 emissions was changed. Transition from the old NEDC measurement procedure to the new WLTP will take place gradually and come fully into effect by 2021 (Trafi 2018a). The new measurement procedure is supposed unify measurement policies around the world and it captures the consumption profile and thereby emissions more realistically than its predecessor (Trafi 2018a). Measurement rates with the new procedure will be generally higher – for an average-sized ICEV by a factor of 1,21 – which results into higher taxation (Government bill 74/2018). This will be compensated with an additional factor for vehicles whose emissions are over 110 g/km, but even with that the new legislation will further highlight the polluter pays principle. The reform will not have an effect on the existing vehicle fleet, and vehicles that were bought before September 2018 would still use the old procedure (Trafi 2018a). This resulted in record-braking sales in August 2018 (Autoalan tiedotuskeskus 2018a).

The discussion above is illustrated below, in Figure 10. The percentages are estimated for Hyundai i30 Hatchback, which is considered to be an average-sized and affordably priced vehicle. It is assumed that such car would emit 150 g/km and, for simplicity, only gasoline version of the vehicle was considered. *This served also as a basis for parametrization of the model*, which is discussed in further detail in Chapter 6. The use of Hyundai as a proxy was reasoned with the fact that in today, medium-sized and -priced Hyundais are available in all drive-train categories of interest, thus, it would be possible to use BEV, PHEV, and HEV versions of alike vehicles to illustrate the differences in taxation. This would also allow benchmark price development of vehicles (see chapter 6) to real their values today; i.e. how much should a BEV Hyundai retail for in 2018.

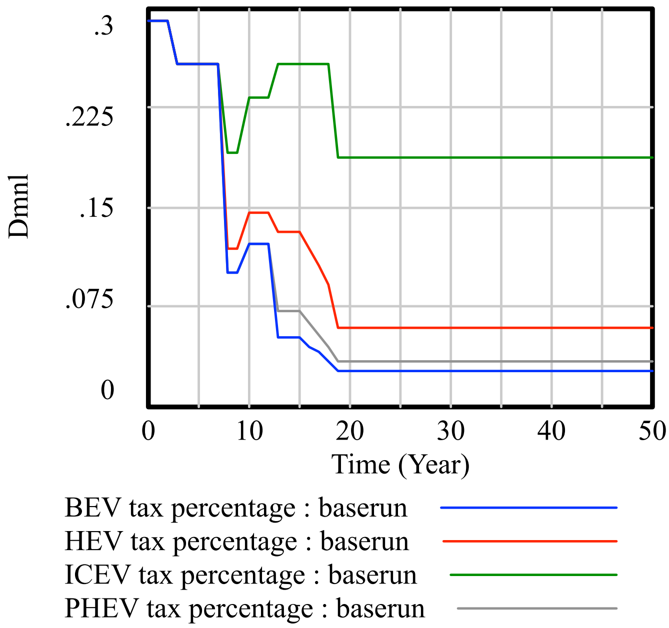

Figure 10. Drive-train taxation for medium-sized vehicle

In addition to the non-recurring vehicle tax, a Finnish car owner pays an annual tax that is comprised of two parts; a base tax and a motive power tax (Ministry of Finance 2018). The former is an annual tax that is paid either on the basis of CO2 emissions or vehicle weight, if emissions are not reported (Ministry of Finance 2018). The latter, in turn, is a tax that is paid on the basis of drive-train, the number of days the vehicle has been in active use, and the weight of the vehicle (Ministry of Finance 2018). For instance, a BEV driver whose vehicle has been in active usage for a whole year pays 1,5 cents/day times 365 days or 5,475 euros per every 100kg the vehicle weights, while an ICEV driver with a diesel vehicle pays 5,5 cents/day times 365 days or 20,075 euros per 100kg. The corresponding figures for hybrids are 0,5 cents per day for a gasoline hybrid and 4,9 cents per day for a diesel hybrid. Gasoline ICEVs do not pay any motive power taxes. (Ajoneuvoverolaki 1281/2003; Ministry of Finance 2018)

The WLTP reform affects also the annual base tax as it changes the emission rate of a vehicle. Prior to the reform, the medium-sized gasoline vehicle with 150 g/km emissions would pay approximately 225 euros a year (Ajoneuvoverolaki 1281/2003, Verotaulukko 1). After the reform, the corresponding emission figure would be approximately 182 g/km (Government bill 74/2018) and equal to a tax of 250 euros a year (Ajoneuvoverolaki 1281/2003, Verotaulukko 1A).

Third tax instrument the Finnish government has used to influence the driving behaviour is fuel taxation. In Finland, fuel taxes can have more than doubled the price of diesel, and more than tripled the price of gasoline. This is illustrated below, in Figure 11, with 95 octane gasoline prices from 2000 to September 2018.

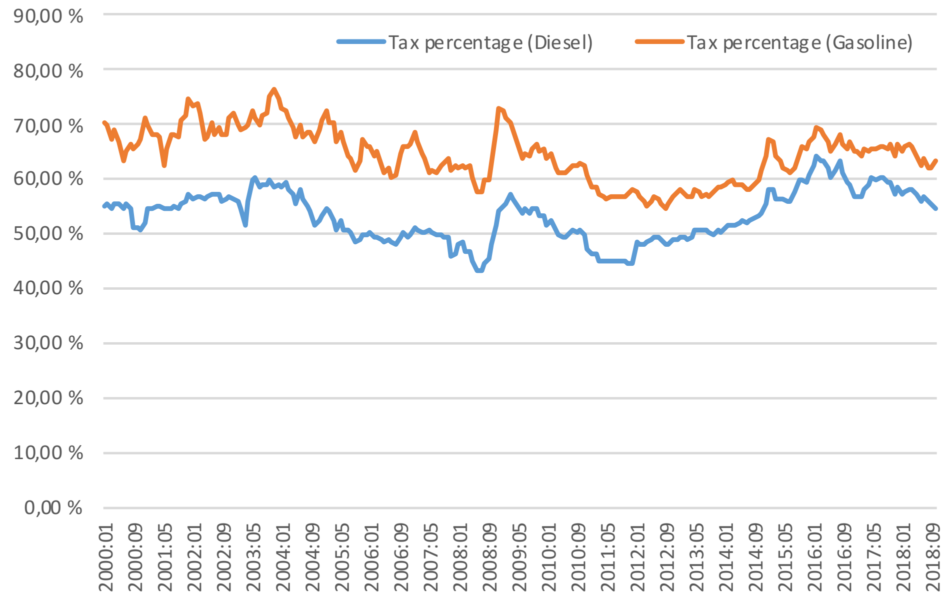

Figure 11. Fuel tax percentages in 2000-2018/Q3 (Oil and Petroleum Association 2018)

The Finnish government has also implemented its own set of policies in order to induce EFV diffusion. First initiatives were established in the Energy investment program in 2011 (www.sahkoinenliikenne.fi), when approximately 10 million euros were budgeted for subsidizing chosen organizations in building charging infrastructure and leasing electric vehicles as company cars. The government supported participating organizations with 35 % share of charging investments and offered a financial aid of 30 % for the capital share of leasing expenses (www.sahkoinenliikenne.fi/energiainvestointituki). The program was initially planned to last two years, but in 2013 the Ministry of Employment and Economy extended the program till the end of 2017 (www.sahkoinenliikenne.fi/energiainvestointituki).

In 2016, the Ministry of Employment and Economy decided to extend the program again and allocated 4,8 million euros for developing public charging infrastructure in Finland as a part of *Biotalous ja puhtaat ratkaisut* -program in 2017-2019 (Ministry of Employment and Economy DNro 609/521/2016; www.sahkoinenliikenne.fi). The government plans that the program will induce 15 million investments from commercial actors, which would triple the number of public charging points during the time frame (www.lataustuki.fi). The funds are invested so that both fast and slow charging points each get 50 %, i.e. 2.4 million euros, and the shares of total building costs are 35 % and 30 %, respectively (www.lataustuki.fi).

Since the energy investment program subsidizes only commercial organizations in terms of charging infrastructure, the government has also budgeted a separate fund for housing cooperatives and condominiums (www.lataustuki.fi; The Housing Finance and Development Centre of Finland 2018). In 2017, the Housing Finance and Development Centre of Finland, or Asumisen rahoittamis- ja kehittämiskeskus (ARA), budgeted 1,5 million euros that will be granted for housing co-operatives, condominiums, and alike organization that are willing to build charging points for their residents (The Housing Finance and Development Centre of Finland 2018). Such organizations can apply for a subsidy during the calendar year of 2018 and it will cover 35 %, or 90 000€, of the total expenses (The Housing Finance and Development Centre of Finland 2018). A requirement for the subsidy is that the organization must build charging points for at least five vehicles (The Housing Finance and Development Centre of Finland 2018).

At the same time, another measure was taken in 2015 when the Finnish government spent eight million euros in total for scrapping bonuses that were admitted as part of the national scrapping program (Government bill 251/2014). The goal of the initiative was to induce renewal of the relatively old vehicle base, and to get consumers to buy lower emitting vehicles (Government bill 251/2014; Government bill 156/2017). Admission requirements were that a vehicle owner would have to deliver a vehicle with at least ten years of age to an official scrapping operator and to buy a vehicle whose emissions were less than 120 g/km (Government bill 251/2014; Government bill 156/2017). At the time, average emissions of a vehicle were 130 g/km, so to get the bonus, consumer would have to buy either a small ICEV or an AFV (Government bill 251/2014). Afterwards the Finnish government concluded that the program increased notably the sales of small ICEVs (Government bill 156/2017).

In 2018, the Ministry of Transport and Communications started another scrapping bonus program that lasted till the end of September 2018 (Ministry of Transport and Communications 2017). This time, the bonus was either 2 000€ or 1 000€, depending on the type of the new vehicle (Ministry of Transport and Communications 2017). The limit for low emission vehicles was lowered to 110 g/km, thereby inducing AFV purchases more directly (Ministry of Transport and Communications 2017). The government supported the purchase of a BEV, PHEV, ethanol, or gas vehicle with 2 000€ per vehicle, while HEVs and other vehicles below the aforementioned emission limit received a 1 000€ support per vehicle (Ministry of Transport and Communications 2017). Further, the automotive industry added another 500€ to the scrapping bonuses (www.romutuskampanja.fi/romutuspalkkio).

The Ministry of Transport and Communications ruled in the same law that the government will support BEV purchases with a direct purchase subsidy of 2 000€ (Ministry of Transport and Communications 2017). Subsidies are granted in 2018-2021 and are planned to double the number of BEVs from the level of 2017 (Government bill 156/2017). The purchase subsidy could not be combined with the scrapping bonus and it is only admitted to private persons who purchase or leases a BEV that costs less than 50,000€ (Government bill 156/2017).

Third subsidy that was ruled in the same law was conversion support for gas and ethanol vehicles. In 2018-2021, a consumer who convers his/her vehicle into a gas or ethanol vehicle will receive a 1 000€ or 200€ support, respectively (Government bill 156/2017).

The government budgeted eight million euros for scrapping bonuses and 24 million euros for conversion and purchase subsidies (Government bill 156/2017). It believes, however, that less than four million euros is actually needed for purchase subsidies to meet the target of 1 875 new BEVs (Government bill 156/2017), thus there may be less subsidies available for BEV purchases if goals are met earlier.

Lastly, the Finnish Transport Safety Agency Trafi started an information campaign called *Ole edelläkävijä* (Be a forerunner) in the fall of 2017, which goal is to educate consumers about alternative fuel vehicles (Trafi 2017). They provide information about differences in drive-train technologies, taxation of fuel types, charging requirements and infrastructure, etc. EFVs have also gained a little momentum in mass media during last recent years (Melliger et al. 2018), which also an important means of information campaigns.

4.6 Summary

There are various policy instruments that can be used to induce EFV adoption among consumers. They can be implemented by different stakeholders, they can have different purposes and locus, and they can be introduced to the market at different times along the diffusion lifecycle. Their importance in EFV diffusion is evident, but it is not as clear that all policies would work equally well in all countries and at all times.

Norway has been the global forerunner in transportation electrisation. The Norwegian government has implemented its first policies already in 1990s, and nowadays it appears that the growth has reached a stable state and the government can start to cancel certain subsidies. The most important policies have been the generous tax exemptions that can have halved the price of an electric vehicle. The country has never offered direct purchase subsidies and has applied the bonus malus principle, where the more polluting vehicles account for a bigger share of the country's tax revenues.

In Finland, multiple stakeholders have also taken their measures to induce EFV adoption among consumers. The government, together with the car manufacturing industry, has offered direct purchase subsidies to EV buyers, enacted favourable taxation to EFV drivers, started an investment program, and also through public organizations it pursues to educate consumers about electric vehicles. However, regarding the findings of other studies, there are a couple of aspects in the Finnish policy portfolio that are slightly alarming. First, during a scrapping program, not only BEVs can receive purchase subsidies, but also PHEVs, HEVs, and even small ICEVs can receive financial aids for buying a new vehicle. While this likely to be very useful in terms of GHG emission reductions, it will also hinder the transition to BEVs. Second, infrastructural investments have favoured commercial organizations until recently, when ARA started to also admit financial aid to condominiums. While on one hand this reasonable, one could question whether some of those funds could been offered to housing organizations and condominiums earlier. Lastly, it appears that use-based policies have not been widely adopted: the city of Helsinki has offered a 50 % discount in charging for low emitting vehicles, but those vehicles include virtually all categories with sufficiently low emissions, not just EFVs (Helsingin kaupunki 2018). Other than that, it seems that no use-based policies have been widely applied, as for example in Norway (Testa 2017). In this regard, they are not also considered in the present study. This will be further argued in Chapter 6.

5. VEHICLE MARKET DYNAMICS

5.1 Dynamic systems

In a dynamic system, the state of the system evolves as the time progresses (Sterman 2000, p. 22). Changes can occur in various time scales: something that is seemingly stable or unchanging might actually evolve, but just over a longer time horizon, while another change can be more easily and quickly observed. (Sterman 2000, p. 21-23; Law 2015, p. 1).

The effect of time is also present in time delays, as mentioned in Chapter 2. When an output lags behind its input, the difference is accumulated into stock, which represents a delay in the system. Delays are the cause of instability in systems and they give rise to oscillatory behaviour. They are also the reason why decision making in dynamic systems is challenging and why they tend to be characterized by trade-offs: due to delays in feedback systems, the long-term response of a system to an action initiated by an actor is often different from its short-term response. (Sterman 2000, p. 21, 411)

Dynamic systems are also adaptive; actors within the system learn over time, as they gain experience. They modify their decision rules accordingly and in interaction to the actions of others. This underlines the fact that dynamic systems are often governed by several feedback structures. Further, this implies that such systems tend to be self-organizing; the behaviour of systems arises endogenously which generates patterns in time and space and can create path dependence. (Sterman 2000, p. 22)

Path dependence can occur is systems that are dominated by reinforcing feedbacks. As defined by Sterman (2000, p. 350), path dependence is: "a pattern of behaviour in which the ultimate equilibrium depends on the initial conditions and random shocks as the system evolves." In such systems, small and unpredictable events early on can have significant impacts on the final state of the system. Especially, in systems where the equilibrium is unstable, the initial perturbation can lead to a lock-in, where it can become extremely difficult to reverse that development. (Struben 2000, p. 350-352)

All aspects above give rise to complexity in a system, which then manifests itself through non-linearities, counterintuitive behaviour of the system, and policy resistance of the actors within. Due to the fact in complex systems, there are numerous actors that participate in decision making, all of which interact, the effect is rarely proportional to the cause (Sterman 2000, p. 22). Further, as those effects may be far in time and/or space, the complexity of the system can be overwhelming and prevent actors from making efficient decisions (Sterman 2000, p. 22). As stated by Sterman (2000, p.22), this can lead us to focusing on symptoms rather than underlying causes and presenting solutions to seemingly obvious problems that actually make the situation even worse. Such *counterintuitive effects* are discussed later in this chapter.

Regarding the context of the present study, there are clear dynamic features in the EFV system. Firstly, as noted by Testa (2017), there is considerable inertia in the system: consumers may take days to form an opinion or change their habits; regulation can take up to months; while improvements in infrastructure can take even years. Secondly, as noted by Struben (2006), the system is distributed in several ways. There are numerous stakeholders that each have their own perceptions and possibly conflicting goals, the adoption population is distributed and heterogenous in physical and socio-economic space, and there are many alternative technologies that serve the same purpose. (Struben 2006) Thirdly, there are many relationships that are non-linear by nature. For instance, in the early stages of EFV diffusion when there are only few charging stations, adding one or two more will not deliver that much value to a consumer, but as the number of charging points grows, also their importance grows until it saturates again once there are enough charging points (Struben 2006). A somewhat similar non-linearity can be found in consumers' perception of attractiveness, as implied in Chapter 3. That is, when making decisions under risk and uncertainty, consumers use heuristics and rules of thumb rather than analysis as a basis for the decision, which can lead to biases and "false assumptions". In particular, they tend to behave differently when risking losses or seeking gains: if a consumer would lose 100€ from whatever they versus he/she would win an additional 100€, those changes in wealth would be evaluated differently (see Chapter 3; Kahneman & Tversky 1979). It is reasonable to assume that similar non-linearities can be found when a consumer compares an EFV to a reference point, that is, to an ICEV.

Fourthly, as discussed in Chapter 1, there is a zero-sum game between ICEVs and EFVs, as the success of EFV diffusion can only be achieved at the expense of ICEVs. In this regard, Sterman (2000, p. 349-406) has pointed out several cases where competition between technologies has generated path dependency and lead to technological lock-ins. Struben & Sterman (2008) also state that technological lock-in is one of the biggest challenges in technological transitions, and given the long history and well-established network of complementary goods for ICEVs, it seems that we are facing a similar situation right now.

As illustrated above, there are several dimensions in dynamic systems, three of which are discussed in further detail in the following subchapters. Namely, delays that have been recognized in other studies; central causal feedback structures; and counterintuitive effects of policies that can or have been applied.

5.2 Delays

In general, elements in the vehicle system change with long time delays (Struben 2006). Plausibly the most obvious one is the long replacement times of vehicles (Struben 2006;

Shepherd et al. 2012; Testa 2017). According to Testa (2017), the average lifetime of a vehicle in Norway is 18 years. And, according to Autoalan tiedostuskeskus (2018b), the corresponding figure in Finland is nowadays approximately 20 years. This inevitably leads to the fact that market share diffusion is delayed (Struben & Sterman 2008; Benvenutti et al. 2017): even if all vehicles sold next year would be EFVs, ICEVs sold *hitherto* would still be in market for a long time, unless new regulation or scrapping programs are introduced earlier.

Market share diffusion is delayed also due to delays in information diffusion (Walther et al. 2010). That is, as implied in Chapter 3, once a product has been introduced to the market, consumers first have to become aware that a new alternative exists, then they have to be exposed to it with a sufficient intensity in order to familiarize themselves with it before they actually make a judgment and decide to add it to their choice set. According to Testa (2017), there can even be a delay thereafter, as it takes time for consumers to move from *expectations* to *experiences* and build trust towards the industry newcomer. Therefore, even if a comparable product would be launched to compete with ICEVs, customers would not adapt it instantly (Walther et al. 2010).

A similar delay process can also be observed in infrastructure development. That is, as pointed out by Testa (2017), the incentive for commercial organizations to invest in charging infrastructure is dependent on the number of electric vehicles in the market, which, in turn, is dependent on consumers becoming willing to consider an electric vehicle as an alternative. A key driver here is the expected return on investment, which naturally is determined through the number of potential customers. Therefore, if the development of charging infrastructure is market-led, there can be a significant delay before the market is tempting enough for commercial organizations to invest in it. (Testa 2017)

Since ICEVs have been introduced to the market a long time ago and car manufacturers have produced millions of vehicles ever since, they have accumulated experience and learned by doing (Struben 2006; Bosshardt et al. 2007; Struben & Sterman 2008). The effect of learning can push down the costs of electric vehicles and the battery in particular, which can bring EFVs closer to cost parity, as discussed in Chapter 3. The learning by doing, however, can take a notable amount of time, which is why several studies have recognized it as an important delay in the system (e.g. Stuben 2006; Bosshardt et al. 2007; Stuben & Sterman 2008; Shepherd et al. 2012)

Another source of delay in the vehicle system that has been recognized by Struben (2006), Struben & Sterman (2008), and Testa (2017) is the competition between ICEVs and EFVs. As mentioned above, the competition between the two can create path dependency, but it can also delay the diffusion of EFVs, if the relative prices are low and the relative performance is high (Testa 2017). This highlights the meaning of policies and incentives in EFV market diffusion.

Further, the vehicle market is a complex and delayed system in the sense that there can be long time delays before any effects of a decision can be realized (Testa 2017). This is what Sterman (2000, p. 432-434) refers as a reporting delay: if the goal of a policy is to double the number of electric vehicles in three years, it takes three years to measure whether the target was met. This implies that decisions have to be based on estimates or merely historical data, which can be problematic when introducing policies to a new market. Further, as mentioned in the beginning of this chapter, delays are generally long within the vehicle system, which naturally means that reporting delays might also be long.

An illustration of such delay can be found from California, where the state government decided to stipulate civil penalties for car manufacturers if they failed to meet AFV and/or GHG targets (Walther et al. 2010). However, the issue was that they also gave 3-5-year time intervals to failing manufacturers to adjust their sales or emissions, which also means that if a penalty was to be put in place, it would be in a couple of years (Walther et al. 2010).

5.3 Causal structures

Competitive dynamics of the vehicle market are determined by interaction of several feedback structures (Struben 2006). Consumers go through a sales funnel, car manufacturers learn by experience which improves their performance, and infrastructure and other complementary services develop simultaneously (Struben 2006).

These processes can be captured in a model through a set of causal relationships. Depending on the approach and interest of the modeller, some relationships may be excluded, others may be modelled in greater detail, and some may be common across studies.

Causal maps are rarely fully detailed representations of systems, but rather they capture the essence of the problem at hand and serve as a starting point for more detailed modelling. Regarding Chapter 2, such causal representations can serve as a dynamic hypothesis; an initial explanation for problematic behaviour in a system.

As described in Chapter 3, Struben (2006) presented his model in several parts. In his first essay, he describes the process of vehicle adoption by consumers. This particular essay was found highly useful regarding the present study and it draws, in part, on the works of Struben (2006). This is illustrated in detail in Chapter 6.

Struben (2006) models the adoption of a vehicle as interplay of several feedback loops. Most essentially, he decouples the traditional Bass model into different communication channels and further distinguishes the role of non-driver word of mouth. In Figure 12, this forms the *Social exposure* reinforcing loop.

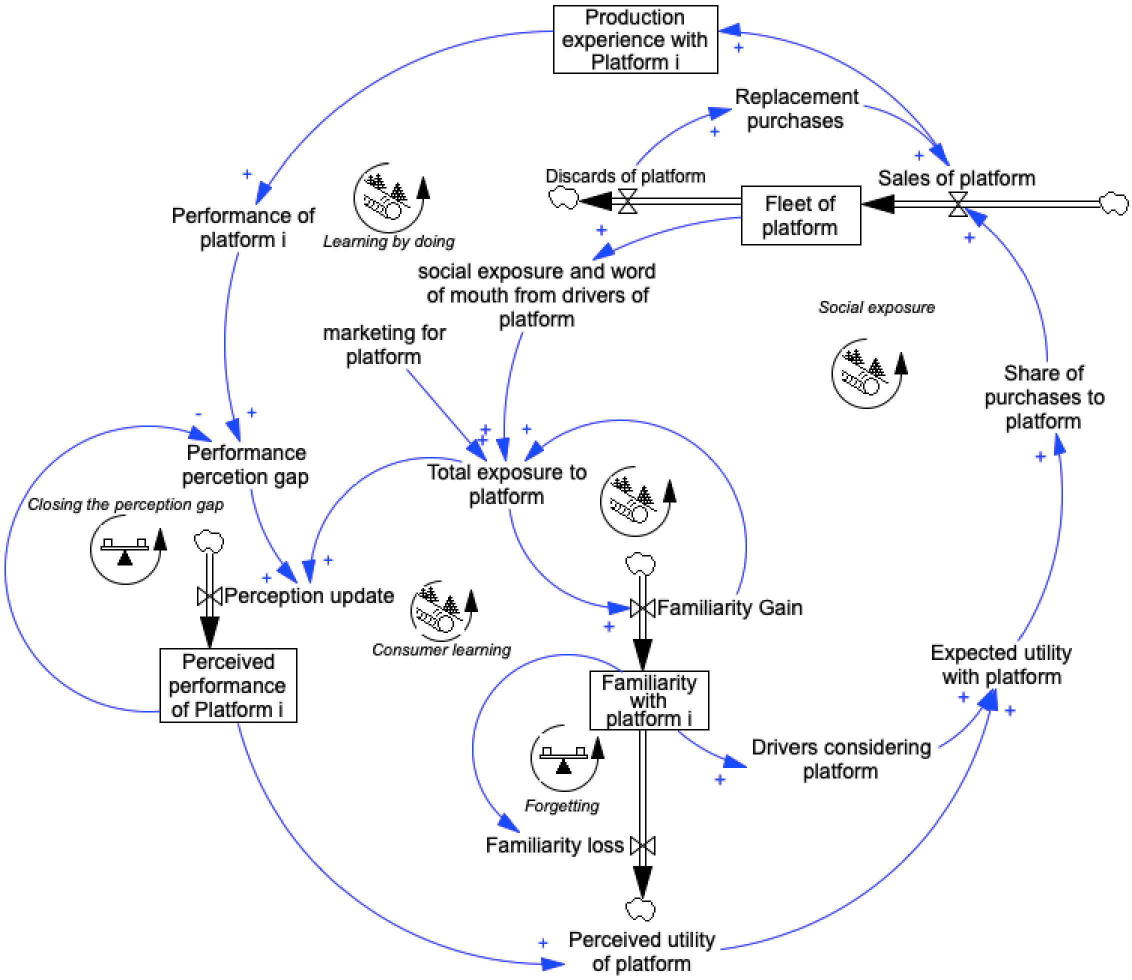

Figure 12. Alternate vehicle adoption in Struben (2006)

The Social exposure loop is not only important in Struben's model, but it has also been adopted by several studies, such as Struben & Sterman (2008), Shafiei et al. (2012), Shepherd et al. (2012), and Harrison & Thiel (2017). It will also be used in this study as a part of Willingness to Consider formation.

The decoupling of communication channels also affects consumer learning. That is, consumers do not directly learn about new products and update their perceptions, but rather, similar to word of mouth, they learn through social interactions and gradually update their perceptions about new products (Stuben 2006). Struben (2006) refers to diesel vehicles and notes that it took years before consumers adjusted their perceptions about the new type of gasoline, even though it is almost the same as the market incumbent.

These reinforcing loops are balanced by the *Forgetting* loop. As stated by Struben (2006) and Struben & Sterman (2008), if the exposure to the new alternative decays, it is likely that consumers will start to forget it, or they fail to keep up with platform development, which can decrease their familiarity with the platform – or Willingness to Consider, as in Struben & Sterman (2008). The phenomenon is often included in more traditional Bass models as well, as done in Sterman (2000, p. 344) and Walther et al. (2010). This is illustrated below, in Figure 13.

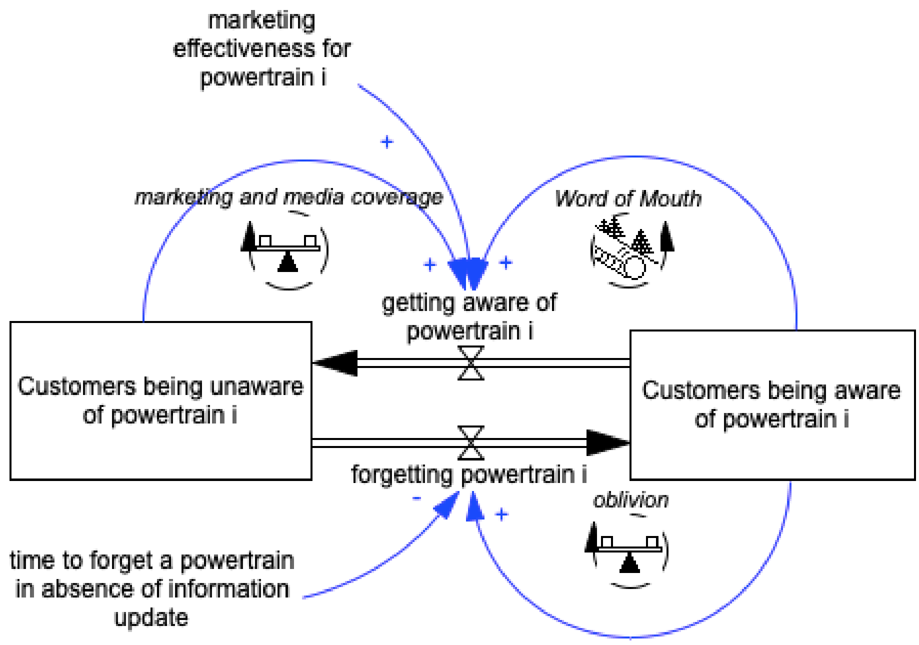

Figure 13. Word of Mouth and oblivion (adapted from Walther et al. 2010)

Regarding the present study and EFVs nowadays, there still exists a gap in platform performance, which is obviously perceived by consumers as well. As the market grows and manufacturers gain experience, i.e. they learn by doing, performance of the platform increases, which further increases the sales and production experiences, and the performance gap gets constantly smaller (Struben 2006). In Figure 12, the effect of learning is captured in the reinforcing *Learning by doing* loop and it is balanced by the *Closing the Perception Gap* loop.

The inclusion on word of mouth, whether that is in its simpler form or as decoupled, is essential in technological diffusion modelling. Sterman (2000, p. 323-346) presents it as one of the most powerful feedback structures driving innovation diffusion. Figenbaum & Kolbenstvedt (2016) have also noted this and state that in EV diffusion, peer-to-peer contact is the main source of information leading to a purchase, since it helps in building trust towards them. This is in line with Rogers (1995, p. 5; retrieved from Straub 2009), as he describes diffusion as a special type of communication where innovations and new ideas spread ideas from individual to individual.

Another essential causal relationship in EFV market dynamics is the Chicken and Egg problem of electric vehicles. That is, the more there are charging points, the more attractive electric vehicles may appear, as consumers can relief their range anxiety (Struben & Sterman 2008; Testa 2017). But, until there are enough electric vehicles on the road, the government, the fuel industry, and car manufacturers may be reluctant to take chances and build a wide-scale network of charging stations (Stuben & Sterman 2008; Testa 2017). A visualization of the dilemma is presented in Figure 14.

As implied earlier, a key driver in infrastructure development is the expected return on investment for charging station suppliers. The more there are electric vehicles on the roads, the more there are potential customers, and the more a supplier can expect returns on investments. This is captured in the *Chicken and Egg* loop, as presented by Testa (2017).

If the initial perturbation is strong enough, the Chicken and Egg loop will generate exponential growth (Testa 2017). However, as mentioned in Chapter 2, a reinforcing loop can also be vicious, if the initial "push" is not strong enough. This, in part, underlines the meaning of policies and subventions. Also, as implied in Chapter 5.1, the number of charging points need not to grow forever. As the desired density of charging stations gets closer, the need for charging points decreases, and so does the number of planned charging points (Testa 2017). This forms the balancing *Closing the Gap* loop, presented below.

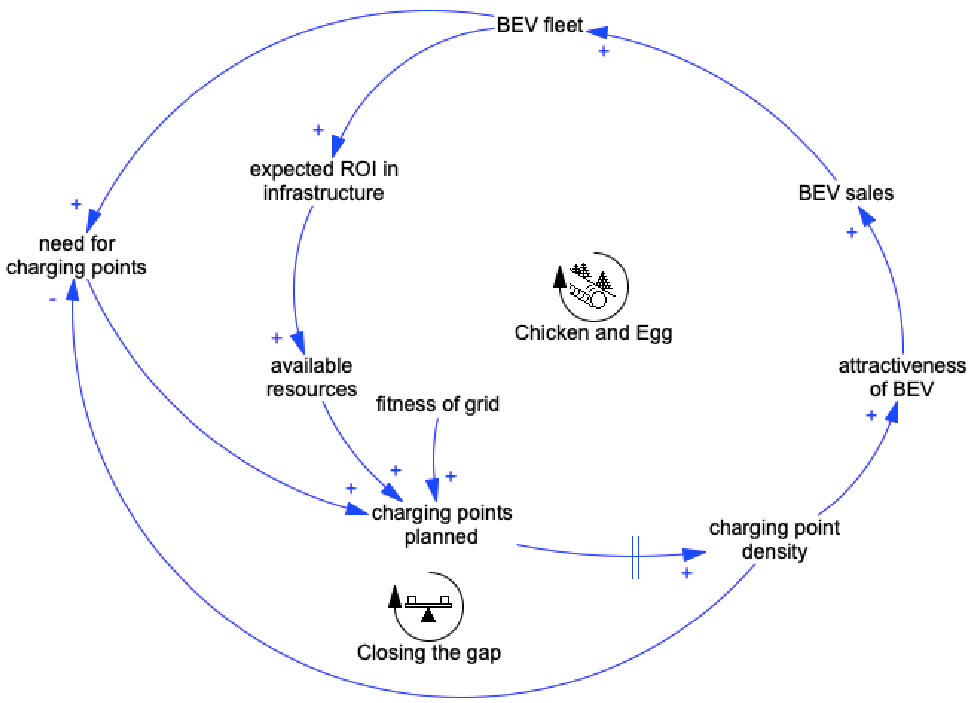

Figure 14. Chicken and Egg (Adapted from Testa 2017)

Regarding Chapter 3 and the mismatch of supply and demand in EV model diversity, there is another Chicken and Egg problem in the market. As noted by Testa (2017), the causal relationship between model diversity and platform attractiveness gives rise to another Chicken and Egg problem, as high model diversity increases the attractiveness of platform; which increases sales; which, again, increases the expected ROI and thereby the incentive to invest in EV production. (Testa 2017) This situation is visualized below, in Figure 15.

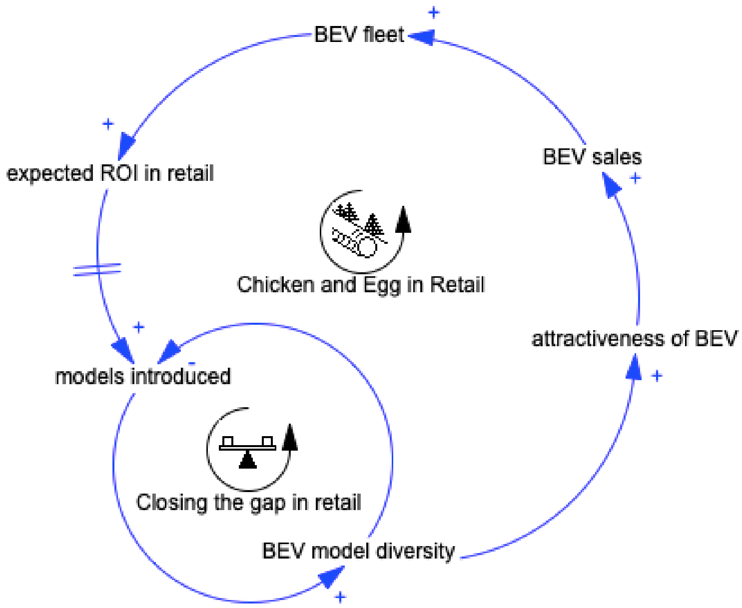

Figure 15. Chicken and egg in retail (adapted from Testa 2017)

Similar to the charging point Chicken and Egg situation, the number of models offered will not grow endlessly. As discussed in Chapter 3, after a certain threshold the likelihood of finding a desired model is already high enough, and the incentive for car manufacturers to keep investing in new model launches decreases. This forms another *Closing the Gap* loop that balances the reinforcing Chicken and Egg loop (Testa 2017).

A generic way to capture goal-seeking behaviour is to present it by means of current and desired states, and gaps between them. This structure appears e.g. in figure 14, and is also visualized a simplified form below, in Figure 16. The structure commonly applied in the present study to capture a gradual development of an attribute. This will be illustrated in Chapter 6.

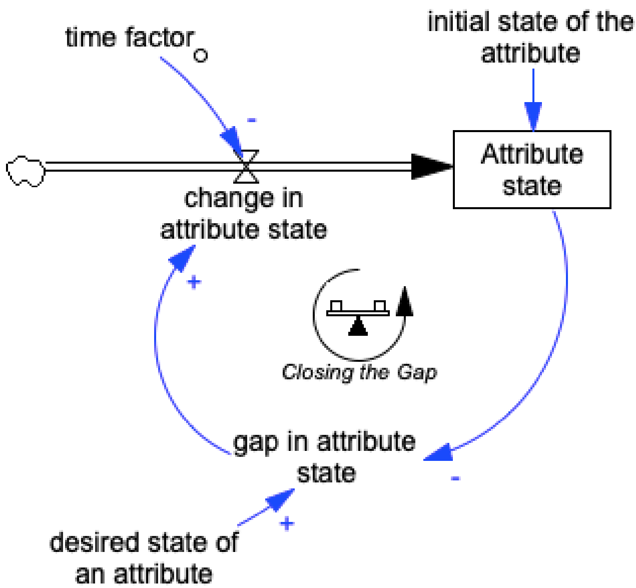

Figure 16. Generic Closing the gap -loop structure

5.4 Counter-intuitive effects

Although there is evidently a place for policies and subsidies in accelerating EFV diffusion, there are studies that have observed counterintuitive effects caused by different policies. Regarding Chapter 5.1, these are one of the most characteristic features of systems with dynamic complexity.

The first observation is that in terms environmental friendliness, combining the best greenhouse gas policy and the best electric vehicle policy may not result in the best overall result (Walther et al. 2010). This observation is based on the study of Wather et al. (2010), who state that policies should not be designed and evaluated in isolation, but rather their synergies and possible contradictions should be noted. This will, according to the authors, lead to best overall results. (Walther et al. 2010)

Struben & Sterman (2008), Shepherd et al. (2012), and Benvenutti et al. (2017) complement this observation by noting that if the target is indeed to reduce greenhouse gases, the focus should not be solely on EFVs. Due to aforementioned long vehicle lifetimes and are lengthy delays, the sole focus on EFV is not likely to yield notable results very quickly. The aggregated share of EFVs in all countries studied in those papers are small and, again, even if every single vehicle sold next year, they would still not account for the majority of vehicle parc. (Struben & Sterman 2008; Shepherd et al. 2012; Benvenutti et al. 2017) In this regard, Shepherd et al. (2012) and Benvenutti et al. (2017) state it could be more efficient, in terms of GHG emissions, to pay also more attention to low emitting ICEVs instead of just pushing electric vehicles to the markets. According to Struben (2006), however, this can hinder the take-off of EFVs.

Another source of counterintuitive behaviour is purchase-subsidies. That is, since electric vehicles are still purchased mainly by Innovators who are on average wealthier, subsidizing electric vehicle purchases can mean re-distribution of income (Langbroek et al. 2016; Laukkanen & Sahari 2018) In this regard, Langbroek et al. (2016) point out that attention should be given to equity effects of such subsidies.

In a similar fashion, cheap taxation on electric vehicles means often that taxes for higher emitting vehicles rise. For instance, the *bonus malus* principle mentioned in Chapter 4, can increase the prices of ICEVs that would otherwise be cheaper than e.g. BEVs, or make gasoline much more expensive for people for whom driving is a necessity (Laukkanen & Sahari 2018). Such situations can hurt people with the lowest income (Laukkanen & Sahari 2018), which probably is not the purpose of any policy or subsidy.

Langbroek et al. (2016) and Laukkanen & Sahari (2018) also point out that through taxation a government can accidently send consumers a false message. That is, if a government lowers fuel taxation, it can be interpreted as an encouragement to drive – not just with green alternatives – but with all vehicles (Laukkanen & Sahari 2018). It would also mean that in order to get the most out of that policy, consumers should drive as much as possible which, again, can be against the overall goals (Langbroek et al. 2016). This also applies with other use-based subsidies: if a city or municipality offers free parking, free ferries, free road tolls, and/or allows the use of bus lanes, drivers should drive in that area as much as possible to achieve the biggest advantage (Langbroek et al. 2016). In this case, however, the city is likely to become congested, public transport can become slower if their lanes are stuck, and free parking is likely to crowd city streets with vehicles (Langbroek et al. 2016).

Lastly, the government will always get its share from somewhere (Shepherd et al. 2012). If there are generous subsidies offered somewhere or to someone, this likely means that something else is going to be more expensive. This is a holistic observation but indicates that governmental policies are also trade-offs between benefits and costs.

5.5 Dynamic hypothesis

The dynamics of a vehicle market are determined as an interplay of several feedback structures, most of which are strong and reinforcing loops. There are also multiple actors within the system that interact and take part in decision making, but who at the same time can have conflicting targets. They affect the development of a market from various perspectives: car manufacturers have a vital role in developing the model offering for consumers, the fuel industry can greatly affect the development of charging infrastructure, the government can decide how big of an external force it wants to direct to the market, and consumers ultimately decide what they want to buy. In this regard, as stated by Struben (2006, p. 3), "Technology transitions require the formation of a self-sustaining market through alignment of consumers' interests, producers' capabilities, infrastructure development and regulations". Testa (2017) complements this by stating that without prospects of an interesting market, many stakeholders may be reluctant to make risky investments that are however needed to make the new entrant appealing to consumers and to avoid the lock-in with the existing technology.

What can be interpreted from the discussion above is that the importance of policy measures is significant. There are long delays within the system, which implies that any notable change is likely to take time if occurring on its own. The system is also dominated by reinforcing loops, which can create path dependency to the system (Struben & Sterman 2008). Depending on the initial perturbation, those reinforcing loops can be vicious or virtuous. This is the part where policies and subsidies manifest their importance: in both Chicken ang Egg -loops, the government can increase available resources through investment programs, or they can mitigate the cost barrier by offering purchase subsidies and tax exemptions and increase the number of EFVs. In the Social exposure -loop, the government can start its own information campaigns, and/or encourage public organizations to educate people about electric vehicles, and thereby increase the exposure to electric vehicles. Regarding the delay in information diffusion and market-driven infrastructure development (Walther et al. 2010; Testa 2017), intensive education and marketing efforts could also induce EFV adoption. Further, this could make the market more interesting for commercial organizations that would then increase their own investments in the market.

6. MODEL DESCRIPTION

6.1 Conceptual model

The model presented herein draws on the existing body of modelling studies, especially on the works of Struben (2006), Struben & Sterman (2008), and Testa (2017). The concept of *Willingness to Consider* (see Chapters 3.3 and 5.3) is in the heart of the model and it captures the social and cognitive processes a consumer goes through before considering an alternative and making a decision. The decision is then made based on the *relative attractiveness* of an alternative, which is modelled by applying prospect theory and using ICEVs as a reference point. This approach is adopted from Testa (2017), but the present model extends it to consider PHEVs and HEVs separately from BEVs and ICEVs. Then, these decisions collectively determine the development of vehicle stocks, i.e. the vehicle market.

A conceptual model with sub-system definitions, model boundaries, and key endogenous, exogenous, and decision variables are illustrated in Figure 17, and discussed in further detail below.

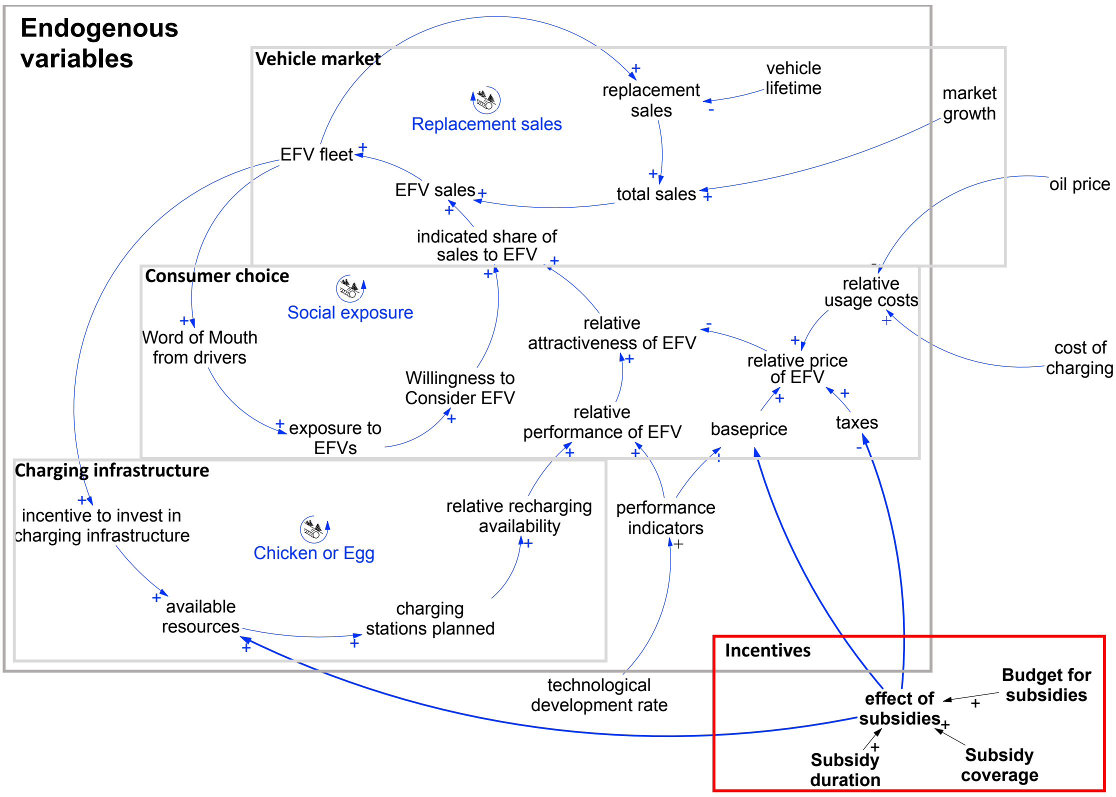

Figure 17. Model boundary and sub-systems

Depending on the modelling approach and chosen point of view, studies have distinguished various subsystems within vehicle markets. By far the most common subsystem, or sector, is the customer section. Terminology slightly differs, as Walther et al. (2010) and Bosshardt et al. (2007) refer to customers, while Struben (2006), Struben & Sterman (2008), Pasaoglu et al. (2016), and Testa (2017) refer to consumer section. Kieckhäfer et al. (2017) talk about purchase decision section, and similarly Shepherd et al. (2012), while drawing on Struben & Sterman (2008), talk merely about discrete choice model, rather than actual subsystem. Other common subsystems have been vehicle stock or market, or installed base (Watlher et al. 2010; Kieckhäfer et al. 2017; Testa 2017); refuelling infrastructure or sector (Bosshardt et al. 2007; Kieckhäfer et al. 2017; Testa 2017); and automotive industry (Struben 2006; Struben & Sterman 2008; Walther et al. 2010; Pasaoglu et al. 2016). This study mixes the approaches used by Bosshardt et al. (2007), Struben & Sterman (2008), Walther et al. (2010), Pasaoglu et al. (2016) and Testa (2017), and recognizes Vehicle market, Customer choice, Charging infrastructure, and Incentives as subsystems.

The vehicle market is modelled as an aging chain with 4 classes (Struben 2000, p. 469-512; see Chapter 6.2.1). Structurally it is similar to the one used in Testa (2017), but the present model extends it to include HEVs and PHEVs as well. Aging chain structures have also been used e.g. in Struben (2006) and Struben & Sterman (2008).

An aging chain structure is very functional in cases where the outflow rate of a stock depends on the age of those units within the stock (Struben 2000, p. 469). Vehicle market is an example of such cases, as the discard rate of vehicles from the fleet depend on the age of those vehicles (Struben 2006).

In Western countries the majority of vehicle sales comes from replacement sales (Struben 2006). When old vehicles meet the end of their lives they are scrapped and consumers by either new or second-hand vehicles from the market. In the present study, however, there is no separation between those categories; discards are only age-dependent, and the change of owner will not affect.

Although the majority of sales come from replacement sales, the market has grown quite steadily during the last 50 years or so. In this study, the market growth is modelled exogenously and using linear interpolation. This will be discussed in further detail in chapter 6.3, and the model will be tested for robustness in the Chapter 7.3. It is possible that in future trends like car-pooling (e.g. McKinsey 2014) will slow down the market growth, but such phenomena are beyond the scope of this study.

Replacement sales and market growth comprise the *market pool* from which all purchases are within a year. Shares of sales to different platforms are determined by means of relative attractiveness of each of those platforms, as described in Chapter 3. The method draws on the works of Struben (2006), Struben & Sterman (2008), and Testa (2017), but again the present study extends them to consider a greater number of platforms.

The development of charging infrastructure is based on the Chicken and Egg loop presented in Chapter 5 and, in part, on Testa (2017). The underlying idea is that the collective market share of EFVs serves as a proxy for the incentive of commercial organizations to invest in charging infrastructure development. A similar approach was used in Testa (2017) but with the share of BEVs. The present approach is in line with the conclusions of Walther et al. (2010) who encourage car manufacturers to use HEVs and PHEVs to support market development for BEVs and to initiate necessary charging infrastructure development by other commercial organizations.

In particular, the incentive of those organizations is modelled as *private investment coverage*. Governmental investments, then, complement the resources that are available from commercial organizations. Together they can cover 100 % of the costs and in such case the value would equal to unity. Similar approach has been applied in Testa (2017).

Slow and fast charging stations are modelled separately, but they both contribute to one variable, which is then compared against a reference point. The idea is that instead of stating the exact number of how many charging stations there should be, the model illustrates how investments in charging infrastructure can bring plug-in vehicles closer parity in refuelling/recharging availability.

This study recognizes the fact that electric grid might not in all places compatible with charging points. This has been pointed out in McKinsey's (2014), who state that consumers and organizations wishing to use high power chargers may need to upgrade their electric grid so that it can handle the increased usage of electricity. Modelling-wise, this is handled in a simplified fashion and assuming that in year 2000, the grid was "60 %" fit and by 2050 that number will rise 100 %, i.e. the variable will be valued to unity. This method has been adopted from Testa (2017).

The present study models the consumption of subsidies through 3 main variables, namely subsidy duration, coverage, and budgeted funds. The purpose is to illustrate how diffusion of EFVs would change if current policies were continued and/or new were launched. However, since there are clearly stated amounts of resources for policies, the model should keep track of subsidy consumption. These are discussed in further detail, in Chapter 6.2.10.

The present study *does not* consider local policies, such as free parking, access to bus lanes, or free ferries, as they have been applied in Finland in wide-scale; they are subject to municipal decision making instead of governmental; and, e.g. in Struben (2006) and Testa (2017) their utility is calculated solely on the basis of value of time. This is argued to be too abstract and error prone measure to be applied here. The present study recognizes them as a means to make electric driving more appealing, especially in Greater Helsinki area, but simultaneously argues that the utility they deliver should not be measured only in monetary terms. While parking costs can likely accumulate into hundreds of euros in Helsinki, even based on a heuristic estimation it is easy to argue that the corresponding cost elsewhere in Finland could be notably lower. Thus, using only Helsinki levels in analysis could bias the conclusions of their effectiveness and, further, the greatest utility from such policies is still likely to be based psychological aspects rather than monetary. Having said that this study recognizes them as a need for further research and calls for RP/SP studies in the national context.

The effect of learning is modelled exogenously. The study argues that production experience on a *global* scale can induce learning effects that can lead to several percent annual price declines, such as those reported by Kocchan et al. (2014), Nykvist & Nilsson (2015), or Knüpfer et al. (2017). However, the Finnish market with its 5-6 million residents is roughly the size of Berlin, and if the study were use the development of the national market as a proxy and model the price decline as a power law, this would result in unrealistically strong price decline. This is illustrated in Appendix B.

Changes in oil and electricity prices are also modelled exogenously. Although policy measures can influence those prices through taxation, the commodity price of oil and production costs of electricity are assumed independent from EFV market. Again, on a global scale these would likely be connected, and their prices would be determined endogenously, but this is not in the interest of the present study.

6.2 Model structure

The model consists of 10 *modules*. In Vensim, these are referred as *views.* Through these views the conceptual model presented in Figure 17 is translated into a stock-and-flow map and the relationships between variables are formalised into equations. These are presented in subchapters 6.2.1-10. A thorough documentation of equations, units, and functions is also presented in Appendix A.

6.2.1 Vehicle market module

As mentioned in Chapter 6.1, the vehicle market is modelled as an aging chain structure with 4 classes. A similar approach is also used in Testa (2017), but it only considers BEVs and ICEVs. *The present model extends the structure to include HEVs and PHEVs as well.* The resulting structure is presented below, in Figure 18.

Each class has 2 cohorts, young vehicles and mature vehicles. Vehicles accumulate into the first stock through new vehicle sales rate which, in turn, depends on the indicated share of sales of a vehicle type and the market pool. Then, through an aging rate flow, they move to the mature stock and eventually are scrapped and removed from the system.

The categorization to young and mature vehicles is done similarly as in Testa (2017). New vehicles represent such vehicles whose age is less or equal to 1/3 of the average vehicle lifetime in that category. For electric vehicles that is an increasing figure, while the total lifetime of ICEVs is kept constant at 20 years.

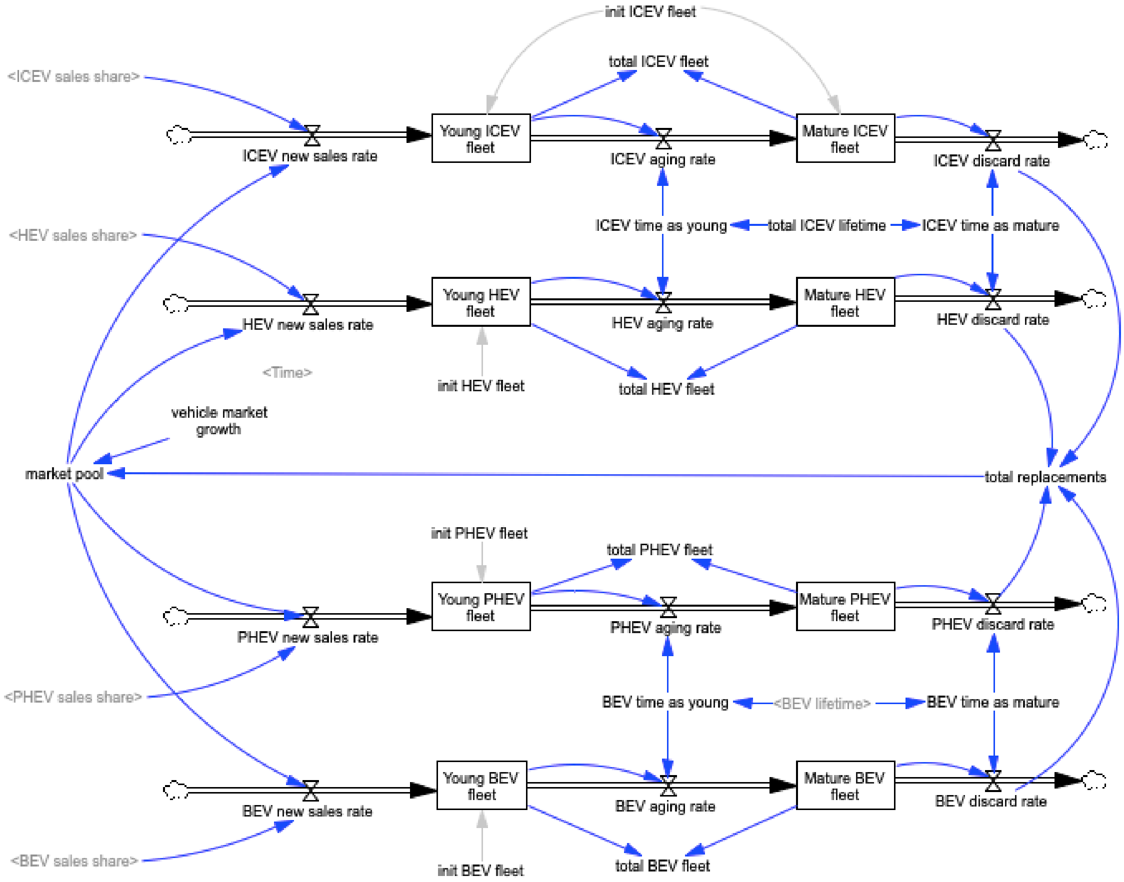

Figure 18. Aging chain structure of the vehicle market

6.2.2 Consumer choice

The choice of vehicle type is based on an applied form of multinomial logit function, equation (7), which combines those social processes preceding innovation adoption with relative affinities of vehicle types. Relative attractiveness of a vehicle type is determined using equation (3); it is a product of relative performance and relative costs. For instance:

$$\text{perceived BEV affinity} = \text{effect of performance on perceived affinity} * \\ \text{effect of cost on perceived affinity} * \text{Willingness to Consider platform} \qquad (8)$$

Relative performance is determined on the basis of attributes that were discussed in Chapter 3.5.1, and those attributes are compared to their reference points (see Chapters 6.2.4-6). Relative costs are determined similarly (see chapter 6.2.7).

Sales share for the reference type is then determined by subtracting indicated EFV sales shares from unity:

$$\text{ICEV sales share} = 1 - \text{BEV sales share} - \text{PHEV sales share} - \text{HEV sales share} \qquad (9)$$

The resulting model structure is presented below, in Figure 19.

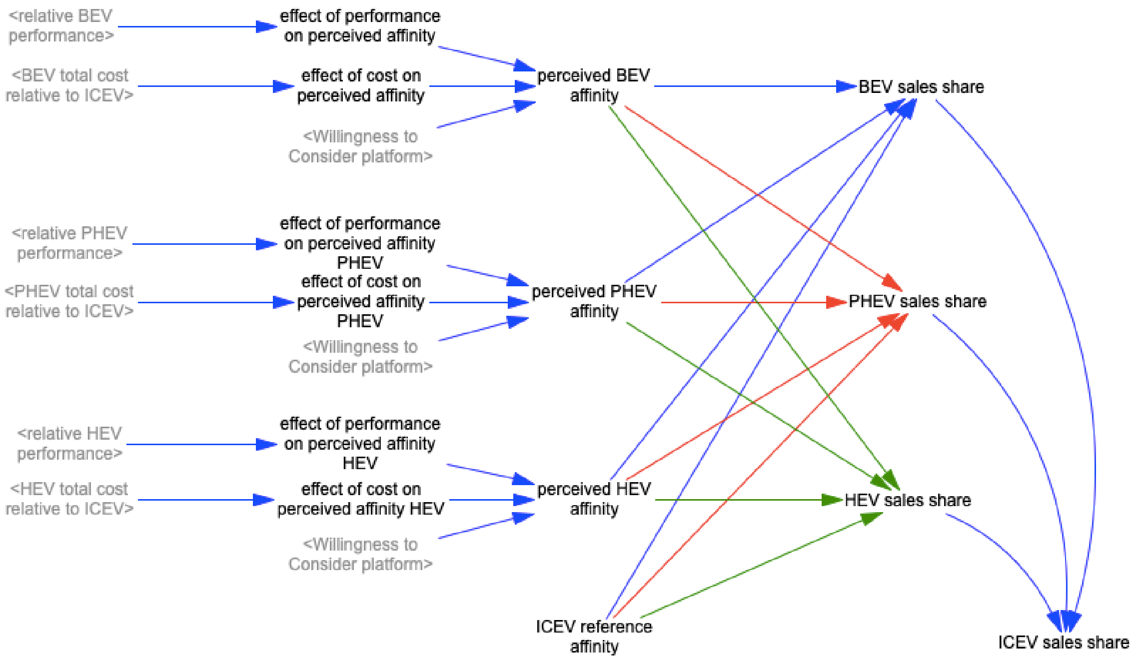

Figure 19. Consumer choice module

As stated before, this study applies prospect theory to vehicle selection, which implies that there exists an asymmetric relationship between possible gains and losses. Such relationships are difficult model mathematically and, thus, those relationships are modelled using table functions (Sterman 2000, p. 552-563). In practice, this means that the form of non-linear relationship is drawn manually and used as lookup function for a normalized value. Applied relationships are presented in Figure 20.

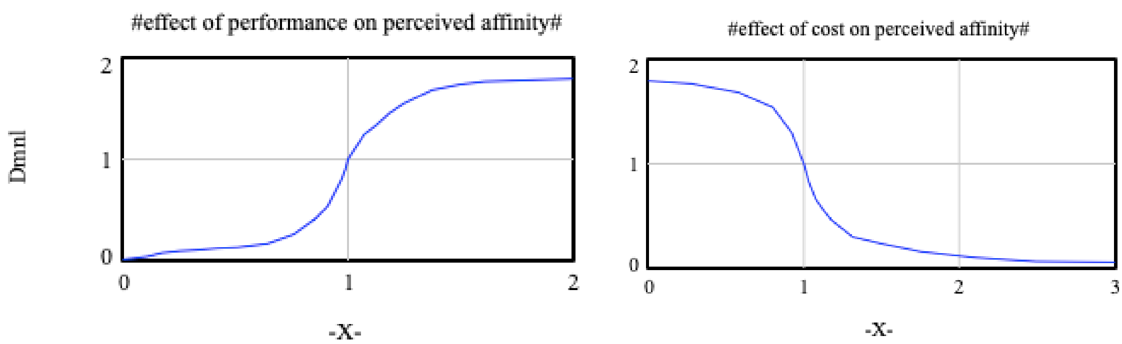

Figure 20. Effects of performance and price on affinity

As an example, the relative performance of BEV is calculated by dividing travel range, charging availability, model diversity, lifetime, and emission values by those of ICEVs; forming power functions; and totalling them into a weighted sum (except for emissions, see Chapter 6.2.4). Then, the resulting figure is looked up from the table to get its effect on the perceived affinity. As discussed in Chapter 3.4, a similar approach has been applied in Sterman (2000, p. 392-396) and Testa (2017).

6.2.3 Social exposure

Model structure and parameters for social exposure are adapted from Struben (2006) and Struben & Sterman (2008). This is presented below, in Figure 21. Similar to Struben (2006) and Struben & Sterman (2008), total exposure to EFVs consists of word of mouth from platform drivers, word of mouth from non-drivers, and marketing efforts. It should be noted that mainstream media, commercial marketing, and information campaigns are all aggregated into one variable. This increases consumers' willingness to consider an EFV, but the willingness also decays due to oblivion and forgetting, if consumers do not get constant reminders through different channels. Its value is time-dependent, as will be discussed in further detail in Chapter 6.4.2.

The balancing WtC decay function is adapted from Struben & Sterman (2008), as well as the reference rate of exposure. The function is formed as follows:

$$f(\eta_{ICEV,EFV}) = \frac{\mathrm{EXP}[-4\varepsilon(\eta_{ICEV,EFV}-\eta^*)]}{1+\mathrm{EXP}[-4\varepsilon(\eta_{ICEV,EFV}-\eta^*)]} \qquad (10),$$

where $\eta_{ICEV,EFV}$ is the total exposure to EFVs, η^* is the reference rate of social exposure, and ε is the slope of WtC decay rate at reference rate and equals to $1/2\eta^*$ (Struben & Sterman 2008).

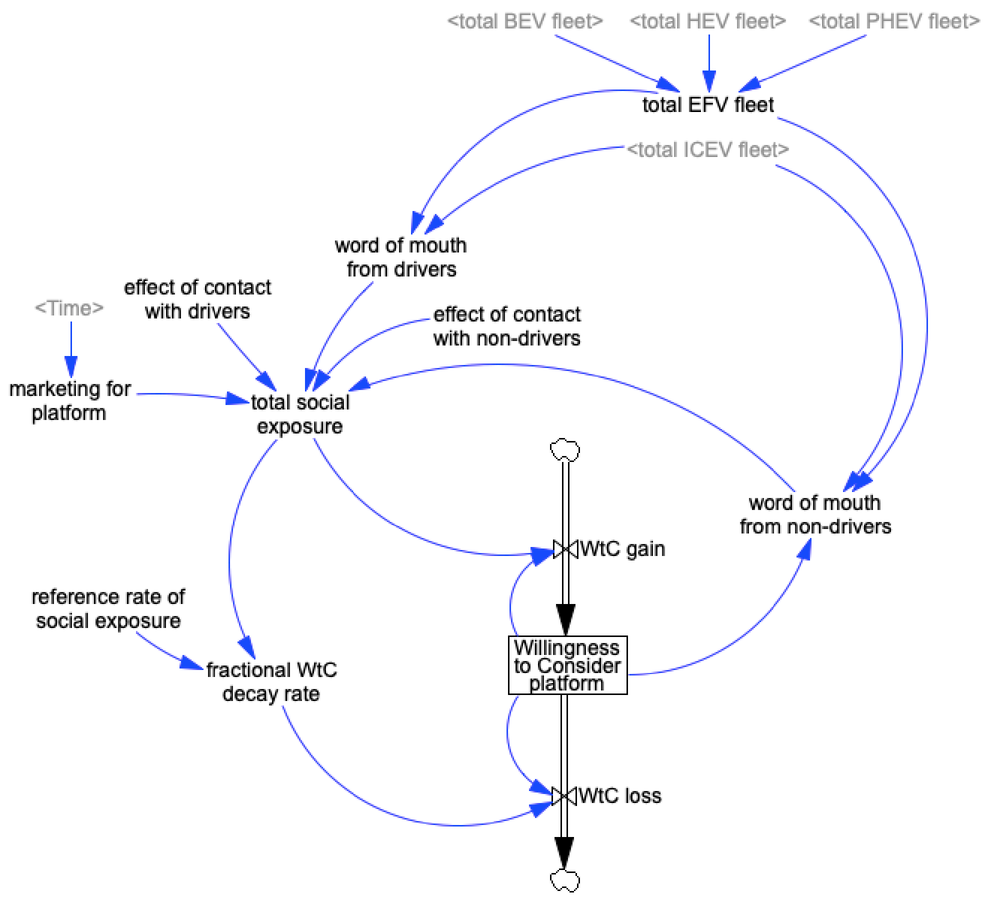

Figure 21. Applied structure for social exposure (adapted from Struben & Sterman 2008)

6.2.4 BEV performance

The core structure for modelling the performance of BEV relative to ICEVs is adapted from Testa (2017). The underlying idea there is the same as in Sterman (2000, p. 391-397) and, as stated already, implies that the performance of BEVs is evaluated with factors that are notably different from those of ICEVs and the two platforms are compared together. Then, using Equation (4) and weightings presented in Chapter 6.3.5, these attributes are aggregated into one representative figure; that is, *relative BEV performance*.

An essential structure herein is the generic closing the gap structure, which was presented in Figure 16. For travel range, vehicle lifetime, emissions, and charging availability the levels of ICEVs' serve as the desired levels of attribute states and as time progresses, the model exhibits goal-seeking behaviour. The charging availability is discussed in further detail in chapter 6.2.9. The resulting structure is presented below in Figure 22.

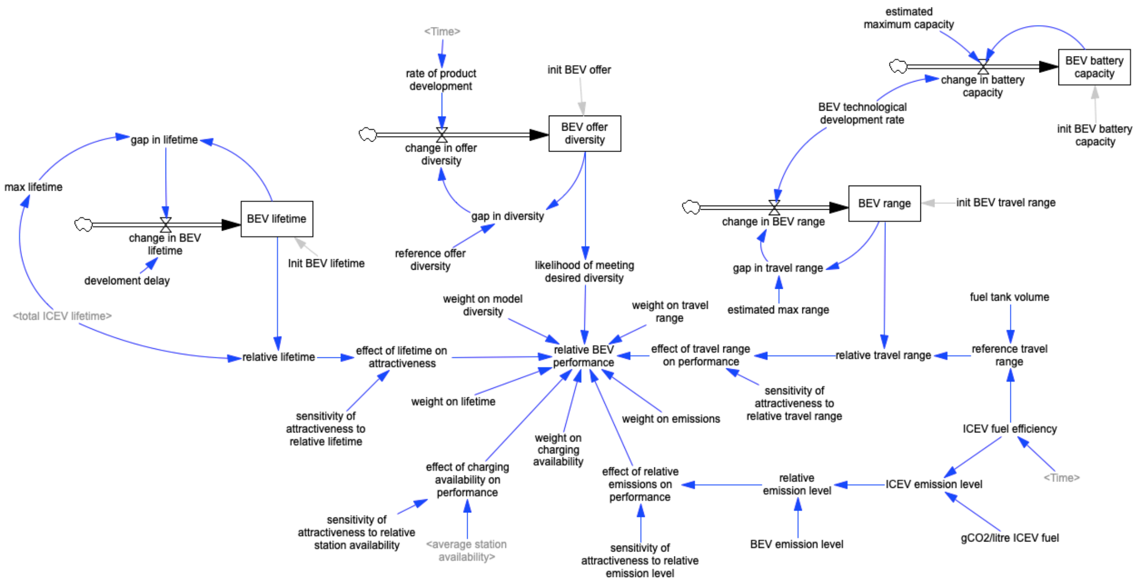

Figure 22. BEV performance (adapted from Testa 2017)

The modelling logic for relative emissions slightly differs from the other four attributes. Although the attribute reference points are roughly stable, it is likely that also the emission levels of ICEVs mildly decline over time, due to more efficient technology. In her study, Testa (2017) refers to IEA's Fuel Economy study and models a subtle decline *ICEV fuel efficiency*. It is assumed that the average consumption declines from 0.8 litres to 0.6 over the 50-year time horizon, while the emissions of BEVs remain constant and near zero. (Testa 2017) This means that the relative emission level of BEVs' *grows* and the effect of emissions on performance has to *decay*. Therefore, the effect of emissions on BEV relative performance is modelled as:

$$\text{Effect of emissions of performance} = \text{relative emissions}^{(-\text{sensitivity of performance to relative emission level})} \tag{11}$$

This approach was also used in Testa (2017). Also, a similar phenomenon is described in Stuben (2006) and Struben & Sterman (2008), as they model technological spill-overs as an own causal structure. Using a constant elasticity of substitution (CES) model, they illustrate how the competition between vehicle platforms can induce spill-overs *between* those platforms (Struben & Sterman 2008). For instance, in an attempt to lengthen the travel range of electric vehicles, car manufacturers could design lighter materials that would reduce the weight of the car and thereby electricity consumption, but such technologies could also be implemented in ICEVs and, thus, the new technology would *spill* to the competing platform.

The model structure necessitates that a set of assumptions is made. Drawing upon Testa (2017), the present study assumes that

- The travel range of BEVs will ultimately be equal to the reference value
- There is a maximum capacity for BEV batteries
- The lifetime of BEVs will increase as time progresses

The *estimated* maximum capacity is estimated heuristically and on the basis of relevant literature. A similar procedure has been taken with the *rate of product development* as well as *BEV technological development*.

6.2.5 PHEV performance

The core structure for PHEV performance is similar to that of BEV's. Vehicle lifetime is the same as in BEV, since it is simply assumed that the lifetime of a PHEV is equal to the lifetime of the battery and, thus, equal to the lifetime of BEV. This is naturally a simplifying assumption that could be overturned in the future if new business models and forms of charging are presented to the market. That is, Knüpfer et al. (2017) recognize battery replacements as such a prospect and should that happen, the abovementioned mentioned assumption could become overturned.

PHEV model diversity, emissions, and battery capacity are also modelled similarly as in BEV performance module. Their development rates behave similarly and are of the same magnitude as those of BEVs'. Further, the weights of different performance remain also the same. The resulting structure is presented below, in Figure 23.

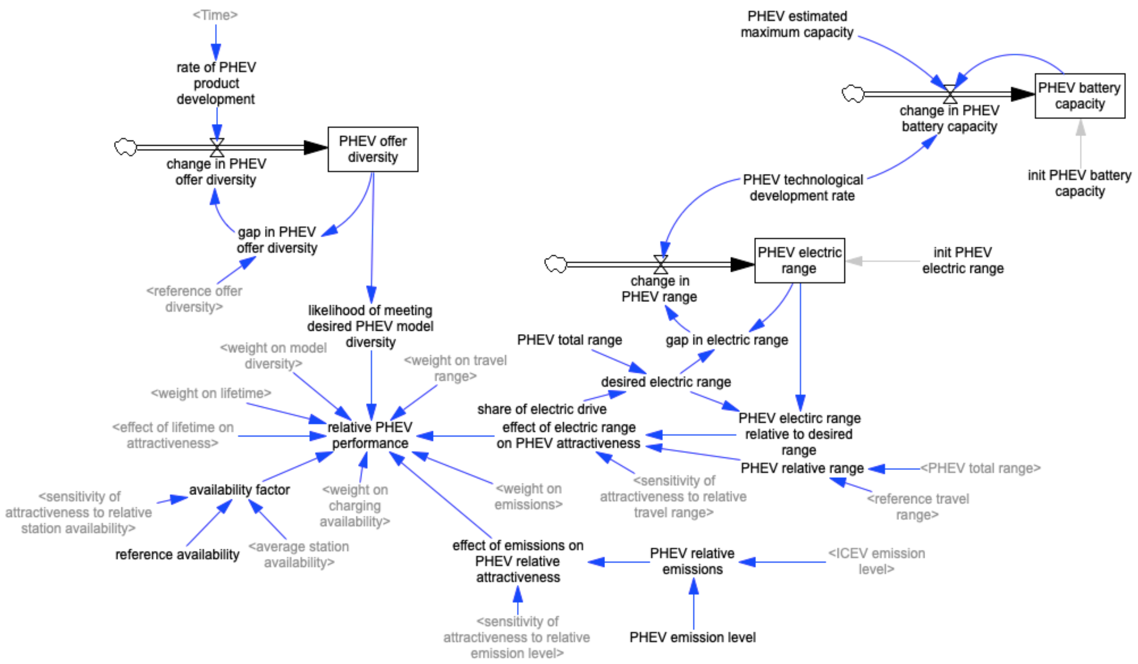

Figure 23. PHEV performance

The most notable differences are PHEV travel range and in charging availability. Given the fact that hybrid vehicles carry both engine types, the electric functionality is likely to cover a *share* of the total travel range of the vehicle. In the case of HEVs that share can be little and the battery is merely used to assist internal combustion engine. In case of PHEVs, however, the share can already be significantly bigger, and the vehicle can drive using only electricity. Especially, if the vehicle is an extended range plug-in hybrid (REEV) (EEA 2016), the electric travel range can account for the majority of the total range. In this study though, REEVs are aggregated into PHEVs and they are treated as one category.

According to European Energy Agency (2016), a PHEV can drive roughly 20-85km on electricity. Considering that a medium-sized vehicle, such as the aforementioned Hyundai Ioniq Plug-in, can travel up to 1,100km (www.hyundai.fi), the share of electric range would account for less than 10 % of the total. In this regard, it is assumed that the share of electric drive for such vehicles will increase over time, and the desired share was estimated to be at one quarter of the total. Due to the heuristic approach, this is a source of uncertainty and will be tested for sensitivity.

Another clear difference is the availability of charging points. As mentioned above, hybrid vehicles contain both drive-trains. In the case of PHEVs this also means that such vehicles can use both “charging stations” (i.e. gas stations and charging points) which further means that it has a superior charging availability. Modelling-wise, this is done by totalling up the reference availability and the availability of actual charging stations.

6.2.6 HEV performance

Similar to PHEV performance, the relative performance of HEVs builds upon the structure presented in chapter 6.2.4. It still uses the same weightings for different attributes, and the essential idea remains the same. The structure for HEV performance is presented in Appendix B.

HEVs are notably closer to ICEVs than BEVs and, thus, there are less distinctive features to be considered. HEVs can only charge their batteries when driving, which means that the charging availability is equal to the reference value. HEVs also have an equal number of charging points as ICEVs. Similarly, it is assumed that the total travel range is roughly the same as the reference value. This is a simplifying assumption which could be argued, but it is reasoned with the fact that the battery pack also used in HEVs – although notably smaller than those in PHEVs or BEVs – still adds weight to the vehicle, which can increase fuel consumption when not using electricity. In this regard, if a consumer drives mainly in urban areas where travel speeds are lower and the vehicle can utilize breaking energy, its consumption can be 2/3 of ICEVs': combined consumption for Hyundai Ioniq Hybrid is 3.4 l/100km while the corresponding number for i30 Hatchback is 4.5-5.6 (www.hyundai.fi). However, if the consumer drives mainly on highways, the vehicle will not drive on electricity but still carry those batteries along, which would increase consumption. Thus, the net effect in terms of travel range would be zero.

6.2.7 Cost module

Besides relative performance of a vehicle type, another distinctive feature is its relative cost. As discussed in Chapter 3, there several cost items that relate owning a vehicle. In the present model, they are separated into non-recurring and annual costs; or more simply, to *price* and *costs*. The core structure is adopted from Testa (2017) but is modified so that the aforementioned use-based policies are removed, and maintenance costs are added. The resulting structure is illustrated below in Figure 24, and the whole module is visualised in Appendix B. The structure is applied to determine the relative costs for HEVs and PHEVs as well, instead of only BEVs.

The price of a vehicle consists of a car tax, value added tax, and a retail price. For low emitting vehicles, there can be purchase subsidies, scrapping bonuses, and alike, that reduce the net price of a vehicle. Then, drawing on the approach of Testa (2017), the net price of the vehicle devaluates over the vehicle lifetime, which highlights the meaning of vehicle lifetime. In practice, this means that the net price of a vehicle is divided by its lifetime and the resulting value is divided by a reference value, again, to retrieve the representative relative value.

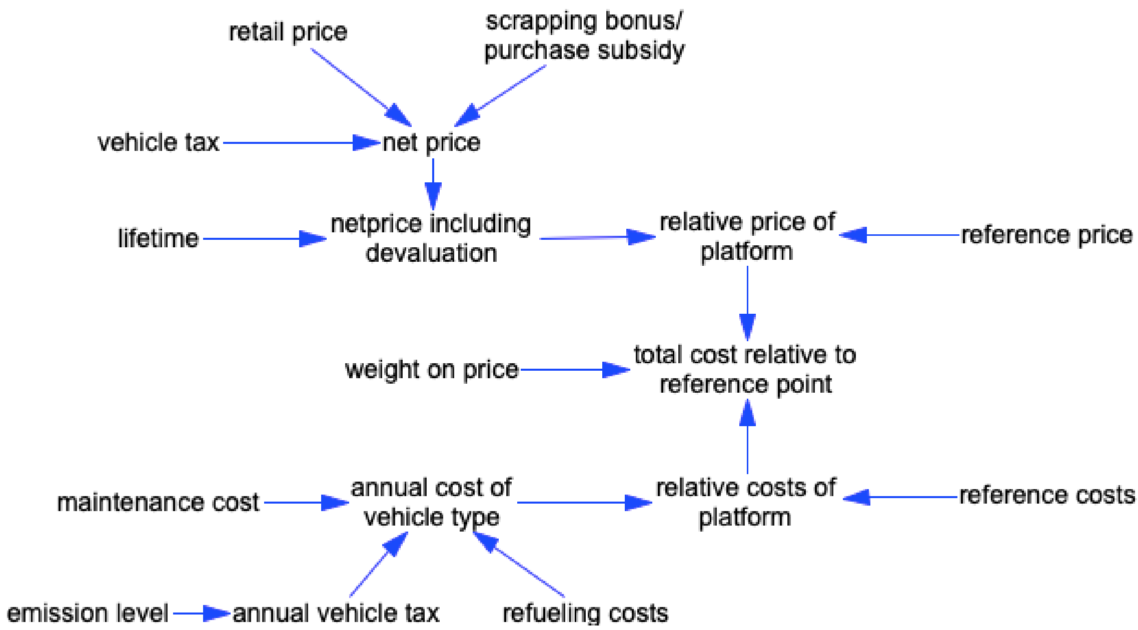

Figure 24. Cost structure for vehicle types

Costs of a vehicle are modelled as follows; the annual cost of a vehicle is decoupled to maintenance costs, annual vehicle taxes, and refuelling costs. As mentioned before, the present study does not consider the value of time, as done e.g. in Struben (2006) and Testa (2017). The resulting sum of annual costs is then divided by the reference value, i.e. annual costs of an ICEV, to get a representative value. And lastly, these values are *weighted* to illustrate the attitude of consumers: According to Hagman et al. (2017), previous work on vehicle choice has concluded that consumers put little weight on the operating costs of owning a vehicle, instead they tend to merely consider the purchase price. Wu et al. (2015) have noted the same and call for consumer education to mitigate this barrier.

Refuelling costs are calculated on based fuel efficiency, annual mileage, and fuel price. For ICEVs and HEVs these costs are calculated using the following equation:

$$\text{refueling costs} = \text{oil price} * \text{annual driving range} * \text{vehicle type fuel consumption} \quad (12)$$

Recharging costs, in turn, are calculated as follows:

$$\text{recharging cost} = \text{annual driving range} * \text{power price} * \frac{\text{battery capacity}}{\text{travel range}} \quad (13)$$

In the model, the term $\frac{battery\ capacity}{travel\ range}$ is denoted with *battery efficiency*. Similar to charging points and travel range, PHEVs have both powertrains and, thus, they can use both fuel types. Therefore, in the case of PHEVs, refuelling costs are decoupled to refuelling and recharging costs and weighted based electric and conventional travel shares:

$$\text{weight on PHEV electirc drive} = \frac{\text{PHEV electric drive}}{\text{PHEV electric drive+PHEV total range}} \quad (14)$$

Lastly, the transition in annual vehicle taxation from NEDC measuring to WLTP and to the new tax model is captured in model using a lookup function (see Chapter 6.3.3 for Figures 37 and 38) and a simple IF THEN ELSE -structure:

$$\text{Annual vehicle tax} = \text{IF THEN ELSE}(\text{Time} \geq 19, \text{new tax model}, \text{old tax model})$$

6.2.8 Base price

As discussed in Chapter 3, the base price of an electric vehicle consists of costs unrelated powertrain, value added tax, and the cost of the battery. The cost of a battery, in turn, depends on its capacity and on the cost of a kilowatt-hour. For PHEVs, there are additional costs due higher energy density in the battery and the additional that come from having a combustion engine as well. The structure is presented below, in Figure 25.

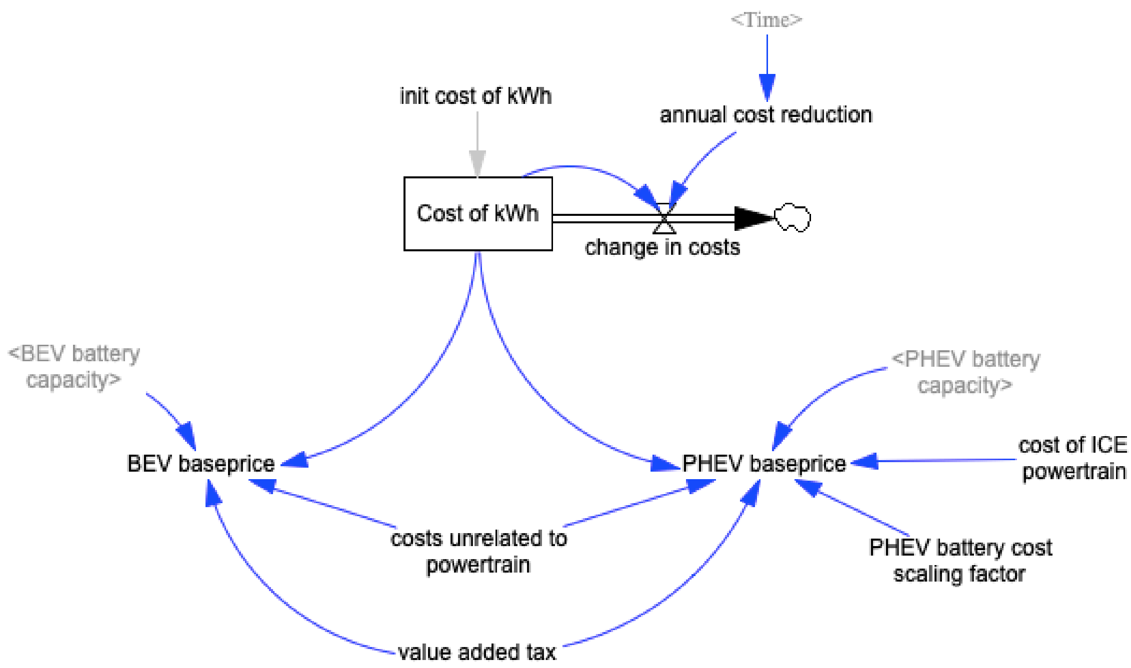

Figure 25. Base price structure

Kocchan et al. (2014), Nykvist & Nilsson (2015), and Knüpfer et al. (2017) have all reported promising numbers for annual decline in cost of kWh. Nykvist & Nilsson (2015) especially did a systematic review on estimates presented in the beginning of the decade and conclude that the most likely estimate for large manufacturers is around 8% annually. They argue that higher estimates are merely corrections to previous overestimations and the 8% estimate for Li-ion batteries is also close the long-term decline in Ni-MH batteries, which has been around 9% annually. (Nykvist & Nilsson 2015) On this premise, the present model applies the estimate of Nykvist & Nilsson (2015) in the base case scenario, but the model robustness will also be tested against this choice in Chapter 7.3.

6.2.9 Charging infrastructure

The aggregated market share of all EFVs serves as a proxy for the incentive to make private investments in charging infrastructure development. These resources can be complemented with governmental subsidies, as done in Finland since 2011. As described in Chapter 6.1, decision variables for policies are their duration, monetary, coverage, and budget. Further, it would naturally have to be decided when a policy would start.

The structure contains own variables for slow charging point investments, fast charging stations, and further models the energy investment program in 2011-2017 as its own. Although the more recent investments are also part of the same, continued program, this allows the model to separate funds that were used in 2011-2017 from those that were allocated to infrastructural development more recently.

As discussed in Chapter 6.1, the availability of resources, fitness of the electric grid, and the need for charging stations determine how many stations are planned and built per year. As mentioned before, it is assumed that the fitness of electric grid will improve linearly as time progresses. In the model, this is done using a simple lookup function where the value rises steadily from 0.6 at time 0 to 1.0 at time 50. The resulting equation is thus in the following form:

$$\text{charging stations planned per year} = \\ \text{available resources} * \text{gap in station availability} * \text{fitness of grid} \quad (15)$$

There are a number of factors that influence the need for charging stations requirements. As discussed in Chapter 3, transition to plug-in vehicles means also that recharging/refuelling culture will change quite significantly. Due to shorter travel ranges electric vehicles have to be charged more often, but the possibility to charge a vehicle while at home, at work, or for example at a grocery store means that there needs to be less fast charging points on the roads that would otherwise serve the same purpose as conventional gas stations. In the present model, this is modelled using an approximately linear lookup function. The approach has been adopted from Testa (2017). The purpose of the function is merely to illustrate that as the average range of electric vehicles increase and consumers can charge their vehicles while they are parked somewhere, the importance of fast charging stations decreases. The effect is illustrated below, in Figure 26.

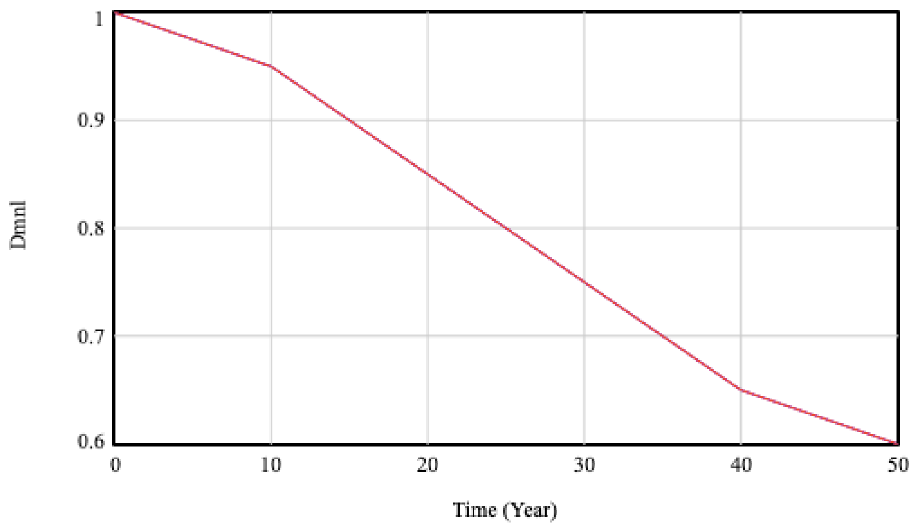

Figure 26. The effect of change in charging behaviour on station requirements

Secondly, as the travel range of electric vehicles increases, the need for charging stations decreases. This is modelled as an exponential decay using a similar formula as in Equation (11):

$$\text{effect of range on station requirements} = \text{effect of travel range on performance}^{(-\text{sensitivity of station density to range})} \quad (16)$$

The resulting relationship between charging station density and travel range is presented below in Figure 27.

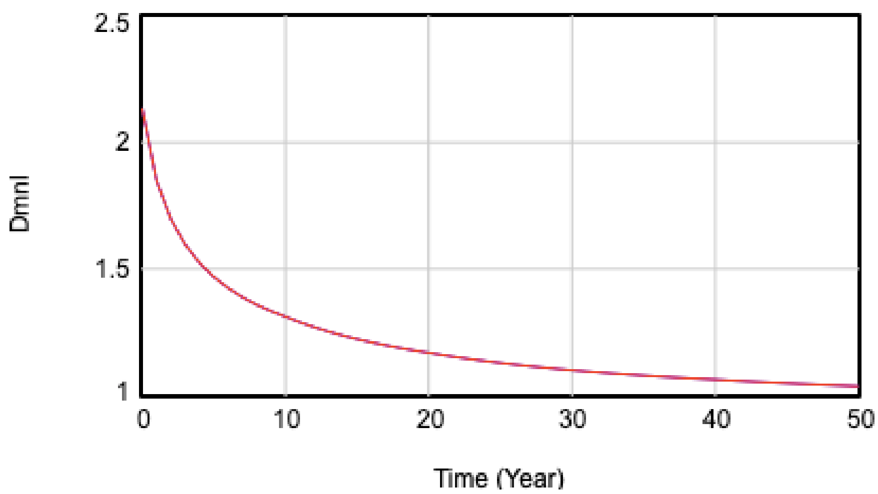

Figure 27. The effect of range on station requirements

Thirdly, the desired number of plugs per vehicle also affects the building rate of charging points. For fast charging points, this is determined on the basis of the reference number charging stations; that is, the number of gas stations. For slow charging points, this is determined based on the desired ration of plugs per vehicle. Testa (2017) uses a value of 2, which indicates that in each electric vehicle would have one plug at home and one at work. The author aggregates household parking, parking lots at work, and public parking places, such as those of grocery stores, into the same variable. (Testa 2017) The European Union, in turn, enacted the Directive 2014/94/EU, also known as the Alternative Fuel Infrastructure Directive (AFI), which states that each member country should provide a sufficient number of public charging points relative to the number of electric vehicles (European Union 2014). More specifically, each country should have 1 charging point per 10 electric vehicles in 2020 (European Union 2014; EEA 2016). Considering that the desired number of charging points is determined based on the number of plug-in electric vehicles *times* the desired number of points per vehicle, the difference between Testa's (2017) and EU's (2014) numbers is twentyfold. It is therefore essential to describe what chargers are considered and should be the ratio between plugs and vehicles.

In this study, no distinction in slow chargers is made between public and private chargers. As described in Chapter 3, all subsidies admitted in the energy investment program are targeted to public charging stations, but nowadays also condominiums can receive financial aid for building charging points for their residents. Still, however, individual consumers cannot receive subsidies for charging solutions. In this regard, the present study makes a simplifying assumption that all subsidies used for building slow charging are in line with the guiding restrictions, and all home charging appliances are still privately acquired. Reasoning for the applied approach is that there appears to be very little evidence from Finland regarding the share of electric vehicle drivers that *have* bought and installed a home charging station. Therefore, it is considered more practical to aggregate them into one variable that serves an explanatory variable for vehicle market growth. Thus, the structure is line with Testa (2017), and the desired ratio of EU (2014) can be used to assess whether the behaviour seems realistic.

It would also be impractical to compare the number of gas stations to the aggregate number of slow charging points and fast charging stations as there would not only be so much more of them in the long run, but also due to the fact that they are not really comparable. In this regard, the availability of charging stations is determined similarly as in Testa (2017): there are two types of charging stocks that each have their own densities relative to their desired levels. The equations for these are formulated as:

$$density\ of\ charging\ stations = \frac{Stock\ of\ charging\ stations}{desired\ number\ of\ stations} \tag{17}$$

These are then averaged to get a representative number. The resulting structure is presented below, in Figure 28. Again, all equations used in the model are documented in detail in Appendix A.

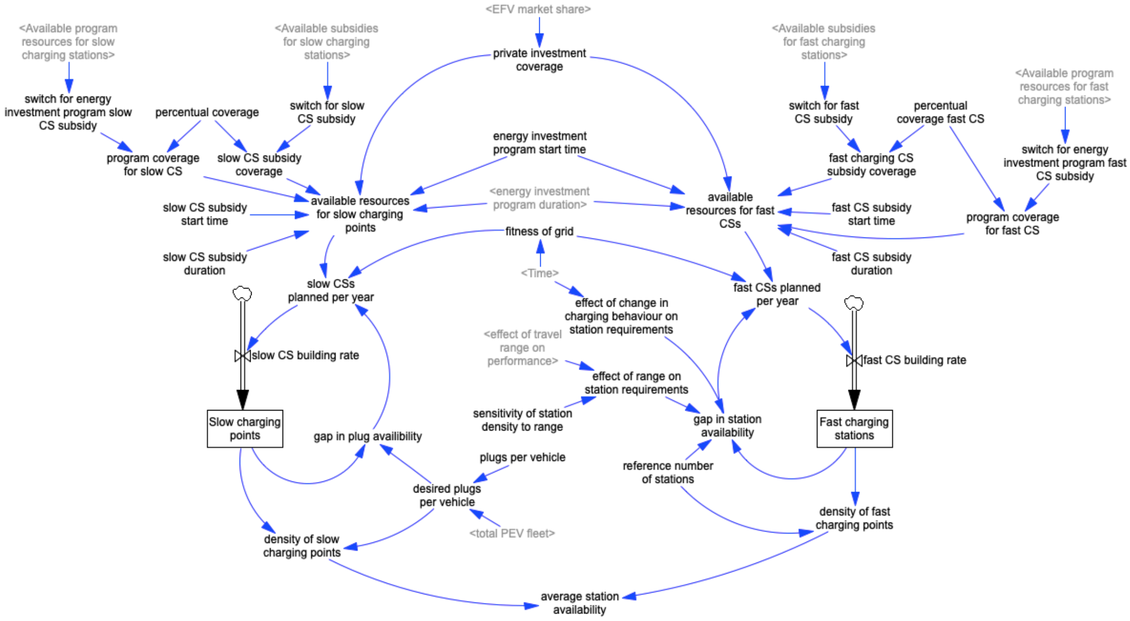

Figure 28. Model structure for charging infrastructure

6.2.10 Subsidy coverage

Subsidy coverage builds on budgeted funds that are allocated for subsidies, the monetary coverage they are supposed to cover, and the timeframe during which those subsidies are admitted. They also include detailed restrictions on where those funds can be used. For example, in the energy investment program more recently, where it was stated that 50 % of the available funds should be used to subsiding fast charging station investments and 50 % should be allocated for public slow charging stations. The monetary coverage for fast charging stations would be 35 % while the corresponding number for slow charging stations would be 30 %. (www.lataustuki.fi; DNro 609/521/2016) Similarly, if a consumer buys a BEV, the person will get a *purchase subsidy*, but if the person buys a low emitting vehicle during a scrapping program, the subsidy will be in the form of *scrapping bonus* and it can be smaller. Therefore, different policies are modelled individually.

The underlying logic is that policies have a certain amount of funds allocated for them, which forms the stock of available resources. They each also have a duration along which subsidies are given. The outflow of available resources will be determined as a product of number of units used per year and the cost or coverage per unit. Further, if there are no funds left or the subsidy has expired, no funds will be given, and the usage of subsidies will fall to zero. The resulting structure is presented in Appendix B as a whole and an illustrative figure is also presented below, in Figure 29.

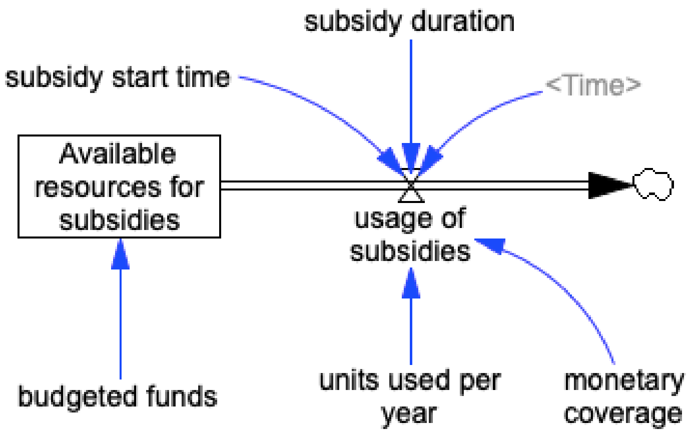

Figure 29. An illustration of Subsidy coverage model structure

An exception to the logic is the usage of scrapping bonuses in 2015 and in 2018 in the base case set up. That is, scrapping bonuses were only admitted to low emitting vehicles, but those vehicles could also be ICEVs; the limits were 120 g/km and 110 g/km in 2015 and 2018, respectively. It would therefore be misleading to allocate 8 million euros (in the model) to available funds for scrapping bonuses which could then be used by BEVs, HEVs and PHEVs, but not ICEVs. Therefore, the discount is modelled using a STEP function which means that all BEVs, HEVs and PHEVs that are bought during the program periods received a discount. This function structure is documented in Appendix A.

6.3 Parametrization

Parametrization to Finnish context in the base case requires the parametrization of vehicle market growth, vehicle costs, marketing effectiveness, oil and electricity prices, and the preferences of consumers, i.e. the weights of different performance attributes. As described in Chapter 2, sources for these parameters are various and include empirical statistics, scientific papers, governmental publications, and even in parts commercial data. These will be discussed separately in subchapters 6.3.1-4.

6.3.1 Vehicle market growth

As of 1960s the vehicle market in Finland has grown quite steadily. There have been two notable slumps that would appear to have occurred during the recession in the beginning of 1990s and the financial crisis in 2008. Both seem to have halted the growth, if not even made the market decrease, but the market has always recovered. The slope of the curve has also remained approximately similar at the time of growth. This is illustrated below, in Figure 30, along with three estimates on future market development that will be discussed next. It should also be noted that as of 2007 the stock of vehicles has only included vehicles that are in active use (Autoalan tiedostuskeskus 2018c). Until then, the stock included all registered vehicles (Autoalan tiedotuskesku 2018c). In the absence of further information, it is difficult to assess how much this may impact the market development, but it is possible that the curve would have been steeper had the change not occurred. By using linear interpolation on the 1960-2017 development, the curve would indicate that there would be roughly 4.3 million passenger cars in Finland in 2050. As mentioned above, the measurement procedure has changed in between, which could explain the rather poor fit between the trendline and last couple of year. However, even with that in mind, it seems that the linear estimate may not be the best estimate for vehicle market development. By changing the interpolation method from linear to a second-order polynomial, the new trendline would seem to better describe the market development. This scenario would result in roughly 3.1-3.2 million passenger cars in 2050. In comparison to the linear estimate, the difference is quite significant: over a million vehicles less. If we use only the values from 2007 onwards, we can eliminate the effect of measurement changes, but the number of known y's drops drastically. By using linear interpolation to the remaining data points, the linear estimate falls between the latter two, but is notably closer to the estimate that was received with second-order polynomial estimate. These three estimates are all visualised below in Figure 30.

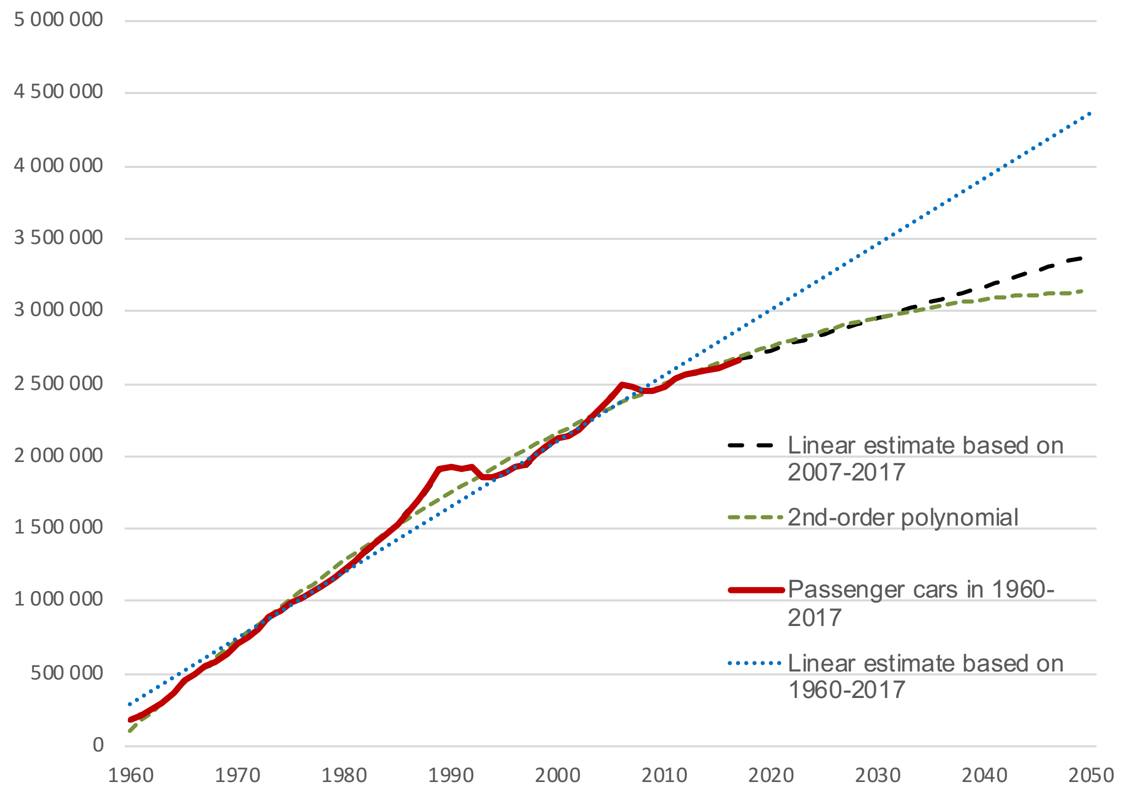

Figure 30. Estimates on market development (Autoalan tiedotuskeskus 2018c)

Since the linear estimate based on 2007-2017 and the polynomial interpolation are relatively close in their estimates, the present study models the vehicle market growth in the same magnitude and using the linear estimate. In comparison to 2007's levels, the annual growth would be roughly 20,000 new vehicles annually: in 2007, there were 2,480,880 passenger cars on the roads, and in 2050 there approximately 3.4 million vehicles that would mean 21,375 new vehicles a year. The robustness of model will be tested against this assumption in Chapter 7.

6.3.2 Marketing efforts

In Struben (2006), marketing effectiveness is kept constant at 0.01 expect during the first 10 years. The author reasons this by noting that upon introduction, the new entrant receives free media attention and public interest, as they are novel compared to the market incumbent. (Struben 2006) A similar approach is used in Struben & Sterman (2008), and they also refer to the study of Easingwood et al. (1981) for further discussion.

Testa (2017) uses a concept that is somewhat similar to that of Stuben (2006) and Struben & Sterman (2008), but instead of marketing effectiveness she talks about information campaigns. The idea there is that information campaigns increase the exposure to EFVs, BEVs in particular, which increases consumers' confidence towards the vehicle platform. Similar to Struben (2006) and Struben & Sterman (2008), the effect of information campaigns is modelled as a dimensionless variable with interval [0, 1]. Testa (2017) also treats marketing efforts periodically: marketing efforts increase as interest grows towards the platform, but once the market has been taken over, the novelty of the new alternative has faded away and the efforts put into marketing decrease. This results in decaying behaviour and the efforts will settle to a lower level. (Testa 2017) Sterman (2000, p.339) also states that this is a common phenomenon in technological diffusion, and especially among products that considered as fads.

Neither of the approaches described above can be applied as they are. In case of Struben (2006), the issue is that it would be inaccurate to keep marketing efforts at a higher level upon the introduction of EFV. As stated in Melliger et al. (2018), the media attention and marketing efforts for electric vehicles have gained momentum in Finland just *recently*, although electric vehicles were introduced to the market roughly a decade ago. This would slightly imply that there may occur similar periodical behaviour as noted by Struben (2000) and Testa (2017). In this regard it would also be inaccurate to use constant marketing efforts.

The problem with Testa's (2017) approach, then, is that the magnitude of effect of information campaigns on consumers' confidence is tenfold to the marketing effectiveness used by Struben (2006) and Struben & Sterman (2008). In this regard, the behaviour of information campaigns in Testa (2017) is more believable and could be applied in the present context as well, but the values per se are not. In this regard, the table function is used in the present study is presented in Figure 31. Form-wise, the table function is in line with Testa (2017), and the domain for marketing effect is similar to that in Stuben & Sterman (2008). However, the function evidently is heuristic and indicative, and therefore error prone. The sensitivity of the model results will for different values for marketing effectiveness. Having said that the above-presented form is slightly heuristic, it is also one the central decision variables in the present study. Thus, if the model appears to be highly sensitive to marketing values, it can also mean that the *development of the market* is sensitive to marketing efforts.

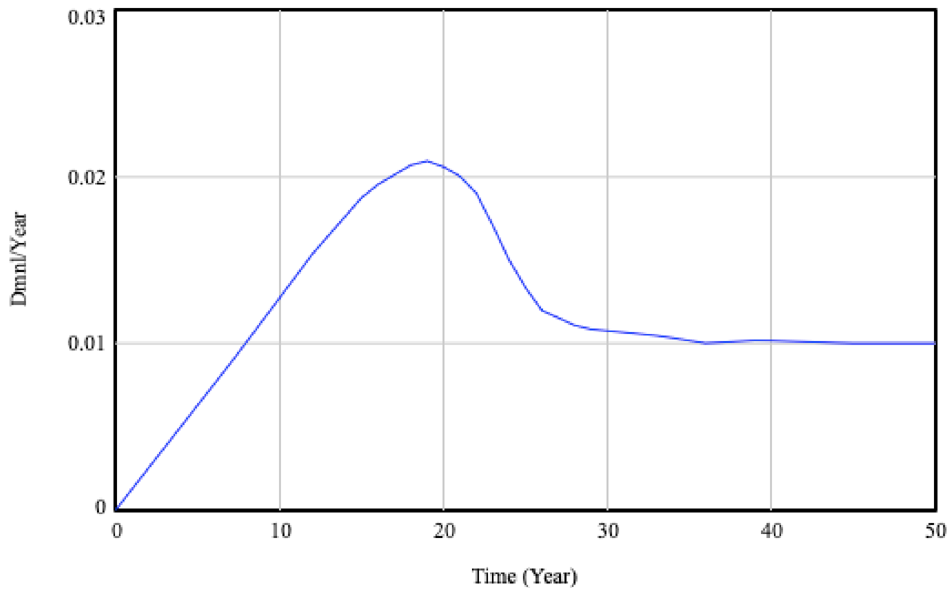

Figure 31. Marketing effort as a function of time

6.3.3 Vehicle prices

Vehicle prices are estimated on basis of Hyundai i30, Ioniq Hybrid, Ioniq Plug-in hybrid, and Hyundai Ioniq electric. As mentioned in Chapter 4, these are regarded as medium-sized and medium-prized vehicles that would serve as appropriate proxies for cost estimations.

Vehicle costs are modelled in two parts: annual costs of a vehicle and its price. The former is parametrized according to discussion in Chapter 4.5; a vehicle driver has to pay an annual vehicle tax based on its motive power type, emissions and/or weight. In particular, the driver will have to pay an annual base tax that is determined primarily on the basis of vehicle emissions, but if those are not available, the taxation will be based on vehicle weight (see Chapter 4.5; Ajoneuvoverolaki 1281/2003). Then, if a vehicle uses other drive fuels than gasoline, it has to pay a motive power tax which is determined as a product of motive power coefficient, number of days the vehicle has been in active use during the year, and its weight. As mentioned in Chapter 4.5, a simplification is done in the present model, and only gasoline vehicles are considered. Thus, no motive power taxes will accrue for ICEVs. The study does recognize this as an area for further development, since this would affect the perceived attractiveness of a diesel vehicle: for an average-sized diesel vehicle the motive power tax is annually 440€, while for a same-sized electric vehicle that would be approximately 100€ (The Ministry of Finance 2018).

Values for motive power tax are the following: ICEVs and HEVs pay 0€, as they are either fully or partly driving on gasoline (Trafi 2018d). PHEVs pay approximately 36.5€ a year, and BEVs pay 104€ a year. These values were retrieved from Trafi's vehicle tax calculator (Trafi 2018d) and using the following parameters: A Hyundai Ioniq Plug-in electric weights 1,970kg (rating value; www.hyundai.fi) and emits 21.5g/km. The latter value is estimated on the basis that for Hyundai i30, the manufacturer has reported WLTP-measured values, but no indication is given for Ioniq HEV, PHEV, or BEV on whether their emission values are measured using NEDC or WLTP measure. Emission levels for the latter three are 79, 26, and 0, respectively, and it is only assumed that these values are also WLTP measures. Thus, to get a corresponding value, these figures are divided by the *WLTP coefficient* 1.21, which in the case of PHEV results in roughly 21.5g/km. A similar procedure was done on BEVs, but with 1880kg (www.hyundai.fi), 0g, and fully electric.

Table 3. Motive power taxes for vehicle types

Motive power	**Tax**
BEV	104 €
HEV (gasoline/electric)	0 €
ICEV (gasoline)	0 €
PHEV (gasoline/electric)	36.5 €

As stated above, the annual base tax is determined primarily on the basis of vehicle emissions. Until 2018, the tax has been based on NEDC measures and the old tax model, but as of September 2018, the taxation will gradually move to WLTP-based taxation. The tax base itself will slightly drop, but the measuring procedure increases the average emissions of a vehicle by roughly 20%. Differences in tax bases and emission measures are illustrated below, in Figure 32 and Figure 33, respectively.

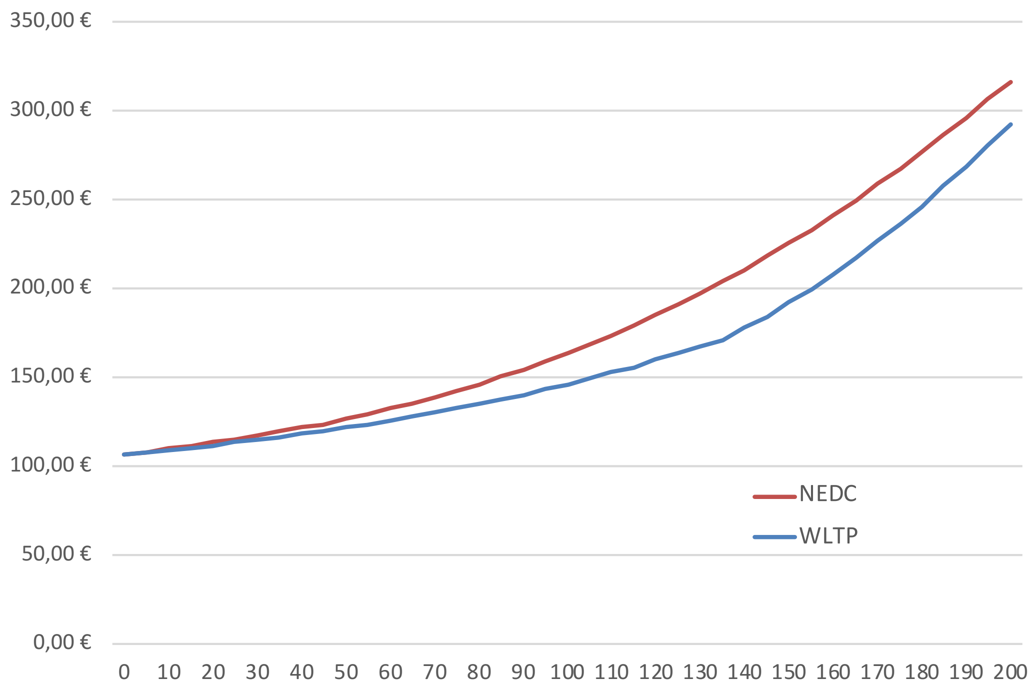

Figure 32. Annual base taxation (Ajoneuvoverolaki 1281/2003)

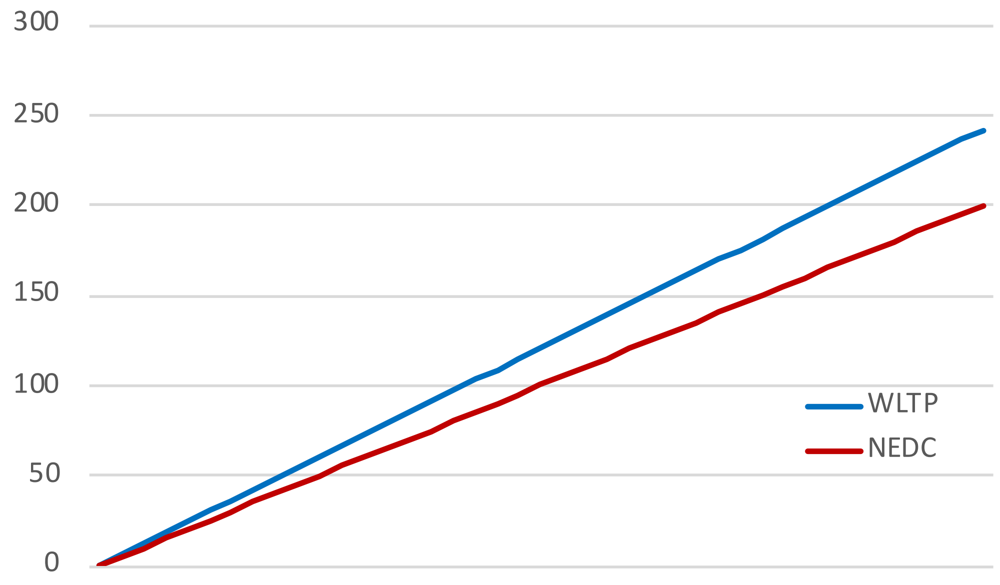

Figure 33. Corresponding CO2 (g) emissions with NEDC and WLTP measures

The emission level of BEVs, HEVs, and PHEVs are kept constant in the present model, excluding the drop in 2019, when the new tax model comes into effect. It is likely that also their emissions – especially those of HEVs' – will drop as the technology develops, but for the sake of simplicity they are kept constant. ICEV emission levels do decay from relatively high levels to near those they are in real-life today. This approach was adopted from Testa (2017), and in part illustrates the effect of competition between vehicle platforms. These are visualized below in Figure 34.

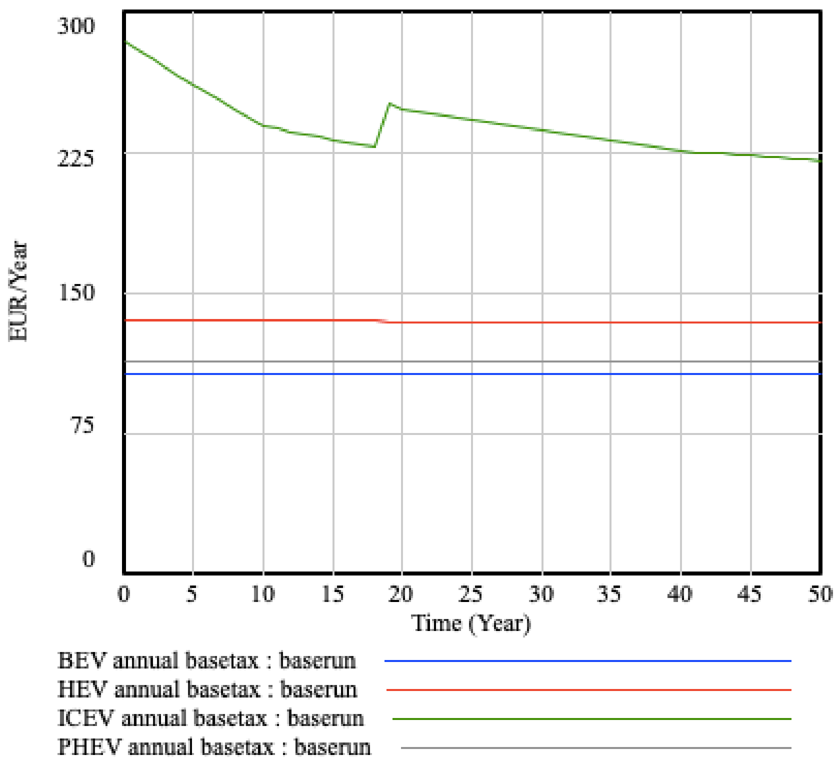

Figure 34. Annual base taxes for vehicle types

It should also be kept in mind that in the present study, for example range-extended electric vehicles are aggregated into PHEVs and mild-hybrid vehicles to HEVs, which both could have lower emissions levels than the ones applied here. In this regard, it should be noted again that the model results are indicative *projections* rather than *predictions*.

Although the applied emission levels are slightly error prone, they do capture the effects of transition from NEDC to WLTP. For instance, the annual base tax of PHEVs drops upon the introduction of new measuring procedure and tax base, while the behaviour in ICEV taxation is total opposite. This can especially be seen in ICEV taxation in Figure 34 above. The effect is present in other curves as well, although significantly less visibly.

Regarding the other significant dimension in vehicle costs, namely price, the parametrization again draws on the values of Hyundai models. In particular, there are three components that need to be parametrized: costs unrelated to powertrain, cost of ICE powertrain, and vehicle tax that is paid at the time of purchase.

For simplicity, the retail price of ICEVs is kept constant and it is the pre-tax list price of Hyundai i30 Hatchback in Finland (www.hyundai.fi). This serves as the basis for car tax calculation, where that retail price is multiplied with the applied tax percentage of that year. Tax percentages are the same that were presented in Chapter 4.5, in Figure 10. A similar approach is applied with HEVs; retail price is the same as the pre-tax list price for Hyundai Ioniq Hybrid.

As described in Chapter 6.2.8, price of a BEV is comprised of the cost of the battery, which determined as a product of cost of kWh and battery capacity; costs unrelated to powertrain, and value added tax. In case of PHEVs, additional costs come from having an ICE powertrain as well and a high-power battery, whose cost of kWh is higher than those of BEVs'. The *cost of ICE powertrain* is a rough figure, which merely represents the cost effect of incorporating two drivetrains. Drawing upon Kocchan et al. (2014), Küpper et al. (2018), and Hyundai's list prices, the costs are assumed to be the following:

Table 4. Base price parameters for BEVs and PHEVs

Variable	**Value**
Cost unrelated to powertrain	10,000 €
Cost of ICE powertrain	14,000 €
PHEV scaling factor	0.5

Further, as discussed in Chapters 3.5.1 and 6.2.8, the cost of kWh will decay as the global production increases. A number of authors have presented their own estimates for annual decline percentages and with different time horizons. Drawing on the discussion therein, this study applies the estimate of Nykvist & Nilsson (2015) and models the cost decline as a constant 8 % decline. This assumption results in the following price development:

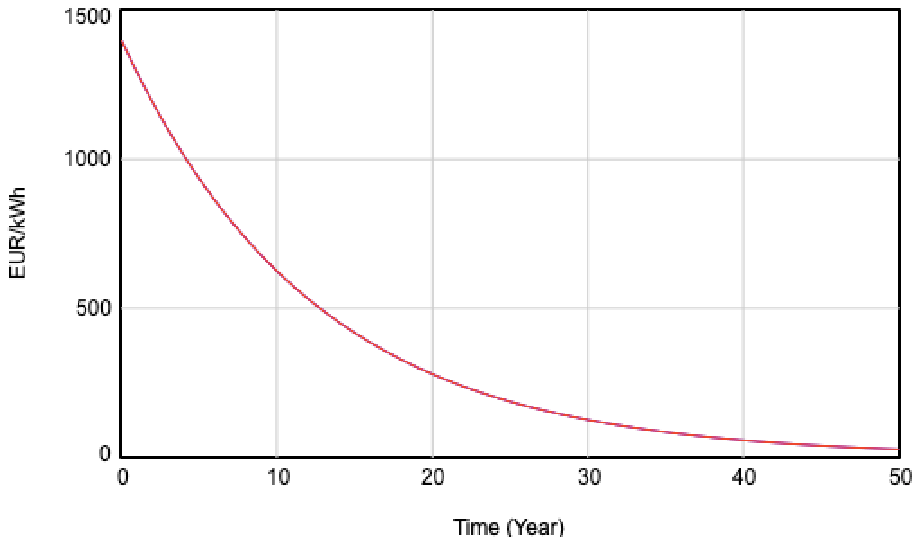

Figure 35. Development of Cost of kWh in the present study

Reflecting to the discussion in Nykvist & Nilsson (2015), who state that cost parity between BEVs and ICEVs could be reached when the cost of kWh is less than \$150, in the present scenario that would be close to 2030.

6.3.4 Oil and power prices

Use costs of a vehicle depend in part on the cost of fuel. For ICEVs and HEVs that is the cost of gasoline (or diesel) and for BEVs that is the cost of electricity. For PHEVs, it can be either fuel or electricity, or both.

As discussed in Chapter 4.5, the present study applies a simplified approach and considers only gasoline vehicles. Taking also diesel vehicles into consideration is a potential area for further research, but it is not in the interest of this study. Having said that, the cost of fuel for is parametrized to be such that it would be realistic for diesel vehicles as well.

As illustrated in Figure 36, the cost of diesel litre has been only a few cents apart from the cost of gasoline during the last few years. Especially, in 2014, the consumer price for diesel was at times virtually equal to the price of gasoline. In this regard, the present study will apply a simplified approach in the base case scenario and use a constant *1.4 €/litre* value for gasoline. The figure is indicative and a constant value will not present entirely realistic behaviour, but it does illustrate the effect of fuel costs on to the relative cost of a vehicle platform and its reference point.

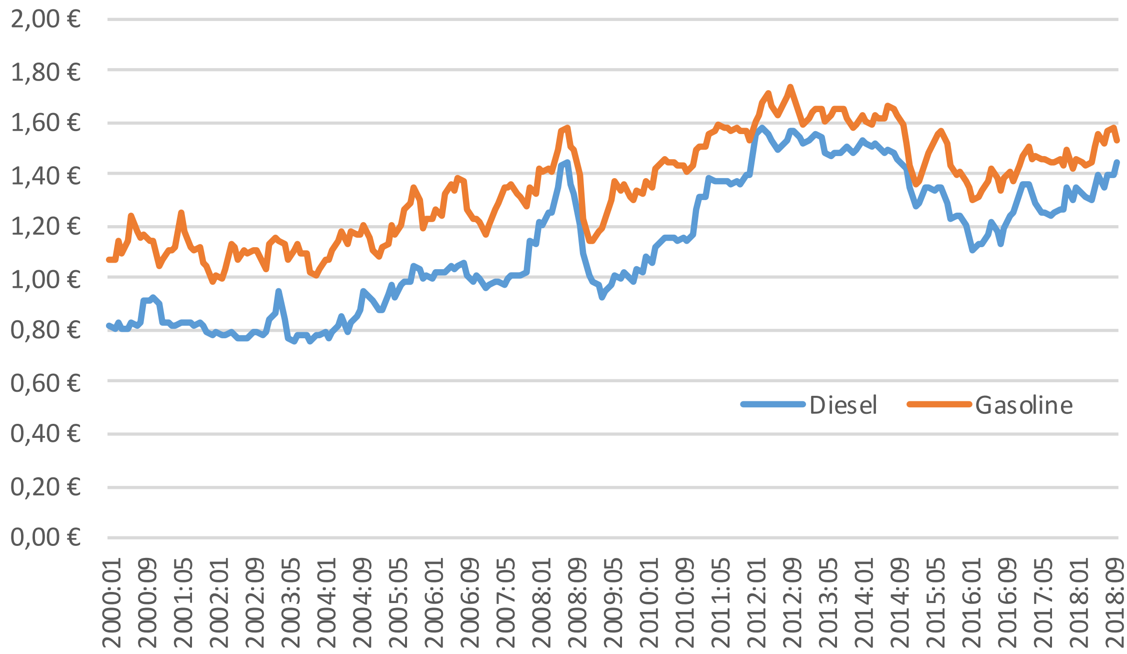

Figure 36. Diesel and gasoline prices in 2000-2018 (Oil and petroleum association 2018)

Cost of electricity depends on a number of factors. Consumer prices may differ across electric companies, “green” electricity can be more expensive, and the type of household a consumer lives in can affect the price. Differences between electricity prices for different housing types are presented below in Figure 37. Prices and categorization are retrieved from Energiavirasto (2018). As can be seen from the figure, the trend was ascending in the beginning of the century, then stabilized into distinctive levels, and has slightly started to increase again since 2016. This could indicate that home charging for electric vehicle owners will become more expensive in the future, and it is even likely that the increasing home charging is a (partial) cause for the increase in prices.

By using linear interpolation on the basis of averaged values across different housing types, an estimate for consumer price in 2050 would be approximately 0.32 €/kWh. This would mean that the price of electricity will double in 30 years. Depending on the cost of public charging availabilities, it is possible that such price development would encourage consumers to prefer public charging stations. At the time being, public charging can already compete with home charging: a Finnish electricity company, Helen (www.helen.fi), charges 0.15 €/kWh plus an hourly service fee of 0.5-2 €/hour, when a consumer uses its slow charging stations in Helsinki area (Helen 2018). In comparison to the reported numbers above, the charge per kWh is already below the level of blocks and some small houses, but the service fee makes home charging more affordable. Helen also offers fast charging availabilities in Helsinki, but there the pricing basis is purely time-based: the consumer pays 0.22 €/min (Helen 2018). Regarding the required charging times reported by McKinsey (2014) and Trafi (2018b), if a consumer charges his/her vehicle for 30 minutes, that would mean approximately 6.6 € per charging.

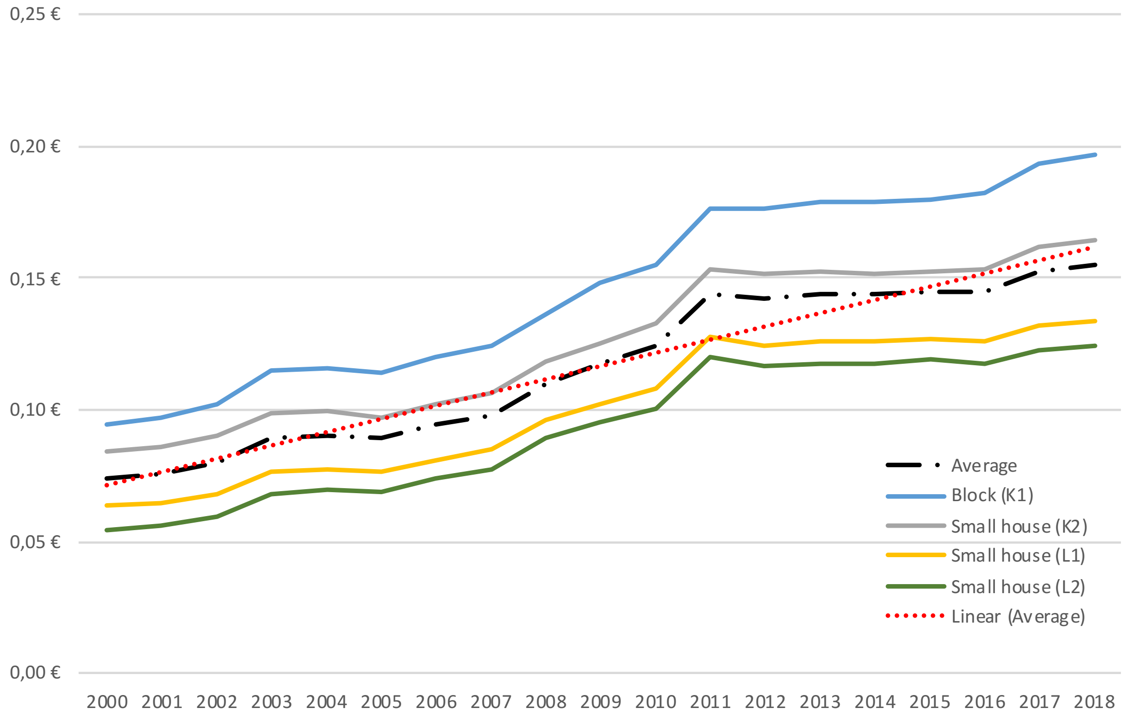

Figure 37. Electricity prices in 2000-2018 (Statistics Finland 2018)

In the base case scenario, a simplified approach is applied, and the electricity price is kept constant at 0.15 €/kWh. This is reasoned with the fact that no distinction is made among public and private slow charging points, and the 0.15 €/kWh would be an appropriate number for both. Regarding the discussion above, however, model robustness and the sensitivity of results will be tested against a scenario where the cost of electricity rises to the aforementioned 0.32 €/kWh by 2050.

6.3.5 Consumer preferences

Attribute weights indicate what attributes consumers consider the most in making the risky decision. It should be noted again that in the present study, those attributes are such that distinctively separate EFVs from ICEVs, and as such they should not be considered similar to those attributes used in e.g. random utility models.

The parametrization of attribute weights is somewhat heuristic: it builds, in part, upon relevant literature such as Clean technica (2016) and Testa (2017), but since neither of those studies were conducted in Finland per se, they have to be treated with caution. To this end, the survey conducted by Kesko was used as a benchmark to evaluate if the conclusions in the literature are in line with the perceptions of Finnish consumers, but as it is not a scientific study, it might also be biased. In this regard, its findings should be treated as indicative. This also marks a clear area for further research.

In the base case scenario, the following weight vector is applied:

Table 5. Base case weight vector

Attribute	**Weight**
weight on travel range	0.40
weight on charging availability	0.30
weight on model diversity	0.15
weight on emissions	0.10
weight on lifetime	0.05

As stated in Chapter 3.5.2, the attribute set considered herein is simplified, and the approach has been adopted from Testa (2017). In her study, Testa (2017) uses a somewhat similar weight vector, and model results will also be tested for sensitivity using those weights. The most notable difference in the present study compared to Testa (2017) is that according to Kesko's survey (2018), Finnish consumers are most concerned with the prices of electric vehicles, but in addition to that they are primarily concerned with the travel range of electric vehicles, as well as with the effect cold weather has on that. In this regard, *weight on travel range* should a bit bigger. In the same study, consumers expressed high anxiety towards charging availability, which increases the its weight relative to other attributes (Kesko 2018). This was also weighted heavily in Testa (2017).

There are still fewer models available in all EFV categories, as illustrated in Chapter 3.5.2. According to Technology Industries of Finland (Teknologiateollisuus 2018), this has halted especially the sales of BEVs, which is why they are also important to address.

The importance of lower emissions and a shorter lifetime were already discussed in Chapter 3.5.2. The former is important especially for Innovators, as also observed by Clean technica (2016), who reported that the main reason for 42 % of the European first movers to buy an electric vehicle was their low emissions. It is reasonable to assume that Finnish first movers are also concerned with the environment and that it has affected their vehicle choice.

Lastly, as noted by Testa (2017) and discussed earlier, EFVs tend to have shorter lifetimes which may also reduce their popularity. However, this has not been observed as widely as the other 4 attributes, hence it receives little weight relative to others.

All parameters used in the model as well as their sources are reported in the Appendix A. Further, sensitivity of results against different values and weightings are tested and discussed in the Chapter 7.3.

7. SIMULATION

7.1 Base case scenario

The base case scenario of the present model and of the development of Finnish EFV market is received by letting the model run over the selected time horizon. This scenario is presented below, in Figure 38.

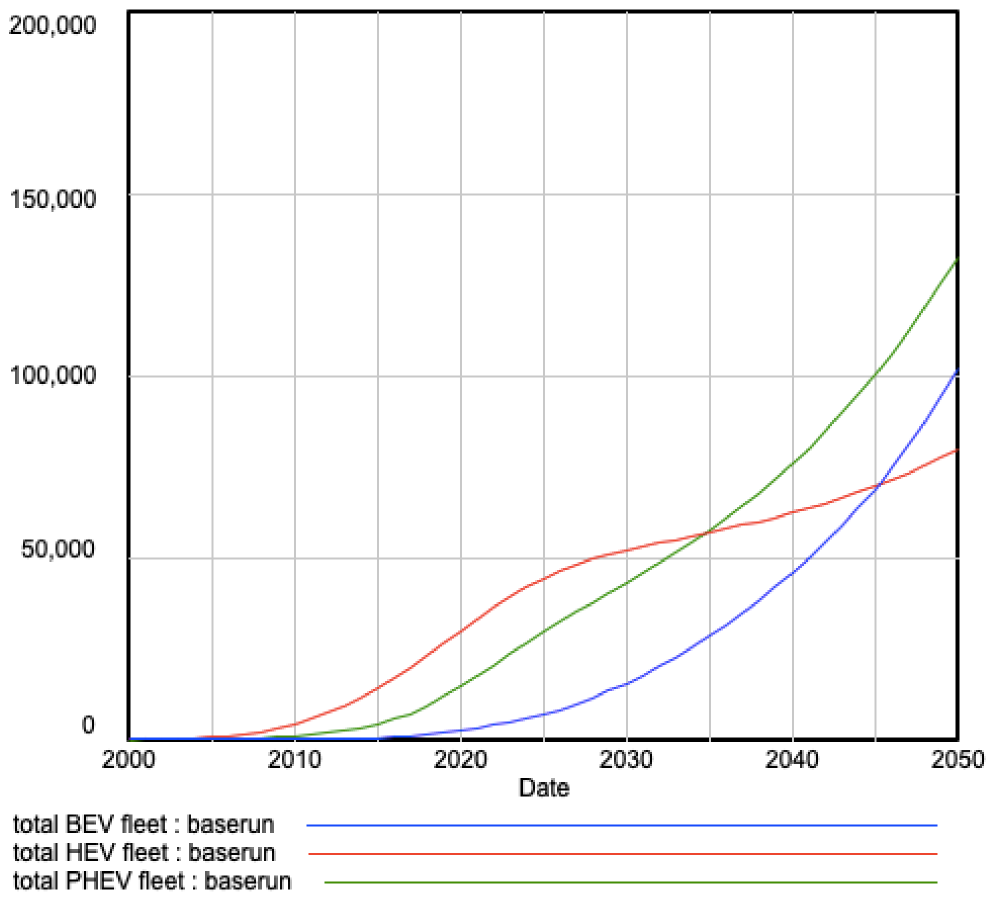

Figure 38. Base case simulation for market development in 2000-2050

HEVs are the first to be introduced to the market and grow faster than the other two platforms. HEVs remain as the dominant EFV technology until late 2030s, when they are surpassed by PHEVs and later in 2040s by BEVs as well. The number of battery electric vehicles grows exponentially despite the slow start. They seem to slightly gain on PHEV sales in 2040s but fail to become the dominant EFV design in the simulated timeframe. Although the simulated numbers are only indicative, it would seem unlikely that the targets of the Ministry of Transport and Communications (see Chapter 1) are met unless corrective actions are taken after the current policies come to end.

7.2 Model validation

7.2.1 Comparison to historical values

By comparing model results to historical values, it is possible to evaluate how well the model performs in *replicating* history and system behaviour (Sterman 2000, p. 859-889). It is also a way to evaluate how well the model *simulates* realistic behaviour (Testa 2017).

The development of vehicle fleet in BEV, HEV, and PHEV categories in 2000-2017 along with their simulated values are presented below in Figure 39. In reality, HEVs were the first to be introduced to the market and started to become popular already by 2010, when there were already a couple of thousands HEVs on the road. BEVs were next to be introduced to the Finnish vehicle market, but they have not taken off equally well: in June 2018, there were 1,875 electric vehicles (Teknologiateollisuus 2018a). PHEVs were the last to be introduced to the market, but they soon passed BEVs in annual sales. In June 2018, there were already over 9,000 PHEVs (Teknologiateollisuus 2018a). In order to be credible, the model should be able simulate similar behaviour and the magnitude of numbers should be reasonably close.

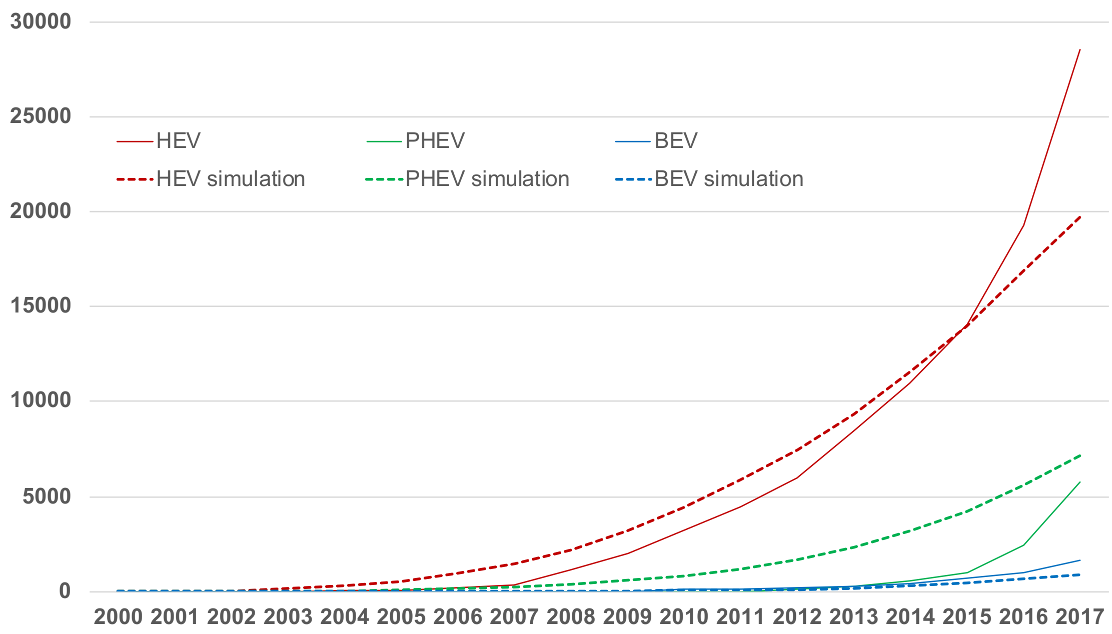

Figure 39. Historical and simulated values in 2000-2017

In the *baserun* simulation, the model is capable of replicating observed system behaviour. HEVs are the first to be introduced to the market, they grow notably faster the other two platforms, and their values are relatively close. The HEV stock grows faster than what has been observed in reality, but the real historical curve reaches the simulated growth levels in 2015, and the passes it. In other words, the historical curve is more strongly exponential than the simulated curve.

The model is incapable of simulating the late introduction of PHEVs but works otherwise credibly. The magnitude is also relatively close: In reality there were roughly 5,700 PHEVs on the road by the end of 2017, while in the simulation there are roughly 7,100 (Teknologiateollisuus 2018b). Similar to HEVs, simulated values grow faster in the beginning and fail to capture the exponential behaviour that seem to arise in reality, but again, the model is capable of replicating realistic behaviour and the magnitude of sales numbers is reasonable.

The BEV stock grows slowly, as in reality. According to Trafi (2018f), in the end of 2017 there were 1,651 BEVs in Finland. In the *baserun* simulation, there are roughly 900. Considering that the present model does *not* take company owned and imported second-hand vehicles into account, the accuracy is within reasonable limits. That is, according to Teknologiateollisuus (2018a, b), over 20 % of BEVs registered in 2017 were second-hand vehicles, and the share of company owned BEVs was as much as 33 %. Thus, as these are not considered, there are inevitably differences in real and simulated values. Lastly, the third condition for model credibility is also fulfilled: the PHEV stock grows faster than that of BEVs. In sum, it seems that the model is fairly capable of replicating historical and realistic behaviour and in that regard, it is credible to satisfactory degree.

7.2.2 Dimensional consistency

Dimensional consistency was tested in Vensim DSS using the built-in functionality (Model -> 'Check Units'). The tool checks if left and right sides match in all equations. No errors were found so in that sense, the model was dimensionally consistent.

A model should not contain fuzzy variables that have meaningless names, arbitrary units (e.g. $widgets^2/month^3$), or are parameters that are not dimensionless, but are valued to unity (Sterman 2000, p, 866). The present model satisfies these conditions as there no variables valued to unity, nor are there any fuzzy factors with arbitrary units. This is illustrated in Appendix A.

7.2.3 Integration error tests

By default, Vensim and many other SD simulation software use Euler's method for numerical integration (Sterman 2000, p. 904). It requires less computation per time step, yet it is adequately accurate for most modelling cases. In some cases, however, greater accuracy may be needed, and the modeller may want to use Runge-Kutta method in integration. (Sterman 2000, p. 908)

To test if the presented results are sensitive to the choice of integration method, four runs were simulated. The first two were simulated using Euler's method and time steps of 0.25 and 0.125, respectively. According to Sterman (2000, p. 910), if there are no significant differences in behaviour when the time step is halved, it is appropriate to use the longer one. The other two runs were simulated using fourth-order Runge-Kutta and the same time steps. These runs are visualized in Appendix C. The simulation shows results are not sensitive to the choice of integration method or to the applied time step, hence Euler's method with the longer time step were chosen.

7.2.4 Extreme conditions

Extreme condition testing was done in two parts. First, the model is tested in situations that are indeed extreme, such as if the willingness to consider an EFV was zero or the electric grid simply was not fit for adding charging stations. Second, robustness of the decision rules used in the model are tested against a set of assumption that were made regarding the initial conditions of the model. In this regard, the following five extreme condition tests were conducted in order to test model's credibility:

1. If the relative performance of a platform is zero, indicated sales share should be zero (Testa 2017)
2. If Willingness to Consider EFV falls to zero, sales to platform should be zero
3. If there is no marketing for EFVs, sales should be very little (as WtC grows only through word-of-mouth)
4. If electric grid is not fit for charging points (fitness of grid = 0), there should not be any charging points built (Testa 2017)
5. If there are no available resources for stations, there should not be any stations built (Testa 2017)

The results show that the model performs credibly in all of the extreme conditions. These are visualized in Appendix D.

7.3 Sensitivity analysis

There are two main reasons for doing sensitivity analysis on a simulation model. The first is that it allows the modeller to assess how sensitive the numerical results, model behaviour, and the resulting policy recommendations are to the selection of initial conditions and used parameter values (Sterman 2000, p. 883-887). The other one is that the variations that may occur are also a source of insights; as stated by Harrison et al. (2007): "observing significant behavioural changes when conditions vary slightly may indicate discontinuities or bifurcation points due to nonlinearities in the model's behaviour, warranting further investigation and perhaps new insights."

Numerical sensitivity analysis was carried out using Vensim DSS and its built-in Sensitivity analysis -tool. The tool allows user to study variables individually as well as to do a multivariate analysis on several variables simultaneously. The user can also determine which distribution is used for drawing values and what are variables of interest, i.e. the variables whose behaviour are studied. According to Vensim, the software uses Uniform Distribution by default as it is suitable for most sensitivity testing. It works well in cases where the real distribution of a variable is not known; all values within the given range are equally likely to occur. (Vensim Documentation) This method has been applied in all cases that are tested for sensitivity herein. This is because the variables of interest are such that data was not either available or it cannot be acquired; i.e. the measure needs to be judgementally estimated based on literature and heuristics.

As stated in Vensim tutorial, “Sensitivity simulations generate a huge amount of data, so it is necessary to limit the data saved to only those variables that we are really interested in.” (Vensim Documentation) In this regard, variable selection has been limited to those variables that are assumed to have a significant impact on model behaviour, or for which there were no valid sources for values and therefore need to be tested. Thus, sensitivity analysis was ultimately done to:

- weight on cost
- technological development rate
- PHEV estimated maximum capacity
- PHEV share of electric drive
- weights on charging availability, emissions, vehicle lifetime, model diversity, and travel range
- marketing efforts
- market growth (see chapter 6.3.1)
- cost of kWh development, and
- cost of electricity (see Chapter 6.3.4)

These are presented and discussed below in subchapters 7.3.1-6. Subsidy durations, budgeted resources, their start times, and policy instruments are assumed to be known exactly, since they are decisions that can be set by policy makers (Vensim documentation). Hence, they are not tested for sensitivity.

7.3.1 Weight on cost

In the base case scenario, consumers weight the purchase price 50 % more than operating costs. In practice, the weight put on costs is 0.4. This value was heuristically chosen and is slightly higher than the value used in Testa (2017), namely 0.25, but it is considered to be appropriate and in line with findings of Hagman et al. (2016), who state that consumers rarely put much weight on operating costs of a vehicle relative to its purchase price.

In order to test how different weightings would affect the model results, a sensitivity analysis was carried out so that the *weight on cost* variable would receive random numbers between 0.4 and 0.6, i.e. using a RANDOM UNIFORM(0.4, 0,6) function. The effects of these changes on sales of the three vehicle platforms are visualised in Appendix E.

It appears that all three vehicle types are highly sensitive to the choice of weight put to costs rather than price. In all three cases differences can be even hundreds of thousands of vehicles. Parametrization in the base case is reasoned with literature as there are studies that have reported and/or observed that consumers tend to put little weight on usage costs in comparison to the purchase price (e.g. Hagman et al. 2016). Therefore, it is considered as an appropriate value, but inevitably is a source of uncertainty.

The fact that weight on cost is such an important variable is also a finding of this study. As stated in Hagman et al. (2016) and Knüpfer et al. (2017), it is a challenge for EV diffusion to get consumers putting more weight on usage costs and vehicle TCO, instead of just being horrified by the high purchase price. If that would happen, it could quickly be seen in sales figures for all three platforms.

Another interesting conclusion that can also be drawn from the sensitivity test is that the growth of PHEV fleet is the most sensitive to the weight put on costs (*NB: The scale is different from the other two*). This could be reasoned by stating that PHEVs are in many dimensions close to ICEVs, but when driving on electricity, the cost of usage is significantly lower than ICEVs'. The cost of usage for a BEVs is also very affordable, but there are numerous other factors that might also affect the perceived attractiveness. Thus, although highly significant, the importance of price sensitivity is could be slightly smaller for BEVs than for PHEVs. The importance of weight put on costs versus purchase price is also high for HEVs as for PHEVs, but the distinctive feature is that the cost of usage for an HEV is *not* as low as for a PHEV. Therefore, if consumers would place more weight on usage costs than vehicle price, PHEVs would gain the most advantage.

7.3.2 Technological development sensitivity

In order to reduce the number of sensitivity test that would be carried out, the two technological development rate variables were combined into one multivariate sensitivity analysis. The results of this analysis are presented in Appendix F. The analysis was conducted so that both variables were given a relatively long domain for values, which were then simulated using uniform distribution. The parameters were:

- BEV technological development rate = RANDOM UNIFORM(0, 0.5)
- PHEV technological development rate = RANDOM UNIFORM(0, 0.5)

Based on the analysis, it appears that the sales of BEVs are the most sensitive to the choice of technological development rates. This seems reasonable, given that the rate of technological development determines the number of kilowatt-hours in a vehicle battery – and thereby its price – and the travel range of an electric vehicle. Therefore, the parameter will greatly affect the relative performance of BEVs.

PHEVs are less sensitive to the chosen level of technological development, which is probably because the initial as well as the estimated maximum values for travel range and battery capacity are notably smaller than those of BEVs'. In other words, even though a faster technological development can increase the relative performance on PHEVs, the electric range and battery capacity are not likely to be the key drivers of relative PHEV performance and a faster development would therefore not affect the PHEV stock development as much. It will be, however, tested in the next subchapter if the results are sensitive to the chosen maximum levels of battery capacity and share of electric range.

When it comes to HEVs, the chosen level of technological development in either category does not affect the *performance* of HEVs, but it might have an indirect effect in HEV *sales*. For instance, if BEVs would develop quickly and their relative performance would increase, it could reduce the sales of HEVs. Alternatively, provided that the assumption of nested willingness to consider an EFV holds true, a faster development in BEV category could also benefit HEV by increasing the aggregate WtC and thereby their sales.

In the base case scenario, the value for technological development was chosen so that the simulated battery capacity and travel range for BEVs and PHEVs would be near to the values of Hyundai Ioniq Electric and Ioniq Plug-in Hybrid, respectively, in 2018 (this is illustrated in Appendix G). However, these values serve only as proxies and there may be differences in other vehicles' values. Furthermore, technological development rate is unlikely to be stable in reality. Upon introduction the development may be slow, but as experience accumulates, the quality of products can increase more quickly; i.e, the technological development rate accelerates. Both of these mark areas for further research, but for purposes of the present study, the applied approach is considered sufficient.

7.3.3 Sensitivity to PHEV attributes

As mentioned in Chapter 6.2.5, the estimated maximum capacity of PHEV battery, as well as the share which a consumer would wish to drive with electricity, were chosen heuristically so the model sensitivity to these assumptions needs to be tested. In this regard, the following sensitivity runs were simulated:

- estimated maximum capacity RANDOM UNIFORM(15, 30)
- share of electric drive RANDOM UNIFORM(0.25, 0.5)

The results of these runs are visualized in Appendix H. As could expected based on the discussion above, the stock of PHEVs varies only a little depending on estimated maximum capacity. When it comes to share of electricity, it seems that model results are also insensitive to the choice of desired share. These findings complement the conclusion that electric travel range and battery capacity are not the underlying drivers of PHEV performance.

7.3.4 Weight vector sensitivity

The chosen weight vector determines what attributes consumers value the most and is therefore likely to affect simulation results. Thus, the effects of weight vector selection needed to be tested. In the first weight vector test, all five attributes are equally weighted. This may not represent a realistic case, but it does illustrate the effect of weight selection.

Weight vector test 1: all equal

- Weight on charging availability = 0.2
- Weight on emissions = 0.2
- Weight on lifetime = 0.2
- Weight on model diversity = 0.2
- Weight on travel range = 0.2

The results are visualized in Figure 40. Regarding the base case scenario presented in Chapter 7.2, it can be noted that the stock of BEVs grows significantly faster. While in the base case PHEVs become the dominant design in 2035 and remain dominant thereafter, in this scenario they finish second while BEVs become the dominant design, even though there are also more PHEVs on the road in 2050. This is a clear behavioural difference which can be reasoned with the fact that now the clearly *superior* attributes of BEVs receive more weight, namely emissions and lifetime. As discussed in Chapter 3.5.2, BEV lifetimes are likely to be shorter early upon wide-scale introduction but is plausible that in the future their lifetimes even exceed the ones of ICEVs. On this premise, they are modelled accordingly and if they are weighted more heavily, the relative attractiveness of BEVs increase. Similarly, BEVs produce significantly less greenhouse gases, which contributes to the emission attribute. In sum, *the more weight is put on attributes that superior to ICEVs, the more appealing BEVs naturally appear*.

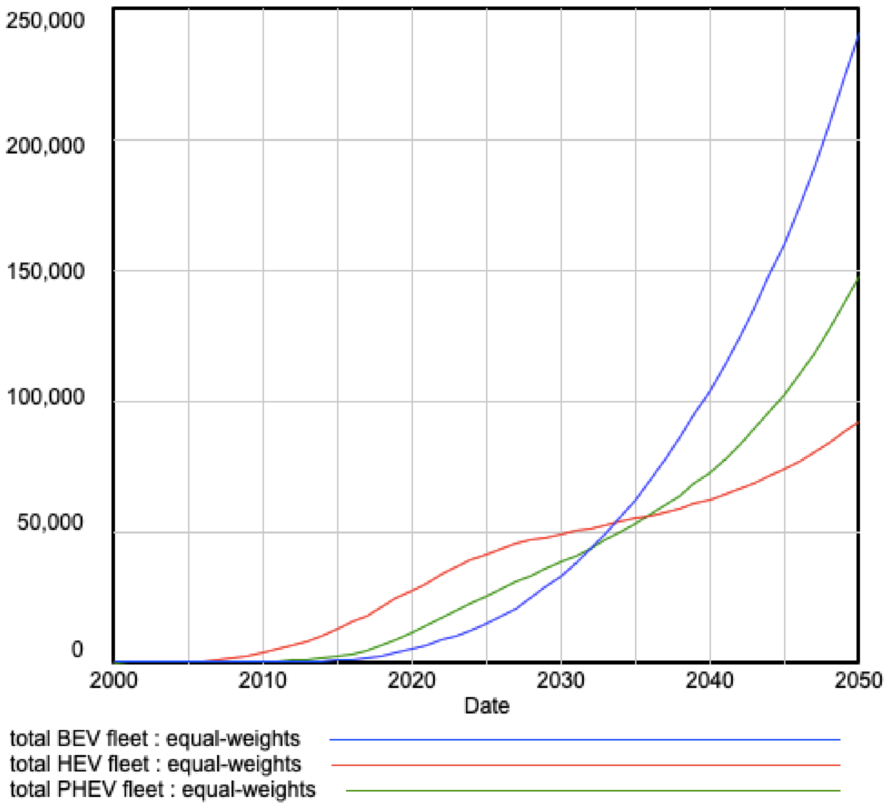

Figure 40. Model results with *equal weights*

As described in Chapter 3, *range anxiety* is a great barrier in electric vehicle adoption. It culminates into two attributes of electric vehicles: the travel range and charging availability. This is also the reason why they are weighted the most in the base case scenario. In order to see if there are any differences in model results if *all weight* is put on these two attributes, the following simulation was run:

Weight vector test 2: all weight on travel range and charging availability

- Weight on charging availability = 0.5
- Weight on emissions = 0
- Weight on lifetime = 0
- Weight on model diversity = 0
- Weight on travel range = 0.5

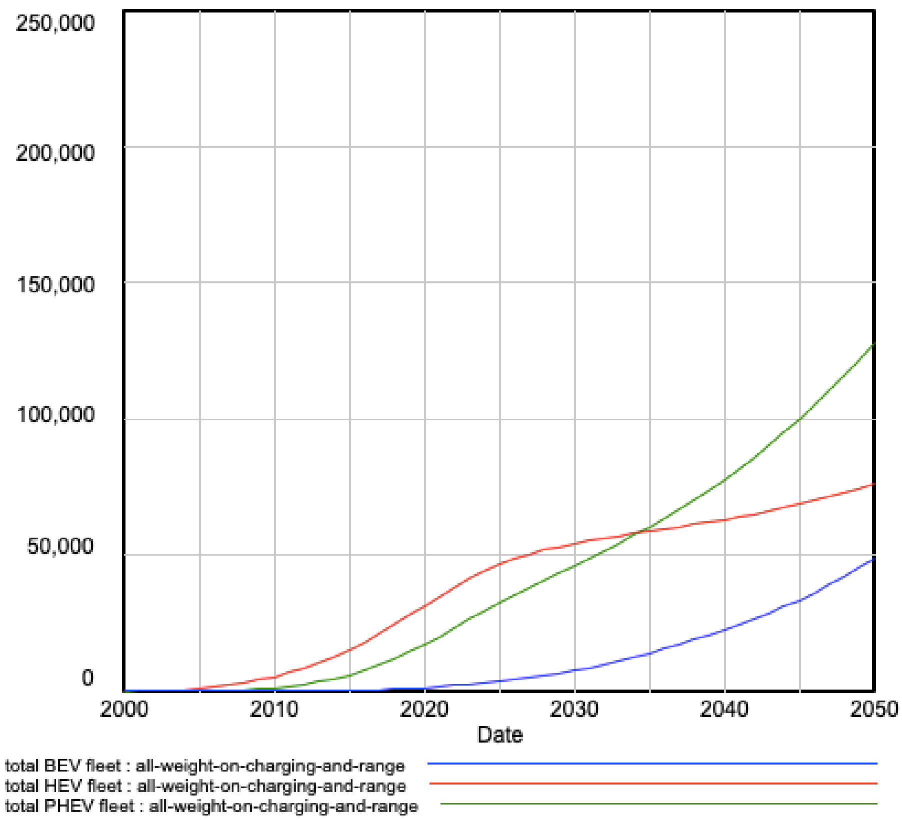

Figure 41. Model results with *all weight on charging and range*

As could be expected, the development of BEV stock is notably slower than in the base case scenario and the other two test runs. If consumers only consider charging availability and travel range, they are likely to miss all the aforementioned superior features of BEVs. Although in the future e.g. charging availabilities might be superior relative to the number of gas stations today, at the time being and in the near future it may well be that BEVs appear as inferior to ICEVs. Similarly, the average travel ranges of BEVs are constantly lengthened, but at the time being they are inferior to those of ICEVs. Thus, the findings are in line with the conclusion above that more weight should be put on BEV strengths rather than weaknesses in order for them to diffuse successfully.

Thirdly, as mentioned in Chapter 6.3.5, the weight vector applied herein is close to but not equal to the one used in Testa (2017). Given that are certain similarities in the two models, it is now tested how the present model would have behaved with those weights.

Weight vector test 3: Same weights as in Testa (2017)

- Weight on charging availability = 0.4
- Weight on travel range = 0.3
- Weight on model diversity = 0.1
- Weight on emissions = 0.05
- Weight on lifetime = 0.15

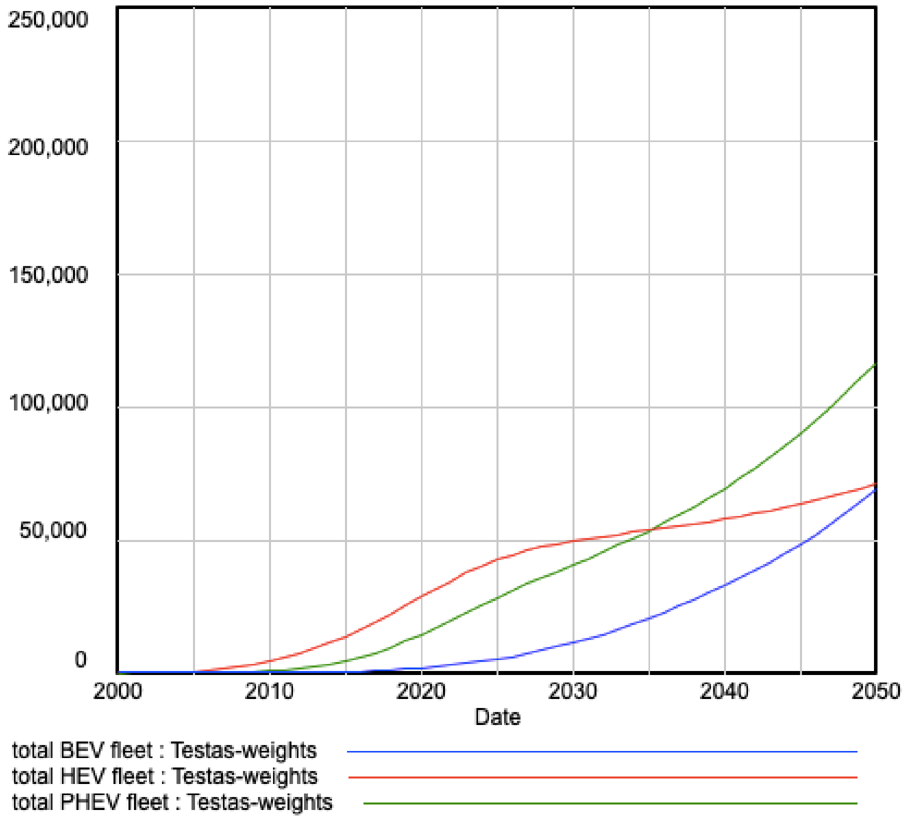

Figure 42. Model results with *Testa's (2017) weight vector*

Considering the base case simulation again, it can be seen that there are differences in model results (*NB: the scale is also different*). Testa (2017) puts more weight on vehicle lifetime than the present study does, but less weight on vehicle emissions and model diversity, which results in a slower stock development for BEVs. This is because the development of BEV lifetime takes time, while emissions are significantly lower right after introduction. The development of relative performance is therefore delayed. Testa (2017) did not consider other vehicle types than BEVs and ICEVs, thus differences in other vehicle type behaviours cannot be assessed.

7.3.5 Sensitivity of model results to marketing behaviour

The sensitivity of model results to the applied form of marketing efforts were studied using the following lookup functions:

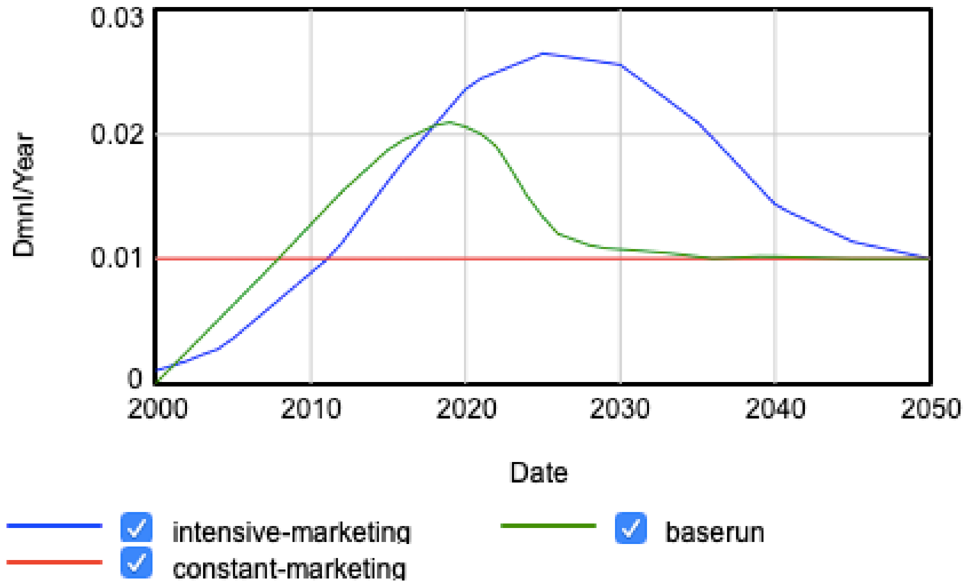

Figure 43. Lookup functions used in marketing effort sensitivity testing

In the base case, it is assumed that EFVs receive "free media" attention and additional hype due to their novelty, which then wears off as they become more common. The constant case, instead, is a simplifying assumption retrieved from Struben (2006): what if the "normal" level was kept throughout the time horizon? Then, thirdly, very intensive and long-lasting marketing efforts are illustrated with the *intensive-marketing* run. It may not fully realistic, but it does capture the effect of raising marketing efforts to the "maximum". The results for *constant-marketing* and *intensive-marketing* scenarios are presented on the next page in Figure 44 and Figure 45, respectively.

Still, the general behaviour of the model is similar. PHEVs become the market leader, BEVs finish second, and HEVs have to settle with a lesser share despite their fastest growth in the early years. At the same time the model exhibits significant numerical sensitivity to the magnitude of marketing efforts: the *intensive-marketing* results in over 700,000 PHEVs and BEVs in 2050, which more than twice the number of PHEVs and BEVs collectively in the base case. On one hand, this evidently highlights the importance of marketing efforts and information campaigns as means of accelerating EFV diffusion, but this also means that the model results can be error prone. The finding is in line with Struben & Sterman (2008), who also conclude that marketing efforts can greatly affect AFV diffusion, but they further add that it would likely be very expensive to do that in real-life.

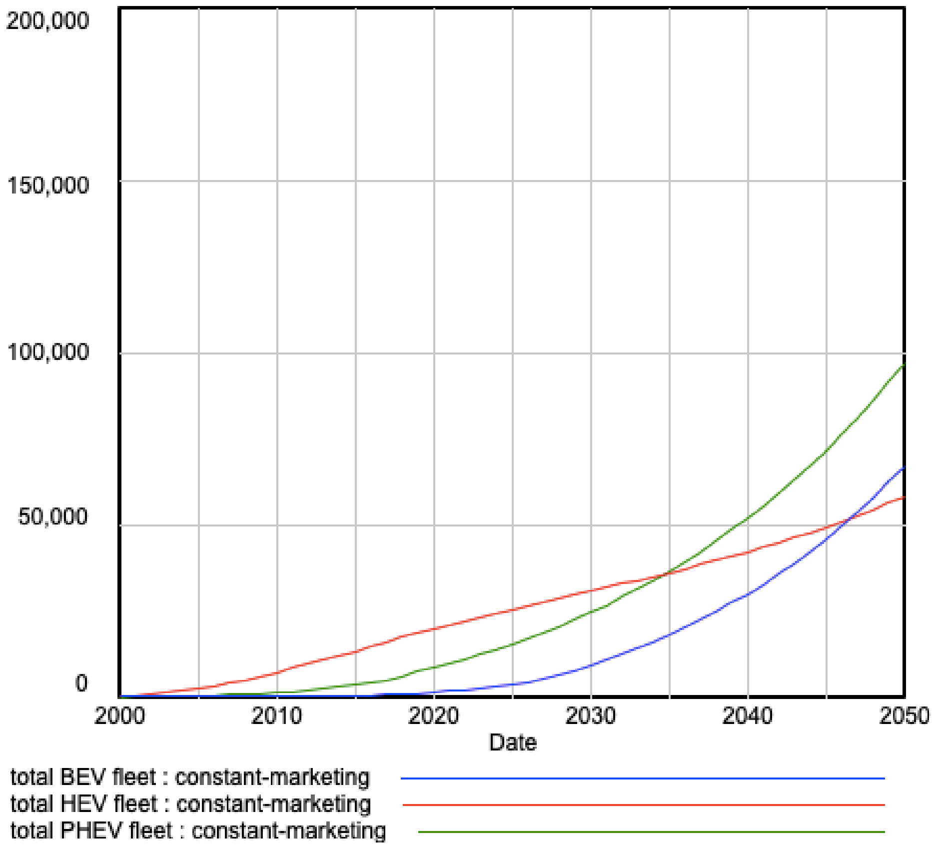

Figure 44. Model behaviour with constant marketing

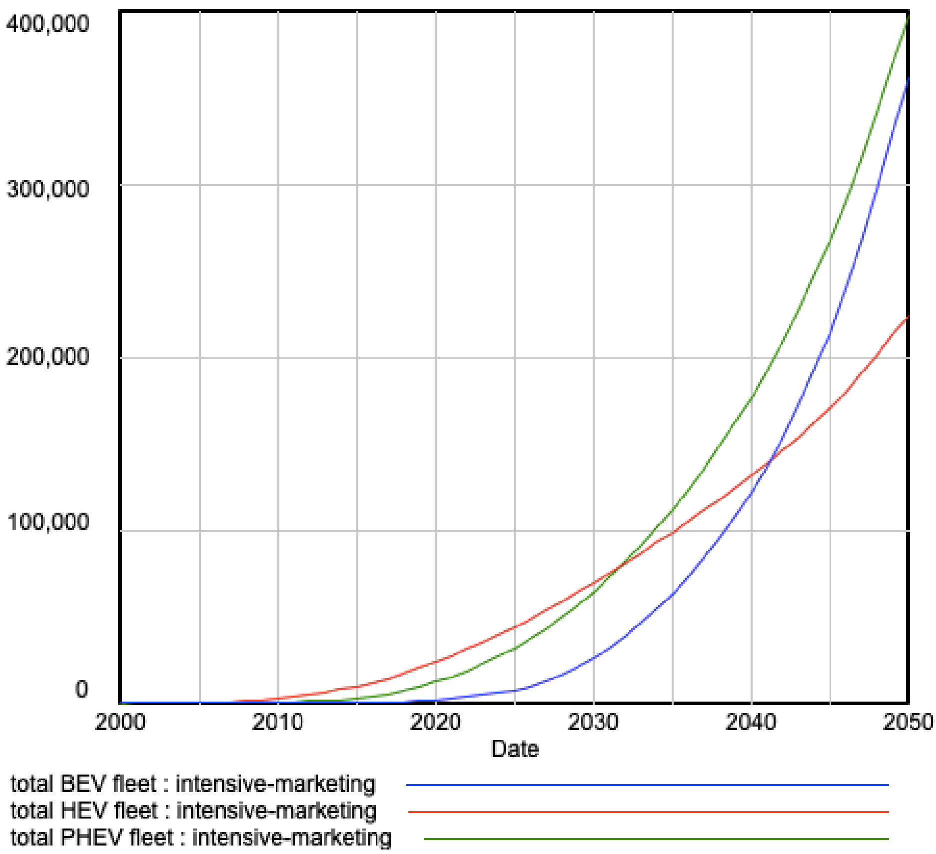

Figure 45. Model behaviour with intensive marketing

7.3.6 Sensitivity of model results to cost of kWh decline

There are multiple estimates for cost of kWh development presented by commercial organizations, public authors, as well as the academia. Nykvist & Nilsson (2015) present a systematic review on some of them and conclude that the most likely estimate for cost of kWh development would be around 8-9%. In order to test how sensitive the model behaviour and simulation results are to those estimates, the following scenarios were run:

- the average cost of kWh will decline at a constant 6 % rate
- the average cost of kWh will decline at a constant 10 % rate
- the average cost of kwh will decline logarithmically so that the decline is fast in the beginning but slows down as time progresses

The four scenarios will result in the following trends for cost development:

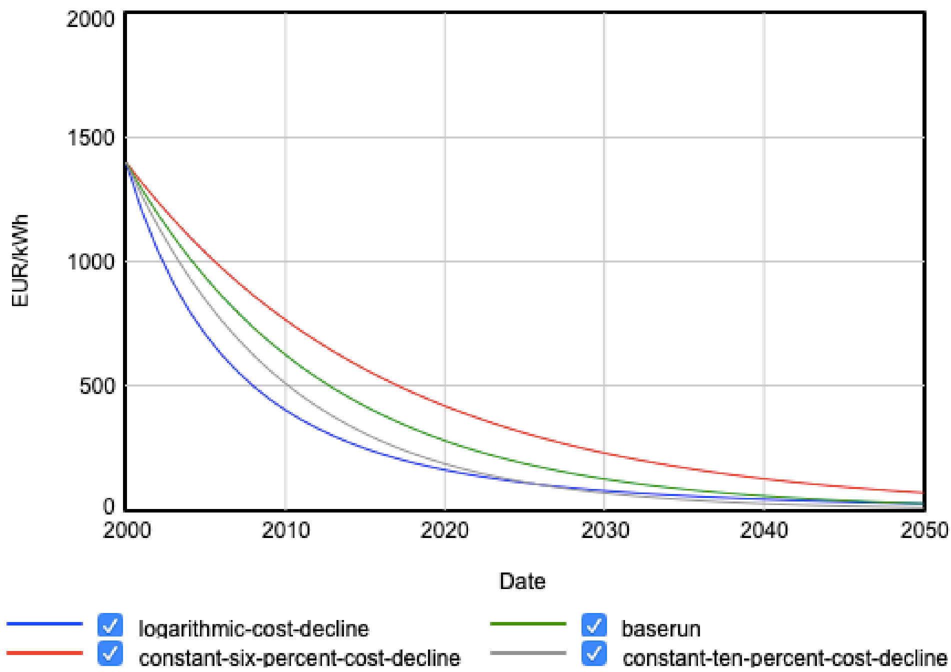

Figure 46. Four alternatives for cost of kWh development

As can be seen from the figure above, different estimates result in notably different trends for cost development. In the most pessimistic scenario, the cost of kWh is several hundreds of euros more expensive in 2010s than in more optimistic scenarios. In particular, the logarithmic trend results in steep decline in cost of kWh in 2000-2020, which then wears off towards the end of the time horizon. The constant 10 % decline also results in fast decline in cost of kWh, even though the difference is only 2 % relative to the base case scenario. These scenarios then result in following market development in the three categories:

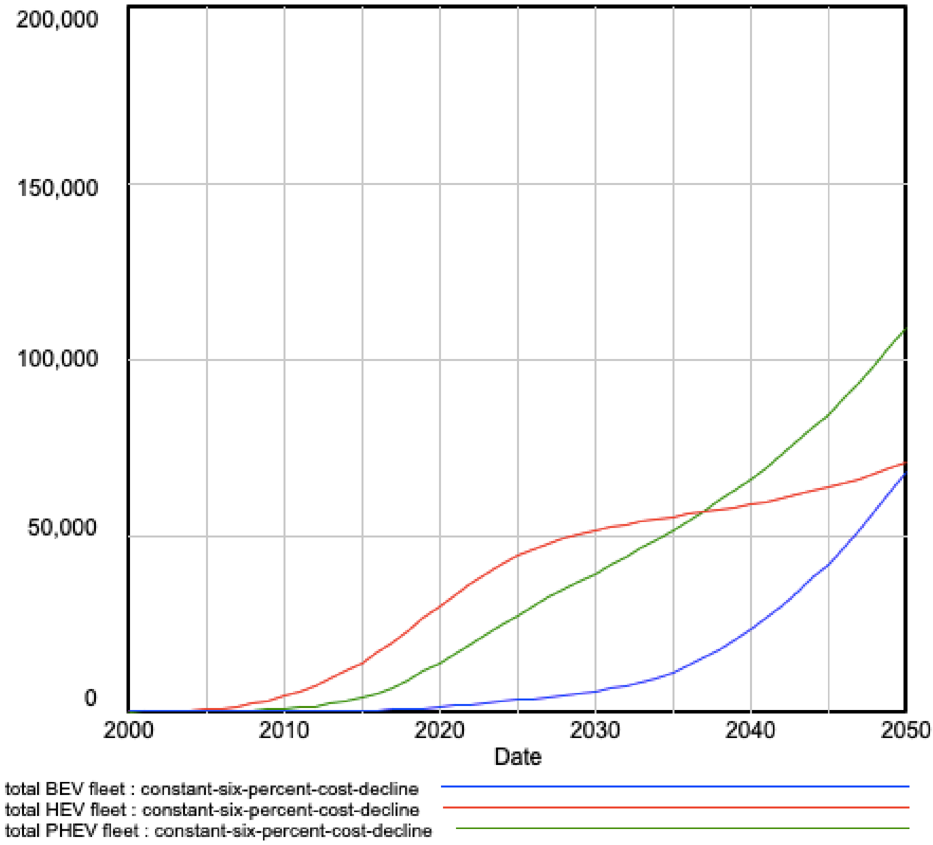

Figure 47. Model results with constant 6% decline in cost of kWh

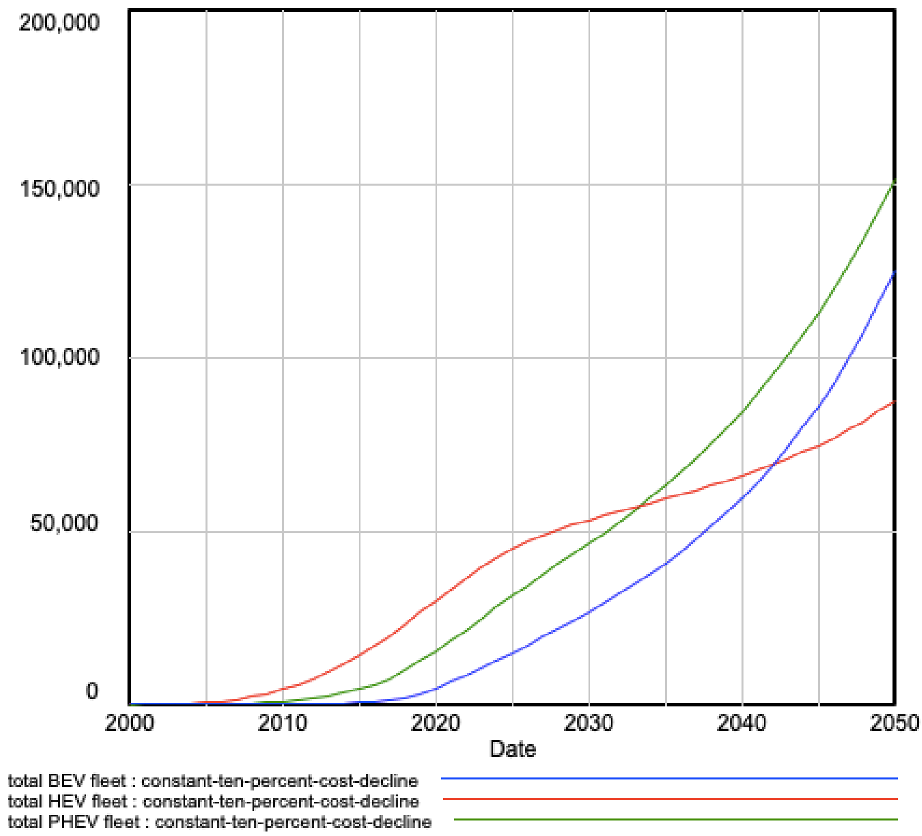

Figure 48. Model results with constant 10% decline in cost of kWh

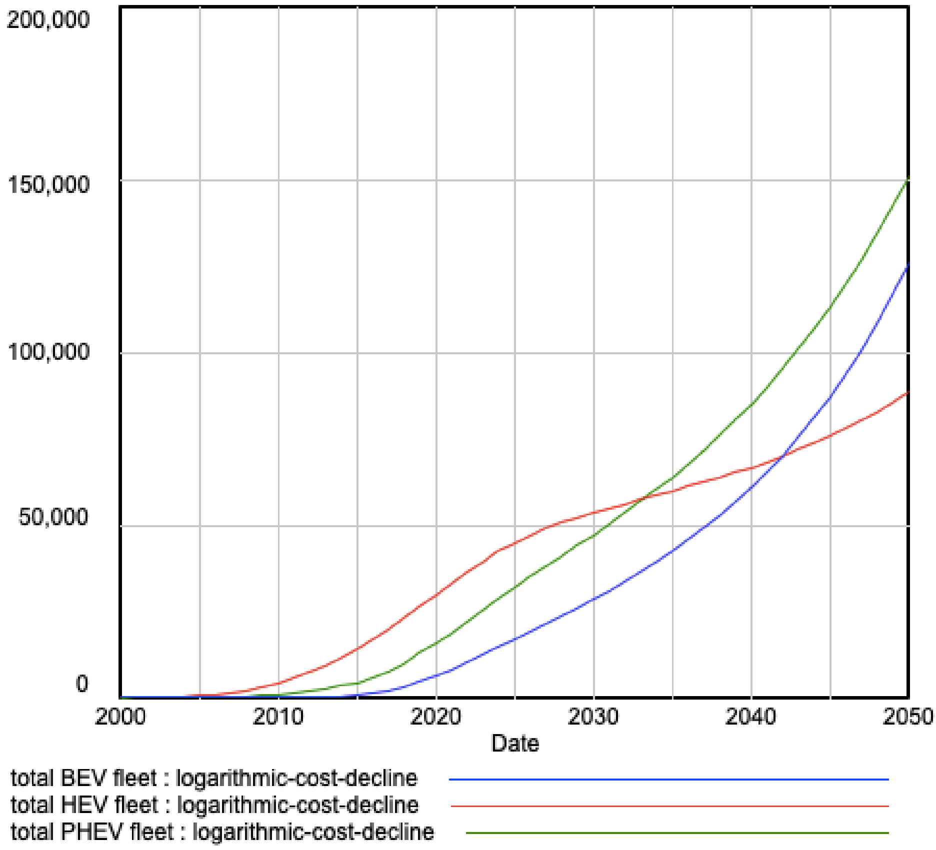

Figure 49. Model results with logarithmic decline in cost of kWh

The figures above illustrate that the model is numerically sensitive to the estimate used for cost of kWh development. While doing so, it also underlines the fact that the whole market development of the Finnish EFV market is dependent on the global market where the cost of a kilowatt-hour is really determined. This implies a promising future in the sense that virtually all estimates for cost of kWh development show that cost parity will be reached around 2030s, but at the same time means that the development of BEV market in Finland is, at least in part, beyond decision-makers reach.

The figures above also illustrate that *if* the cost of kWh comes done fast, BEVs will pass HEVs a couple of years earlier, and there will be more BEVs on the road in 2050. PHEVs remain as the number one, but it does seem that BEVs would be gaining on. Alternatively, if the decline of cost of kWh is slow, BEVs remain few and far between. Thus, the more time it takes to reach cost parity with ICEVs, the longer it takes for BEVs to fully penetrate into the market.

The rate of cost decline also affects the diffusion of PHEVs: If the cost of kWh comes down, the cost of battery comes down, and the cost of PHEV comes down. This can greatly contribute to the perceived attractiveness of PHEVs. However, the figures indicate that differences in stock development between scenarios are not quite as big as with BEVs. This is likely due to the fact that PHEV batteries are notably smaller than those of BEVs, which naturally means there is also less capacity in the battery. Then, if the cost of kWh declines quickly, the effect is the stronger the more is capacity in the battery.

For HEVs the effect of cost decline is supposedly smaller, as in the present model the cost of battery is not considered to a similar extent as those of PHEVs and BEVs. HEVs' ranges are notably shorter than those of PHEVs and BEVs and similarly their electric drivetrains are not as big. Hence, the battery accounts for a smaller share of the purchase price than in PHEVs and BEVs and was therefore excluded from the present model. Having said that it marks an area for further model development.

7.4 Alternative scenarios

7.4.1 Zero-subsidy scenario

Similar to Testa (2017), it is in the interest of this study find out what would have happened, if there had not been any policies implemented to the market. For this purpose, a *zero-subsidy* simulation was run. Therein, budgeted resources for purchase subsidies, scrapping bonuses, charging infrastructure investments, and the energy investment program were all set to zero. The simulation results are illustrated below in Figure 50.

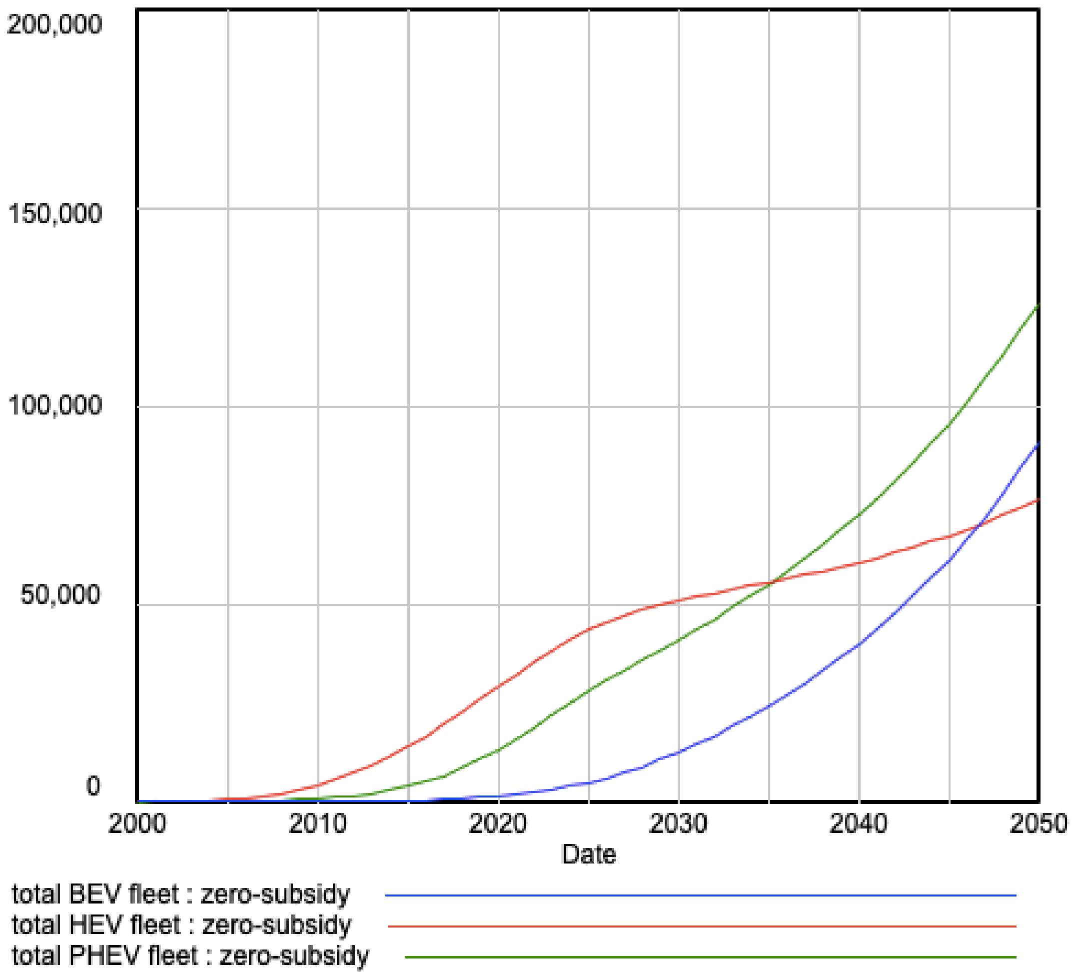

Figure 50. Zero-subsidy simulation in 2000-2050

It can be noted that there are differences in market development. The adoption of BEVs is lower throughout the time horizon which ultimately results in a notable difference in 2050. This is illustrated also below in Figure 51.

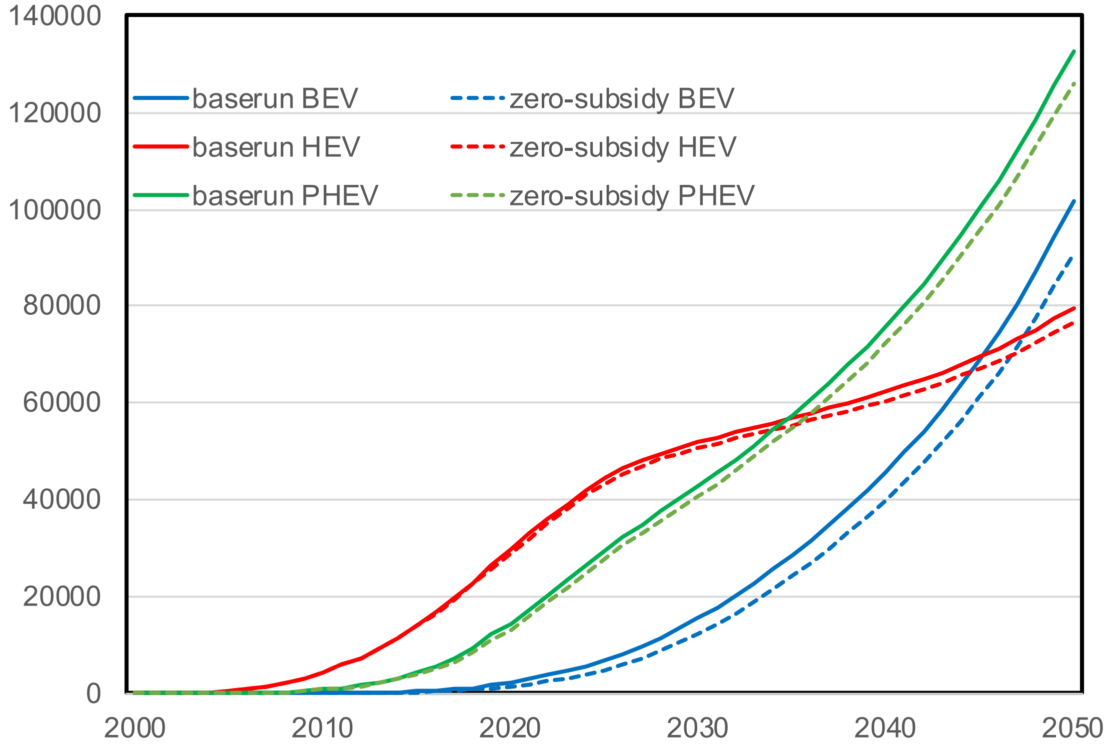

Figure 51. Differences in BEV, HEV, and PHEV stock developments between *baserun* and *zero-subsidy* scenarios

While the difference is notable for BEVs, the removal of all aforementioned incentives and policies does not seem to be as harmful for the other two categories. For PHEVs, a small difference can be observed early upon introduction, which then slightly amplifies towards the end of the simulated time horizon. For HEVs, the difference is also small and manifests itself only as of 2020s.

It seems that the policy portfolio the Finnish government has used hitherto is effective in inducing BEV adoption. If none of the policy measures had taken place upon BEV introduction, their growth would have been slower than it has been and will be. PHEVs and HEVs have also benefitted from policies, but to a smaller extent.

7.4.2 2025-scenario

In addition to seeing how altering history would change the market development, it is the interest of the present study to find out what might happen in the future if the current policy portfolio was kept in place. For this purpose, a *2025-scenario* was run with the following assumptions: Resources are allocated in a similar fashion as they are now: In 2018-2021, BEVs will receive 2,000€ purchase subsidy from the government, and 12 million euros are budgeted for this purpose. Thus, in years 2022-2025 there will be an additional 12 million euros budgeted for this purpose. Similarly, between 2017-2019 4.8 million euros are spent in subsidizing charging infrastructural investments. It is assumed that also for 2020-2022 and 2023-2025 there will be 4.8 million euros, thus in total 14.4 million euros would be spent in 2017-2025. Lastly, another scrapping program would take place in 2022. All other conditions remain the same as in current programs and in the base case scenario. The results of *2025-scenario* are visualized below, in Figure 52.

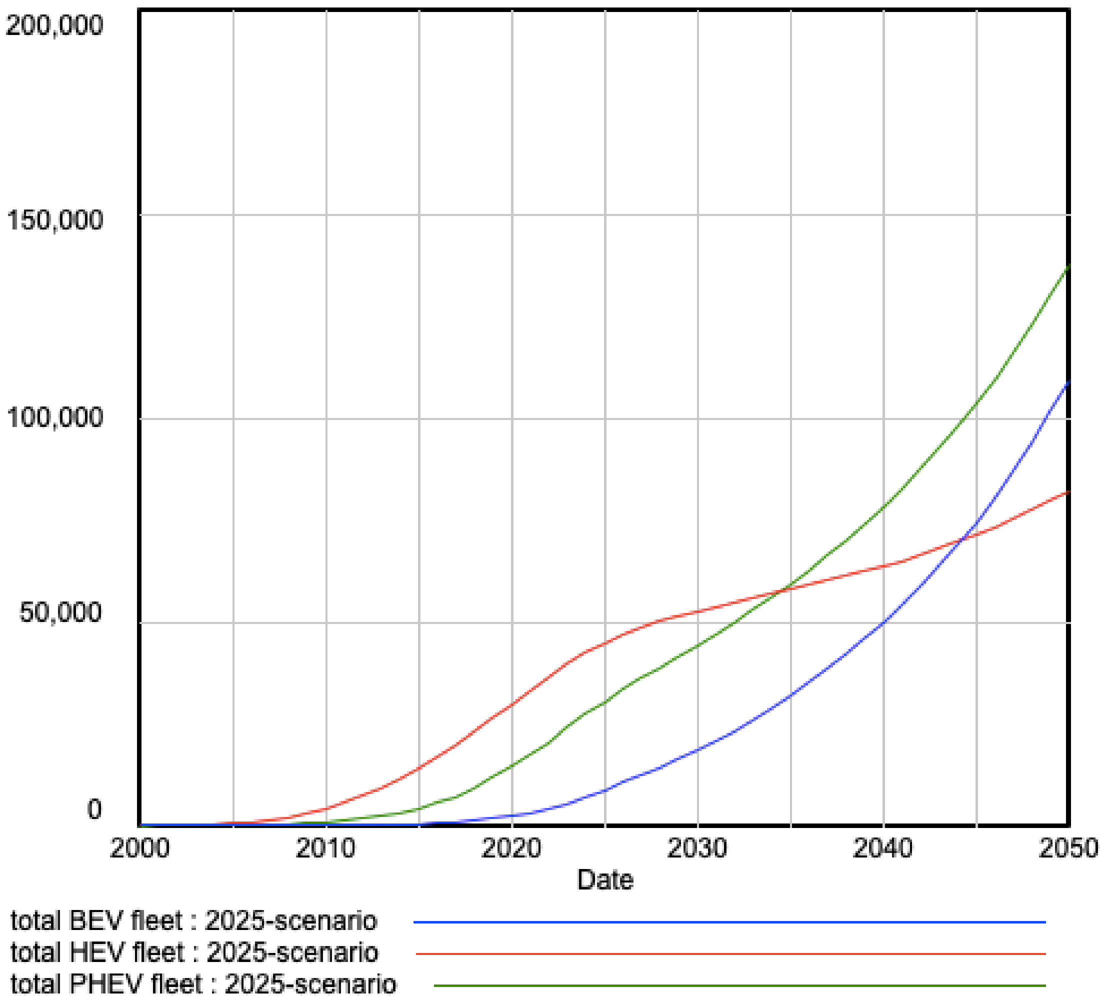

Figure 52. Results of *2025-scenario*

As could be presumed based on the discussion in the previous chapter, continuing the usage of policies until 2025 has an impact on market development. As in removing the policies, the difference is biggest in BEV stock development. There are also differences in PHEV and HEV stock development, but the differences do not seem to be as big.

7.4.3 Logistic market growth

Different estimates for market development were discussed in Chapter 6.3.1. It was reasoned that there were two more likely estimates, out of which the constant growth was applied in the base case. Here, however, the model robustness is tested against a scenario were the market growth slows down to less than 10,000 vehicles a year. The growth trend was modelled using a table function, where the growth is constant at 21,375 until 2030, when it starts decay exponentially. The results of this scenario are presented in Figure 53.

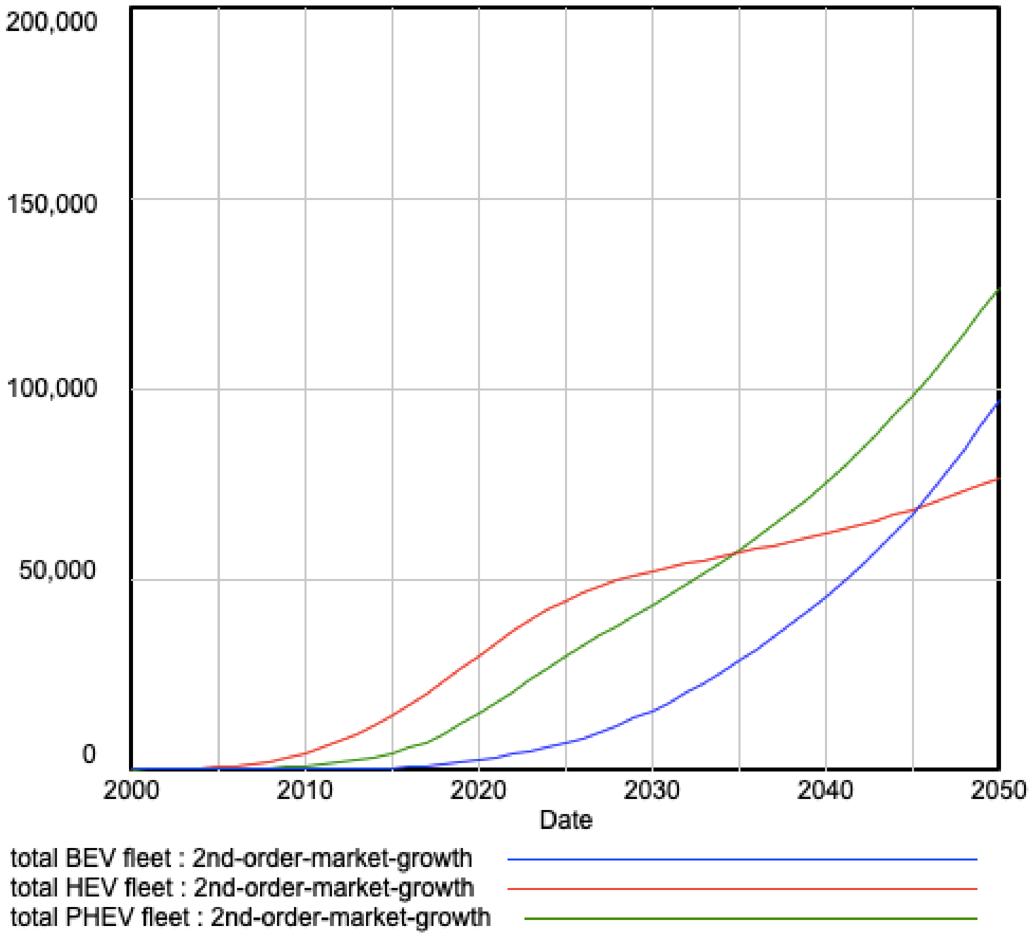

Figure 53. Model results with slowing market growth

Should such a scenario be realized, there would be a little less EFVs on the road since there would be less vehicles sold annually, BEVs suffering the most. Structurally, however, the model is robust as the underlying behaviour remains the same.

7.4.4 Electricity demand

As discussed in Chapter 6.3.4, the trend for electricity consumer prices appears to be ascending, even though it reached a saddle point around 2010. As of 2016, the curve has started point upwards again, and it is presumable that the increasing sales of electric vehicles, combined all other electricity usage, will also increase the prices in years to come. In this regard, it should be tested whether the model results in the base case are sensitive to the cost of electricity.

The rise of cost of electricity was modelled similarly as described in Chapter 6.3.4: using linear interpolation to the *averaged values* and using a linear estimate where the electricity price eventually rises to 0.32 €/kWh. The effects of such a scenario are presented for all vehicle types below, in Figure 54.

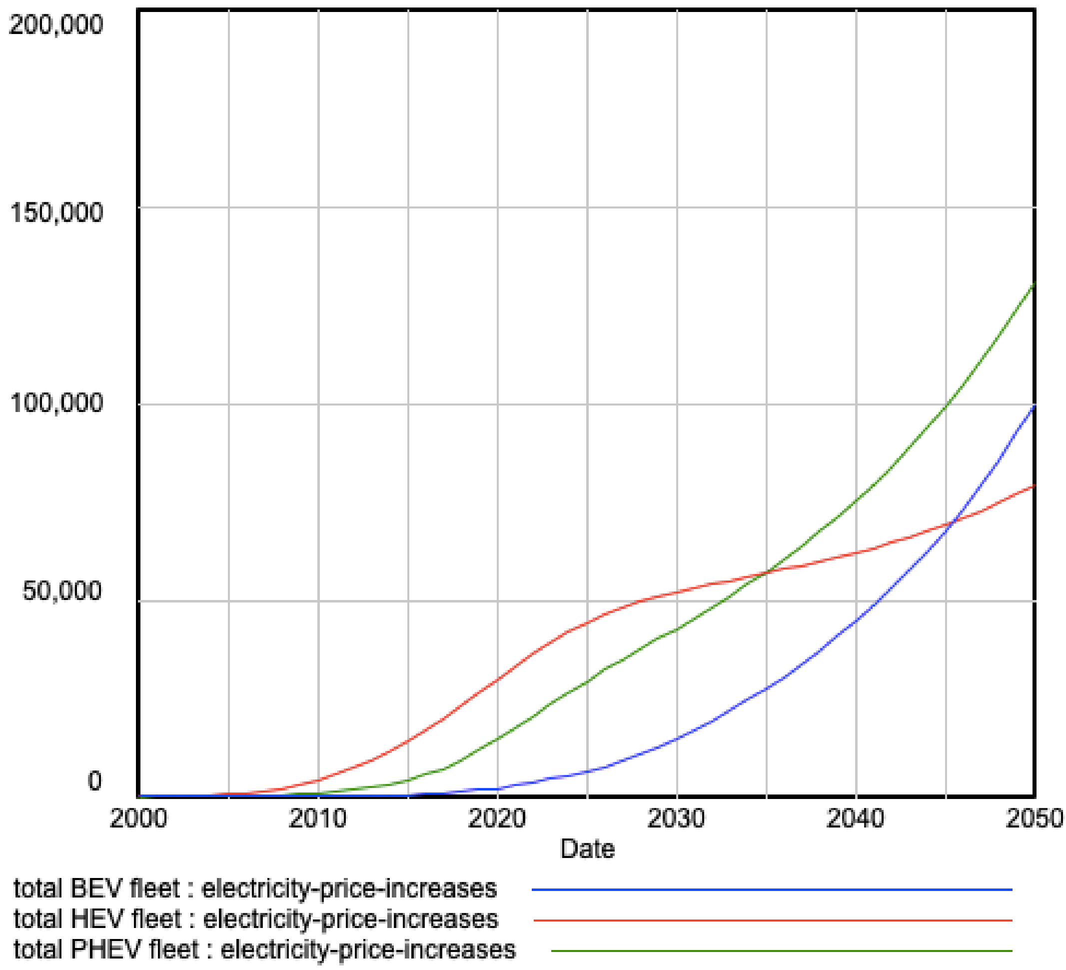

Figure 54. Effect of electricity price increase of sales

In comparison to the base case scenario, there seems to be a small difference, but only a marginal one. The cost of usage of an electric vehicle depends not only on the cost of electricity, but also on the annual mileage of that vehicle. Thus, it may be that with the estimated annual mileage the difference is not yet that evident. Furthermore, the *relative* cost of usage depends also on the cost of gasoline, which in the base case was heuristically set at 1.4€/litre. Should the price of gasoline be lower, an increase in electricity price would likely be more effective, due to the bigger impact on relative costs of usage.

7.5 Policy experimentation

7.5.1 Policy removal

The usage of policies in market guidance is expensive and it could be the case that the Finnish government decided to remove a policy, or even several policies, if they did not seem to work sufficiently well. In this regard, it is the interest of this study find out which policy removal would, then, the least damaging in terms of EFV diffusion.

Options for policy removal were the following:

- Stop investing in charging infrastructure, i.e. remove the 4.8 million euros budgeted for investments
- Remove the 12 million euros budgeted for purchase subsidies
- Remove scrapping bonuses

The results are illustrated below in Figure 55, Figure 56, and Figure 57

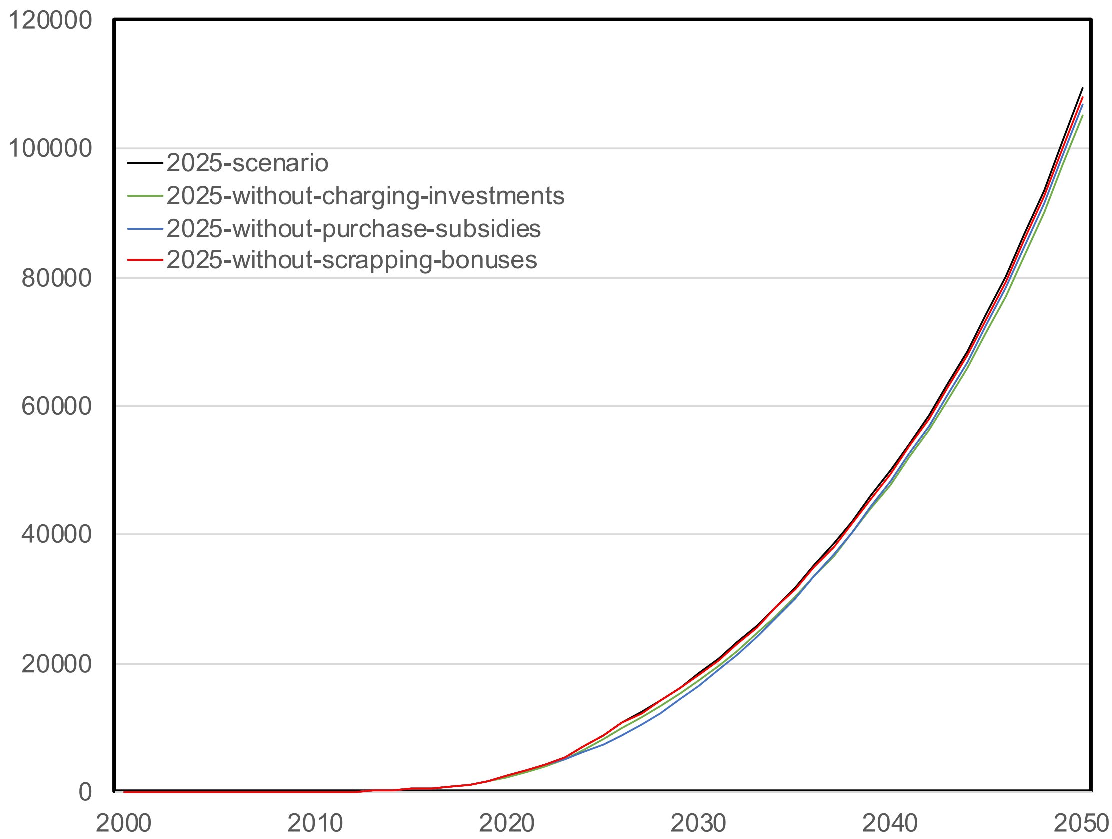

Figure 55. Effects of policy removal on BEV stock development

Differences in the effects of removal of policies are small. By closely examining the curves, it can still be seen that the removal of scrapping bonuses has the least effect on BEV sales. In the short term, the removal of purchase subsidies has the biggest effect on

BEV sales, but in the long term it seems that removing charging infrastructural investments is the most harmful option.

Although scrapping bonuses are not even admitted to BEVs – if they are given a purchase subsidy (The Ministry of Transport and Communications 2017) – they seem to benefit a little from it. This could be reasoned with the notion of e.g. Sterman (2000) and Figenbaum & Kolbenstvedt (2016) that word of mouth is one of the most powerful reinforcing loops, which in the context of electric vehicles is the best way to increase consumers' confidence towards them. If the assumption of aggregate willingness to consider EFV holds, this would explain this phenomenon.

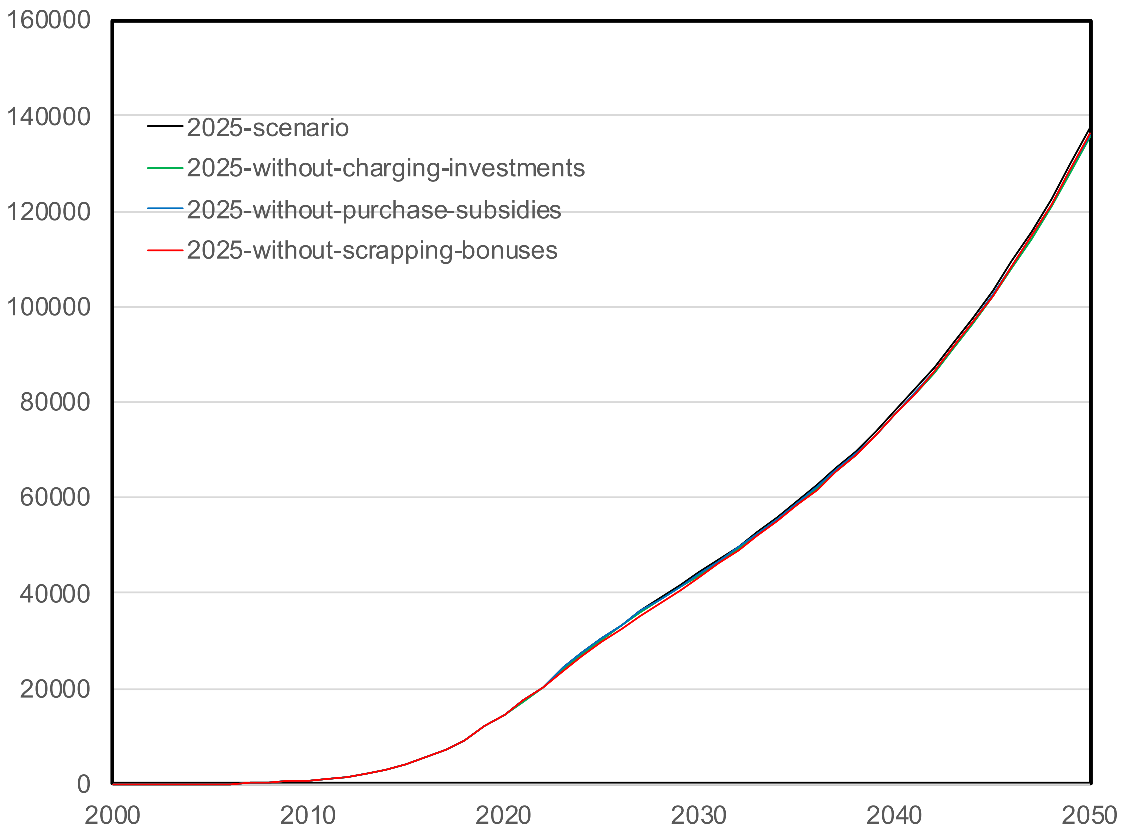

Figure 56. Effects of policy removal on PHEV stock development

Similar to BEVs, the differences in stock development in different scenarios for PHEVs are small. The difference between the base case and the other simulations is however even smaller, as it appears that all four lines are basically overlapping. This would imply that if any one subsidy (out of the subsidies considered) was removed tomorrow, the sales of PHEVs would not be drastically affected.

The behaviour of HEV stock development is close to that of PHEVs. In Figure 57 all four lines are again overlapping, and any notable differences are difficult to observe visually. It seems that there is a small difference between the *2025-scenario* and the four removal scenarios, but it is difficult to assess their mutual superiority. The only one that stands out a little is the removal scrapping bonuses in 2020s, i.e. removing the purchase subsidy from HEVs.

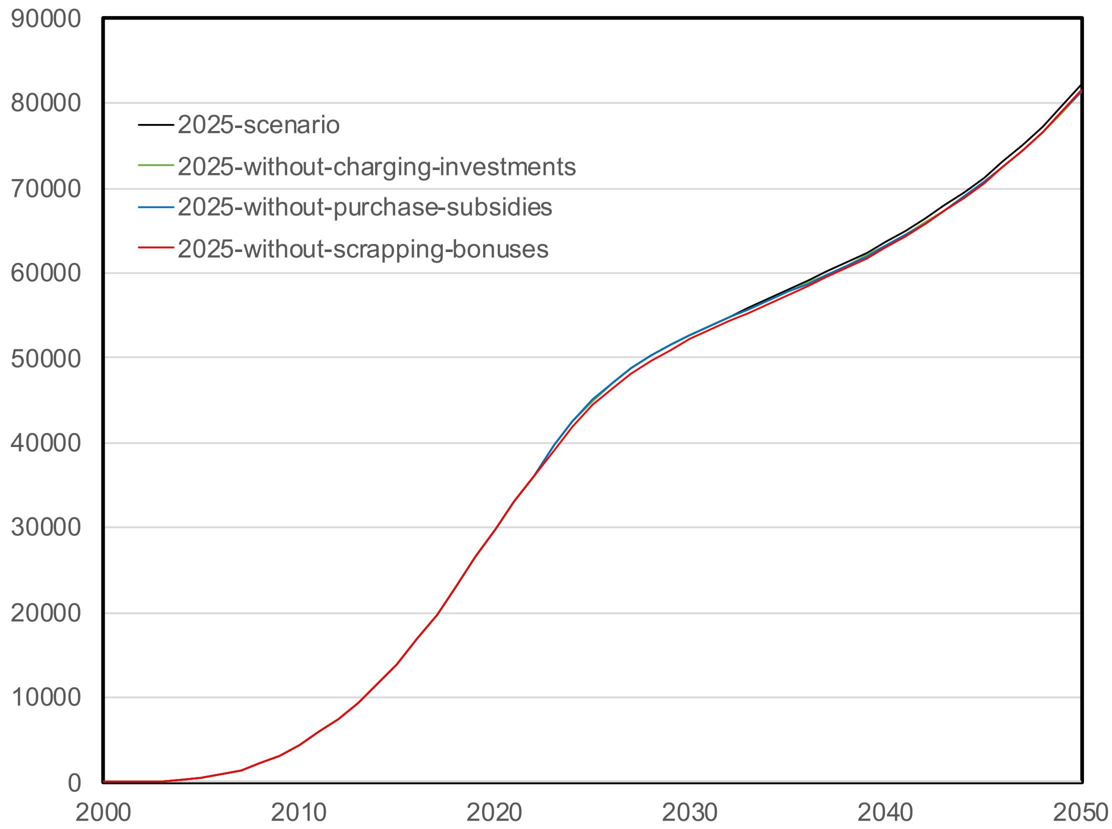

Figure 57. Effects of policy removal on HEV stock development

In sum, the effects of subsidy removal are small, indicating that the market development is hardly dependent on any individual subsidy. It could be that if their magnitudes were greater, the effects of their removal would also be more visible.

In light of these findings, the most important subsidy in the long run appears to be charging infrastructure investments, as the removal of had the biggest impact on BEV stock development by 2050. In the short term, subsidizing the purchase of a BEV would also seem effective. When it comes to PHEVs and HEVs, it seems that the removal of subsidies would not have any drastic effects on their stock developments. Both platforms are likely to benefit from direct purchase subsidies, and PHEVs can also benefit from investments in charging infrastructure, but the differences are not nearly as big as for BEVs.

7.5.2 Policy introduction

In the last chapter it was concluded that if one of the subsidies applied today were removed and all others would be continued until 2025, the removal of charging infrastructural investments would have the biggest impact in the long run, while the removal of purchase subsidies would affect the short-term development on vehicle stocks the most. However, as discussed in Chapter 5, systems that are dominated by reinforcing feedback structures can be path dependent. In this regard, the present study will also test if the findings remain the same when the initial conditions are changed. In practice, this is done through the following scenarios:

What if nothing was done before 2020, and then in 2020-2025

i) 20M€ was spent on *charging infrastructure* (slow and fast charging stations)?
ii) 20M€ was spent on *purchase subsidies* as they are now (no scrapping bonuses)?
iii) 20M€ was spent on *purchase subsidies and scrapping bonuses (50-50)*?

Further, as pointed out in Chapter 4.4, the biggest reason for successful BEV diffusion in Norway has been the removal of value added tax from BEVs. In this regard, an additional scenario was run:

iv) What if the 20M€ was spent on *BEV VAT exemption (25%)*?

The results for these scenarios for BEVs, PHEVs, and HEVs are presented in Figure 58, Figure 60, and Figure 61, respectively, and will be discussed below.

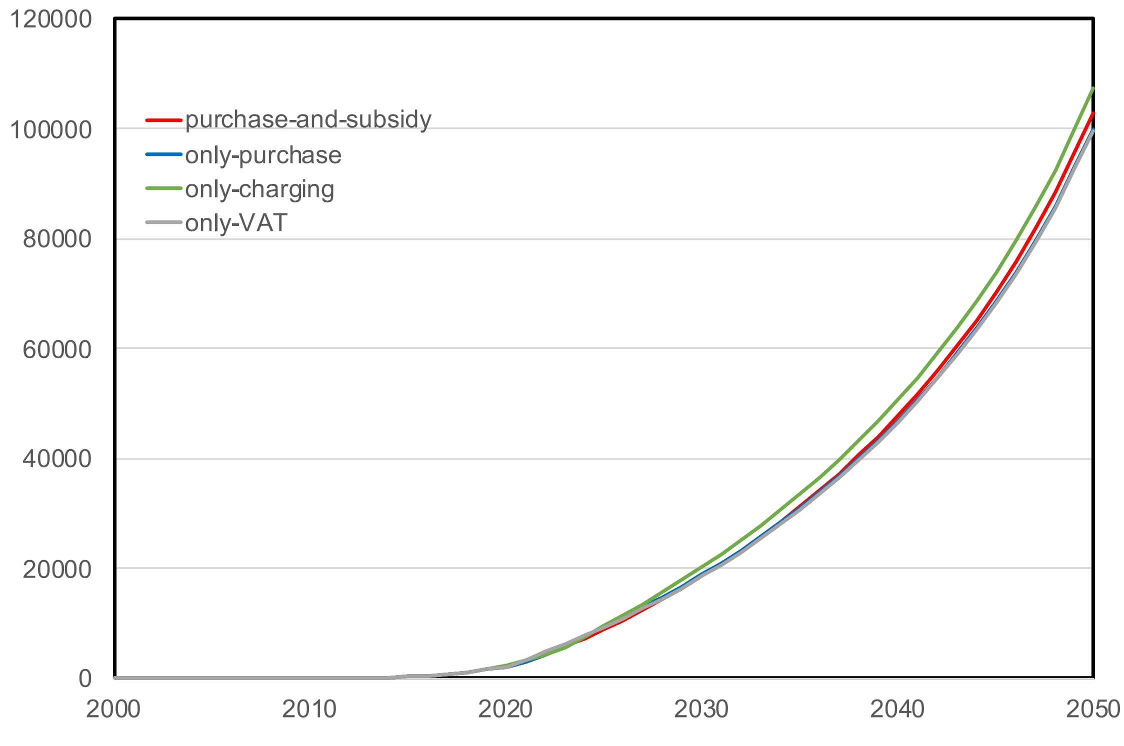

Figure 58. Effects of different policies on BEV long term sales

The effect of charging infrastructural investments is still the most significant for BEV stock development in the long term. In that scenario, 20 million euros are invested in both slow and fast charging stations, and subsidies are admitted during the 5-year timeframe or as long as there are resources left.

In the short term, the most effective policy appears to be the introduction of VAT exemption. In that scenario, BEV are given a 75 % discount on value added tax. It is valid as long as there is room in the 20-million-euro budget, which means that it can also end prematurely, if there is more demand for vehicle discounts. This visualized in greater level of detail in Figure 59. However, in the long term they are actually the least effective in inducing BEV adoption.

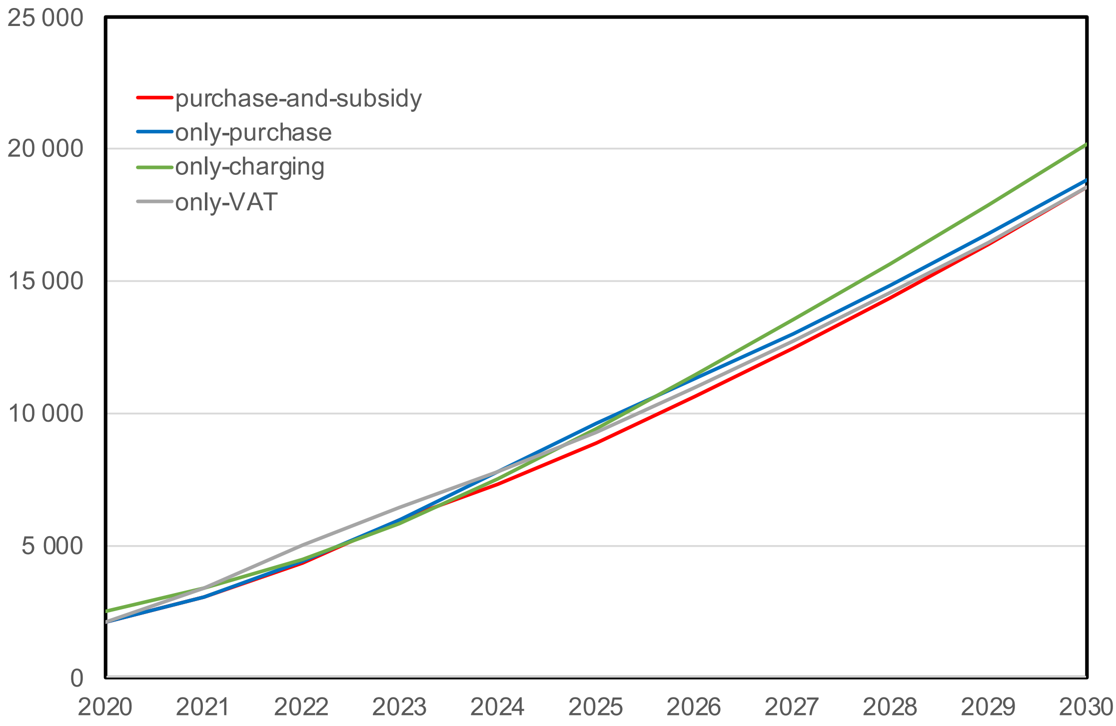

Figure 59. The short-term effects of policies on BEV stock development

Similar to VAT exemptions, purchase subsidies seem to be effective in the short-term, but in the long term they are not as effective as charging investments. The difference between VAT exemptions and purchase subsidies seems to be that the latter can be applied longer, but the mechanism remains the same – they increase relative attractiveness of BEVs by reducing their purchase prices. The difference between purchase subsidies and VAT exemptions will be discussed in further detail in the next subchapter.

The fourth alternative is the combination of purchase subsidies and scrapping bonuses. When combining the two, 10 million euros are budgeted for both, and the subsidies are admitted in a similar fashion as they are at the time being, or as long as there are available resources left. What follows naturally is that BEVs receive less purchase subsidies, but in turn PHEVs and HEVs are subsidized as well. It appears that such policy would not be particularly effective in the short-term, but in the long term it results in a greater stock of BEVs than the two scenarios where direct subsidies are given in a more generous fashion. It is *counterintuitive* that using a share of limited funds on subsidizing PHEVs and HEVs as well would have a greater impact than subsidizing only BEVs in the long term, but it in fact seems to be the case. Regarding what was said earlier about the importance of word of mouth in technological diffusion and in the context of electric vehicles, this may well be the reason why the combination is more effective than subsidizing only BEVs.

The findings above complement the previous conclusion that investments in charging infrastructure are the most effective policy (in the long run) that is currently being used. In this regard, it would seem reasonable that if there is a limited amount resources available, those were targeted to infrastructural investments so that long lasting benefits could be received.

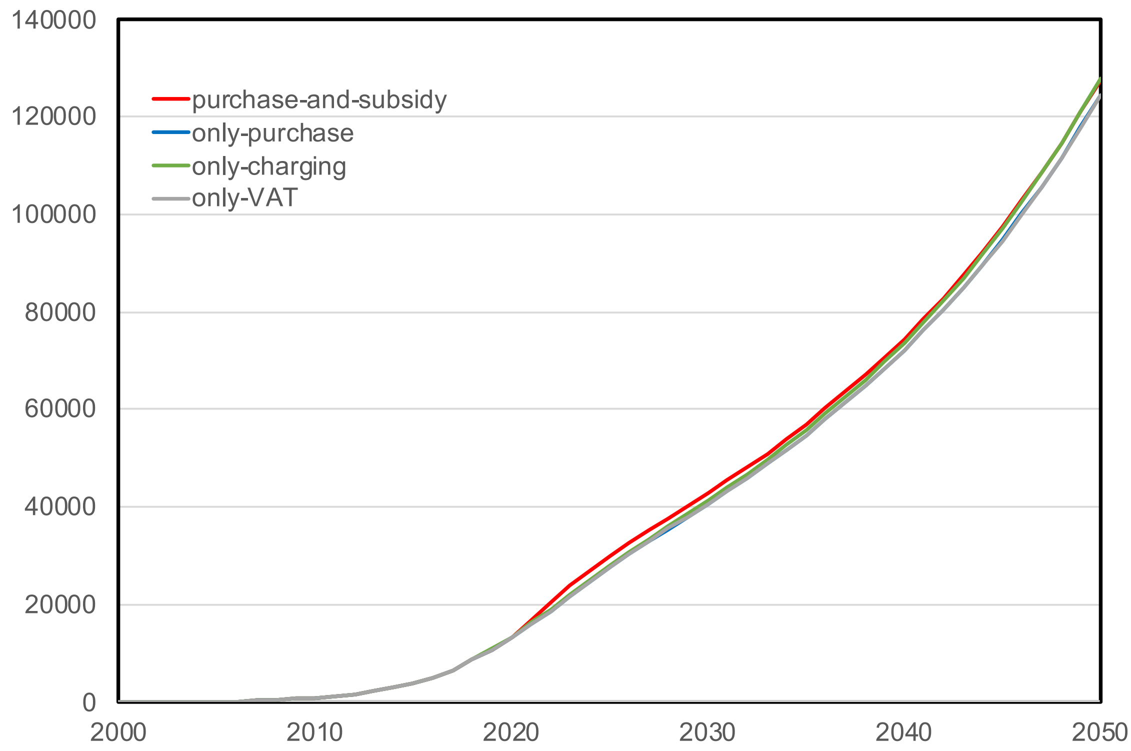

Figure 60. Effects of different policies on *PHEV* long term sales

In case of PHEVs, it seems that *in the short-term*, the combination policy is the most effective. This seems reasonable, since it can lower the relatively high purchase prices of PHEVs. However, *in the long-term*, the scenario where only charging infrastructure is subsidized gains on and results in approximately an equal number of PHEVs on the road. Thus, the behaviour is similar to what was observed with BEVs; direct subsidies are effective in the short-term, but infrastructural investments are mode effective in the long run. This illustrates again an important aspect of policy making; one which was also described in Chapter 5.1. That is, while a policy may appear as the most effective in the short-term, its long-term effects can be inferior to another alternative. Especially in a case where there are resource restrictions, the longevity of investments should be considered.

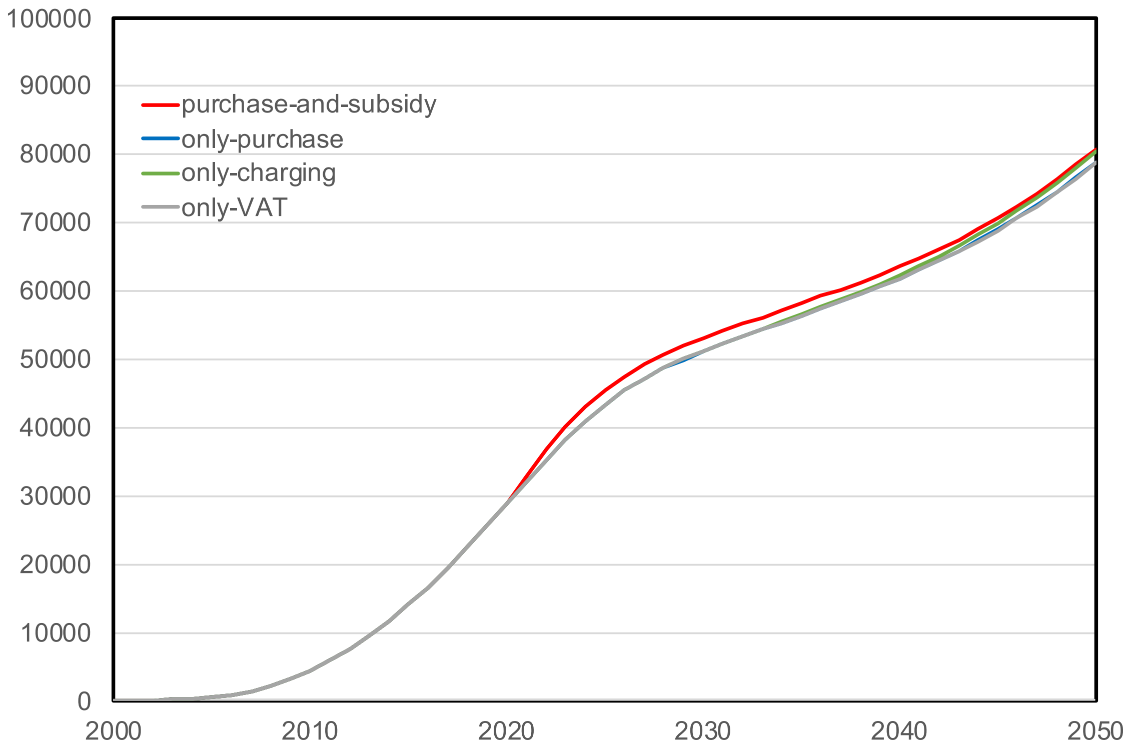

Figure 61. Effects of different policies on *HEV* long term sales

Similar to PHEVs, in the short-term, HEVs supposedly get the biggest benefit from scrapping bonuses. This can be observed from the figure above. In addition, although HEVs cannot be charged while they are parked, they also seem to benefit from investments in charging investments as well; the *only-charging* scenario results in roughly equal numbers as the *purchase-and-scrapping* scenario. This could again be reasoned with long-term word of mouth effects: as the collective number of EFVs increase, also HEVs benefit from it. Further, as discussed above, charging infrastructure are the most effective in inducing BEV *and* PHEV diffusion in the long run, thus, it may also help HEVs.

It is interesting, however, that the effect of scrapping bonuses is notably stronger for HEVs than for PHEVs, even though the bonus they receive is smaller than those of PHEVs. This could be argued with the fact that even with a 2,500€ scrapping bonus a medium-sized plug-in vehicle might still cost over 30,000€, while a medium-sized HEV bought with a 1,500€ scrapping bonus can be already near the price of an ICEV.

7.5.3 Effectiveness of VAT exemption

As mentioned in Chapter 7.5.2, even though purchase subsidies and VAT exemption are both direct subsidies that are given at the time of purchase, the latter is much more effective. Figenbaum (2017) illustrates this in Norwegian context by stating that for VW Golf the VAT discount will be approximately 5,000€. It can therefore better mitigate the cost barrier of BEV adoption. However, a closer examination to the policy reveals that even VAT exemption could lose its strength, if applied sufficiently long. For this purpose, four additional simulations were run, where VAT discounts were granted during a 5-year period. Unlike previously, in these runs there were no resource restrictions, but instead all vehicles sold during the time frame would receive a discount. Further, these runs took place in different points of time, starting in 2010, 2015, 2020, and 2025. This is illustrated in Figure 62, where the effect of these policies on BEV base price can also be seen. In the figure, the initial rise in the simulated base price is caused by battery development as the capacity of vehicle batteries grow faster than the cost of kWh decreases. This is corrected already around 2005, after which the model performs realistically.

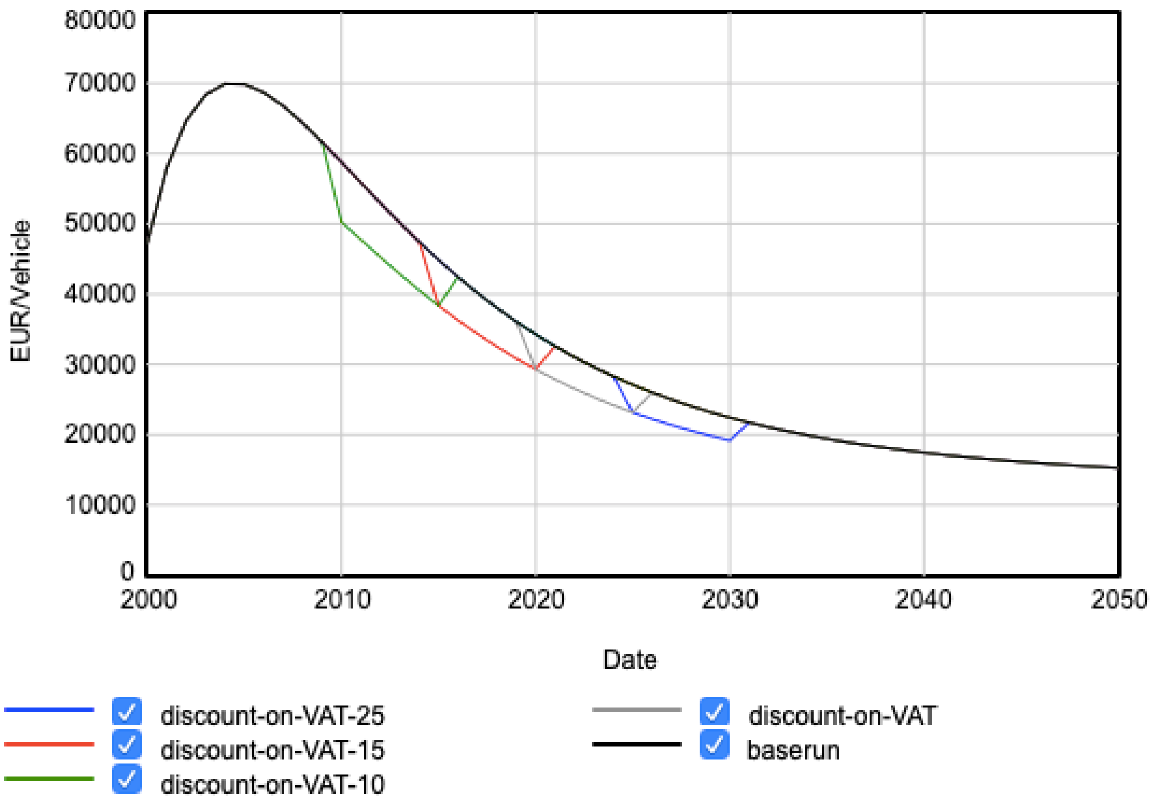

Figure 62. VAT discounts during 2010-2030

If those discounts take place at different points in time and the discount *percentage* is kept constant during the whole time, the monetary coverage will depend on the base price at that time. In other words, if the percentage is chosen independently from market development, it may turn out be rather generous. This is illustrated in Figure 63.

In the simulated case, applying the “Norwegian discount” in 2010 would mean that every BEV buyer saves over 8,000€. The monetary coverage decays as the base price of BEVs decay, and in 2030, the monetary coverage would be only about 3,000€. Although the relative coverage remains roughly equal throughout the time, it may well be that similar biases come into play as in the prospect theory; a 3,000€ discount does sound much lower than an 8,000€ discount, even if their relative share was equal. This marks another are of further research and remains merely as speculation herein.

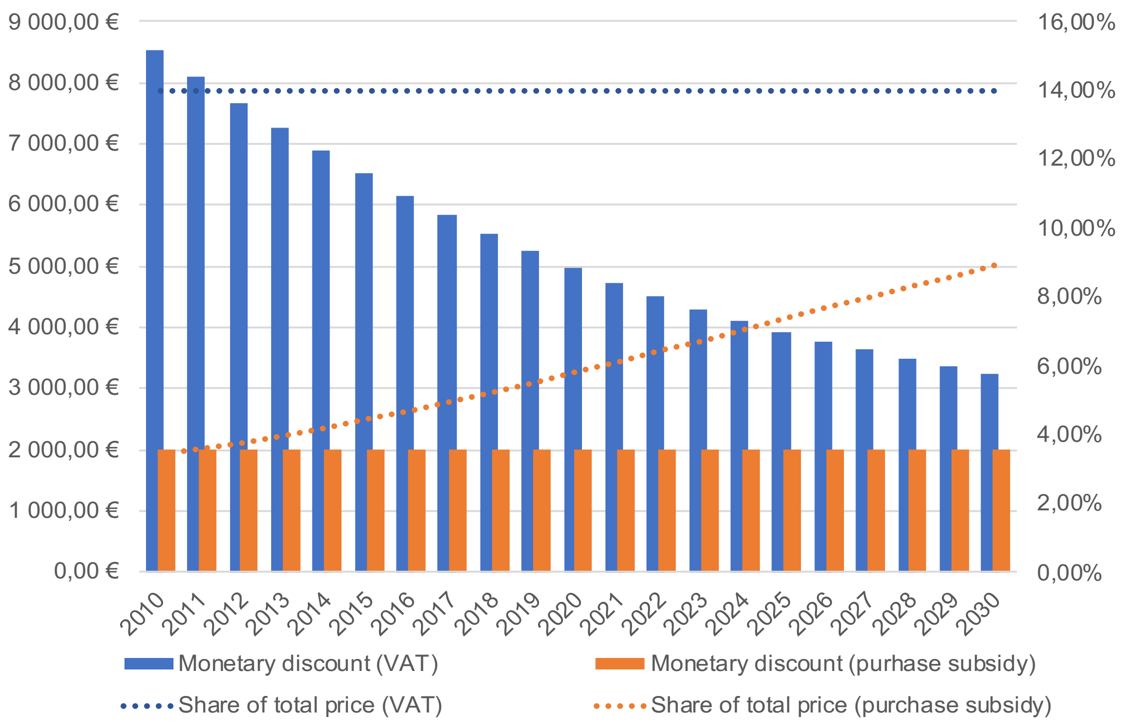

Figure 63. Simulated *VAT exemption* and *purchase subsidy* in 2010-2030 and its share of price

On the contrary, if the monetary coverage of purchase subsidies remains the same, their relative share increases as the base price of a BEV decreases. This is also illustrated in Figure 63. This implies that if purchase subsidies are applied *late enough*, they might turn out to be more effective than VAT exemption. Alternatively, if the monetary coverage of purchase subsidies was big enough, they might appear as more effective. In both cases, however, it depends on the *time when they are applied* and, in particular, to the current base price of electric vehicles. Considering what was discussed in Chapter 5.1, it does seem that whether these policies are considered effective is path dependent. In this regard the present study also complements the findings of e.g. Kangur et al. (2017).

8. CONCLUSIONS

8.1 Results

8.1.1 Policy analysis

Simulation results show that differences in effectiveness of policies are generally small, but their role in inducing EFV adoption is important. By simulating the market development without any subsidies in place, we could see clear differences in EFV stock development. This conclusion was complemented by another scenario, wherein current subsidies were kept in place until 2025 and a scrapping program was renewed in 2021. The difference between simulation runs was especially visible for BEVs, which leads us to the conclusion that **the importance of policies is the greatest for BEV diffusion**.

A number of alternative scenarios were simulated in order to study the differences in policy effectiveness in inducing adoption in different EFV categories. First, 4 simulations were run so that one of the policies were removed at a time, ceteris paribus. Then, alternative scenarios were simulated, where only one policy was implemented and kept in place until 2025. In both cases, the simulations show that out of the policies studied, **the most effective in inducing BEV adoption was investing in charging infrastructure**. In the short term, VAT exemptions – as applied in Norway – could be effective as well, but in the long-run charging investments were clearly the most effective.

Interestingly, the study shows that if there are limited resources and *only one policy* could be implemented, **subsidizing PHEVs and HEVs in addition to BEVs would seem to have a bigger impact on BEV long-term diffusion than subsidizing only BEVs**. This seems counter-intuitive, but it could be reasoned with the word-of-mouth effect; by subsidizing HEVs and PHEVs as well, policy-makers can induce EFV adoption *more broadly* and thereby increase also other consumers' willingness to consider them as an option. In light of the finding of Walther et al. (2010) that hybrid vehicles could serve as a transitional option while moving towards electric vehicles, and the conclusion of Ben-Akiva (1973) that vehicle purchase decisions are nested to distinctive categories, the finding does seem reasonable. The greater aggregate number of EFVs can also increase the perceived potential of the market for car manufacturers and the fuel industry, which has also been found to drive the investments that are needed to increase the relative attractiveness of EFVs (Walther et al. 2010; Testa 2017). Considering the discussion in Chapter 5.3, this would imply that by subsidizing all EFV categories, the policy-maker can increase the attractiveness of the market and thereby give the needed initial momentum to the Chicken-and-Egg-loop(s). This would give rise to reinforcing behaviour, which would also be a plausible explanation for the slightly counterintuitive finding.

The present study also shows that purchase subsidies in their current form are not particularly effective in inducing long-term BEV adoption. Among the alternative scenarios that were run, the scenario were only BEVs received purchase subsidies resulted in the smallest number of BEVs on the road in the long term, even though they turned out to be helpful in the short-term. A closer examination of the effectiveness of purchase subsidies revealed that their effectiveness is time-dependent. That is to say, in the Norwegian subsidy model the *percentage* of monetary coverage is kept constant, which means that as the cost of kWh declines, the purchase price of BEVs declines, and so does the *absolute* monetary coverage of the tax exemption. On the contrary, the Finnish model – if continued long enough – would keep the absolute monetary coverage constant, while its relative share of the purchase price would increase. Therefore, if the current fixed purchase subsidies were applied later on, they may turn out to be more effective than VAT exemptions, due to their greater monetary coverage. Still, early upon the introduction of the new alternative, when the purchase prices are still relatively high, VAT exemptions seem to be more effective.

For PHEVs, it appears that purchase subsidies (i.e. scrapping bonuses) can induce vehicle adoption in the short term, but in the long-term, charging infrastructural investments are also effective. The smallest impact was supposedly received with BEV purchase subsidies; as mentioned, they were the least effective in inducing BEV adoption, thus they are also the least effective in generating word-of-mouth. Further, as they are not admitted to PHEV purchasers, they have the smallest effect.

For HEVs, then, it appears that if only one policy was *removed* there would be hardly any differences. The only one that stands out a little is the removal of scrapping bonuses, i.e. purchase subsidies, that can mitigate the price gap between HEVs and ICEVs. Similarly, if only one policy could be *implemented*, purchase subsidies would again be the most effective in the short-term, but in the long-term their effect would vanish.

8.1.2 Effects of exogenous factors

As stated in Chapter 7.3, sensitivity analysis serves a dual purpose. It allows the modeller to study the effects of initial conditions to simulation results, but it can also provide new insights by revealing changes in model behaviour. In this regard, the present model was also tested not only for its ability to reproduce realistic behaviour, but also to require insights on the importance of exogenous factors to EFV adoption in Finland.

It appears that model results are numerically very sensitive to the weight put on costs versus purchase price. By increasing the weight put on costs by 50 %, differences of even hundreds of thousands of vehicles could be observed in all categories, but especially in PHEV stock development. This, on one hand, increases the uncertainty relating to simulated results, but on the other hand **highlights the meaning of educating consumers and making them more conscious about vehicle TCO instead of just purchase price**.

Model results are also **highly sensitive to the chosen level of marketing efforts**. If the *marketing for platform* would be kept constant at a low level, there would approximately thousands of BEVs less in 2050. On the contrary, if the marketing efforts are kept high for more than a decade, it seems that there would be several hundreds of thousands of BEVs on the road in the end. This is also an interesting finding in terms of the use of marketing and information campaigns as policy instruments, but it also increases the uncertainty of model results.

Sensitivity analysis revealed that the model results are **sensitive to the chosen rate at which the cost of kWh declines**. There are several estimates for possible trends cost development, out of which the one presented by Nykvist & Nilsson (2015) was applied in the base case scenario. By altering this assumption, it could be realized that the faster cost of kWh declines, the faster BEV diffusion gains momentum. PHEVs – and even – HEVs benefit from faster decline as well, but it seems that the effect is the biggest in BEV stock development. This was reasoned with the fact that BEV batteries are notably bigger, thus if the cost of kWh declines faster, the impact will be more prominent. While this in part introduces another source of uncertainty to the model, it underlines an important aspect of the Finnish EFV market: the successful development of EFVs, BEVs in particular, is closely related to the development of global EFV market, where the cost of kWh will be determined.

The technological development rate of battery technologies will practically determine the relative performance of BEVs, which increases the importance of careful parametrization. Sensitivity analysis revealed that the development of BEV stock was numerically very sensitive to the chosen level of technical development, while the difference in PHEV stock development was significantly smaller. This was reasoned by stating that the electric range and battery capacity are not as important drivers of relative performance for PHEVs as they are for BEVs, simply because both of these attributes are, at best, only a fraction of those of BEVs'. Similar to the cost of kWh, this in part increases the uncertainty of model results, but at the same time it highlights the fact that the success of BEVs in Finland is tied to the global EFV market, which determines the rate of technological development in the field.

If the scenario of electricity price increase discussed in Chapter 6.3.4 is realized, there will be a little less BEVs and PHEVs in 2050 if gasoline prices will not increase as well. In the base case scenario, however, the cost of gasoline is also kept relatively high, which reduces the impact of electricity price increase, as the relative costs of usage for electric vehicles do not increase that much. In this regard, the present model seems to be robust, but this is recognized as an area for further development.

If the market growth slows done as discussed in Chapter 6.3.1, there will be a difference in resulting BEVs in 2050, due to shrinking market pool. This would slow down the growth of all vehicle categories, as less vehicles would be sold annually. This is line with the conclusion of Struben & Sterman (2008) that long vehicle lifetimes greatly affect the diffusion of AFVs, as long lifetimes imply that less vehicles need to be bought annually.

8.1.3 Comment on model validity

As discussed in Chapter 2.3, the research approach applied herein is deductive in the sense that the model's results are only as good as the underlying assumptions. Regarding the findings presented in the last chapter, plausibly the most important assumption of the model is the nested decision making in vehicle choice: Consumers decide between distinctive vehicle groups and then within the group based on perceived utility. Here, the distinctive groups are *electrified vehicles*, i.e. BEVs, HEVs, and PHEVs, and internal combustion engine vehicles (ICEVs).

The assumption of nested decision making is based on the findings of Ben-Akiva (1973), and it is further reasoned with the fact that Struben (2006), Struben & Sterman (2008), Shafiei et al. (2012), and Shepherd et al. (2012) have also applied somewhat similar approaches. Struben (2006) and Struben & Sterman (2008) assume that the vehicle purchase decision is nested to ICEVs and alternative fuel vehicles (AFVs). In other words, they assume that consumers would be equally willing to consider biofuels, gas vehicles, and electric and hybrid vehicles altogether. Although vehicle types *within* the AFV category can be notably different from each other, e.g. a biofuel-ICEV versus FCEV, the authors still aggregate them into one group, which consumers will consider. In comparison, the present study merely assumes that all *electrified* vehicles that are considered collectively.

Shepherd et al. (2012) are closer to the present study as they seem to aggregate PHEVs and BEVs into same category, namely electric vehicles (EV). EVs gain WtC collectively, and then based on their perceived utility, a consumer decides between the two alternatives. Shafiei et al. (2012) use also an aggregate variable to illustrate the willingness of consumers to consider EVs.

Harrison et al. (2016) do not aggregate WtC stocks at all, but rather they model all vehicle types separately. An interesting assumption therein is, however, that they assume that consumers' initial willingness to consider petrol HEVs equals to unity, similar to petrol and diesel ICEVs. Had this assumption been implemented herein and the remaining two been aggregated into one variable, the approach would have been the same as in Shafiei et al. (2012) and Shepherd et al. (2012). Thus, the only difference between the present study and the studies of Shafiei et al. (2012), Shepherd et al. (2012), and Harrison et al. (2016) is that the present study assumes that consumers do aggregate HEVs into same category as PHEVs and BEVs, rather than ICEVs. However, model behaviour was also tested with this assumption, and it turned out inapplicable; if the WtC HEV would equal to unity, as with ICEVs, the simulation would result in over 150,000 HEVs in already 2005, which evidently does not match reality. This is also illustrated in Appendix I.

The fact that similar assumptions have been made in other studies as well increases confidence in the results of the present study. Nevertheless, in order to fully verify this assumption, national surveys should be carried out, which marks an area for further research.

8.2 Implications

It appears that there are two distinctive ways through which policies can induce EFV adoption. Namely, either by increasing social exposure and generating word of mouth or by increasing the relative attractiveness of a vehicle type. Considering the effectiveness of policies in BEV diffusion, purchase subsidies that are offered also to PHEVs and HEVs are effective because they can increase the aggregate number of EFVs, and thereby increase exposure and induce word of mouth. At the same time, the greater aggregate number can increase the incentive for commercial and public organizations to make the needed investments.

Charging infrastructural investments, on the other hand, are effective because they can provide the initial momentum needed in the chicken and egg loop to induce reinforcing behaviour. A greater number of charging points can mitigate functional risks that are related to BEVs, and therefore increase their relative attractiveness. Such investments are also effective because they can benefit more than one vehicle category which, in turn, can further induce word of mouth.

Although both types of incentives can be effective, it is important to recall that the accumulation of willingness to consider a new alternative can take time and is therefore delayed. An underlying difference between direct subsidies and charging infrastructural investments is that once the purchase subsidy is removed, its effect also disappears immediately, but when those funds are used to build charging points, those points can be used for a long time. Thus, they can provide longer-lasting benefits with the same limited amount of resources.

If we consider the *key drivers of EFV adoption*, it could be argued that they are the same as the ways through which policies affect EFV diffusion. That is to say, word of mouth marketing – or more broadly, social exposure to the new alternative – and the relative attractiveness of the vehicle category.

If we look at those drivers more closely, we can distinguish certain aspects that are more important for one EFV category than for another. Based on the analyses, it seems that, the **key drivers of BEV adoption are the cost of kWh, weight put on costs, marketing efforts** (i.e. commercial marketing and consumer education) **and charging infrastructural investments**. In the short term, purchase subsidies will also have an impact. Reflecting to the drivers of EFV diffusion, marketing efforts are important because of their capability to generate word of mouth marketing, while the others are effective in increasing the relative attractiveness of BEVs. Cost of electricity and the growth of vehicle market as a whole can also affect BEV diffusion, but not to a similar extent.

Out of the policies and exogenous factors considered, weight put on costs, marketing efforts, and charging infrastructural investments seem to be also the key drivers for PHEV diffusion. In the short term, purchase subsidies can contribute to PHEV diffusion as well.

In particular, **it seems that the weight put on costs versus price determines how attractive a PHEV appears**. As with BEVs, weight on costs and charging infrastructure investments affect the perceived relative attractiveness of PHEVs, and marketing efforts can again generate word of mouth marketing.

HEVs are technology-wise close to ICEVs and the only clear differences can be found in emissions and thereby in taxation, fuel consumption, and purchase price. In this regard, it is rather presumable that the key driver is weight put on costs. Based on the analyses, this also seems to be the case. Another key driver for HEVs is, as implied in several occasions, marketing efforts due to their ability to induce word of mouth marketing and further the ability to increase WtC.

8.3 Discussion

In the present study, underlying dynamic features were first discussed on the basis of theoretical groundings on innovation diffusion and consumer adoption (Chapter 3) and existing modelling studies (Chapters 2 & 5), and then applied in the Finnish context by formulating a system dynamic model (Chapter 6). Then, in Chapter 7, the model was used to study the effects of a number of policies on to the diffusion of electrified vehicles in the Finnish market. Lastly, in Chapter 8, central findings and implications were presented in order to answer the main research question of the present study.

The present study builds upon existing modelling studies but extends them to consider PHEVs and HEVs separately from BEVs and ICEVs. Thus, the model presented herein can provide more insights into the effects of different policies *on different platforms*. The study also accounts for resource restrictions, unlike many other studies, to the knowledge of the writer. This is also a strength of the study as it does not assume endless tanks of resources, but rather can also provide insights into what to do with *limited* resources. Furthermore, as it was argued in Chapter 3, the present study considers gains and losses relative to a reference point, which could generate more accurate behaviour. At the very least, the present model can introduce another application of prospect theory and thereby complement the theoretical discussion. Lastly, at the time of writing EFVs have been a hot topic in the Finnish press. Several authors have presented their own targets and portfolios for measures through which EFV adoption could be induced, such as the one of Sitra (2018), many of which have also been remonstrated by other authors (e.g. Tekniikan maailma 2018). In this regard, the present study can complement the discussion by possibly providing new insights to the domestic context.

It appears that the findings are in many parts in line with the existing body of research. Kangur et al. (2017) found that if both PHEVs and BEVs are subsidized, their aggregate amount would increase because the number of PHEVs would increase. Instead, if only BEVs are subsidized, their sales would grow, but PHEVs' sales would stay unharmed. The present study is in line with these findings to the extent that if both vehicle types are subsidized, their aggregate number will grow. However, the present study indicates that also BEVs would benefit from that due to increased exposure to EFVs and word of mouth marketing.

Sierzchula et al. (2014) found that the strongest explanatory variable in forecasting electric vehicle stock development was the number of charging points per 1,000 residents. Another significant factor was the use of financial incentives, while level of education, annual income level, and an eco-friendly mindset did not appear as important explanators. Considering the findings of the present study, they are in line underlying the importance of charging stations, as well as the general effectiveness of policies, but as implied already the present study fails to capture the effects of consumer characteristics. Hence, they merely mark an area for further research and cannot be addressed.

Shehperd et al. (2012) and Harrison & Thiel (2017) conclude that even with heavy purchase subsidization, long-term diffusion of electric and other alternative fuel vehicles cannot be guaranteed, but they do induce short-term adoption even if no other policies were applied. Considering the findings and discussion above, the present study is in line with this conclusion and recognizes the short-term benefits of direct purchase subsidies in all three vehicle categories. However, the present study also concludes that in the long-term there may be more effective alternatives than these.

Benvenutti et al. (2017) further state that even with radical policies the diffusion of AFVs is unlikely to be very rapid. A relevant aspect to the matter was presented by Testa (2017), who noted that “The effects of public policies are not instantaneous and cannot compensate for the misbeliefs and miscalculations of people” (Testa 2017, p. 30). Instead, it is ultimately the system conditions that drive the development of EFV attractiveness, and the role of policies and subsidies is merely to help the system in the beginning (Testa 2017). Another conclusion that is somewhat in line with this was presented by Harrison & Thiel (2017) who state that in order to be realistic purchase alternatives, attitudes towards electric vehicles need to change and consumers need to become aware of their benefits. In other words, marketing efforts and information campaigns are needed to increase exposure to the new alternative and thereby willingness consider them (Harrison & Thiel 2017). Considering the discussion in Chapter 5.2 and Chapter 8.1.2, the present endorses this conclusion and underlines that it may take time for consumers to become genuinely willing to consider e.g. BEVs as an option.

Testa (2017) concludes in her study that while the growth of BEV stock seems inevitable both in Sweden and in Norway, the inertia of the transition from ICEVs to BEVs can only marginally be overcome. Significant delays and barriers are underestimated and even though policy actions can notably encourage consumers in both countries to move towards BEVs, targets set in either country are not met in any of the scenarios carried out in the study. She further concludes that in Sweden, where the policy strategy has been more technology neutral than in Norway, charging infrastructural investments appear to be the key subsidies, while in the latter the usage of VAT exemptions has been the key. (Testa 2017) Considering that in Finland HEVs, PHEVs, and other alternative fuel vehicles have also received purchase subsidies as a part of scrapping programs, it could be argued that the policy strategy applied thus far has also been more on the technology neutral side. In this regard, it seems also reasonable that charging infrastructural investments were found to be effective in the long-term, and especially in the case of BEVs.

Testa (2017) further adds that one of the main challenges for strong BEV growth is the fact that BEVs need become competitive in not only price, costs, and the attributes considered, but consumers need to simultaneously gain enough confidence to actually buy one. (Testa 2017) Considering what was mentioned about the findings of Harrison & Thiel (2017), this conclusion seems to complement it.

Benvenutti et al. (2017) state that short-sighted policies can do more harm than good also in the context of alternative fuel vehicle introduction. A seemingly effective policy can induce desired behaviour in the system in the beginning, but then backfire after a delay. Strongly endorsing one technology to quickly penetrate the market might hide such a backfire effect underneath. That is, *if* it would later turn out that lithium ion batteries were not the dominant BEV battery design after all, heavy subsidization of lithium battery vehicles would have then helped to create a technological lock-in. Or, even if a lock-in would not be created, many governments would have spent millions of euros subsidizing “wrong vehicles”. This is a concern also pointed out by Harrison & Thiel (2017).

If we assume that in the future, traffic will still be largely electrified, despite what the dominant design will ultimately turn out to be, by concentrating the available funds on subsidizing charging infrastructural development the Finnish government can create favourable conditions for endogenous market development. In other words, as long as the transition in drivetrains is towards *batteries*, they will need charging points and other supplementary services. Then, if the government would use its restricted funds on building a favourable ecosystem wherein electric vehicles can diffuse, the development of EFV stocks would be market driven, and possible lock-ins could be avoided.

Despite the fact that vehicle markets are characterized by long delays and slow transitions, both in terms of vehicles themselves as well as consumer perceptions and exceptions, many subsidies still seem to be planned a couple of years ahead. Regarding what was said in Chapter 5 about the different kinds of delays, and further what was noted by Testa (2017) about the delayed effects of policies, it is not only possible but even likely that policy making is biased if immediate effects are assumed, and critical delays are neglected. In this regard the present study again endorses the role of government as facilitator of technological development and calls for longevity in policy making. More specifically, given the evident resource restrictions in market guidance, by using available funds in building the needed charging infrastructure and supporting the development of other supplementary services, the government can reach long lasting effects with same amount of available capital.

8.4 Further research

The present study recognizes several areas for further research and ways through which the model could be extended. Starting with areas where the model could be extended, the first one would be to consider use-based incentives (see Chapter 4) as well. Struben (2006) and Testa (2017) take bus lane access, free parking, ferry fees and road tolls into consideration, but the present study consciously decided not to do so. This was reasoned with the fact that such use-based incentives have not been applied in Finland to date and the exemption from parking expenses, for instance, is considered relevant merely to consumers living in the Helsinki metropolitan area. Such cost items combined, however, could add up to hundreds of euros annually and therefore make a notable difference between vehicle categories. In this regard, use-based policies mark an area where the model could be extended and where additional insights could be found.

Another area where the model could be expanded is the inclusion of driving behaviour to model. As discussed in Chapter 3.5, the TCO of a vehicle is depended on the annual mileage of the vehicle. Furthermore, the consumption profile for electric driving is highly different from that of internal combustion engines. Hence, if the model would make a difference between urban driving and longer travels and include the characteristic driving behaviour of Finnish people (e.g. Liikennevirasto 2018), the model could tell more accurately how much cheaper/more expensive each vehicle type would be for a consumer. Given the importance of costs and prices in vehicle adoption, this would evidently contribute to model accuracy and credibility.

A higher level of detail in driving behaviour would also be beneficial in the sense that different charging patterns could be identified. Depending on where a consumer lives, how much and where the person drives with an electric vehicle could imply how often and where the person would like to charge the vehicle. This would then indicate long the charging would take (e.g. charge mostly on fast-charging stations along highways vs. charge only at home) and how much that would cost.

Modelling of driving and charging behaviour only by means of system dynamics could be challenging. As discussed in Chapter 2, SD is primarily used to simulate the behaviour of a system as a whole, rather than its components or incumbents. Therefore, in order to increase the level of detail in simulation, the SD model could be coupled with other simulation modelling methods, agent-based modelling (ABM) in particular. Such an approach was taken by Kieckhäfer et al. (2017), who combined SD and ABM modelling techniques in studying the impacts of competition and manufacturers' efforts on EV market development.

A higher level of detail in consumer behaviour, and the possible application of other simulation methods, would imply that more detailed data would also be needed. As discussed in Chapter 3.4, revealed and stated preference studies have not been carried out in Finland, which marks a highly promising area for further research. Not only would such data allow more accurate modelling of consumer behaviour and agent-based modelling, but it would also allow the usage of random utility models which have been applied in the majority of EV studies to date. Although it was argued in Chapter 3.4 that the application of prospect theory in the present context is also a good alternative, it would be interesting to see if the conclusions presented herein would still apply if the theoretical background was altered. Lastly, such data would allow the inclusion of *consumer characteristics*, which is one the greatest shortcomings of the present model.

If a consumer lives in an older apartment building, it might be the case that home charging points simply cannot be installed. Or, even if the installation of home charging equipment was technically possible, it might still be problematic due to the principle of equality in condominiums (Asunto-osakeyhtiölaki 1599/2009), which states all residents in the building have to be treated on equal grounds. Thus, if a home charging stations is built, it might become property of the condominium, which further implies that other residents should get one as well. What follows in both of these cases is that the importance of public charging infrastructure is likely to be greater than when home charging is available. In this regard, by considering also different housing types and related challenges in the model, the importance of e.g. public charging points for consumers could be captured more realistically. Also, regarding the discussion in Chapter 6.3.4, this would allow the cost of charging to be modelled more accurately.

Another dimension where the cost of charging could be further elaborated is the differentiation of pricing principles between slow and fast charging points. When charging a vehicle on a slow charging point, the cost of charging accrues on the basis of number of kilowatt-hours used. However, for example in Helsinki area, if a consumer charges an electric vehicle on Helen's (www.helen.fi) fast charging station, the cost of charging is determined based on the number of *minutes* spent charging. The present model only considers the former pricing principle, which can induce biases into conclusions.

A third dimension where the cost of charging could be modelled more accurately, which also relates to the TCO of a vehicle, is the consideration of value of time, as done in Struben (2006) and Testa (2017). Given that "refuelling" of an electric vehicle can take from 20-30 minutes to several hours, while for an ICEV the corresponding figure can be only a few minutes, it may well be that the loss of time generates also monetary losses for a consumer. The measure was considered somewhat abstract and difficult to validate and was therefore excluded from the present model. Further, regarding slow charging, it was reasoned that a consumer could charge his/her vehicle while being e.g. at work, which would compensate the loss of time. However, if there were data on how much Finnish consumers value their time, the effect of slower charging on vehicle attractiveness could be quantified, and also the effectiveness of use-based policies such as bus lane accesses could be estimated. Similar to the inclusion of driving behaviour, this would contribute to more accurate determination of TCO and thereby more realistic behaviour.

In addition to charging arrangements and consumers, the level of detail could also be amplified in the vehicle module. In the present model, diesel and gasoline vehicles are aggregated into one variable and ICEVs include not only conventional vehicles, but also all other hybrid vehicles than EFVs. Those subcategories could be separated into own variables, which would likely induce even more realistic the market development. Then, if a diesel ban mentioned in Chapter 4 was actually implemented, its impacts could be anticipated via simulation. Similarly, the model currently distinguishes only young and old vehicles, but it could be extended so that vehicles would be categorized into several categories. For instance, vehicles with 0-5 years of age, 5-10, 5-15, etc. could each have their own stock, respectively, or the model could be even more detailed and have own stocks for each year of age.

The separation of vehicle types would also be beneficial in the sense that there can be significant differences in emissions across vehicle categories. Given the role of vehicle emissions in taxation and perceived attractiveness, a higher level of detail could capture the movement towards other green alternatives as well. Here, however, it is important to keep in mind that the present study is especially interested in studying the movement from combustion engine vehicles to *electrified vehicles*, thus, demarcation applied herein is considered appropriate.

There can be differences in emissions not only *across* vehicle categories, but also *within* a category. Small ICEVs can have notably lower emissions and thereby cheaper taxation than bigger ICEVs, and similarly a small PHEV can be even less polluting than its bigger counterpart. In this regard, a logical and promising area for further model development would be to establish emission distributions to different vehicle types. Thereby, the model could incorporate more diverse vehicles in each category. Considering the scrapping bonuses that were admitted to consumers at the time of purchase of a low-emitting vehicle in 2018 (see Chapter 4), the more diverse selection of ICEVs in the model would mean that some of the ICEVs sold that year would also receive a purchase subsidy. In real-life this is exactly what happened, so in that regard, the model could behave more realistically if there were also low-emitting ICEVs. A similar approach could even be taken with other vehicle features as well, such as prices and travel ranges.

Although it would be tempting to further develop the model to include more variables and a higher level of detail, there is a risk that it would do more harm than good. As stated by Harrison et al. (2007), "Undoubtedly, a model can be made more realistic by adding more variables or processes. At the same time, it usually becomes more difficult to understand what drives the results in more complex models." They further state that for theory building purposes, the role of a model is to offer a simplified abstraction of the system at hand, not to represent an unduly complicated imitation of it. They conclude that "The simpler the model, the easier it is to gain insight into the causal processes at work." (Harrison et al. 2007)

8.5 Limitations

"All models, mental or formal, are limited, simplified representations of the real world." (Sterman 2000, p. 846) Instead of being valid or verifiable, a model can be useful for its intended purpose (Sterman 2000, p. 890). As stated by Forrester (1961, p. 122-129), economic systems contain behavioural laws that cannot be explained explicitly, unlike laws of nature. Therefore, it may be more reasonable to study the kind of behaviour the system is exhibiting. (Forrester 1961, p. 122-129) Bosshardt et al. (2007) complement this by noting that when a complex system is translated into a formal model, it is built using simple mathematical functions and equations. Such simplistic functions are naturally incapable of replicating the detailed and complex behaviour of the real system, but they do allow the modeller to study the most prominent characteristics of system behaviour (Bosshardt et al. 2007). In this regard, the model results should not be observed by solely looking at numerical accuracy, but rather by paying attention to its behaviour.

As implied in Chapter 2.1, in simulation studies the data used for analyses is *generated* rather than *collected*. In statistical forecasting, a modeller may use historical values to predict the next outcome. In simulation and in the present study, however, historical values for BEV, HEV, and PHEV stock developments are only used for validation. What follows is that there are slight errors in values early upon introduction and again the reported values should be considered as indicative projections rather than point estimates.

Parameter values used in the model are retrieved from secondary sources, which means that they can also include errors. They may have been gathered initially for different purposes and contain errors themselves, which may have then passed onwards into the present study. Further, for some parameters, even a secondary source could not be readily found, which is why they were chosen heuristically. This is another potential source of errors, but one that has been addressed in Chapter 7.3.

As noted by Testa (2017), a certain choice of model boundaries means that some variables are treated endogenously, while others are treated exogenously or even excluded from the model. Evidently, there is a risk that the chosen model boundary fails to capture *all* relevant aspects of a problem at hand. In the present study, for example, the model does not consider external forces that can influence the development of the Finnish EFV stock, but that the Finnish government and commercial organizations really cannot affect. An illustration of such effects is the availability of lithium needed in the electric drive-trains. Scarcity of lithium can cause delays in vehicle production which, in turn, can lead to longer delivery times. As reported by the Technology Industries of Finland (Teknologiateollisuus 2018a), the relatively long delivery times of BEVs have already affected their perceived attractiveness. Furthermore, the present study has little considered other rising trends in the vehicle market. If for example autonomous driving and car-pooling would gain in popularity, they might change way vehicles are used in our daily lives. This may not only affect the size of the annual market pool, but also change the way how consumers use the vehicle and therefore what kind of features they value.

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APPENDIX A: MODEL DOCUMENTATION

A1. Base case setup

Variable name	Equation/Value	Unit
annual cost BEV	recharging cost+BEV annual vehicle tax+BEV maintenance cost	EUR/Year
annual cost HEV	HEV annual vehicle tax + HEV refueling cost + HEV maintenance cost	EUR/Year
annual cost ICEV	ICEV annual vehicle tax + ICEV refueling cost + ICEV maintenance cost	EUR/Year
annual cost PHEV	PHEV annual tax + PHEV refueling cost + PHEV recharging cost + PHEV maintenance cost	EUR/Year
annual cost reduction	0.08	1/Year
annual driving range	15000	km/Year
availability factor	(reference availability+average station availability)^sensitivity of attractiveness to relative station availability	Dmnl
Available program resources for fast charging stations	INTEG (-usage of resources on fast CSs, budgeted resources for energy investment program*share of available resources for fast charging stations)	EUR
Available program resources for slow charging stations	INTEG (-usage of resources on slow CSs, budgeted resources for energy investment program*(1-share of available resources for fast charging stations))	EUR
available resources for fast CSs	(STEP(program coverage for fast CS , energy investment program start time) + STEP(-program coverage for fast CS, energy investment program start time+energy investment program duration))+(STEP(fast charging CS subsidy coverage, fast CS subsidy start time) + STEP(-fast charging CS subsidy coverage, fast CS subsidy start time+fast CS subsidy duration))+private investment coverage	Dmnl
available resources for slow charging points	(STEP(program coverage for slow CS , energy investment program start time) + STEP(-program coverage for slow CS , energy investment program start time+energy investment program duration))+(STEP(slow CS subsidy coverage , slow CS subsidy start time) + STEP(-slow CS subsidy coverage, slow CS subsidy start time+slow CS subsidy duration))+private investment coverage	Dmnl
Available subsidies for BEV	INTEG (-usage of BEV purchase subsidies, budgeted subsidies for purchase subsidies*share of available subsidies for BEV)	EUR
Available subsidies for fast charging stations	INTEG (-usage of subsidies on fast CSs, budgeted subsidies for charging infrastructure*share of available resources for fast charging stations)	EUR
Available resources for scrapping bonuses	INTEG (-usage of scrapping bonuses, budgeted subsidies for purchase subsidies*(1-share of available subsidies for BEV))	EUR
Available subsidies for slow charging stations	INTEG (-usage of subsidies on slow CSs, budgeted subsidies for charging infrastructure*(1-share of available resources for fast charging stations))	EUR
average station availability	(density of fast charging points+density of slow charging points)/2	Dmnl

battery efficiency	BEV battery capacity/BEV range	kWh/km
BEV aging rate	Young BEV fleet/BEV time as young	Vehicle/ Year
BEV annual basetax	IF THEN ELSE(Time >= 19 , new tax model BEV , old tax model BEV)	EUR/ Year
BEV annual cost relative to ICEV	annual cost BEV/annual cost ICEV	Dmnl
BEV annual vehicle tax	BEV annual basetax+BEV motive power tax	EUR/ Year
BEV baseprice	(costs unrelated to powertrain+Cost of kWh*BEV battery capacity)*(1+value added tax)	EUR/ Vehicle
BEV battery capacity	INTEG (change in battery capacity, init BEV battery capacity)	kWh/ Vehicle
BEV discard rate	Mature BEV fleet/BEV time as mature	Vehicle/ Year
BEV emission level	2	(gCO2/km)/Vehicle
BEV lifetime	INTEG (change in BEV lifetime, Init BEV lifetime)	Year
BEV maintenance cost	BEV maintenance cost per km * annual driving range	EUR/ Year
BEV maintenance cost per km	0.059	EUR/km
BEV market share	total BEV fleet/total fleet	Dmnl
BEV monetary coverage	car industry share on BEV subsidy + governmental share on BEV subsidy	EUR/ Vehicle
BEV motive power tax	104	EUR/ Year
BEV new sales rate	market pool*BEV sales share	Vehicle/ Year
BEV offer diversity	INTEG (change in offer diversity, init BEV offer)	Model
BEV purchase price relative to ICEV	net price BEV including devaluation/net price ICEV including devaluation	Dmnl
BEV purchase subsidy	STEP(BEV purchase subsidy coverage , BEV purchase subsidy start time) + STEP(-BEV purchase subsidy coverage , BEV purchase subsidy start time+BEV purchase subsidy duration)	EUR
BEV purchase subsidy coverage	BEV monetary coverage*switch for BEV purchase subsidy	EUR/ Vehicle
BEV purchase subsidy duration	4	Year
BEV purchase subsidy start time	18	Year
BEV range	INTEG (change in BEV range, init BEV travel range)	Km/ Vehicle
BEV reference	WITH LOOKUP (Time, ([(0,0)-(17,2000)], (0,2), (1,6), (2,8), (3,8), (4,9), (5,9), (6,11), (7,11), (8,11), (9,12), (10,93), (11,124), (12,186), (13,244), (14,442), (15,723), (16,1005), (17,1657)))	Vehicle
BEV sales share	perceived BEV affinity/(perceived BEV affinity+perceived HEV affinity+perceived PHEV affinity+ICEV reference affinity)	Dmnl
BEV tax percentage	WITH LOOKUP (Time, ([(0,0)-(50,0.5)], (0,0.29), (2,0.29), (3,0.258), (7,0.258), (8,0.1), (9,0.1), (10,0.122), (12,0.122), (13,0.052), (15,0.052), (16,0.044), (17,0.04), (18,0.033), (19,0.027), (50,0.027)))	Dmnl

BEV technological development rate	0.025	1/Year
BEV time as mature	BEV lifetime*2/3	Year
BEV time as young	BEV lifetime/3	Year
BEV total cost relative to ICEV	weight on cost*BEV annual cost relative to ICEV + BEV purchase price relative to ICEV*(1-weight on cost)	Dmnl
BEV car tax	BEV baseprice*BEV tax percentage	EUR/ Vehicle
budgeted resources for energy investment program	5.00E+06	EUR
budgeted subsidies for fast charging stations	2.40E+06	EUR
budgeted subsidies for purchase subsidies	4.80E+06	EUR
budgeted subsidies for slow charging stations	2.40E+06	EUR
car industry share on BEV subsidy	500	EUR/ Vehicle
change in battery capacity	(estimated maximum capacity-BEV battery capacity)*BEV technological development rate	kWh/Vehicle/Year
change in BEV lifetime	gap in lifetime/develoment delay	Year/ Year
change in BEV range	gap in travel range * BEV technological development rate	km/Year
change in costs	Cost of kWh*annual cost reduction	EUR/kWh /Year
change in HEV offer diversity	gap in HEV offer diversity*rate of HEV product development	Model/ Year
change in offer diversity	gap in diversity*rate of product development	Model/ Year
change in PHEV battery capacity	(PHEV estimated maximum capacity-PHEV battery capacity)*PHEV technological development rate	kWh/Vehicle/Year
change in PHEV offer diversity	gap in PHEV offer diversity*rate of PHEV product development	Model/ Year
change in PHEV range	gap in electric range*PHEV technological development rate	km/Year
cost of fast CS	50000	EUR/ station
cost of ICE powertrain	14000	EUR/ Vehicle
Cost of kWh	INTEG (-change in costs, init cost of kWh)	EUR/ kWh
cost of slow CS	2000	EUR/ station
costs unrelated to powertrain	10000	EUR/ Vehicle
density of fast charging points	Fast charging stations/reference number of stations	Dmnl
density of slow charging points	XIDZ(Slow charging points , desired plugs per vehicle , 0)	Dmnl

desired electric range	PHEV total range/4	km/ Vehicle
desired plugs per vehicle	total PEV fleet*plugs per vehicle	station
develoment delay	15	Year
effect of change in charging behaviour on station require- ments	WITH LOOKUP (Time, ([(0,0)-(50,2.5)], (0,1), (10,0.95), (20,0.85), (30,0.75), (40,0.65), (50,0.6)))	Dmnl
effect of charging availability on per- formance	average station availability^sensitivity of attractiveness to relative station availability	Dmnl
effect of contact with drivers	0.25	1/Year
effect of contact with non-drivers	0.15	1/Year
effect of cost on perceived affinity	WITH LOOKUP (BEV total cost relative to ICEV, ([(0,0)-(3,2)], (0,1.8), (0.274949, 1.77251), (0.580448, 1.6872), (0.800407, 1.54502), (0.922607, 1.29858), (1, 1), (1.03259, 0.824645), (1.07536, 0.663507), (1.11813, 0.56872), (1.17923, 0.454976), (1.31365, 0.293839), (1.50305, 0.227488), (1.75356, 0.151659), (2.09572, 0.0947868), (2.49287, 0.056872), (3, 0.05)))	Dmnl
effect of cost on perceived affinity HEV	WITH LOOKUP (HEV total cost relative to ICEV, ([(0, 0)-(3, 2)], (0, 1.8), (0.274949, 1.77251), (0.580448, 1.6872), (0.800407, 1.54502), (0.922607,1.29858),(1,1),(1.03259,0.824645), (1.07536, 0.663507), (1.11813, 0.56872), (1.17923, 0.454976), (1.31365, 0.293839), (1.50305, 0.227488), (1.75356,0.151659), (2.09572, 0.0947868), (2.49287, 0.056872), (3, 0.05)))	Dmnl
effect of cost on perceived affinity PHEV	WITH LOOKUP (PHEV total cost relative to ICEV, ([(0, 0)(3, 2)], (0, 1.8), (0.274949, 1.77251), (0.580448, 1.6872), (0.800407, 1.54502), (0.922607, 1.29858), (1, 1), (1.03259, 0.824645), (1.07536, 0.663507), (1.11813, 0.56872), (1.17923, 0.454976), (1.31365, 0.293839), (1.50305, 0.227488), (1.75356, 0.151659), (2.09572, 0.0947868), (2.49287, 0.056872), (3, 0.05)))	Dmnl
effect of electric range on PHEV at- tractiveness	(PHEV electirc range relative to desired range+PHEV relative range) ^ sensitivity of attractiveness to relative travel range	Dmnl
effect of emissions on PHEV relative attractiveness	PHEV relative emissions^(-sensitivity of attractiveness to relative emission level)	Dmnl
effect of lifetime on attractiveness	relative lifetime^sensitivity of attractiveness to relative lifetime	Dmnl
effect of perfor- mance on per- ceived affinity	WITH LOOKUP (relative BEV performance, ([(0,0)-(2,2)], (0, 0.05), (0.101833, 0.0284361), (0.175153, 0.0663507), (0.252546, 0.0853081), (0.325866, 0.0947868), (0.419552, 0.113744), (0.509165, 0.123223), (0.643585, 0.161137), (0.761711, 0.255924), (0.855397, 0.407583), (0.912424, 0.540284), (0.940937, 0.663507), (0.973523, 0.805687), (0.989817, 0.909953), (1, 1), (1.03462, 1.11848), (1.07536, 1.25118), (1.12424, 1.33649), (1.18534, 1.45972), (1.25051, 1.5545), (1.37271, 1.6872), (1.49898, 1.74408), (1.60896, 1.77251), (1.74338, 1.78199), (2, 1.8)))	Dmnl

effect of performance on perceived affinity HEV	WITH LOOKUP (relative BEV performance, ([(0,0)-(2,2)], (0, 0.05), (0.101833, 0.0284361), (0.175153, 0.0663507), (0.252546, 0.0853081), (0.325866, 0.0947868), (0.419552, 0.113744), (0.509165, 0.123223), (0.643585, 0.161137), (0.761711, 0.255924), (0.855397, 0.407583), (0.912424, 0.540284), (0.940937, 0.663507), (0.973523, 0.805687), (0.989817, 0.909953), (1, 1), (1.03462, 1.11848), (1.07536, 1.25118), (1.12424, 1.33649), (1.18534, 1.45972), (1.25051, 1.5545), (1.37271, 1.6872), (1.49898, 1.74408), (1.60896, 1.77251), (1.74338, 1.78199), (2, 1.8)))	Dmnl
effect of performance on perceived affinity PHEV	WITH LOOKUP (relative BEV performance, ([(0,0)-(2,2)], (0, 0.05), (0.101833, 0.0284361), (0.175153, 0.0663507), (0.252546, 0.0853081), (0.325866, 0.0947868), (0.419552, 0.113744), (0.509165, 0.123223), (0.643585, 0.161137), (0.761711, 0.255924), (0.855397, 0.407583), (0.912424, 0.540284), (0.940937, 0.663507), (0.973523, 0.805687), (0.989817, 0.909953), (1, 1), (1.03462, 1.11848), (1.07536, 1.25118), (1.12424, 1.33649), (1.18534, 1.45972), (1.25051, 1.5545), (1.37271, 1.6872), (1.49898, 1.74408), (1.60896, 1.77251), (1.74338, 1.78199), (2, 1.8)))	Dmnl
effect of range on station requirements	effect of travel range on performance^(-sensitivity of station density to range)	Dmnl
effect of relative emission level on HEV performance	HEV relative emission level^(-sensitivity of attractiveness to relative emission level)	Dmnl
effect of relative emissions on performance	relative emission level^sensitivity of attractiveness to relative emission level	Dmnl
effect of station availability on HEV performance	relative station availability^sensitivity of attractiveness to relative station availability	Dmnl
effect of travel range on HEV performance	relative HEV travel range^sensitivity of attractiveness to relative travel range	Dmnl
effect of travel range on performance	relative travel range^sensitivity of attractiveness to relative travel range	Dmnl
EFV market share	BEV market share+HEV market share+PHEV market share	Dmnl
energy investment program duration	6	Year
energy investment program start time	11	Year
estimated maximum capacity	120	kWh/ Vehicle
estimated max range	1000	km/ Vehicle
fast charging CS subsidy coverage	percentual coverage fast CS*switch for fast CS subsidy	Dmnl
Fast charging stations	INTEG (fast CS building rate, 0)	station
fast CS building rate	fast CSs planned	station/ Year
fast CS subsidy duration	3	Year
fast CS subsidy start time	17	Year

fast CSs planned per year	available resources for fast CSs*fitness of grid*gap in station availability	station/ Year
FINAL TIME	50	Year
fitness of grid	WITH LOOKUP(Time, ([(0, 0.6)-(50, 1)], (0, 0.6), (50,1)))	1/Year
fractional WtC decay rate	EXP(-4*(1/(2*reference rate of social exposure))* (total social exposure - reference rate of social exposure))/(1+EXP(-4*(1/(2*reference rate of social exposure))* (total social exposure - reference rate of social exposure)))	1/Year
fuel tank volume	50	Litre/ Vehicle
gap in diversity	reference offer diversity - BEV offer diversity	Model
gap in electric range	MAX(desired electric range-PHEV electric range, 0)	km/ Vehicle
gap in HEV offer diversity	MAX(reference offer diversity-HEV offer diversity,0)	Model
gap in lifetime	max lifetime - BEV lifetime	Year
gap in PHEV offer diversity	MAX(reference offer diversity-PHEV offer diversity, 0)	Model
gap in plug availibility	desired plugs per vehicle-Slow charging points	station
gap in station availability	reference number of stations*effect of range on station requirements*effect of change in charging behaviour on station requirements - Fast charging stations	station
gap in travel range	reference travel range - BEV range	km/ Vehicle
gCO2/litre ICEV fuel	2300	(gCO2/ litre)/ Vehicle
governmental share on BEV subsidy	2000	EUR/ Vehicle
governmental share on PHEV subsidy	1000	EUR/ Vehicle
HEV aging rate	Young HEV fleet/ICEV time as young	Vehicle/ Year
HEV annual basetax	IF THEN ELSE(Time >= 19, new tax model HEV, old tax model HEV)	EUR/ Year
HEV annual cost relative to ICEV	annual cost HEV/annual cost ICEV	Dmnl
HEV annual vehicle tax	HEV annual basetax+HEV motive power tax	EUR/ Year
HEV car tax	HEV tax percentage*retail price HEV	EUR/ Vehicle
HEV discard rate	Mature HEV fleet/ICEV time as mature	Vehicle/ Year
HEV emission level	65.3	gCO2/ km/ Vehicle
HEV fuel efficiency	0.034	litre/km
HEV maintenance cost	HEV maintetance cost per km * annual driving range	EUR/ Year
HEV maintetance cost per km	0.071	EUR/km
HEV market share	total HEV fleet/total fleet	Dmnl

HEV motive power tax	0	EUR/ Year
HEV new sales rate	market pool*HEV sales share	Vehicle/ Year
HEV offer diversity	INTEG (change in HEV offer diversity, init HEV offering)	Model
HEV purchase price relative to ICEV	net price HEV including devaluation/net price ICEV including devaluation	Dmnl
HEV reference	WITH LOOKUP (Time, ([(0,0)-(17,30000)], (0, 0), (1, 3), (2, 3), (3, 4), (4, 17), (5, 48), (6, 228), (7 ,367), (8, 1144), (9, 2006), (10, 3200), (11, 4470), (12, 5987), (13, 8446), (14, 10949), (15, 14056), (16, 19242), (17, 28515)))	Vehicle
HEV refueling cost	HEV fuel efficiency*annual driving range*oil price	EUR/ Year
HEV relative emission level	HEV emission level/ICEV emission level	Dmnl
HEV sales share	perceived HEV affinity/(perceived BEV affinity+perceived HEV affinity+perceived PHEV affinity+ICEV reference affinity)	Dmnl
HEV tax percentage	WITH LOOKUP (Time, ([(0,0)-(50,0.5)], (0,0.29), (2,0.29), (3,0.258), (7,0.258), (8,0.119), (9,0.119), (10,0.145), (12,0.145), (13,0.131), (15,0.131), (16,0.119), (17,0.105), (18,0.092), (18.75,0.072), (19,0.059), (50,0.059)))	Dmnl
HEV total cost relative to ICEV	weight on cost*HEV annual cost relative to ICEV + (1-weight on cost)*HEV purchase price relative to ICEV	Dmnl
HEV travel range	reference travel range	km/ Vehicle
ICEV aging rate	Young ICEV fleet/ICEV time as young	Vehicle/ Year
ICEV annual basetax	IF THEN ELSE(Time>=19 , new tax model ICEV , old tax model ICEV)	EUR/ Year
ICEV annual vehicle tax	ICEV annual basetax + ICEV motive power tax	EUR/ Year
ICEV car tax	ICEV tax percentage*retail price ICEV	EUR/ Vehicle
ICEV discard rate	Mature ICEV fleet/ICEV time as mature	Vehicle/ Year
ICEV emission level	ICEV fuel efficiency*"gCO2/litre ICEV fuel"	gCO2/km/ Vehicle
ICEV fuel efficiency	WITH LOOKUP (Time, ([(0,0)-(50,0.1)], (0,0.08), (10,0.069), (20,0.065), (30,0.063), (40,0.061),(50,0.06)))	litre/km
ICEV maintenance cost	ICEV maintenance cost per km * annual driving range	EUR/ Year
ICEV maintenance cost per km	0.073	EUR/km
ICEV market share	total ICEV fleet/total fleet	Dmnl
ICEV motive power tax	0	EUR/ Year
ICEV new sales rate	market pool*ICEV sales share	Vehicle/ Year
ICEV reference affinity	1	Dmnl
ICEV refueling cost	annual driving range*ICEV fuel efficiency*oil price	EUR/ Year
ICEV sales share	1-BEV sales share-HEV sales share-PHEV sales share	Dmnl

ICEV tax percentage	WITH LOOKUP (Time, ([(0,0)-(50,0.5)], (0,0.29), (2,0.29), (3,0.258), (7,0.258), (8,0.19), (9,0.19), (10,0.232), (12,0.232), (13,0.258), (15,0.258), (16,0.258), (17,0.258), (18,0.258), (18.75,0.194), (19,0.187), (50,0.187)))	Dmnl
ICEV time as mature	total ICEV lifetime*2/3	Year
ICEV time as young	total ICEV lifetime/3	Year
init BEV battery capacity	16	kWh/Vehicle
init BEV fleet	1	Vehicle
Init BEV lifetime	5	Year
init BEV offer	1	Model
init BEV travel range	30	km/Vehicle
init cost of kWh	1400	EUR/kWh
init HEV fleet	2	Vehicle
init HEV offering	2	Model
init ICEV fleet	2.1e+06	Vehicle
init PHEV battery capacity	5	kWh/Vehicle
init PHEV electric range	20	km/Vehicle
init PHEV fleet	0	Vehicle
INITIAL TIME	0	Year
likelihood of meeting desired diversity	WITH LOOKUP (BEV offer diversity, ([(0,0)-(100,1)], (0,0), (12.5,0.05), (20,0.25), (25,0.5), (30,0.75), (37.5,0.95), (50,1), (100,1)))	Dmnl
likelihood of meeting desired HEV model diversity	WITH LOOKUP (BEV offer diversity, ([(0,0)-(100,1)], (0,0), (12.5,0.05), (20,0.25), (25,0.5), (30,0.75), (37.5,0.95), (50,1), (100,1)))	Dmnl
likelihood of meeting desired PHEV model diversity	WITH LOOKUP (BEV offer diversity, ([(0,0)-(100,1)], (0,0), (12.5,0.05), (20,0.25), (25,0.5), (30,0.75), (37.5,0.95), (50,1), (100,1)))	Dmnl
market pool	total replacements + vehicle market growth	Vehicle/Year
marketing for platform	WITH LOOKUP (Time, ([(0,0)-(50,0.05)],(0,0),(7.33198,0.0092417),(12.0163,0.0154028),(15.3768,0.0191943),(18.6354,0.02109),(20.6721,0.0203791),(22.3014,0.0187204),(23.6253,0.0156398),(25.7637,0.0120853),(28.4114,0.0109005),(30.9572,0.0106635),(33.2994,0.0104265),(36.0489,0.01),(39.2057,0.0101896),(44.8065,0.01),(50,0.01)))	1/Year
Mature BEV fleet	INTEG (BEV aging rate-BEV discard rate, 0)	Vehicle
Mature HEV fleet	INTEG (HEV aging rate-HEV discard rate, 0)	Vehicle
Mature ICEV fleet	INTEG (ICEV aging rate-ICEV discard rate, init ICEV fleet / 3 * 2)	Vehicle
Mature PHEV fleet	INTEG (PHEV aging rate-PHEV discard rate, 0)	Vehicle
max lifetime	total ICEV lifetime*1.2	Year
net price BEV	BEV baseprice + BEV car tax - BEV purchase subsidy + STEP(-1500, 15) + STEP(1500, 16)	EUR/Vehicle

net price BEV including devaluation	net price BEV/BEV lifetime	EUR/Year
net price HEV	HEV car tax + retail price HEV + STEP(-1500, 15.5) + STEP(1500, 16) + STEP(-1500, 18) + STEP(1500, 18.76)	EUR/Vehicle
net price HEV including devaluation	net price HEV/total ICEV lifetime	EUR/Vehicle/Year
net price ICEV	retail price ICEV + ICEV car tax	EUR/Vehicle
net price ICEV including devaluation	net price ICEV/total ICEV lifetime	EUR/Vehicle/Year
net price PHEV	PHEV baseprice + PHEV car tax + STEP(-1500, 15) + STEP(1500, 16) + STEP(-2500, 18) + STEP(2500, 18.76)	EUR/Vehicle
net price PHEV including devaluation	net price PHEV / BEV lifetime	EUR/Vehicle/Year
New tax model BEV	WITH LOOKUP (BEV emission level*WLTP coefficient, ([(0,0)(200,300)],(0,106.21),(5,107.3),(10,108.8),(15,109.9),(20,111.3),(25,112.8),(30,114.2),(35,115.7),(40,117.5),(45,119.4),(50,121.2),(55,123),(60,125.2),(65,127.4),(70,129.6),(75,131.8),(80,134.3),(85,136.9),(90,139.8),(95,142.7),(100,145.6),(105,148.9),(110,152.2),(115,155.5),(120,159.1),(125,162.8),(130,166.8),(135,170.8),(140,177),(145,184),(150,191.6),(155,199.3),(160,207.8),(165,216.8),(170,225.9),(175,235.8),(180,246),(185,257),(190,267.9),(195,279.6),(200,291.6))	EUR/Year
New tax model HEV	WITH LOOKUP (HEV emission level*WLTP coefficient, ([(0,0)(200,300)],(0,106.21),(5,107.3),(10,108.8),(15,109.9),(20,111.3),(25,112.8),(30,114.2),(35,115.7),(40,117.5),(45,119.4),(50,121.2),(55,123),(60,125.2),(65,127.4),(70,129.6),(75,131.8),(80,134.3),(85,136.9),(90,139.8),(95,142.7),(100,145.6),(105,148.9),(110,152.2),(115,155.5),(120,159.1),(125,162.8),(130,166.8),(135,170.8),(140,177),(145,184),(150,191.6),(155,199.3),(160,207.8),(165,216.8),(170,225.9),(175,235.8),(180,246),(185,257),(190,267.9),(195,279.6),(200,291.6))	EUR/Year
New tax model ICEV	WITH LOOKUP (ICEV emission level*WLTP coefficient, ([(0,0)(200,300)],(0,106.21),(5,107.3),(10,108.8),(15,109.9),(20,111.3),(25,112.8),(30,114.2),(35,115.7),(40,117.5),(45,119.4),(50,121.2),(55,123),(60,125.2),(65,127.4),(70,129.6),(75,131.8),(80,134.3),(85,136.9),(90,139.8),(95,142.7),(100,145.6),(105,148.9),(110,152.2),(115,155.5),(120,159.1),(125,162.8),(130,166.8),(135,170.8),(140,177),(145,184),(150,191.6),(155,199.3),(160,207.8),(165,216.8),(170,225.9),(175,235.8),(180,246),(185,257),(190,267.9),(195,279.6),(200,291.6))	EUR/Year
New tax model PHEV	WITH LOOKUP (PHEV emission level*WLTP coefficient, ([(0,0)(200,300)],(0,106.21),(5,107.3),(10,108.8),(15,109.9),(20,111.3),(25,112.8),(30,114.2),(35,115.7),(40,117.5),(45,119.4),(50,121.2),(55,123),(60,125.2),(65,127.4),(70,129.6),(75,131.8),(80,134.3),(85,136.9),(90,139.8),(95,142.7),(100,145.6),(105,148.9),(110,152.2),(115,155.5),(120,159.1),(125,162.8),(130,166.8),(135,170.8),(140,177),(145,184),(150,191.6),(155,199.3),(160,207.8),(165,216.8),(170,225.9),(175,235.8),(180,246),(185,257),(190,267.9),(195,279.6),(200,291.6))	EUR/Year
oil price	1.4	EUR/litre
old tax model BEV	WITH LOOKUP (BEV emission level, ([(0,0)-(200,400)],(0,106.2),(5,107.7),(10,109.1),(15,111),(20,112.8),(25,11	EUR/Year

	4.6),(30,116.8),(35,118.6),(40,121.2),(45,123.4),(50,126.3),(55,128.8),(60,131.8),(65,135),(70,138.3),(75,142),(80,145.63),(85,149.7),(90,153.7),(95,158),(100,162.8),(105,167.9),(110,173),(115,178.5),(120,184.3),(125,190.1),(130,196.7),(135,203.3),(140,210.2),(145,217.5),(150,225.2),(155,232.9),(160,240.9),(165,249.3),(170,258),(175,267.2),(180,276.7),(185,286.2),(190,296.01),(195,305.9),(200,316.1))	
old tax model HEV	WITH LOOKUP (HEV emission level, ([(0,0)-(200,400)],(0,106.2),(5,107.7),(10,109.1),(15,111),(20,112.8),(25,114.6),(30,116.8),(35,118.6),(40,121.2),(45,123.4),(50,126.3),(55,128.8),(60,131.8),(65,135),(70,138.3),(75,142),(80,145.63),(85,149.7),(90,153.7),(95,158),(100,162.8),(105,167.9),(110,173),(115,178.5),(120,184.3),(125,190.1),(130,196.7),(135,203.3),(140,210.2),(145,217.5),(150,225.2),(155,232.9),(160,240.9),(165,249.3),(170,258),(175,267.2),(180,276.7),(185,286.2),(190,296.01),(195,305.9),(200,316.1))	EUR/Year
old tax model ICEV	WITH LOOKUP (ICEV emission level, ([(0,0)-(200,400)],(0,106.2),(5,107.7),(10,109.1),(15,111),(20,112.8),(25,114.6),(30,116.8),(35,118.6),(40,121.2),(45,123.4),(50,126.3),(55,128.8),(60,131.8),(65,135),(70,138.3),(75,142),(80,145.63),(85,149.7),(90,153.7),(95,158),(100,162.8),(105,167.9),(110,173),(115,178.5),(120,184.3),(125,190.1),(130,196.7),(135,203.3),(140,210.2),(145,217.5),(150,225.2),(155,232.9),(160,240.9),(165,249.3),(170,258),(175,267.2),(180,276.7),(185,286.2),(190,296.01),(195,305.9),(200,316.1))	EUR/Year
old tax model PHEV	WITH LOOKUP (PHEV emission level, ([(0,0)(200,400)],(0,106.2),(5,107.7),(10,109.1),(15,111),(20,112.8),(25,114.6),(30,116.8),(35,118.6),(40,121.2),(45,123.4),(50,126.3),(55,128.8),(60,131.8),(65,135),(70,138.3),(75,142),(80,145.63),(85,149.7),(90,153.7),(95,158),(100,162.8),(105,167.9),(110,173),(115,178.5),(120,184.3),(125,190.1),(130,196.7),(135,203.3),(140,210.2),(145,217.5),(150,225.2),(155,232.9),(160,240.9),(165,249.3),(170,258),(175,267.2),(180,276.7),(185,286.2),(190,296.01),(195,305.9),(200,316.1))	EUR/Year
perceived BEV affinity	effect of cost on perceived affinity*effect of performance on perceived affinity*Willingness to Consider platform	Dmnl
perceived HEV affinity	effect of cost on perceived affinity HEV*effect of performance on perceived affinity HEV*Willingness to Consider platform	Dmnl
perceived PHEV affinity	effect of cost on perceived affinity PHEV*effect of performance on perceived affinity PHEV*Willingness to Consider platform	Dmnl
percentual coverage	0.3	Dmnl
percentual coverage fast CS	0.35	Dmnl
PEV market share	BEV market share+PHEV market share	Dmnl
PHEV aging rate	Young PHEV fleet/BEV time as young	Vehicle/Year
PHEV annual basetax	IF THEN ELSE(Time >= 19, new tax model PHEV, old tax model PHEV)	EUR/Year
PHEV annual cost relative to ICEV	annual cost PHEV/annual cost ICEV	Dmnl

PHEV annual tax	PHEV annual basetax + PHEV motive power tax	EUR/ Year
PHEV baseprice	(costs unrelated to powertrain + Cost of kWh* PHEV battery capacity*PHEV battery cost scaling factor + cost of ICE powertrain)*(1+value added tax)	EUR/ Vehicle
PHEV battery capacity	INTEG (change in PHEV battery capacity, init PHEV battery capacity)	kWh/ Vehicle
PHEV battery cost scaling factor	0.5	Dmnl
PHEV car tax	PHEV baseprice*PHEV tax percentage	EUR/ Vehicle
PHEV discard rate	Mature PHEV fleet/BEV time as mature	Vehicle/ Year
PHEV electirc range relative to desired range	PHEV electric range/desired electric range	Dmnl
PHEV electric range	INTEG (change in PHEV range, init PHEV electric range)	km/ Vehicle
PHEV emission level	21.5	gCO2/ (km*Vehicle)
PHEV estimated maximum capacity	15	kWh/ Vehicle
PHEV fuel consumption	1.1	litre/km
PHEV maintenance cost	PHEV maintenance cost per km * annual driving range	EUR/ Year
PHEV maintenance cost per km	0.064	EUR/km
PHEV market share	total PHEV fleet/total fleet	Dmnl
PHEV motive power tax	36.5	EUR/ Year
PHEV new sales rate	market pool*PHEV sales share	Vehicle/ Year
PHEV offer diversity	INTEG (change in PHEV offer diversity, 0)	Model
PHEV purchase price relative to ICEV	net price PHEV including devaluation / net price ICEV including devaluation	Dmnl
PHEV recharging cost	annual driving range*(PHEV battery capacity/PHEV electric range)*power price*weight on PHEV electric drive	EUR/ Year
PHEV reference	WITH LOOKUP (Time, ([(0,0)-(17,6000)], (0,0), (7,0), (8,2), (9,2), (10,0), (11,0), (12,128), (13,296), (14,569), (15,973), (16,2441), (17,5729)))	Vehicle
PHEV refueling cost	PHEV fuel consumption*annual driving range*oil price*(1-weight on PHEV electric drive)	EUR/ Year
PHEV relative emissions	PHEV emission level/ICEV emission level	Dmnl
PHEV relative range	PHEV total range/reference travel range	Dmnl
PHEV sales share	perceived PHEV affinity/(perceived BEV affinity+perceived HEV affinity+perceived PHEV affinity+ICEV reference affinity)	Dmnl

PHEV tax percentage	WITH LOOKUP (Time, ([(0,0)-(50,0.5)], (0,0.29), (2,0.29), (3,0.258), (7,0.258), (8,0.1), (9,0.1), (10,0.122), (12,0.122), (13,0.072), (15,0.072), (16,0.063), (17,0.053), (18,0.044), (18.75,0.041), (19,0.033), (50,0.033)))	Dmnl
PHEV technological development rate	0.01	1/Year
PHEV total cost relative to ICEV	weight on cost*PHEV annual cost relative to ICEV + (1-weight on cost)*PHEV purchase price relative to ICEV	Dmnl
PHEV total range	1100	km/ Vehicle
plugs per vehicle	2	station/ Vehicle
power price	0.15	EUR/ kWh
private investment coverage	EFV market share	Dmnl
program coverage for fast CS	percentual coverage fast CS*switch for energy investment program fast CS subsidy	Dmnl
program coverage for slow CS	percentual coverage*switch for energy investment program slow CS subsidy	Dmnl
rate of HEV product development	WITH LOOKUP(Time, ([(0,0)-(50,10)],(0,0.025),(50,0.1)))	1/Year
rate of PHEV product development	WITH LOOKUP(Time, ([(0,0)-(50,0.1)],(0,0),(9,0.001),(10.7943,0.00521327),(14,0.04),(15,0.05),(16,0.06),(17,0.06),(19.8045,0.05972),(24,0.05782),(26,0.05),(50,0.05)))	1/Year
rate of product development	WITH LOOKUP (Time, ([(0,0)-(50,0.1)],(0,0),(6.21181,0.0085308),(9.06314,0.0161137),(11.3035,0.028436),(14,0.05),(15.0713,0.057346),(17,0.06),(19.8045,0.05972),(24,0.05782),(26,0.05),(50,0.05)))	1/Year
recharging cost	annual driving range*battery efficiency*power price	EUR/ Year
reference availability	1	Dmnl
reference number of stations	1848	station
reference offer diversity	100	Model
reference rate of social exposure	0.05	1/Year
reference travel range	fuel tank volume/ICEV fuel efficiency	Km/Vehicle
relative BEV performance	weight on lifetime*effect of lifetime on attractiveness + weight on travel range*effect of travel range on performance + weight on emissions*effect of relative emissions on performance + weight on model diversity * likelihood of meeting desired diversity+weight on charging availability*effect of charging availability on performance	Dmnl
relative emission level	BEV emission level/ICEV emission level	Dmnl

relative HEV performance	weight on travel range*effect of travel range on HEV performance + weight on model diversity*likelihood of meeting desired HEV model diversity + weight on lifetime*effect of lifetime on attractiveness + weight on emissions * effect of relative emission level on HEV performance + weight on charging availability*effect of station availability on HEV performance	Dmnl
relative HEV travel range	HEV travel range/reference travel range	Dmnl
relative lifetime	BEV lifetime/total ICEV lifetime	Dmnl
relative PHEV performance	weight on travel range*effect of electric range on PHEV attractiveness + weight on model diversity*likelihood of meeting desired PHEV model diversity + weight on lifetime*effect of lifetime on attractiveness + weight on emissions * effect of emissions on PHEV relative attractiveness + weight on charging availability * availability factor	Dmnl
relative station availability	1	Dmnl
relative travel range	BEV range / reference travel range	Dmnl
retail price HEV	25202.3	EUR
retail price ICEV	16172	EUR
SAVEPER	1	Year
scrapping bonus monetary coverage	governmental share on PHEV subsidy + car industry share on PHEV subsidy	EUR/ Vehicle
scrapping bonus	STEP(scrapping bonus coverage , scrapping program start time) + STEP(-scrapping bonus coverage , scrapping program subsidy start time+scrapping progam duration)	EUR/ Vehicle
scrapping bonus coverage	PHEV monetary coverage*switch for PHEV purchase subsidy	EUR/ Vehicle
sensitivity of attractiveness to relative emissions	0.1	Dmnl
sensitivity of attractiveness to relative lifetime	0.5	Dmnl
Sensitivity of attractiveness on relative station availability	0.5	Dmnl
sensitivity of attractiveness to relative travel range	0.5	Dmnl
sensitivity of station density to range	0.5	Dmnl
share of available resources for fast charging stations	WITH LOOKUP (Time, ([(0,0)-(50,1)],(0,0.05),(17,0.5),(50,0.5)))	Dmnl
Slow charging points	INTEG (slow CS building rate, 0)	station
slow CS building rate	slow CSs planned	station/ Year
slow CS subsidy coverage	percentual coverage*switch for slow CS subsidy	Dmnl
slow CS subsidy duration	3	Year

slow CS subsidy start time	17	Year
slow CSs planned per year	available resources for slow charging points*fitness of grid*gap in plug availibility	station/ Year
switch for BEV purchase subsidy	1	Dmnl
switch for energy investment program fast CS subsidy	IF THEN ELSE(Available program resources for fast charging stations>0 , 1 , 0)	Dmnl
switch for energy investment program slow CS subsidy	IF THEN ELSE(Available program resources for slow charging stations>0 , 1, 0)	Dmnl
switch for fast CS subsidy	IF THEN ELSE(Available subsidies for fast charging stations>0 , 1 , 0)	Dmnl
switch for PHEV purchase subsidy	IF THEN ELSE(Available subsidies for BEV>0, 1, 0)	Dmnl
switch for slow CS subsidy	IF THEN ELSE(Available subsidies for PHEV>0, 1, 0)	Dmnl
TIME STEP	0.25	Year
total BEV fleet	Young BEV fleet+Mature BEV fleet	Vehicle
total EFV fleet	total BEV fleet+total HEV fleet+total PHEV fleet	Vehicle
total fleet	total BEV fleet+total HEV fleet+total ICEV fleet+total PHEV fleet	Vehicle
total HEV fleet	Young HEV fleet+Mature HEV fleet	Vehicle
total ICEV fleet	Young ICEV fleet+Mature ICEV fleet	Vehicle
total ICEV lifetime	19	Year
total PEV fleet	total BEV fleet+total PHEV fleet	Vehicle
total PHEV fleet	Young PHEV fleet+Mature PHEV fleet	Vehicle
total replacements	BEV discard rate+HEV discard rate+ICEV discard rate+PHEV discard rate	Vehicle/ Year
total social exposure	effect of contact with drivers*word of mouth from drivers+"word of mouth from non drivers"*"effect of contact with non-drivers"+marketing for platform	1/Year
usage of BEV purchase subsidies	IF THEN ELSE(Time >= BEV purchase subsidy start time :AND: Time<=BEV purchase subsidy start time+BEV purchase subsidy duration , IF THEN ELSE(Available subsidies for BEV>0 , BEV new sales rate*BEV purchase subsidy coverage , 0) , 0)	EUR/ Year
usage of resources on fast CSs	IF THEN ELSE(Time >= energy investment program start time :AND: Time<=energy investment program start time+energy investment program duration , IF THEN ELSE(Available program resources for fast charging stations>0 , cost of fast CS*fast CSs planned per year , 0) , 0)	EUR/ Year
usage of resources on slow CSs	IF THEN ELSE(Time >= energy investment program start time :AND: Time<=energy investment program start time+energy investment program duration , IF THEN ELSE(Available program resources for slow charging stations>0 , cost of slow CS*slow CSs planned per year , 0) , 0)	EUR/ Year

usage of subsidies on fast CSs	IF THEN ELSE(Time >= fast CS subsidy start time :AND: Time<=fast CS subsidy start time+fast CS subsidy duration , IF THEN ELSE(Available subsidies for fast charging stations>0 , cost of fast CS*fast CSs planned per year , 0) , 0)	EUR/ Year
usage of subsidies on slow CSs	IF THEN ELSE(Time >= slow CS subsidy start time :AND: Time<=slow CS subsidy start time+slow CS subsidy duration , IF THEN ELSE(Available subsidies for slow charging stations>0 , cost of slow CS*slow CSs planned per year , 0) , 0)	EUR/ Year
value added tax	0.24	Dmnl
vehicle market growth	21375	Vehicle/ Year
weight on charging availability	0.3	Dmnl
weight on cost	0.4	Dmnl
weight on emissions	0.1	Dmnl
weight on lifetime	0.05	Dmnl
weight on model diversity	0.15	Dmnl
weight on travel range	0.4	Dmnl
Willingness to Consider platform	INTEG (WtC gain-WtC loss, 0)	Dmnl
WLTP coefficient	1.21	Dmnl
word of mouth from drivers	total EFV fleet/(total EFV fleet+total ICEV fleet)	Dmnl
word of mouth from non-drivers	total ICEV fleet/(total EFV fleet+total ICEV fleet) * Willingness to Consider platform	Dmnl
WtC gain	total social exposure*(1-Willingness to Consider platform)	1/Year
WtC loss	fractional WtC decay rate*Willingness to Consider platform	1/Year
Young BEV fleet	INTEG (BEV new sales rate-BEV aging rate, init BEV fleet)	Vehicle
Young HEV fleet	INTEG (HEV new sales rate-HEV aging rate, init HEV fleet)	Vehicle
Young ICEV fleet	INTEG (ICEV new sales rate-ICEV aging rate, init ICEV fleet/3)	Vehicle
Young PHEV fleet	INTEG (PHEV new sales rate-PHEV aging rate, init PHEV fleet)	Vehicle

A2. Parameter sources

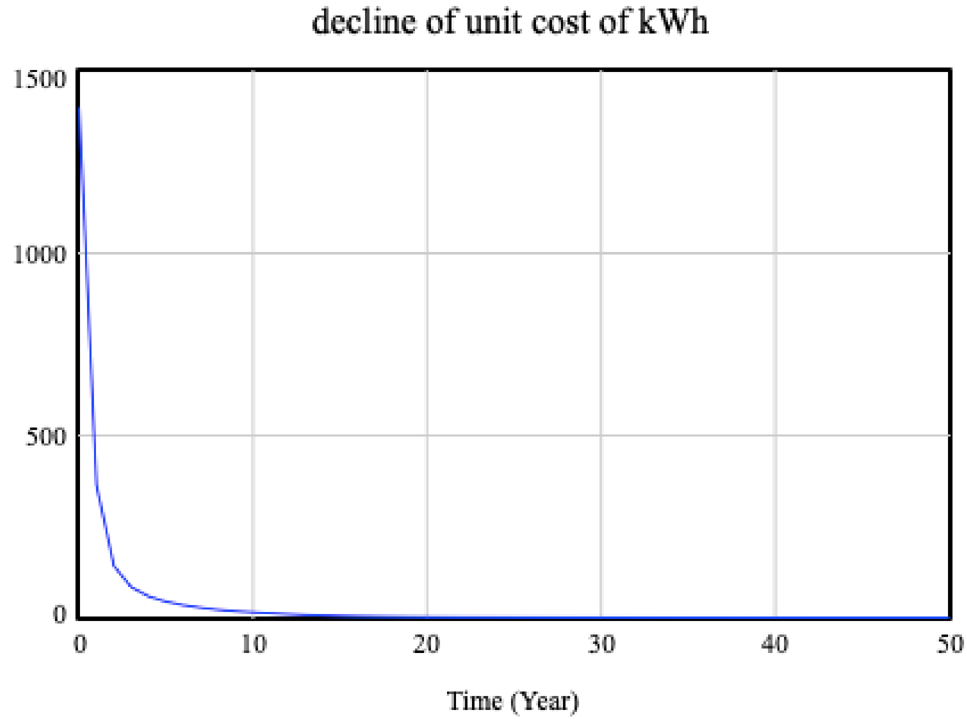
Parameter name	Source
annual cost reduction	Estimated based on Nykvist & Nilsson (2015)
annual driving range	Trafi (2018e)
BEV emission level	Testa (2017)
BEV maintenance cost per km	Propfe et al. (2012)
BEV monetary coverage	Ministry of Transport and Communications (2017)
BEV motive power tax	Trafi
BEV purchase subsidy duration	Ministry of Transport and Communications (2017)
BEV purchase subsidy start time	Ministry of Transport and Communications (2017)
BEV technological development rate	Heuristic, discussed in Chapter 7
budgeted resources for energy investment program	Government bill (156/2017)
budgeted subsidies for fast charging stations	Ministry of Transport and Communications (2017)
budgeted subsidies for purchase subsidies	www.lataustuki.fi
budgeted subsidies for slow charging stations	Ministry of Transport and Communications (2017)
car industry share on BEV subsidy	Finnish Parliament (EV 143/2017)
car industry share on PHEV subsidy	Finnish Parliament (EV 143/2017)
cost of fast CS	OhmHome (www.ohmhomenow.com)
cost of ICE powertrain	Estimated based on Hyundai Ioniq Plug-in Hybrid and Kocchan et al. (2017)
cost of slow CS	OhmHome (www.ohmhomenow.com)
costs unrelated to powertrain	www.hyundai.fi, Küpper et al. (2018)
develoment delay	Heuristic, in line with Testa (2017)
effect of contact with drivers	Struben & Sterman (2008)
effect of contact with non-drivers	Struben & Sterman (2008)
energy investment program duration	Government bill (156/2017)
energy investment program start time	Government bill (156/2017)
estimated maximum capacity	Testa (2017)
fast CS subsidy duration	www.lataustuki.fi
fast CS subsidy start time	www.lataustuki.fi
gCO2/litre ICEV fuel	Testa (2017)
governmental share on BEV subsidy	Finnish Parliament (EV 143/2017)
governmental share on PHEV subsidy	Finnish Parliament (EV 143/2017)
HEV emission level	www.hyundai.fi
HEV fuel efficiency	www.hyundai.fi
HEV maintetance cost per km	Propfe et al. (2012)
HEV motive power tax	Trafi (2018d)
ICEV maintenance cost per km	Propfe et al. (2012)
ICEV motive power tax	Trafi (2018d)
init BEV battery capacity	Testa (2017)

init BEV fleet	Trafi open data
Init BEV lifetime	Testa (2017)
init BEV offer	Trafi open data
init BEV travel range	Testa (2017)
init cost of kWh	Approximation, in line with Kocchan et al. (2014), Nykvist & Nilsson (2015)
init HEV fleet	Trafi open data
init HEV offering	Trafi open data
init ICEV fleet	https://www.trafi.fi/tietopalvelut/tilas-tot/tieliikenne/ajoneuvokanta
init PHEV battery capacity	Spiers et al. (2014); Trafi open data
init PHEV electric range	Testa (2017)
init PHEV fleet	Trafi open data
marketing for platform	Struben & Sterman (2008)
new tax model BEV/HEV/ICEV/PHEV	Ajoneuvoverolaki (1281/2003)
oil price	www.oil.fi
old tax model BEV/HEV/ICEV/PHEV	Ajoneuvoverolaki (1281/2003)
percentual coverage	www.lataustuki.fi
percentual coverage fast CS	www.lataustuki.fi
PHEV battery cost scaling factor	Nykvist & Nilsson 2015
PHEV emission level	www.hyundai.fi
PHEV estimated maximum capacity	Heuristic, discussed in Chapter 7
PHEV fuel consumption	www.hyundai.fi
PHEV maintenance cost per km	Propfe et al. (2012)
PHEV monetary coverage	Ministry of Transport and Communications (2017)
PHEV motive power tax	www.hyundai.fi, Trafi
PHEV purchase subsidy duration	Ministry of Transport and Communications (2017)
PHEV purchase subsidy start time	Ministry of Transport and Communications (2017)
PHEV technological development rate	Heuristic, discussed in Chapter 7
PHEV total range	www.hyundai.fi
plugs per vehicle	Testa (2017)
rate of HEV product development	Heuristic, discussed in Chapter 7
rate of product development	Heuristic, discussed in Chapter 7
reference number of stations	http://www.oil.fi/fi/tilastot-4-huoltoasemat/41-hu-oltoasemien-maara
reference offer diversity	Autotietokanta
reference rate of social exposure	Struben & Sterman (2008)
reference travel range	Heuristic
retail price HEV	www.hyundai.fi
retail price ICEV	www.hyundai.fi
sensitivity of attractiveness to relative emission level	Testa (2017)
sensitivity of attractiveness to relative lifetime	Testa (2017)

sensitivity of attractiveness to relative station availability	Testa (2017)
sensitivity of attractiveness to relative travel range	Testa (2017)
sensitivity of station density to range	Testa (2017)
slow CS subsidy duration	www.lataustuki.fi
slow CS subsidy start time	www.lataustuki.fi
total ICEV lifetime	Autoalan tiedotuskeskus
value added tax	Vero.fi
vehicle market growth	Autoalan tiedotuskeskus
weight on charging availability	Sierzchula et al. (2014),Testa (2017)
weight on cost	Heuristic, discussed in Chapter 7
weight on emission	Testa (2017)
weight on lifetime	Testa (2017)
weight on model diversity	Testa (2017)
weight on travel range	Testa (2017)
WLTP coefficient	Government bill 74/2018

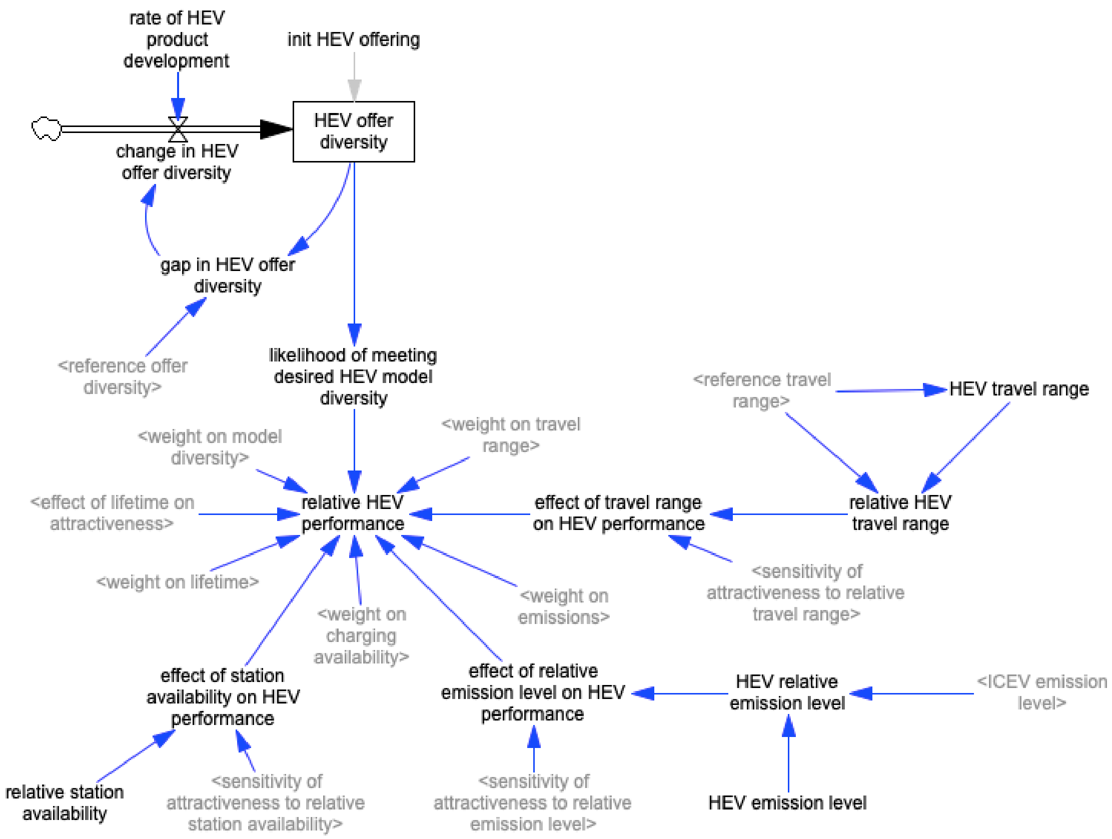
APPENDIX B: MODEL STRUCTURE VISUALIZATION

B1. Price decline with Henderson Law (85 % experience curve)

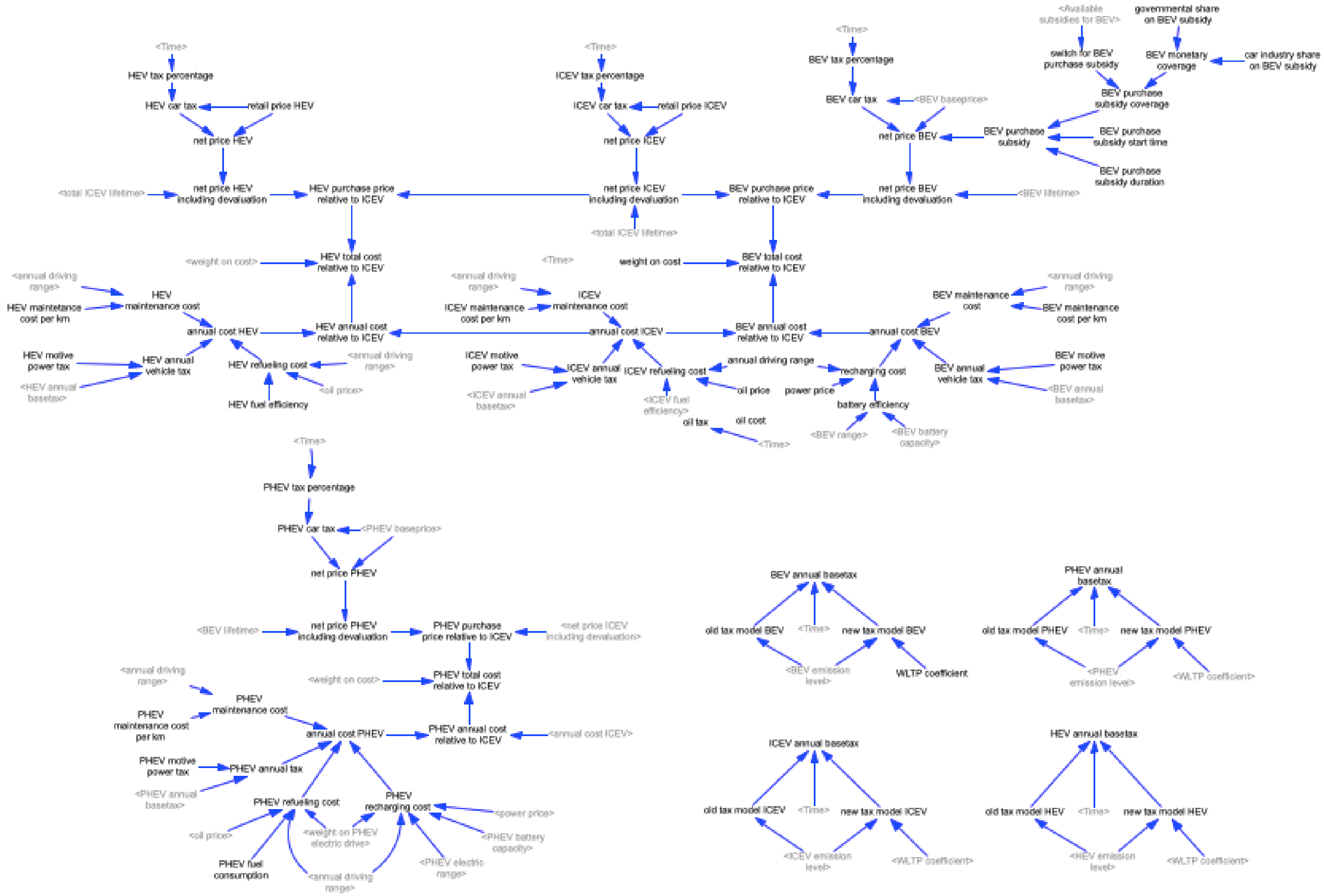


The curve is estimated as a Henderson's Law with 15 % decline every doubling and with 1,500€ initial unit cost of kWh (Henderson 1968). Evidently, this does not represent realistic behaviour and is therefore modelled exogenously. Further details are provided in Chapter 6.2.

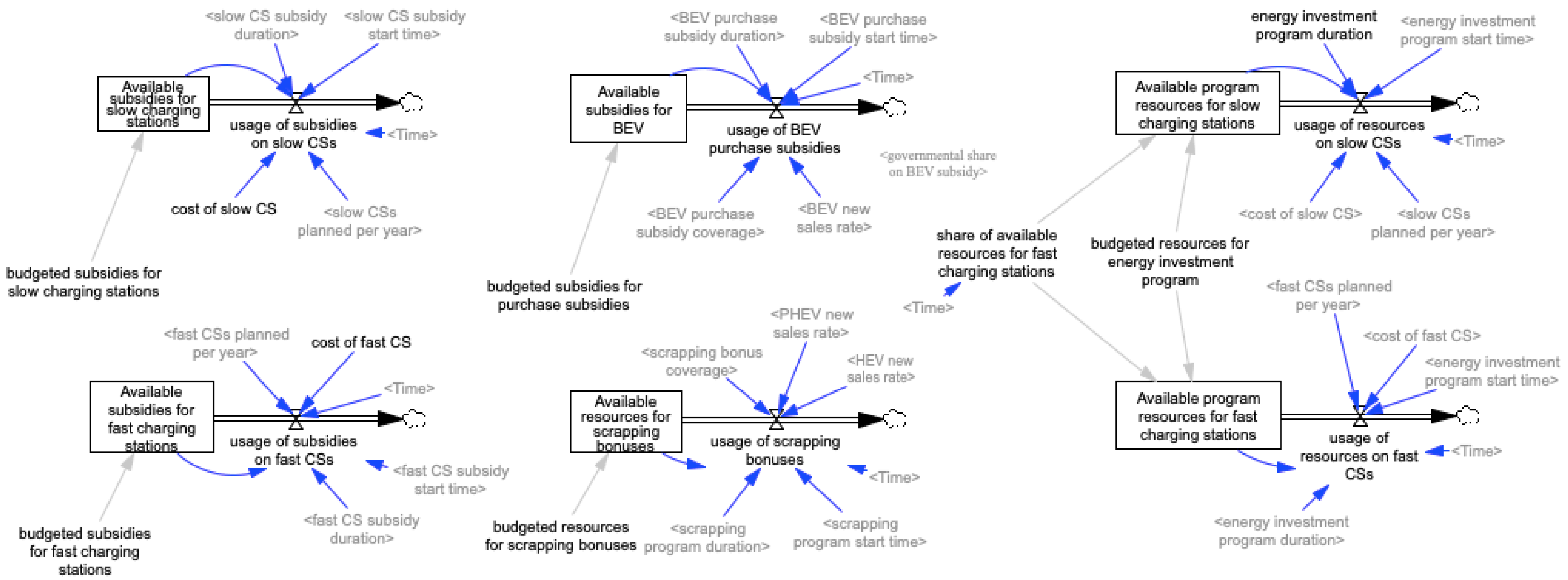
B2. HEV Performance



B3. Model structure for cost module

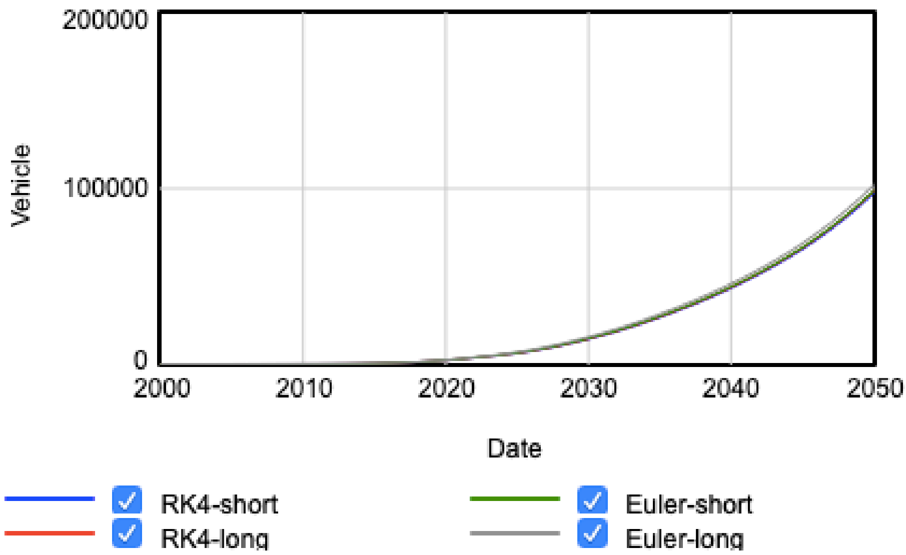


B4. Model structure for subsidy coverage



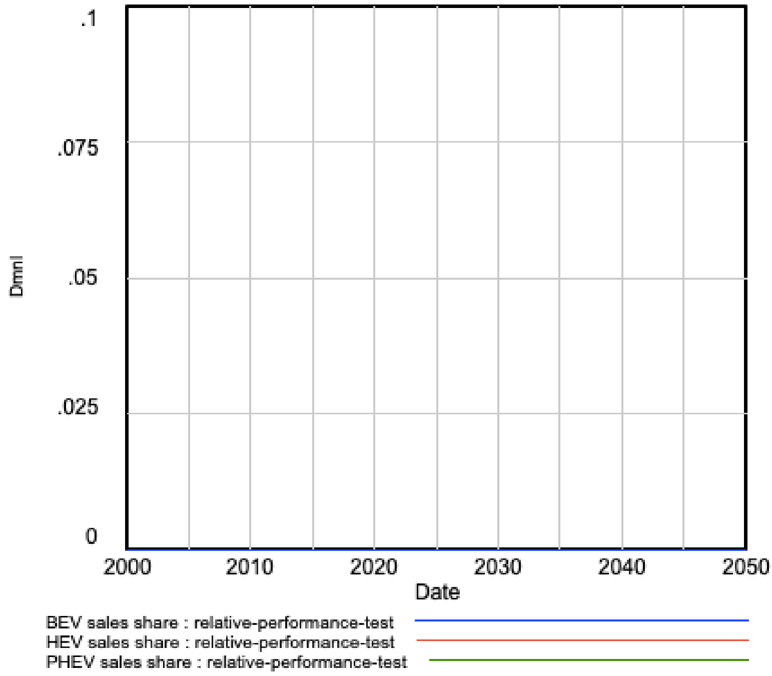
The structure for energy program subsidies slightly differs from the other two. This is because in the absence of more accurate information on the *share of subsidies* that were used for slow and fast charging stations, it is assumed that the share gradually rose towards the 50-50 situation in which it is today. This was modelled with a table function, were the share of subsidies start from 0.05 and rise linearly to 0.5 in 2017. The function is documented in the Appendix A.

APPENDIX C: INTEGRATION TEST



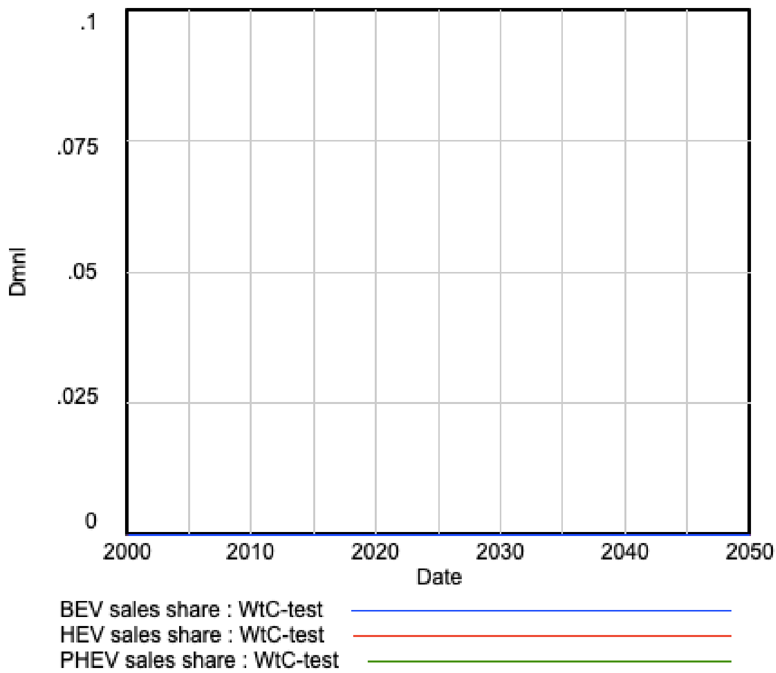
APPENDIX D: EXTREME CONDITIONS TESTS

D1. Relative performance test



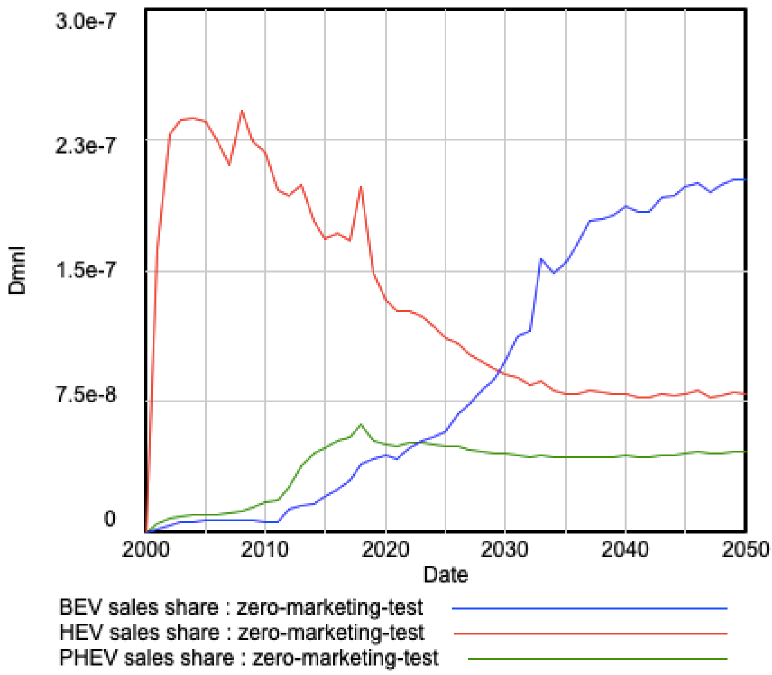
If the relative performance of a platform is zero, sales fall also to zero, thus, the model performs realistically.

D2. WtC-test



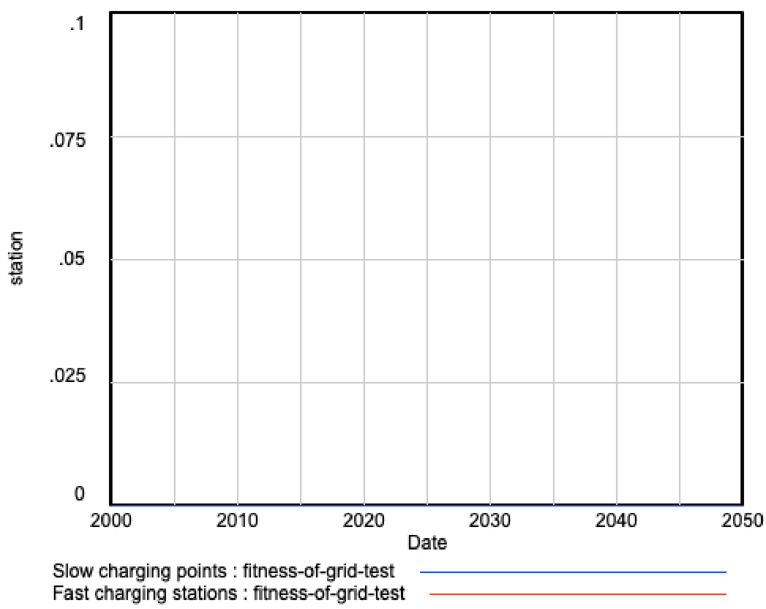
If Willingness to Consider EFV falls to zero, sales fall also to zero, thus, the model performs realistically.

D3. Zero-marketing test



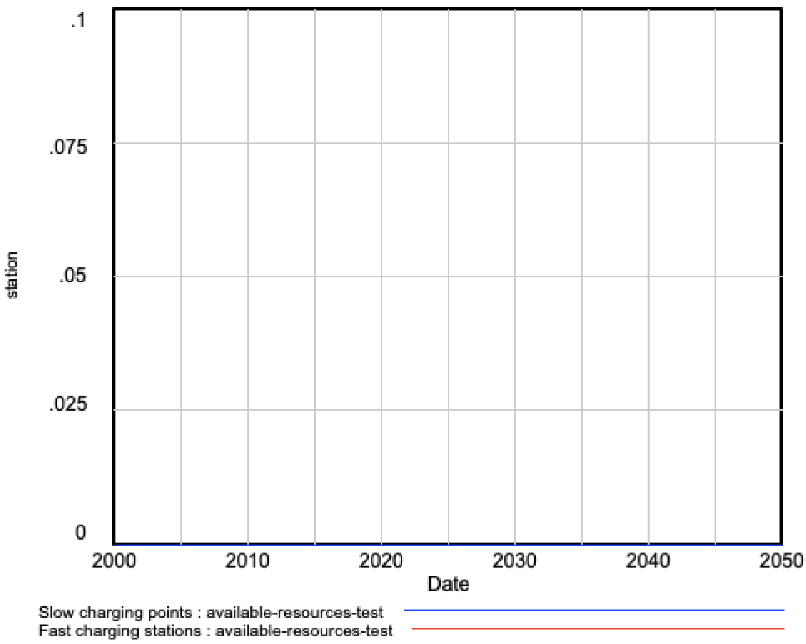
If there is no marketing for EFVs, sales should be very little (as WtC grows only through word-of-mouth). Sales do fall to near zero (less than 0,000001 % of sales), thus, the model performs realistically.

D4. Fitness of grid test



If electric grid does not fit (fitness of grid = 0), there should not be any charging points (Testa 2017). There are no charging points built, thus, the model performs realistically.

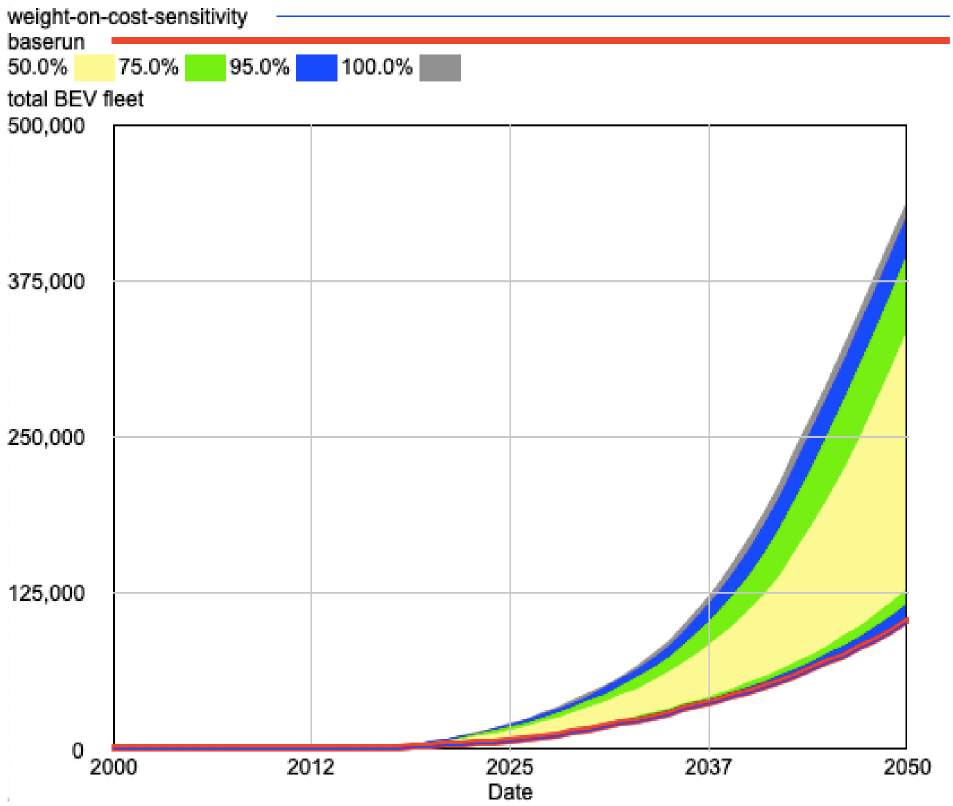
D5. Available resources test



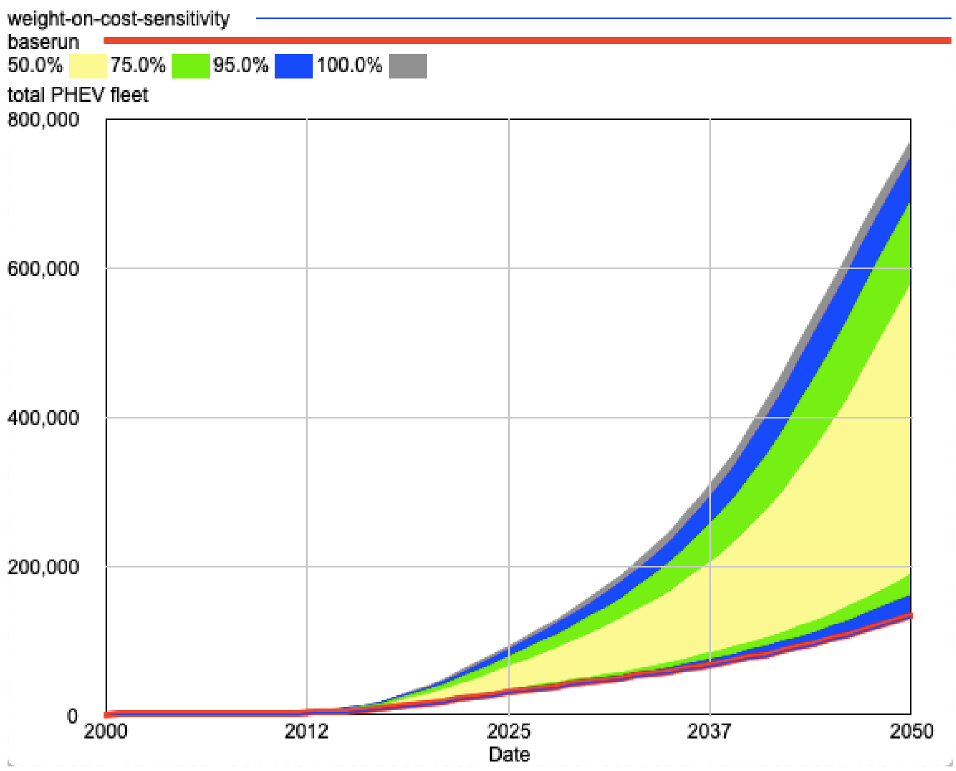
If there are no available resources for stations, there are no charging stations built, thus, the model performs realistically.

APPENDIX E: WEIGHT ON COST SENSITIVITY

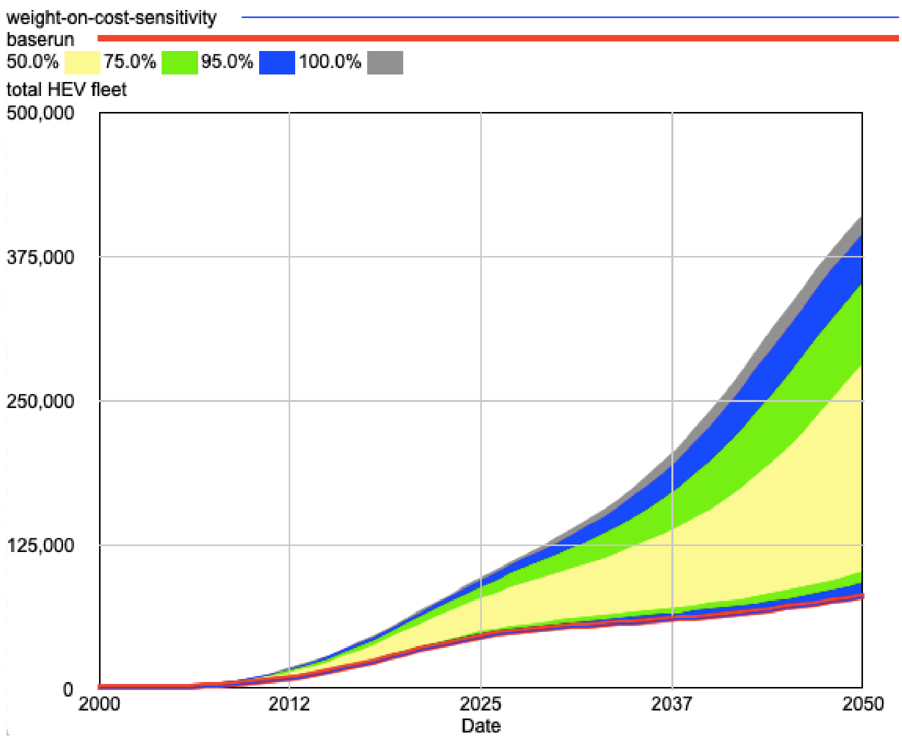
E1. Sensitivity of BEV sales on weight on costs



E2. Sensitivity of PHEV sales on weight on costs

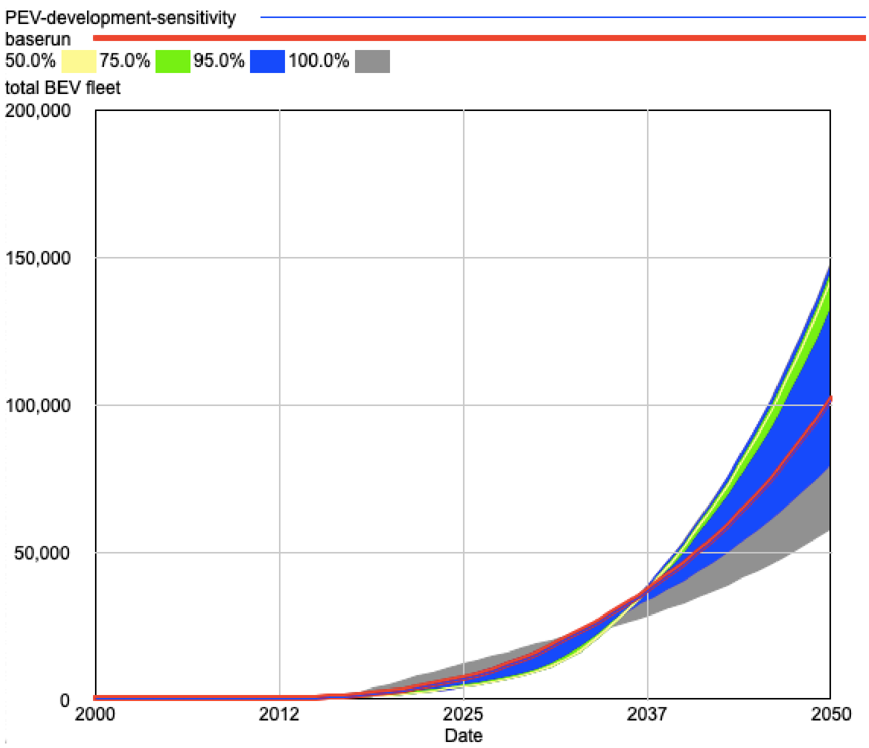


E3. Sensitivity of HEV sales on weight on costs

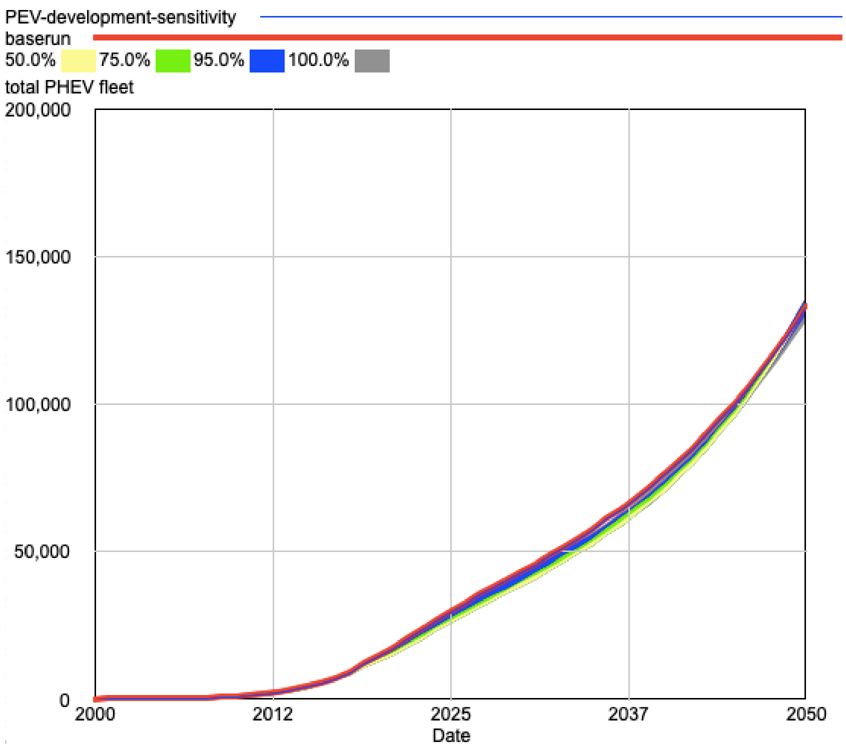


APPENDIX F: TECHNOLOGICAL DEVELOPMENT SENSITIVITY

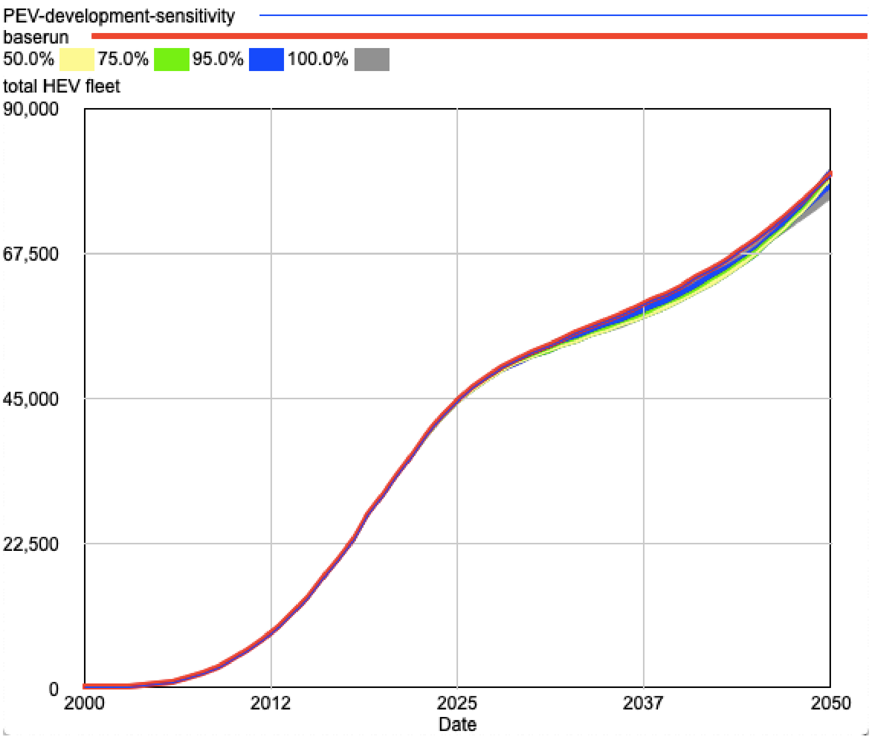
F1. BEV sales sensitivity to PEV technological development



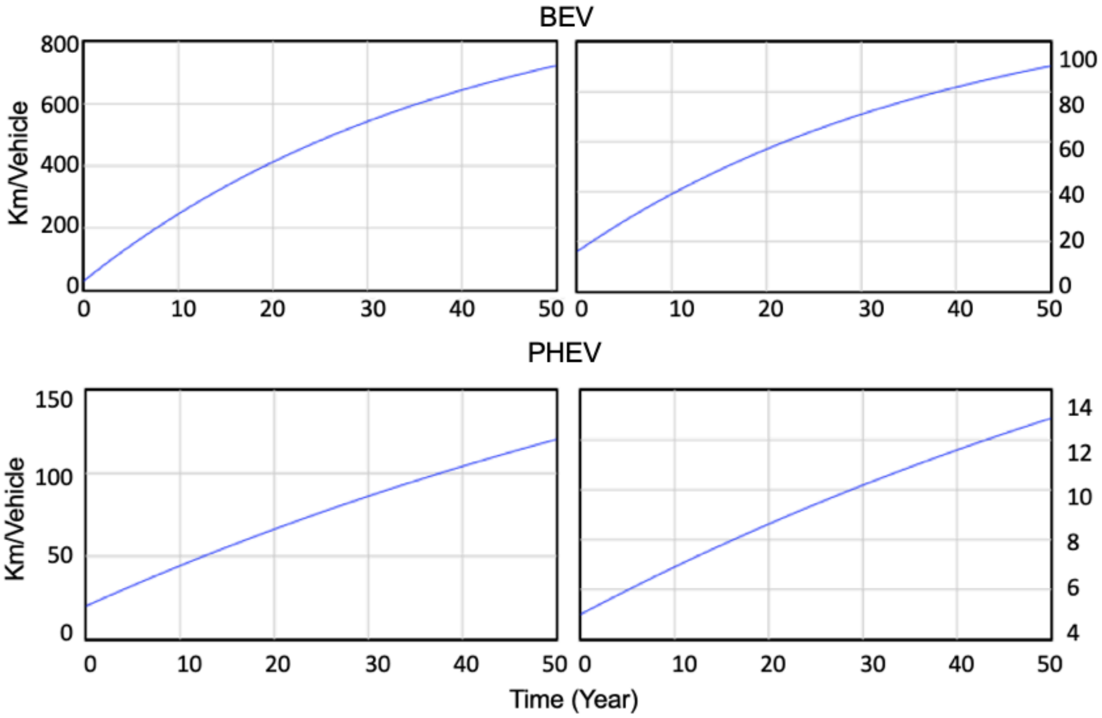
F2. PHEV sales sensitivity on PEV technological development



F3. HEV sales sensitivity on PEV technological development

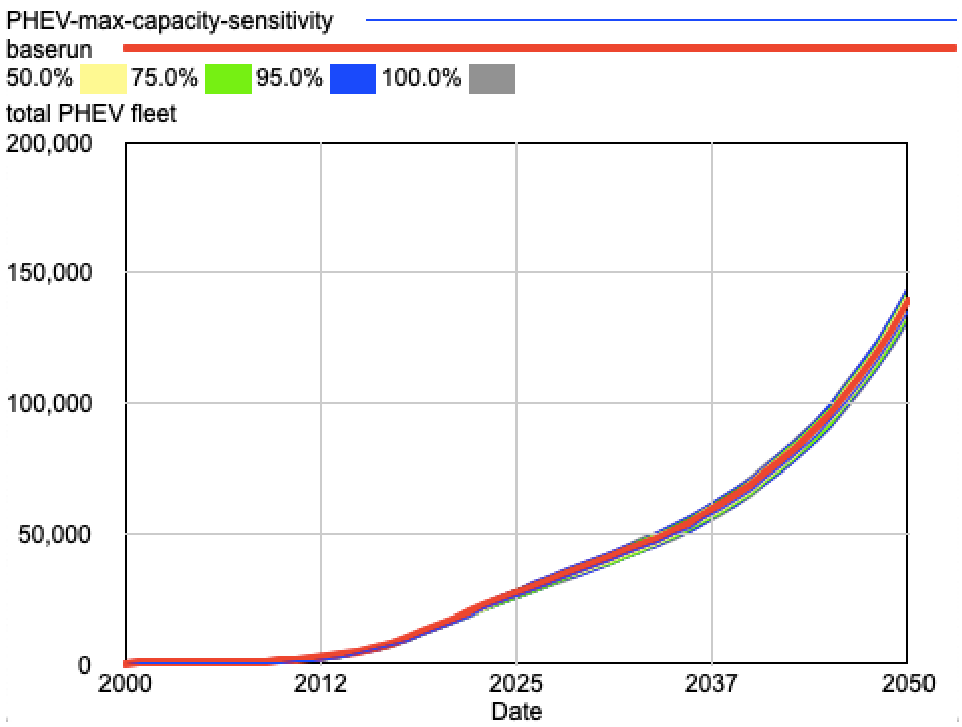


APPENDIX G: BEV AND PHEV TECHNOLOGICAL DEVELOPMENT

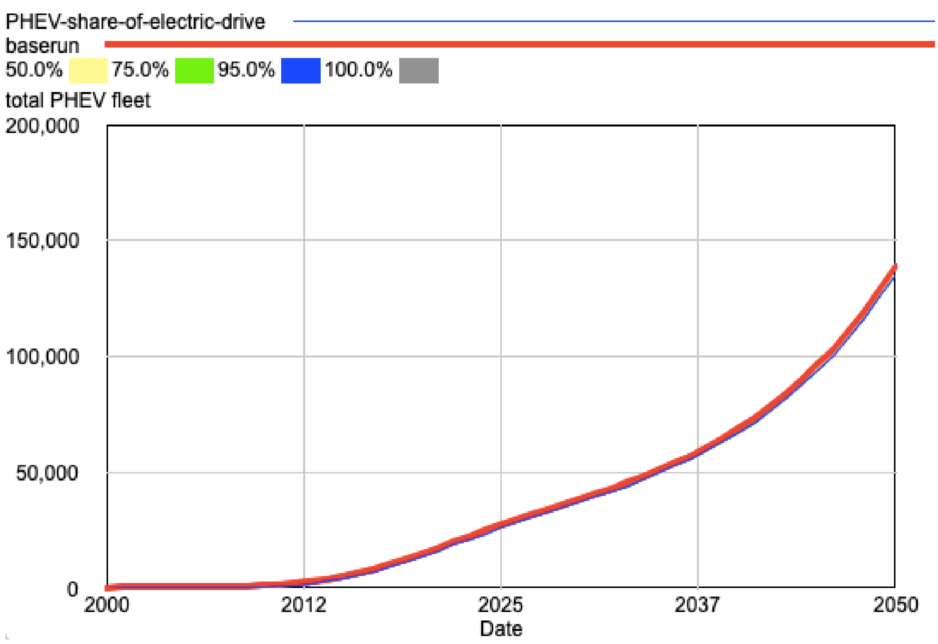


APPENDIX H: PHEV ATTRIBUTE SENSITIVITY

H1. Sensitivity of PHEV sales to chosen maximum capacity of PHEVs



H2. Sensitivity of PHEV sales to chosen share of electric drive



APPENDIX I: HEV WTC TEST