Gabriela Duarte Oliveira de Castro Pita

MARKET DYNAMICS OF ELECTRIC VEHICLES IN PORTUGAL

COUPLING PREFERENCE MODELING AND DIFFUSION ANALYSIS

PhD Thesis in Sustainable Energy Systems, supervised by Luís Miguel Cândido Dias, presented to the Department of Mechanical Engineering, Faculty of Sciences and Technology, University of Coimbra

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ABSTRACT

The significant impact of road transportation on energy consumption and environmental emissions has led to several plans aiming to mitigate those impacts. Electric Vehicles (EVs), by allowing the use of renewable energies to charge electric batteries, have been considered potential solutions to reduce the contribution of road transport to environmental problems. However, the difficult market penetration of EVs in Portugal, along with the ineffectiveness of the implemented policies to stimulate consumers demand for these vehicles, calls for a comprehensive analysis of the EV market. As consumer preferences, and consequently their purchase decisions, have been highlighted as the main driver for a sustainable presence of these vehicles in the market, this thesis addresses the impact of consumer preferences on the market penetration of EVs, considering the Portuguese context.

The extensive literature on consumer preferences of EVs underlines the importance of using consumers' information when designing incentive strategies for EVs penetration in the markets. Two main streams of research are identified in previous studies: the analysis of consumer preferences and the diffusion analysis of EVs. In this thesis a comprehensive approach that encompasses both streams is applied in order to fulfil the overall goal of this research, namely to identify the structure of consumer preferences under different market contexts and to verify its impact on market dynamics of EVs.

The complexity of this challenge required a multiple and interlinked methodology, from consumer preference elicitation methods, namely Choice-based Conjoint Analysis (CBC) and Multiattribute Utility Theory (MAUT), to diffusion analysis techniques, namely System Dynamics. A stated preference survey considering several vehicles with different purchase price, range, fuel/electricity consumption and CO_2 emissions was designed to fulfil the data requirements of the selected methodologies. The research approach allowed contributing to the literature both methodologically and empirically through several analyses at the individual and aggregated levels.

At the individual level, consumer preferences were elicited through CBC and MAUT. CBC was found to better represent consumer preferences for EVs, but MAUT can induce a learning effect on consumer preferences elicited through CBC. At the aggregated level, a diffusion model of EVs was developed for the Portuguese market using a diffusion model from the literature as a starting point. The main novelty of the developed diffusion model was the modelling of dynamic consumer preferences, i.e. preferences were considered to change according to different market conditions. The definition of a transition of preferences within a diffusion model allowed studying the impact of such transition on EVs diffusion and on incentives policies design. Adapting subsidies policies for EVs to dynamic consumer preferences decreases cost and time to achieve policy targets.

Two main overall findings of this thesis shed some light about future pathways towards a significant market share of EVs. First, the fuel/electricity consumption was found to be the most relevant attribute for Portuguese consumers according to different elicitation methods and different market conditions. Second, Plug-in Electric Vehicles (PHEVs) are the most preferred vehicles for consumers and only their purchase price has been preventing their mass introduction on the Portuguese market so far. In this context, directing the subsidies policies to these vehicles, considered as transactional technologies to Battery Electric Vehicles (BEVs), would be an effective measure to promote PHEVs purchases and that may foster future adoption of BEVs.

Keywords: Electric vehicles; consumer preferences; Conjoint Analysis; Multiattribute Utility Theory; System Dynamics; diffusion model; dynamic preferences.

RESUMO

Os impactos significativos do transporte rodoviário no consumo energético e nas emissões ambientais têm levado ao desenvolvimento de vários planos que visam atenuá-los. Os Veículos Eléctricos (VEs), ao permitirem a utilização de energias renováveis para carregar as baterias, têm sido vistos como uma solução que tem potencial para reduzir a contribuição dos transportes rodoviários para os problemas ambientais. No entanto, a dificuldade que os VEs têm enfrentado para entrar no mercado Português, juntamente com a ineficiência das políticas implementadas para estimular a procura desses veículos, denota a necessidade de analisar o mercado de uma forma mais abrangente. O facto de as preferências dos consumidores, e consequentemente as suas decisões de compra, terem sido apontados como os principais fatores para a presença sustentável dos VEs no mercado, justifica que esta tese analise do impacto das preferências dos consumidores na penetração no mercado de VEs em Portugal.

O extenso número de estudos focados na análise de preferências dos consumidores sobre VEs reforça a importância de utilizar informação dos consumidores como base para definir estratégias de incentivo à adopção e penetração de VEs no mercado. A análise de estudos anteriores permitiu identificar duas grandes correntes de investigação, nomeadamente a análise de preferências dos consumidores e a análise de difusão de VEs. A abordagem desta tese é mais abrangente, ao englobar as duas correntes de investigação de forma a alcançar o principal objectivo deste estudo, i.e. identificar a estrutura de preferências dos consumidores em diferentes contextos de mercado e verificar qual o seu impacto nas dinâmicas de mercado dos VEs.

A complexidade subjacente ao objectivo desta tese requereu uma metodologia com vários métodos, interligados entre si, que inclui dois métodos de eliciação de preferências, a Análise Conjunta Baseada na Escolha (CBC) e a Teoria de Utilidade Multiatributo (MAUT), e um método de análise de difusão, a Dinâmica de Sistemas. De forma a obter os dados necessários para as metodologias seleccionadas foi desenhado um questionário de preferências declaradas onde os consumidores comparam um conjunto de veículos relativamente ao seu preço, autonomia, consumo de combustível/electricidade e emissões de

CO_2. Esta abordagem permitiu que esta tese contribuísse para a literatura tanto a nível metodológico como empírico, através de várias análises ao nível individual e agregado.

Ao nível individual, as preferências dos consumidores foram eliciadas através de CBC e MAUT. O método CBC representou melhor as preferências dos consumidores por VEs, mas a MAUT induziu um potencial efeito de aprendizagem das preferências eliciadas através de CBC. Ao nível agregado, foi desenvolvido um modelo de difusão de VEs para o mercado Português, usando como ponto de partida um modelo de difusão de referência. A principal contribuição do novo modelo foi a modelação dinâmica das preferências, ou seja, foi considerado que as preferências se alteram consoante as condições do mercado. A definição de transição de preferências no modelo de difusão permitiu analisar qual seria o impacto dessa transição na difusão de VEs e na definição de políticas de incentivo. A adaptação dos subsídios para VEs às preferências dinâmicas dos consumidores possibilita uma penetração no mercado de VEs mais cedo e com menor custo.

Os dois resultados principais desta tese permitem clarificar que direcções futuras podem vir a alcançar com sucesso uma quota de mercado de VEs mais significativa. O primeiro diz respeito à identificação do consumo de combustível/electricidade como o atributo mais relevante para os consumidores Portugueses, de acordo com diferentes métodos de eliciação e diferentes contextos de mercado. O segundo resultado foi a identificação dos Veículos Híbridos Plug-in (PHEVs) como os veículos que os consumidores Portugueses mais preferem, sendo o elevado preço de aquisição é a maior barreira à introdução em massa destes veículos no mercado Português. Neste contexto, e sabendo que os PHEVs podem ser considerados como uma tecnologia de transição para os Veículos Eléctricos a Baterias (BEVs), os subsídios de incentivo à compra de PHEVs poderão ser uma medida efectiva para aumentar a propensão futura dos consumidores a comprar BEVs.

Palavras-chave: Veículos eléctricos; preferências dos consumidores; Análise Conjunta, Teoria de Utilidade Multiatributo, Dinâmica de sistemas; modelo de difusão; preferências dinâmicas

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ACRONYMS

ABM: Agent-Based Modeling

AFVs: Alternative Fuel Vehicles

AHP: Analytical Hierarchy Process

BEVs: Battery Electric Vehicles

CA: Conjoint Analysis

CBC: Choice-Based Conjoint Analysis

CBC/HB: Choice-Based Conjoint/Hierarchical Bayes

CV: Contingent Valuation

EVs: Electric Vehicles

GEV: Generalized Extreme Value

HEVs: Hybrid Electric Vehicles

ICEVs: Internal Combustion Engine Vehicles

IIA: Independence from Irrelevant Alternatives

IUC: Circulation tax

ISV: Vehicle purchase tax

MAUT: Multiattribute Utility Theory

MCDA: Multicriteria Decision Analysis

MNL: Multinomial Logit Models

NPV: Net Present Value

PHEVs: Plug-in Hybrid Electric Vehicles

RP: Revealed Preferences

RUT: Random Utility Theory

SP: Stated Preferences

SEM: Self-Explicated Method

TtW: Tank-to-Wheels

WOM: Word of Mouth

WtC: Willingness to consider

WtT: Well-to-Tank

WtW: Well-to-Wheels

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CHAPTER 1

Introduction

1.1. Background and motivation

The transports sector raises many concerns from the energy consumption and the energy dependency perspectives. In 2016 this sector accounted for 33% of the final energy consumption in EU (42% in Portugal). Road transportation was the responsible for the highest share of energy demanded (82% in EU and 77% in Portugal), most of them provided from oil and oil derivatives (95% in EU and in Portugal). Moreover, road transportation was responsible for 72% of CO_2 emissions both in EU and Portugal (European Commission, 2018).

In this context, Electric Vehicles (EVs)[1] have been regarded as possible solutions for the mentioned energy use and environmental problems, by using alternative energy sources and potentially reducing greenhouse gas emissions (Hacker et al., 2009). Their contribution comes not only from the use of more efficient engines than Internal Combustion Engine Vehicles (ICEVs) but also from the possibility of using renewable energies to charge electric batteries (Hacker et al., 2009).

The aim of mitigating the environmental burden from transportation led to the development of several plans at European and national levels. At the European level, the EU defined the Climate and Energy Package 2020 where the transports sector targets established that, in 2020, 10% of the energy used in this sector would be from renewable energies. At the national level the Portuguese government implemented several programs to stimulate the adoption of EVs (see Appendix I for more detail). The Portuguese plan of action started in 2007 with the implementation of a global reform of vehicle taxation by

[1] In this study EVs account for the available electric vehicle technologies in Portugal, namely Battery Electric Vehicles, Plug-in Hybrid Electric Vehicles and Hybrid Electric Vehicles.

introducing the exemption of the circulation tax (IUC) and the vehicle purchase tax (ISV) for Battery Electric Vehicles (BEVs) and a reduction of ISV for Hybrid Electric Vehicles (HEVs). Afterwards there were three main encouragement "packages” from the Portuguese government to increase the market penetration of EVs. First, in 2011, an incentive package for BEVs enacted a purchase subsidy (5000€ for the first 5000 purchases), the development of 1320 charging spots and the creation of a pilot network platform for consumers to access to the locations of those spots (Mobi.E). The economic recession in Portugal led the government to withdraw the purchase subsidy in the end of 2012. Second, in 2015, the Plan of Action for Electric Mobility and the Reform of Green Taxation included measures concerning electric mobility, which consisted in the development of 50 fast charging spots and ISV reduction for EVs, respectively. And third, in 2017, a purchase subsidy was reintroduced for BEVs and Plug-in Hybrid Electric Vehicles (PHEVs) (2250€ for the first 1000 purchases) and an Environmental fund was created aiming at providing financial resources to support environmental policies. A budget of 715,000€ from this fund was assigned to Mobi.E in order to perform a technological update and an expansion of the network.

These government efforts were followed by an increment of EV models in Portugal. In 2018 consumers have at their disposal a more diversified portfolio of EVs to choose from, 39 models comprising HEVs, BEVs and PHEVs, than they had in 2011 (18 models comprising only HEVs and BEVs) (see Appendix II). However, the evolution of EVs demand showed a low adoption of these vehicles since their introduction. The sales of BEVs/PHEVs were very low till 2013 (around 500 vehicles total) and reached only 1.8% of LDVs sales in 2017. The sales of HEVs were higher but still with low expression in the market total sales, with a maximum of 2.1% of sales being reached in 2017 (see Appendix III).

Knowing that the Portuguese government estimated a 5% share of BEVs/PHEVs in the LDVs fleet in 2020 (IEA, 2015), the evolution of market share reveals that this estimate would be hardly achieved as the efforts put in place to successfully mass introduce EVs in the market were not as effective as expected. The financial crisis that headed the transport sector did not benefit the penetration of BEVs/PHEVs in Portugal. For instance, the majority of the incentives from government and suppliers took place between 2010 and 2012, when the transport sector faced a drop back on LDVs sales by half (Figure 1.1). Additionally, crossing the government policies for BEVs/PHEVs penetration and the sales allowed verifying that the sales dynamics did not respond to the existence of incentives as they should; in fact in some periods of time they behaved in the opposite direction (Figure 1.2). For instance, BEVs/PHEVs demand increased significantly in 2012 and in 2016 when the purchase subsidy and the ICEVs discards incentives decreased, respectively.

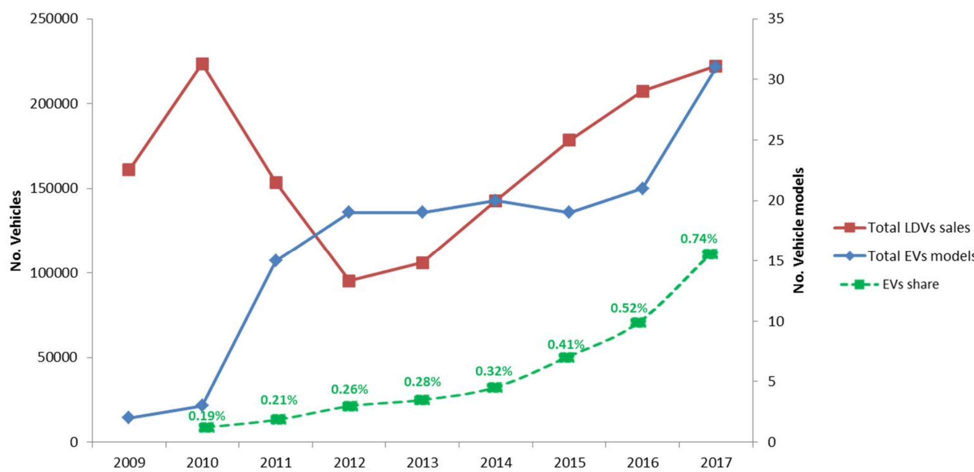

Figure 1.1 - Evolution of LDVs sales, EVs models available and market share of EVs.

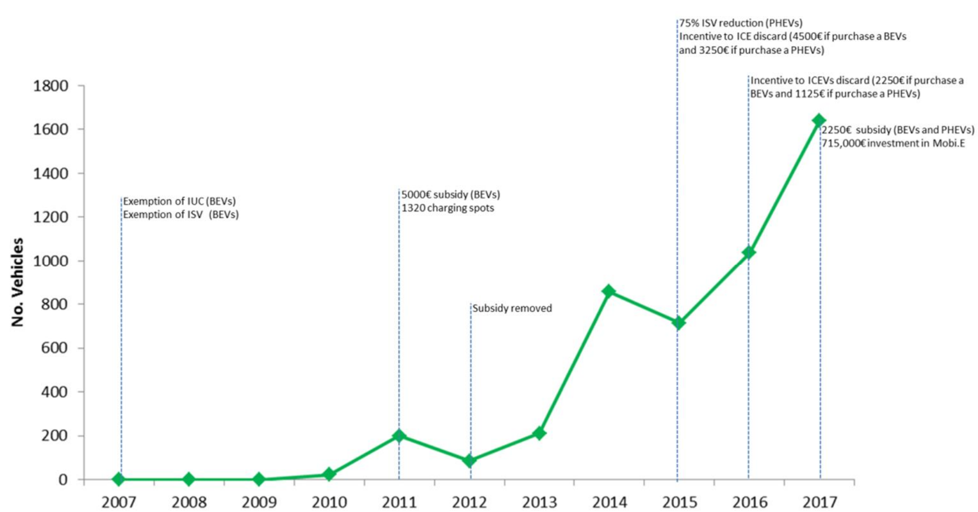

Figure 1.2 - Sales of BEVs/PHEVs crossed with government incentives for electric mobility.

These market dynamics suggest that there is valuable information that has not been taken into account during policies design, namely consumer preferences, which have been pointed out as the main factor for the long-term viability of EVs demand (Ewing and Sarigöllü, 2000). Indeed, the importance of consumer preferences on EVs adoption has been highlighted by the extensive literature on collecting and analysing EVs preference data. Two main streams of research focused on preferences for EVs can be identified. One stream is focused on individual preferences and it aims at understanding the consumer preferences structure that supports their future vehicle purchases, for instance identifying the determinant vehicle attributes on a context of a purchase decision. The other stream is centred on aggregated preferences where preference data is used to analyse the diffusion of EVs in the market in order to identify which policies would be effective to boost EVs market penetration. The common approach in the literature is to address one of these analyses. However, a more comprehensive approach of the market and its players should consist in a global view of the market dynamics of EVs taking into account that consumers' preferences depend on the market conditions and therefore influence the diffusion of EVs. This is a novel approach to the diffusion of EVs because it provides a global view of the consumer preferences impact on EVs adoption and policies design, from an individual to an aggregated level, in order to identify strategies that can lead to a sustainable adoption of EVs.

1.2. Research questions and research approach

As contextualized above, this thesis is framed in a context of difficult market penetration of EVs in the Portuguese market. Acknowledging the importance of consumer preferences and the two main streams of research in the field, this thesis aims at answering to the overall question: *What is the potential of consumer preferences modelling to a better understanding of market dynamics of EVs?* This question comprises the vector of analysing the preferences structure of individual consumers and also the vector of identifying the impact of the consumer preferences in a global perspective through the market penetration of EVs based on those preferences. Therefore, the main goal of this work is to identify the structure of consumer preferences under different market contexts and verify its impact on market dynamics of EVs. The geographical scope of this research is the Portuguese market due to the absence of studies addressing Portuguese consumers' preferences about their willingness to purchase EVs and also due to inefficacy of the implemented incentive policies that demand a more informed policy strategy to stimulate EVs adoption in this market.

The research strategy was outlined in order to provide empirical and methodological contributions. Empirical contributions arise from the challenging context of the introduction of EVs in Portugal previously presented and consist in providing relevant information from Portuguese consumers that can help to understand why the incentive policies failed in stimulating consumers demand for EVs. The methodological contributions consist in applying alternative methodological approaches both in the analysis of consumer preferences and on the diffusion of EVs. Hereupon, the research strategy comprises the analysis of individual and aggregated preferences through a multiple and interlinked methodology, namely two preference elicitation methods, Choice-Based Conjoint (CBC) from Conjoint Analysis (CA) methods and Multiattribute Utility Theory (MAUT) from Multicriteria Decision Analysis (MCDA), and System Dynamics (SD). Preference data was collected through a Stated Preference (SP) survey that considered two different market conditions (current and future scenario).

In order to fulfil the main goal of this thesis, six Research Questions (RQ) are to be answered regarding the survey design process (RQ1), the preference elicitation methods at the individual level (RQ2, RQ3 and RQ4), the analysis of aggregated preferences (RQ5) and the diffusion model of EVs (RQ6):

> RQ1: What is the appropriate survey design to elicit consumer preferences considering the methodological strategy applied in this study?

> RQ2: Which preference elicitation method better represents consumer preferences?

RQ3: Is there a learning effect from the preference elicitation process?

RQ4: What is the influence of individual characteristics of Portuguese consumers on their preferences for EVs? Does it change with different market contexts?

RQ5: What is the preference structure of Portuguese consumers at the aggregated level? Does it change within different market conditions?

RQ6: What is the impact of considering dynamic preferences on EVs diffusion? And what would be the expected impact of incentive policies?

1.3. Contribution

This thesis aims at contributing to the literature through two main streams, the consumer preferences modelling for EVs and the market diffusion of EVs. The specific contributions of each analysis are detailed and classified according to their methodological or empirical nature in Table 1.1.

Research Question	Specific objectives	Type of contribution	Contribution	Chapter
RQ1	To identify the appropriate attributes set to distinguish the vehicles	Empirical	Identifying the vehicle characteristics that influence future vehicle purchases the most, considering the Portuguese market	3
	To define the elicitation procedure of preferences for MAUT methodology	Methodological	Survey design to compare MAUT with CBC	
RQ2	To analyse which method better predicts preferences at an individual and aggregated-level	Methodological	Comparison of CBC and MAUT preference elicitation methods	4
	To verify if the two methods infer similar consumer preferences		Insights from CBC and MAUT for management strategy	
RQ3	To analyse the existence of a learning effect on preferences along a interlinked elicitation process	Methodological	Methodological procedure that may leverage the quality of the preference data collected	4
	To understand the role of MAUT on CBC ability of predicting consumer preferences			
RQ4	To identify which groups of consumers are more willing to purchase EVs	Empirical	Insights about the demographic characteristics of Portuguese consumers more willing to purchase EVs	4
	To analyse the influence of consumers individual characteristics on vehicle attributes sensitivity		Insights about the influence direction of demographic characteristics on consumer preferences	
RQ5	To identify which attributes influence the most vehicle purchase decisions considering different contexts	Empirical	Insights about the importance and sensitivity of EVs attributes	4
	To compare the preferences sensitivity for EVs considering different market contexts		Insights about which policies may have a higher impact on influencing consumer preferences for EVs	
RQ6	To analyse the impact of dynamic preferences on the market penetration of EVs	Methodological	Advance on social diffusion modelling of EVs by incorporating dynamic preferences	5
	To analyse the efficacy of policies adapted to dynamic preferences	Empirical	Insights about the impact of considering dynamic preferences in the EVs market penetration	
			Insights about the design of incentive policies based on dynamic preferences	

Table 1.1 - Specific objectives and main contributions of each RQ.

Most of the research developed in this thesis has been published in or submitted to scientific journals (abstracts and keywords are presented in Appendix IV)

a) **Oliveira, G.**, Dias, L., Neves, L. Preference elicitation approaches for energy decisions. In Lopes M., Hengeller C.A., Janda, K. (eds) *Energy and behaviour: Challenges of a Low-Carbon future.* Elsevier (forthcoming);
b) **Oliveira, G.**, Dias L. (2019). Influence of demographics on consumer preferences for Alternative Fuel Vehicles: A review of choice modelling studies and a study in Portugal. Energies 12(2), 318;
c) **Oliveira, G.**, Dias, L., Sarabando, P. (2015). Modelling consumer preferences for electric vehicles in Portugal: an exploratory study. Management of Environmental Quality: An international Journal. Vol. 26(6): pp 929-950;
d) **Oliveira, G.**, Dias L. (2019). The potential learning effect of a MCDA approach on consumer preferences for Alternative Fuel Vehicles. (under revision)
e) **Oliveira, G.**, Roth, R., Dias, L. (2019). Diffusion of Alternative Fuel Vehicles considering dynamic preferences. (under revision)

The PhD research also led to other publications, conference proceedings and presentations in national and international conferences (see Appendix V).

1.4. Thesis structure

This thesis comprises 6 six chapters, including this introductory chapter, being structured as follows (Figure 1.3):

Chapter 2 gives an overview of the studies focused on two research streams of consumer preferences of Alternative Fuel Vehicles (AFVs), namely the analysis of individual consumer preferences and of the market penetration of AFVs. This review includes a comprehensive analysis of the main methodologies applied and of the main factors that influence AFVs adoption. Besides this review, through Chapters 4 and 5 more specific reviews are presented in order to frame and contextualize the specifications of each analysis.

Chapter 3 describes the data collection process of the consumer preferences with CBC and MAUT methods. As the CBC data collection is a well-established process, but the MAUT data collection required several survey trials to fit the study goals, the main assumptions of MAUT method are presented along with the description of the survey trials. The final consumer preferences survey is described, presenting the alternatives and attributes selection and the main tasks in detail.

Chapter 4 firstly presents the analysis of individual preferences that comprehends three main analyses: the comparison of the predictive validity of CBC and MAUT preference models; the analysis of learning effects on preferences and the influence of demographics on preferences. Then, it presents the analysis of aggregated preferences where the main attributes are identified and the ranking of vehicles are analyzed. For each analysis, this chapter presents a brief literature review, when necessary, as well as the methodological approach, the results and concluding remarks.

Chapter 5 details the diffusion model of EVs developed in this thesis throughout five main parts. The first part consists of two brief literature reviews that contextualize the relevance of this analysis. The second describes the core SD model at the basis of this study, presenting the model structure and modelling definitions. The third regards the incorporation of dynamic preferences in the SD diffusion model, describing the transition of preferences. The fourth part presents the model calibration, regarding to the vehicle attributes and the evolution of the fleet. Finally, the fifth part presents the main results and concluding remarks regarding to the impact of considering dynamic preferences on the market penetration of EVs and also the on the design of incentive policies to increase the circulation of these vehicles.

Chapter 6 presents the main conclusions for each outlined research question for this thesis. The limitations identified throughout this work and future research recommendations are also presented.

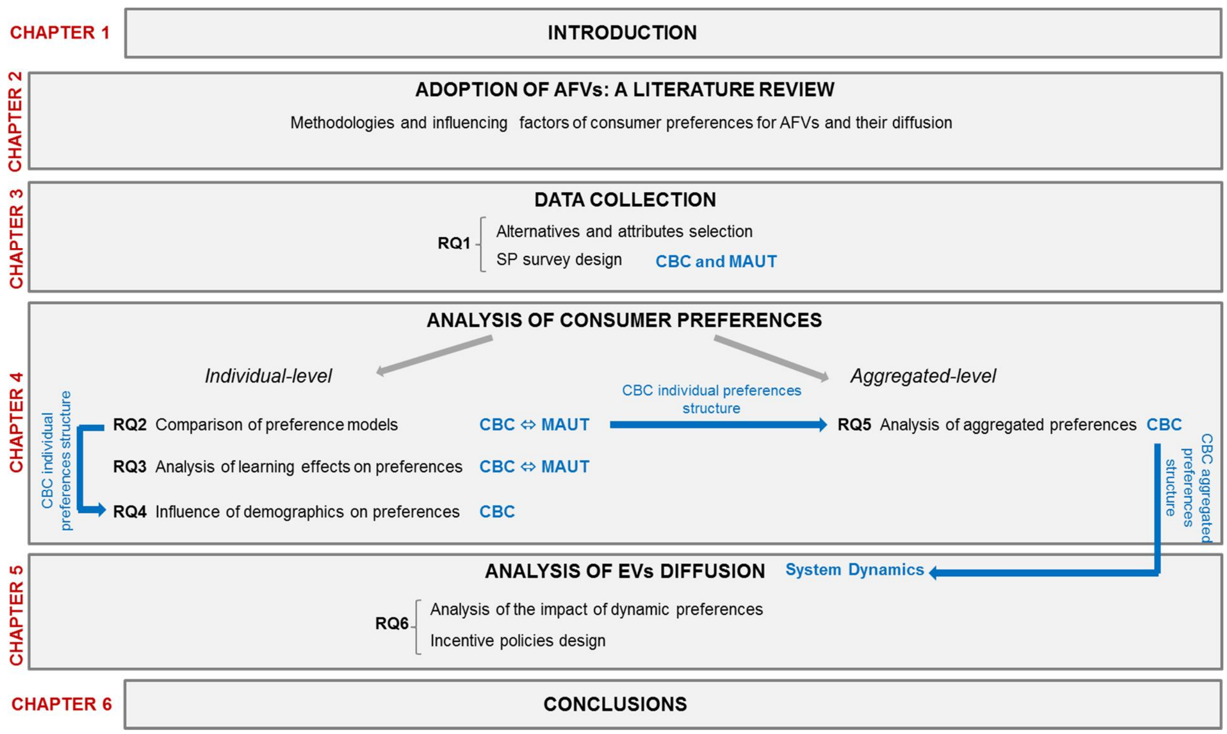

Figure 1.3 - Overview of the core chapters of the thesis with the respective research questions, the used methodologies (in blue) and the data flows between sections and chapters (blue arrows).

CHAPTER 2

Adoption of Alternative Fuel Vehicles[2]: A literature review

Consumer preferences can be defined as comparative judgements between entities (Mcfadden, 1999) or as value measurements made by consumers concerning decision objects (Payne et al., 1999). The analysis of these preferences are a focus of management, mainly marketing (Steiner et al., 2011). Understanding consumer preferences entails knowing what are the consumers' concerns and the characteristics they value, which factors could influence their decisions, and which changes in the market conditions could lead to different opinions and, consequently, different purchase attitudes. Over the years, analysing preferences has become more difficult because consumers are facing a wider range of products. This variety confronts them daily with huge amounts of information about the products, like branding and advertising, which is used by them to form preferences and to make purchase decisions (Verlegh and Steenkamp, 1999). Therefore, a satisfactory match between product characteristics and the consumers' preferences is crucial for gaining market acceptance (Garling and Thogersen, 2001) and is vital in the development of new products (Steiner et al., 2011). Information on preferences for innovative products, such as AFVs, is particularly important to help companies adjust their new vehicles according to consumer evaluations and requirements for future vehicle adoption (Kurani, Turrentine, et al., 1996; Zhang, Gensler, et al., 2011).

The analysis of preferences for AFVs, as innovative technologies and environmentally friendly products, needs to take into account two dimensions of consumer behaviour, namely the innovative and the ecological dimensions. Preferences for innovative products are complex to assess. First, the success of innovative products usually depends on the order at which they enter in the market and on the success of previous products in the

[2] As one of the goals of this review was to find methodological trends in the literature the scope of this review was extended to all Alternative Fuel Vehicles.

same category (Carpenter and Nakamoto, 1989). Second, facing highly innovative products, consumers may reveal difficulties in the attributes assessment and in the expectations management regarding the innovative product (Olshavsky and Spreng, 1996). And third, innovative products usually are developed in contexts of fast technological change where products have short life cycles (Payne et al., 1999).

The ecological products dimension also brings complexity to the consumer preferences analysis due to lack of consensus about the link between environmental concerns[3] and environmental consumers' behaviour. For years, based on Maloney and Ward (1973), the consumers' degree of environmental concern was assumed to have a strong impact on their environmental behaviour, such as recycling or purchasing environmentally friendly goods (Bamberg, 2003). However, despite the increased awareness about environmental problems, the consumer behaviour regarding environmentally friendly products is difficult to anticipate due to several reasons. One is that the consumption or purchase of more ecological products has benefits for the society and not only directly to the consumer as an individual. Additionally, individual benefits are delayed, but costs and sacrifices such as using less harmful products or paying more for more sustainable products are immediate and personal for the consumer (Kronrod et al., 2012). Another reason is related with the consumers feeling that the environment preservation is a government responsibility. This leads consumers to not engage on an environmentally conscious behaviour because they feel that is not their concern (Laroche et al., 2001). In addition, the existence of a relation between higher environmental concern and higher consumers' intention of using more sustainable products cannot be translated into an increment of environmentally friendly behaviour (Bamberg, 2003).

In the context described above, AFVs, as eco-innovations, face more challenges than other innovative products not environmentally-related. Eco-innovations do not follow the common market diffusion that characterizes the introduction of other innovative products in the market; they follow instead a slow diffusion process characterized by long take-off

[3] Environmental concerns are used to describe the perceptions, emotions, knowledge, attitudes, values and behaviours regarding environmental products (Bamberg, 2003).

times and market penetration discontinuities (Zhang, Gensler, et al., 2011). The market of AFVs tends to be developed as niche in a gasoline and diesel market context and it requires unique market conditions for each country (Lee and Cho, 2009). The decision to introduce AFVs in the market depends on the penetration forecasts based on preferences information, which usually involve huge uncertainties, depend on a multitude of influencing factors and face several barriers (Hacker et al., 2009). For these reasons, an extensive literature can be found focused not only in the analysis of consumer preferences for AFVs but also in the market forecasts of these vehicles based on consumers data. A methodological review of these studies was made in order to identify the main methods that have been used to assess consumer preferences and to analyse the AFVs diffusion, which is presented in section 2.1 and 2.2, respectively. As preferences for AFVs can be influenced by several factors related to technology, consumer characteristics or context, the main findings of the studies summarized on the methodological review regarding the influence of each factor are described in section 2.3.

2.1. Methodologies to assess consumer preferences for AFVs

There is a vast literature focused on analysing preferences of consumers in the transportation field. For this reason, this methodological review focused only studies that analyzed individual consumers preference data for AFVs, resulting in 72 studies reviewed. Table 2.1 presents a summary of these studies, allowing detecting some trends. First, two main broad goals were identified: to analyse the consumer preferences for AFVs (84%) and to develop methodologies to better assess consumer preferences for AFVs (16%). Second, the number of preference studies has increased significantly in the last 6 years, when almost 61% of the studies were developed. Third, regarding the targeted consumers, North Americans were the most studied (43%) followed by the Europeans (17%). However, whereas in the 1990s the developed studies were exclusively from North America, since 2000 European and Asian studies started to be developed (Figure 2.1). This trend was clearer in the 2010s when the combined number of European and Asian studies surpassed the North American ones, representing 51% of the developed studies in that period of time. Fourth, when a specific vehicle technology was targeted, BEVs were the focus in 47% of the studies. Finally, considering the vehicles included in the preference surveys, it was observed that the more recent studies compare a more diversified vehicles set than the older studies where BEVs were manly compared with ICEVs (Figure 2.2). Additionally, it was observed that the most common set of vehicles compared were ICEVs, BEVs and HEVs.

The trends regarding the methodological characteristics, i.e. data collection method, the estimation procedure and the targeted sample, are presented in the following sub-sections.

Study	Year	Country	Goal	Scope	Data Collection Method	Estimation Procedure	Sample
Brownstone et al. (1996)	1996	USA	To construct a vehicle choice model for producing annual forecasts of new and used vehicle demand	BEVs	CA	Multinomial Logit (MNL) model	4747 Individuals
Kurani, Turrentine, et al. (1996)	1996	USA	To examine household consideration of a BEV	BEVs	Travel diary CA	Standard statistical analysis	454 Multi-car households
Chéron and Zins (1997)	1997	Canada	To determine which are the most determinant factors blocking the purchase of BEVs	BEVs	CA	Linear regression analysis	37 Car users
Tompkins and Bunch (1998)	1998	USA	To perform an independent survey of consumers in US concerning their vehicle preferences and to compare to the preferences of California households	AFVs	CA	Conditional MNL model	1149 Individuals
Kavalec (1999)	1999	USA	To investigate the potential effects that an aging "baby boomer" generation will have on gasoline use through their vehicle choice decisions	AFVs	CA	Mixed Logit model	4552 Households
Brownstone et al. (2000)	2000	USA	To compare MNL with mixed logit models for data on California households' Revealed Preferences (RP) and SP for vehicles	AFVs	CA and RP	Mixed logit models MNL models	7387 Households
Ewing and Sarigöllü (2000)	2000	Canada	To explore if government regulation can influence consumer preferences for clean-fuel vehicles	AFVs	CA	MNL model	881 Commute who drive regularly
Horne et al. (2005)	2005	Canada	To analyse how people choose between technologies, and incorporate it into energy-economy models	AFVs	CA	MNL model	866 Individuals
Hess et al. (2006)	2006	USA	To apply a modified Latin Hypercube Sampling approach for use in the estimation of Mixed MNL models	AFVs	CA	Mixed MNL model	500 Individuals

Study	Year	Country	Goal	Scope	Data Collection Method	Estimation Procedure	Sample
Potoglou and Kanaroglou, (2007)	2007	Canada	To examine the factors and incentives that are most likely to influence households' choice for cleaner vehicles	AFVs	CA	Nested logit model	482 Potential vehicle buyers
Achtnicht et al. (2008)	2008	Germany	To study the impact of service station availability on the demand of AFVs	AFVs	CA	Nested logit model	600 Potential car buyers
Bolduc et al. (2008)	2008	Canada	To study the application of Hybrid Choice models about personal choices of vehicles with technological innovations	AFVs	CA	Hybrid choice models	866 Consumers
Mau et al. (2008)	2008	Canada	To elicit consumer preferences for HEVs and Fuel Cell Vehicles (FCVs) with manipulation of the respondents' decision environment	HEVs, FCVs	CA	MNL model	916 Individuals (HEV study) 1019 Individuals (FCV study)
Axsen et al. (2009)	2009	Canada and USA	To estimate preference dynamics associated with the adoption of HEVs to improve the behavioural realism of CIMS	HEVs	CA	MNL model	523 Vehicle owners (Canada) 408 Vehicle owners (USA)
Dagsvik and Liu (2009)	2009	China	To specify and estimate models of household demand for conventional gasoline cars and AFVs in Shanghai	AFVs	CA	Generalized Extreme Value random utility model	100 House -holds
Sangkapichai and Saphores (2009)	2009	US	To explore quantitatively Californians' interest in HEVs	HEVs	Questionnaire	Ordered logit model	1907 Respondent s
Caulfield et al. (2010)	2010	Ireland	To examine individual motivations when purchasing vehicles	AFVs	CA	MNL model Nested Logit model	168 Customers of a car company
Petrolia et al. (2010)	2010	USA	To estimate the willingness to pay for ethanol vehicles and to identify the determinants to these vehicles demand	Ethanol vehicles	Contingent valuation (CV)	Probit model	748 Households
Eggers and Eggers (2011)	2011	Germany	To apply CBC to analyse the future acceptance of AFVs	BEVs	CA	CBC HB	242 Individual respondents
Hensher and Greene (2011)	2011	Australia	To apply the random regret minimization model framework to model choice among durable goods	AFVs	CA	MNL	3172 Households who had purchased a vehicle in the last 2 years
Hidrue et al. (2011)	2011	USA	To analyse to which extent experience affects individual preferences and the impact of attitudes on the choice between BEVs and conventional vehicles	BEVs	CA	MNL model Latent class model	3029 Potential car buyers

Study	Year	Country	Goal	Scope	Data Collection Method	Estimation Procedure	Sample
Kudoh and Motose (2011)	2011	Japan	To understand consumer preferences for BEVs in order to define their specifications or policies to expand these vehicles	BEVs	CA	Conditional Logit model	1st wave: 6935 Individuals 2nd wave: 9657 Individuals
Musti and Kockelman (2011)	2011	USA	To model the evolution of household fleet via transaction and choice decisions	PHEVs	CA	Monte Carlo methods	Not mentioned
Nixon and Saphores 2011)	2011	USA	To explore consumer preferences for AFVs	AFVs	CA	Rank-order mixed logit model	489 Potential vehicle buyers
Qian and Soopramanien (2011)	2011	China	To model consumer preferences for AFVs and conventional fuelled cars	AFVs	CA	MNL model Nested Logit model	527 Households
Şentürk et al. (2011)	2011	Turkey	To identify the factors that affect the preferences for vehicle fuel types in Turkey	AFVs	CA	MNL model	1983 Participants
Zhang, Yu, et al. (2011)	2011	China	To identify the factors that impact consumer preferences for AFVs	BEVs	CA	Binary logistics regression models	229 Respondents from driving schools
Achtnicht (2012)	2012	Germany	To analyse the relevance of CO_2 for vehicle choice	AFVs	CA	Logit model Mixed logit model	600 Potential car buyers
Hess et al. (2012)	2012	USA	To investigate the correlation of vehicle and fuel type on the choice process	AFVs	CA	Cross-Nested Logit	Not mentioned
Ziegler (2012)	2012	Germany	To examine the preferences for alternative energy sources or propulsion technologies in vehicles (mainly BEVs)	BEVs	CA	Multinomial probit models	598 Car buyers
Alvarez-Daziano and Bolduc (2013)	2013	Canada	To implement a Bayesian approach to an hybrid choice model in order to analyse choices of Canadian consumers when faced with AFVs alternatives	AFVs	CA	Bayesian hybrid choice model	866 individuals (same sample as Horne et al. 2005)
Alvarez-Daziano and Chiew (2013)	2013	USA	To study the relevance of the prior in a discrete choice model through the use of Bayes' estimator	BEVs	CA	Bayesian discrete choice model	500 Individuals who were intending to purchase a new car within 3 years
Axsen and Kurani (2013)	2013	USA	To compare consumers' stated interest in PHEVs	EVs	Multi-mode survey	Design space game analysis	508 Households representing new car buyers

Study	Year	Country	Goal	Scope	Data Collection Method	Estimation Procedure	Sample
Axsen et al. (2013)	2013	UK	To investigate the roles of social influence in the formation of consumer perceptions and preferences for pro-environmental technologies	BEVs	CA	Content analysis, MNL model Statistical regression analysis	57 Company members
Beck et al. 2013)	2013	Australia	To identify how environmental attitudes can influence how consumers behave under an emissions charge policy	AFVs	CA	Latent class model	650 Recent car buyers
Chorus et al. (2013)	2013	Netherlands	To compare two methodologies, utility maximization and regret minimization model	AFVs	CA	Random regret minimization-based discrete choice model Random utility maximization model	616 Company car leasers
Jensen et al. (2013)	2013	Denmark	To analyse to which extent experience affects individual preferences and the impact of attitudes on the choice between BEVs and conventional vehicles	BEVs	CA	Mixed logit model	369 Households who had bought a car in the last 5 years or intended to buy one
Ko and Hahn (2013)	2013	Korea	To analyse consumer preferences for EVs	BEVs	CA	Mixed Logit model	250 Vehicle owners
Li et al. (2013)	2013	USA	To examine the factors that could influence the likelihood of purchasing a AFVs	Flexi fuel vehicle, HEVs	Questionnaire survey	Bivariate probit model	1516 Vehicle owners
Hoen and Koetse (2014)	2014	Netherlands	To get insight into preferences of Dutch private car owners for AFVs and their characteristics	AFVs	CA	MNL model Mixed logit model	1802 Households (market for privately owned cars)
Jensen et al. (2014)	2014	Denmark	To study the impact of real life experience with EVs over a relatively long period of time on individual preferences and attitudes	BEVs	CA and attitudinal survey	Statistic tests	196 respondents
Knez et al. (2014)	2014	Slovenia	To identify the most determinant factors of consumer behaviour during an AFVs purchase	AFVs	Questionnaire survey	K-Means Cluster	700 Households
Parsons et al. (2014)	2014	USA	To analyse the potential demand for vehicle-to-grid vehicles	BEVs	CA	MNL model Latent Class model	3029 Potential car buyers (same as Hidrue et al. (2011))
Tanaka et al. (2014)	2014	USA and Japan	To estimate and compare consumers' willingness to pay for BEVs and PHEVs in US and Japan	AFVs	CA	Mixed logit model	4202 Consumers (USA) 2000 Consumers (Japan)
Axsen et al. (2015)	2015	Canada	To characterize heterogeneity in preferences and motivations regarding PHEVs	PHEVs, BEVs	CA	Latent class model	1754 New vehicle buying households

Study	Year	Country	Goal	Scope	Data Collection Method	Estimation Procedure	Sample
Bansal et al. (2015)	2015	US	To investigate the impact of various built environment and demographic attributes on fuel-efficient vehicle ownership	HEVs	Census-track-level data	Multivariate models	5188Census tracks
Chen et al. (2015)	2015	Australia	To anticipate Prius hybrid EVs, other EVs, and conventional vehicle ownership levels	EVs	Census block groups	Trivariate Poisson-lognormal conditional autoregressive model	2,225,595 personal vehicle registrations
Hevelston et al. (2015)	2015	USA and China	To identify and compare consumer preferences for BEVs in China and US and to analyse the influence of subsidies in those preferences	BEVs	CA	MNL model Mixed logit model	312 Individuals (US) 572 Individuals (China)
Lieven (2015)	2015	20 countries	To analyse the effect of incentives that influence car buyers voluntary behaviour on the adoption of BEVs	BEVs	CA	Choice-based Conjoint/Hierarchical Bayes (CBC/HB)	8147 Individual respondents in total of the 20 countries
Shin et al. (2015)	2015	South Korea	To assess consumer preferences for various technology options and vehicle fuel types, and to evaluate the marginal willingness-to-pay for various smart vehicle features	AFVs	CA	Multiple Discrete–Continuous Probit model Multinomial Probit model	675 Individuals
Axsen et al. (2016)	2016	Canada	To compare the characteristics, preferences, and motivations of pioneers and potential early mainstream buyers	PHEVs	CA	MNL Latent class model	1754 Conventional new vehicle buyers 94 Plug EV owners
Hackbarth and Madlener (2016)	2016	Germany	To study the heterogeneity of car buyers' preferences	AFVs	CA	MNL model Latent Class model	711 Potential buyers of a new car in a short-term (same as Hackbarth and Madlener (2013))
Rudolph (2016)	2016	Germany	To investigate the impact of five different incentives for buyers of zero emission vehicles	BEVs	CA	Mixed logit model	875 Respondents
Adnan et al. (2017)	2017	Malaysia	To scrutinize the substantial factors that influence a consumer's decision in the context of the EVs adoption	BEVs, PHEVs	CV	Structural equation Modelling	391 Respondents
Anable et al. (2011)	2017	UK	To promote discussion on how the challenges presented by EVs technology can be addressed by both academic research and commercial marketers of EVs, particularly given dynamic consumer preferences and attitudes	BEVs, PHEVs	Attitudinal survey	Statistical tests	2729 Respondents
Beck et al. (2017)	2017	Australia	To examine attributes in a framework relatively new to transportation and energy policy, best–worst scaling	EVs	CA	Rank-ordered logit model	204 Respondents

Study	Year	Country	Goal	Scope	Data Collection Method	Estimation Procedure	Sample
Cherchi (2017)	2017	Denmark	To measure the effect of both informational and normative conformity in the preference for EVs versus ICEVs vehicles	BEVs	CA	Mixed logit model	2,363 Respondents
Cirillo et al. (2017)	2017	US	To analyse household future preferences for gasoline, HEVs and BEVs in a dynamic marketplace	BEVs, HEVs	CA	Mixed MNL model	456 Respondents
Dimatulac and Maoh (2017)	2017	Canada	To study the determinants that led to the observed spatial distribution of HEVs class of vehicles across the different census tracts within the census metropolitan area	HEVs	CA	MNL model	348 HEVs owners
Higgins et al. (2017)	2017	Canada	To examine how preferences for HEVs, PHEVs and BEVs are shaped by vehicle body size or type	EVs	CA	Multivariate analysis of variance and probit model	15,392 Households
Poder and He (2017)	2017	Canada and France	To establish the value that Quebecers and French citizens attribute to a reduction in air pollution emitted from vehicles	Cleaner vehicle	CV	Probit model	933 Respondents
She et al. (2017)	2017	China	To explore public perception barriers to widespread adoption of BEVs in Tianjin	BEVs	Likert scale questionnaire	Statistical tests Structural equations model	476 Urban respondents
Smith et al. (2017)	2017	Australia	To investigate consumer preferences and attitudes towards EVs	BEVs	CA	Nested logit model	440 Households
Byun et al. (2018)	2018	South Korea	To analyse consumer preferences for vehicles and predict the dynamic market share of environmentally friendly vehicles	BEVs, FCVs	CA	Mixed logit model	615 Adult respondents
Costa et al. (2018)	2018	Italy	To investigate consumers' willingness to pay a premium price for lower CO_2 emitting cars	AFVs	CA	Conditional MNL model	278 Potential car buyers
Ferguson et al. (2018)	2018	Canada	To assess attitudes and preferences towards consumer electric vehicles	EVs	CA	Latent class choice model	17,953 Households
Fernández-Antolín et al. (2018)	2018	France	To analyse different policy scenarios and discuss price elasticities and willingness to pay and to accept BEVs and HEVs	BEVs, HEVs	RP	Logit model Cross nested logit model	657 Vehicle owners
Hahn et al. (2018)	2018	South Korea	To understand consumers' preferences of green vehicles	EVs	CA	Mixed model Nested logit model	4,548 consumers
(Huang and Qian, 2018)	2018	China	To investigate consumer preferences for EVs in lower tier cities of China	BEVs, PHEVs	CA	Nested Logit model	348 Respondents
(Liao et al., 2018)	2018	Netherlands	To assess the impact of business models, in particular battery and vehicle leasing, on EVs adoption	BEVs, PHEVs	CA	Latent Class Choice model	1003 Respondents
Rahmani and Loureiro (2018)	2018	Spain	To assess the market preferences for HEVs in Spain, looking at the role of subsidies	HEVs	CA	MNL model	1,200 Drivers
Wolbertus et al. (2018)	2018	Netherlands	To estimate the effect of particular policy measures aimed at EVs adoption and charging behaviour	EVs	CA and RP	Mixed logit model	149 Respondents

Table 2.1 - Studies focused on analysing consumer preferences for AFVs.

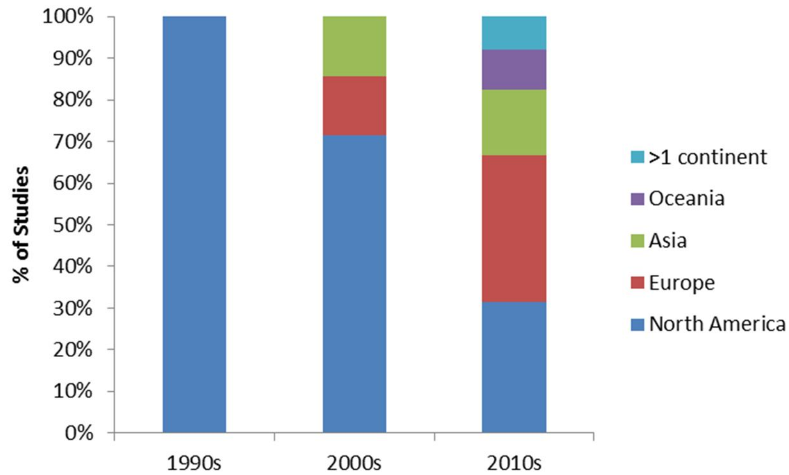

Figure 2.1 - Geographic scope of the studies across time.

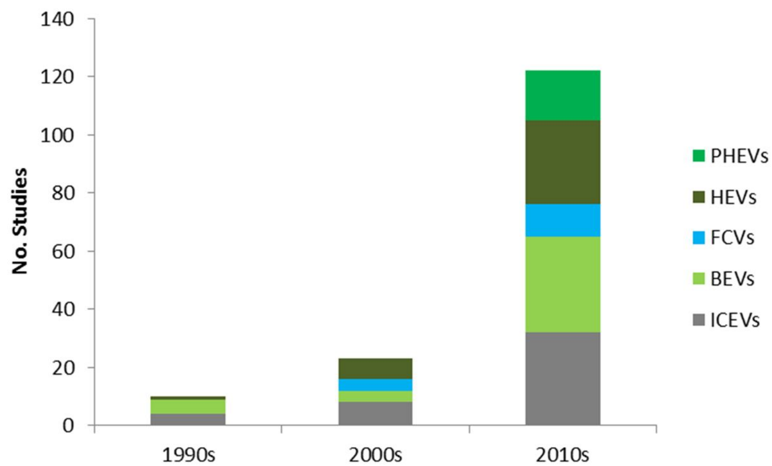

Figure 2.2 - Vehicles included in the consumer preference studies.

2.1.1. Data collection methods

Consumer preferences are commonly inferred through Revealed Preferences (RP) or SP techniques. RP are obtained by observing consumers' choices in the real marketplace. But when the purpose is to analyse preference data for products that are not yet in the market, for attributes that are not present in existing products or for attribute levels that are beyond those currently available in the market, it is impossible to collect RP. In such cases SP are pointed out as the most suitable technique to collect preference data, as they consist in designed experiments that measure preferences of hypothetical alternatives where the new products are included (Kroes and Sheldon, 1988). Since AFVs are relatively new products in most of the markets, a RP approach would not allow obtaining the preference information necessary to understand the consumers' adoption of such technologies (Ahn et al., 2008).

There are two SP techniques that are commonly used in transport studies, the Contingent Valuation (CV) Method and the CA (also known as Choice Modelling method). The CV method is a direct survey approach used to estimate consumer preferences through standard economic values, such as willingness to pay (Hanley et al., 2001; Oerlemans et al., 2016). Consumers are asked about their willingness to pay for a previously determined increase or decrease of the provision level of the product (Hanley et al., 2001; Mogas et al., 2002). This method assumes that the stated amounts of willingness to pay for these level changes are related with the consumers' underlying preferences (Hanley et al., 2001).

The second method, CA, was developed within the conjoint measurement area, in mathematical psychology, by Luce and Tukey (1964), and was later extended to marketing research (Green et al., 2001; Kuhfeld, 2010). Through the analysis of the trade-offs[4] between attributes, CA exploits the consumers' decision process by defining which are the most determinant attributes and the most preferred combinations of attributes levels (Green et al., 2001; Kuhfeld, 2010). There are three CA methods for data collection: rating scale methods, rank methods, and CBC, also known as Choice Experiment or Discrete Choice Experiment methods (Louviere, 1988; Louviere et al., 2010). The first consists in rating a set of products by assigning rates from a pre-defined scale. In the second method consumers are presented with a ranking exercise where they have to rank a set of products from the most preferred to the least preferred. The third conjoint method consists in asking consumers to choose the most preferred product among several sets of

[4] When seeking the preferred balance between criteria levels, consumers have to give up performance on some criteria in order to have gains in other criteria (Green et al., 2001).

alternatives, where each set comprises two or more multiattribute products (Green et al., 1972; Jain et al., 1979).

Considering the selected studies, 83% of the studies used CA and only 4% used CV to collect consumer preferences for AFVs. This highlights the primacy of CA over CV methods to uncover consumer preferences in the transport field. CA surveys provide substantially more information than CV about the alternatives of products and possible policies and allow reducing the sample size demanded for estimation of preferences (Carson, 2000). Another reason for the scarce use of CV is that these methods, by using dichotomous choice or open-ended questions, were not considered completely adequate to deal with products where changes are multidimensional (Hanley et al., 2001).

There are also studies that, instead of using SP survey techniques, applied pre-structured surveys focused on collecting consumers' information measured with Likert-type scales (Erdem et al., 2010; Li et al., 2013; Knez et al., 2014; She et al., 2017).

2.1.2. Sample

The samples for AFVs consumer preference studies frequently comprise consumers with specific requirements, i.e. convenience samples are used. The most common requirements found in the literature are the intention of purchasing a vehicle in the short-term (Potoglou and Kanaroglou, 2007a; Achtnicht et al., 2008; Hidrue et al., 2011; Nixon and Saphores, 2011; Alvarez-Daziano and Chiew, 2013; Hackbarth and Madlener, 2016), the recent purchase of a new vehicle (Lin and Greene, 2010; Hensher and Greene, 2011; Axsen and Kurani, 2013; Beck et al., 2013; Jensen et al., 2013; Axsen et al., 2015, 2016) or the ownership of a vehicle (Axsen et al., 2009; Ko and Hahn, 2013; Li et al., 2013). Convenience samples are commonly used at the cost of not getting representative samples of the targeted population. The low number of studies that had representative samples (24%) hints that this is not a priority in these types of studies.

2.1.3. Estimation procedures

When the focus is the analysis of consumer preferences there are three types of models regarding the level of aggregation (Moore, 1980): aggregation models; segmented models and individual-level models. Considering the studies selected for analysis, the most frequent estimation procedures to model preferences were aggregation models where preferences were estimated in an aggregate manner, i.e. for the whole consumers population. The aggregation models rely on Random Utility Theory (RUT) (Louviere et al., 2010) and were applied in 78% of the reviewed studies.

The most prominent types of aggregation models are Logit, Generalized Extreme Value (GEV), Mixed Logit and Probit. These types differ according to the assumption made about the correlation of the unobserved factors over alternatives, i.e. if the Independence from Irrelevant Alternatives (IIA) property holds or not (Train, 2002). It is said that IIA holds if for a consumer the ratio of the choice probabilities of two alternatives is not affected by the presence or absence of any other alternatives in the choice set. The **Logit model** is the most widely used aggregation model and it assumes that the unobserved factors are uncorrelated between alternatives. This means that this model considers that the IIA property holds. The first Logit models were the Binomial models where the logistic distribution was used to derive the probability of two alternatives being selected. The generalization of this model to more than two alternatives gave origin to the MNL (Multinomial Logit), if the alternatives were not ordered, and to Ranked Logit, when they were ordered (Small, 1981; Bierlaire, 1998). **GEV models** are based on a generalization of the distribution of the extreme value that can take many forms. The common element is that it allows the existence of correlation between the unobserved factors over alternatives. If the correlation is zero this model collapses to the Logit model. The most used GEV method is the Nested Logit model, which is the appropriate model when the alternatives set can be separated into subsets according to some common characteristics, called "nests". For the alternatives placed in the same nest it is considered that the ratio of probabilities is independent of all other alternatives exterior to that nest. For two alternatives that belong to different nests, the ratio of probabilities can depend on the attributes of other alternatives in the two nests (Train, 2002). The Cross-Nested Logit model differs from the Nested Logit model because it allows capturing more correlation patterns by containing multiple overlapping nests, i.e. an alternative is allowed to be part to more than one nest, providing more flexibility in the specifications of the correlation structure (Train, 2002; Hess, Fowler, et al., 2012). **Mixed Logit** models are highly flexible in that they can approximate any RUM, by allowing that the unobserved factors follow any distribution. The distinctive characteristic of this model is that the unobserved factors can be decomposed in two parts, one part that contains all the correlation and heteroscedasticity and another where IIA property holds (Train, 2002). A special form of Mixed Logit models are the Rank-order Mixed Logit models which is the Mixed Logit model for rank-order preferences data (Nixon and Saphores, 2011). Finally, **Probit** models are based on the assumption that the unobserved factors are normally distributed. Similarly to the Logit model, Probit models can be Binomial Probit, if there are two possible outcomes, Multinomial Probit, if there are more than two possible outcomes for the dependent variable, or Ordered Probit if there are more than two outcomes that can be ordered (Train, 2002).

Table 2.2 presents the frequency of each aggregation estimation procedure in consumer preferences studies. It can be observed the MNL models are the most widely used also considering the consumer preference analysis of AFVs.

Aggregation model	Specific Type	Frequency
Logit model	Binomial Logit	1
	Multinomial Logit	23
GEV model	Nested Logit	8
	Cross-Nested Logit	2
Mixed Logit Model	Standard Mixed Logit	15
	Rank-order Mixed Logit	1
Probit Model	Binomial Probit	1
	Multinomial Probit	5

Table 2.2 - Specific type of aggregation model used in consumer preference studies and the number of times it was applied.

Segmented models estimate preferences for homogeneous groups of consumers, i.e. consumers that have similar preferences are grouped on in the same segment. **Latent class** models have been the reference for preferences segmentation. The underlying basis of these models is to integrate attitudinal and socioeconomic factors with information from choice models using a latent variable system (Mcfadden, 1986). In these models consumer preferences are dependent on observable attributes and on latent heterogeneity which varies with factors that cannot be observed by the researcher (Greene and Hensher, 2003). Finally, preferences can be estimated for each consumer individually. **CBC/Hierarchical Bayes (CBC/HB)** model allows performing such analysis. CBC/HB is a random effects model that pools the data through an iterative process and provides utilities for each attribute of each consumer allowing to capture consumers heterogeneity (Allenby and Ginter, 1995; Orme, 2009a).

2.2. Methodologies to assess the AFVs diffusion

The attempts to model consumer preferences for a specific product had, frequently, the ultimate goal of forecasting the impact of marketing strategies, in other words, to understand the diffusion of that product in the market (Urban et al., 1996). Rogers (1995) defined diffusion as a process which consumers pass through towards an innovation, which includes several stages: the first knowledge of an innovation to form an attitude, the decision of accepting or rejecting that innovation, the implementation and use of that innovative idea and, finally, the confirmation of that decision.

There exists a substantial body of research that has tried to forecast the demand of AFVs not only because researchers want to understand the consumer behaviour in face of the introduction of these vehicles, but also due to the importance of the automotive industry and the complexity of its regulation, which is related to the national energy policy and environmental regulation (Lee and Cho, 2009). The research about AFVs adoption using innovation diffusion models has been growing over the years. Al-Alawi and Bradley (2013) performed a literature review of the most used models that aimed to forecast the diffusion a specific group of AFVs, EVs technologies. Three main methodologies were identified: Agent-based modelling (ABM), Consumer choice models and Diffusion models. This section presents a new review that adds to these methodologies another simulation method commonly used in the diffusion of AFVs, SD. Table 2.3 summarizes the studies selected for this review indicating the geographical and vehicle scope, the main goal, the vehicle technologies included in the analysis and the modelling method. Similarly to the consumer preference studies trend, over 50% of the AFVs diffusion studies where performed in North America, namely in the US. Most of the modelling studies (>60%) were developed after 2010 (Figure 2.3). Regarding the main modelling method of each study four main methods were identified: consumer choice models, SD, ABM and Bass-based diffusion models. These methods are briefly described in the next subsections.

Study	Year	Country	Goal	Scope	Vehicles included in the analysis	Modelling method
Beggs et al. (1981)	1981	US	To assess the potential demand for BEVs	BEVs	BEVs and ICEVs	Consumer choice models
Calfee (1985)	1985	US	To estimate the potential demand for BEVs	BEVs	BEVs and ICEVs	Consumer choice models
Bunch et al. (1993)	1993	US	To determine how demand for clean-fuel vehicles is likely to vary as a function of differential attributes	AFVs	BEVs, ICEVs and AFVs	Consumer choice models
Golob et al. (1993)	1993	US	To predict the effect on personal vehicle purchases of differential attributes of clean-fuel vehicles	AFVs	BEVs and AFVs	Consumer choice models
Segal (1995)	1995	US	To forecast the BEVs demand	BEVs	BEVs	Consumer choice models
Sperling et al. (1995)	1995	US	To analyse the potential market for methanol vehicles	Methanol vehicles	Methanol vehicles	Consumer choice models
Kurani, Sperling, et al. (1996)	1996	US	To analyse consumer demand for BEVs	BEVs	HEVs, BEVs, Natural Gas Vehicles and ICEVs	Consumer choice models
Ewing and Sarigöllü (1998)	1998	US	To examine the factors likely to influence the demand for lower emission and zero emission vehicles	AFVs	BEVs, ICEVs and AFVs	Consumer choice models
Jeon (2001)	2001	US	To forecast the sales of HEVs, PHEVs and BEVs	EVs	HEVs, PHEVs, BEVs and ICEVs	Bass-based diffusion model
Dagsvik et al. (2002)	2002	Norway	To analyse the potential demand for AFVs	AFVs	BEVs, Liquefied Petroleum Gas vehicles and dual fuel	Consumer choice models
Kostyniuk et al. (2003)	2003	US	To explore which conditions and incentives would lead to AFVs purchase	AFVs	HEVs and ICEVs	Consumer choice models

Study	Year	Country	Goal	Scope	Vehicles included in the analysis	Modelling method
Batley et al. (2004)	2004	UK	To analyse the consumer demand for AFVs in UK	ICEVs and AFVs	PHEVs, BEVs and ICEVs	Consumer choice models
Cao and Mokhtarian (2004)	2004	US	To forecast the US demand for AFVs	AFVs	ICEVs, Compressed Natural Gas vehicles, HEVs and E85	Bass-based diffusion model
Stephan et al. (2004)	2004	US	To apply ABM to the evolution of hydrogen transportation system	FCVs	FCVs	ABM
Sullivan et al. (2005)	2005	US	To forecast the effects of policy levers that influence individual choices of new passenger cars	HEVs	HEVs	ABM
Janssen et al. (2006)	2006	Switzerland	To estimate the future development of the market diffusion of Natural Gas Vehicles and analyse the reactions of that diffusion after stimulation policies	Natural Gas Vehicles	Natural Gas Vehicles	SD
Schwoon (2006)	2006	Germany	To capture the main interdependencies in order to simulate the diffusion of FCVs	FCVs	FCVs and ICEVs	ABM
Ahn et al. (2008)	2008	South Korea	To analyse how adding AFVs to the market will affect patterns in demand for passenger cars	AFVs	HEVs, Compressed Natural Gas Vehicles, Liquefied Petroleum Gas vehicles and ICEVs	Consumer choice models
Keles et al. (2008)	2008	Germany	To discuss the market penetration of FCVs looking to the market as a whole	FCVs	FCVs	SD
Struben and Sterman (2008)	2008	US	To examine the diffusion dynamics for and competition among AFVs focused on adoption generated by consumer awareness and learning	AFVs	AFVs and ICEVs	SD
Becker et al. (2009)	2009	US	To estimate the adoption market rate of EVs	EVs	HEVs, BEVs and ICEVs	Bass diffusion model
Leaver et al. (2009)	2009	New Zealand	To assess the primary impacts of AFVs technologies	FCVs	BEVs and FCVs	SD
Mcmanus and Senter (2009)	2009	US	To predict PHEVs adoption	PHEVs	PHEVs and ICEVs	Bass-based diffusion model
Meyer and Winebrake (2009)	2009	US	To investigate the vehicle-infrastructure phenomenon currently inhibiting the growth of hydrogen transportation systems	FCVs	FCVs	SD
Sullivan et al. (2009)	2009	US	To characterize new vehicle penetration into the marketplace under a variety of consumer, economic and policy conditions	PHEVs	PHEVs	ABM
Cui et al. (2010)	2010	US	To model the spatial distribution of PHEVs ownership and to evaluate the impact of PHEVs charging load on the electrical grid	PHEVs	PHEVs and other vehicles (HEVs and ICEVs)	ABM
Erdem et al. (2010)	2010	Turkey	To determine the factors that have impact on consumers' willingness to pay for HEVs	HEVs	HEVs	Consumer choice models
Lin and Greene (2010)	2010	US	To understand the effectiveness of incentives and improvement of charging infrastructure in PHEVs purchases	PHEVs	HEVs, PHEVs, BEVs, FCVs and ICEVs	Consumer choice models

Study	Year	Country	Goal	Scope	Vehicles included in the analysis	Modelling method
Köhler et al. (2010)	2010	Germany	To explore the potential for a sustainable hydrogen transition within Europe	FCVs	FCVs	SD
Pellon et al. (2010)	2010	US	To study the adoption pf PHEVs under different scenarios	PHEVs	PHEVs	ABM
Walther et al. (2010)	2010	US	To examine automobile manufacturer strategies for compliance with low emission vehicle regulations	AFVs	PHEVs, HEVs, BEVs and ICEVs	SD
Beresteanu and Li (2011)	2011	US	To analyse the determinants of HEVs purchase	HEVs	HEVs	Consumer choice models
Eppstein et al. (2011)	2011	US	To analyse the interactions between potential influences on PHEVs market penetration	HEVs	HEVs, PHEVs and ICEVs	ABM
Lieven et al. (2011)	2011	Germany	To forecast the market potential of BEVs	BEVs	BEVs	Consumer choice models
Mabit and Fosgerau (2011)	2011	Denmark	To investigate the potential future of AFVs in Denmark	AFVs	HEVs, BEVs, FCVs, and ICEVs	Consumer choice models
Orbach and Fruchter (2011)	2011	US	To demonstrate a methodology for forecasting sales and product (technology) evolution based on data that can be collected before new generations are launched	HEVs and BEVs	HEVs and BEVs	ABM
Park et al. (2011)	2011	South Korea	To develop a new forecasting model for the market penetration of FCVs	FCVs	FCVs	SD
Zhang, Gensler, et al. (2011)	2011	US	To investigate factors that can speed the diffusion of AFVs	AFVs	HEVs, BEVs and ICEVs	ABM
Achtnicht et al. (2012)	2012	Germany	To study the impact of fuel availability on demand for AFVs	AFVs	HEVs, BEVs, FCVs, Biofuel, Liquefied Petroleum Gas vehicles and ICEVs	Consumer choice models
Fazeli et al. (2012)	2012	Portugal	To analyse the bi-directional interaction between the development of the refuelling station network and vehicle sales	AFVs	HEVs, PHEVs, E85 and ICEVs	SD
Higgins et al. (2012)	2012	Australia	To estimate de adoption of EVs	EVs	BEVs, PHEVs, HEVs and ICEVs	Consumer choice models
Hess, Fowler, et al. (2012)	2012	US	To investigate the prevalence of correlation along two dimensions of choice, vehicle type and fuel type	AFVs	HEVs, PHEVs, BEVs and ICEVs	Consumer choice models
Keith (2012)	2012	US	Study 1: Examine the market of Toyota Prius incorporating the production capacity and dealer inventory Study 2: Understand the heterogeneous diffusion of Toyota Prius in US Study 3: Explore the future role of HEVs as a transitional technology in the emerging market for PHEVs	HEVs	HEVs, PHEVs and BEVs	SD
Kwon (2012)	2012	US	To investigate the market barriers necessary to overcome and increase the market share of AFVs	AFVs	AFVs and ICEVs	SD
Lebeau et al. (2012)	2012	Belgium	To examine the market potential of Flanders of PHEVs and BEVs	BEVs and PHEVs	PHEVs, BEVs and ICEVs	Consumer choice models

Study	Year	Country	Goal	Scope	Vehicles included in the analysis	Modelling method
Link et al. (2012)	2012	Austria	To analyse the consumer needs regarding BEVs	BEVs	HEVs, BEVs and ICEVs	Consumer choice models
Shafiei et al. (2012)	2012	Iceland	To study the market share evolution of passenger vehicles in Iceland	EVs	EVs and ICEVs	ABM
Shepherd et al. (2012)	2012	UK	To analyse the uptake of EVs	PHEVs and BEVs	PHEVs, BEVs and ICEVs	SD
van der Vooren and Alkemade (2012)	2012	Netherlands	To analyse the competition between several new and market-ready technologies and an incumbent technology	AFVs	PHEVs, BEVs, FCVs and ICEVs	ABM
Yu et al. (2012)	2012	UK	To study the impact of different governmental interventions on the diffusion of EVs	EVs	EVs	ABM
Brown (2013)	2012	US	To understand the PHEVs diffusion	PHEVs	PHEVs and BEVs	ABM
Brand et al. (2013)	2013	UK	To explore which type of vehicle taxation accelerates fuel, technology and purchasing behavioural transitions the fastest	AFVs	ICEVs, BEVs, HEVs, PHEVs and FCVs	Consumer choice models
Hackbarth and Madlener (2013)	2013	Germany	To analyse the potential demand for AFVs	AFVs	HEVs, PHEVs, BEVs, FCVs and ICEVs	Consumer choice models
Ito et al. (2013)	2013	Japan	To investigate potential demand for infrastructure investment for AFVs	AFVs	HEVs, BEVs, FCVs and ICEVs	Consumer choice models
Lee et al. (2013)	2013	South Korea	To forecast AFVs sales	AFVs	HEVs, BEVs and FCVs	Bass diffusion model
Molina (2013)	2013	US	To analyse how the interplay of uncertainties influences the transition towards AFVs	HEVs and BEVs	ICEVs, HEVs and another AFV	SD
Glerum et al. (2014)	2014	Switzerland	To present an integrated methodology to forecast the demand for BEVs and to enhance the forecasting power of a model developed on stated preference data	BEVs	BEVs and ICEVs	Consumer choice models
Harrison and Shepherd (2014)	2014	US	To identify potential impacts of a transition to a low carbon fleet on both societal inequities	EVs	HEVs, PHEVs and BEVs	SD
He et al. (2014)	2014	US	To develop an alternative choice modelling framework considering the social impact on new product adoption	HEVs	HEVs	Consumer choice models
Liu (2014)	2014	US	To assess consumers' willingness to pay of HEVs	HEVs	HEVs	Consumer choice models
Plötz et al. (2014)	2014	Germany	To analyse the market diffusion of EVs and the policies that may influence that diffusion	EVs	PHEVs, BEVs and extended range EVs	ABM
Shafiei et al. (2014)	2014	Iceland	To develop a SD model of Iceland's energy sector	AFVs	BEVs, PHEVs, HEVs, FCVs, biogas and biodiesel	SD
Qian and Soopramanien (2015)	2015	China	To forecast the demand of green cars in emerging markets accounting for preference heterogeneity and market dynamics	HEVs and BEVs	HEVs and BEVs	Consumer choice models

Study	Year	Country	Goal	Scope	Vehicles included in the analysis	Modelling method
Shafiei, Davidsdottir, et al. (2015)	2015	Iceland	To present a comparative analysis of electric, hydrogen and biofuel transitional pathways to a future sustainable road transport	AFVs	BEVs, PHEVs, HEVs, FCVs, biogas and biodiesel	SD
Shafiei, Leaver, et al. (2015)	2015	Iceland	To explore the potential transition paths towards renewable transport fuels with implications for greenhouse gas emissions and mitigation costs	AFVs	BEVs, PHEVs, HEVs, FCVs, biogas and biodiesel	SD
Valeri and Danielis (2015)	2015	Italy	To evaluate the market penetration of cars with AFVs technologies in Italy under various scenarios	AFVs	ICEVs, Compressed Natural Gas vehicles, Liquefied Petroleum Gas vehicles, HEVs and BEVs	Consumer choice models
Bahamonde-birke and Hanappi (2016)	2016	Austria	To analyse the acceptance of EVs by the Austrian population	BEVs	HEVs, PHEVs, BEVs and ICEVs	Consumer choice models
Braz da Silva and Moura (2016)	2012	Portugal	To estimate the fleet wide energy consumption and corresponding CO_2 emissions up to 2030	BEVs and PHEVs	BEVs, PHEVs, HEVs and ICEVs	SD
Guðmundsdóttir (2016)	2016	Iceland	To analyse the coevolution of AFVs and the corresponding infrastructure	AFVs	HEVs, PHEVs, BEVs, Compressed Natural Gas vehicles and ICEVs	SD
Jensen et al. (2016)	2017	Denmark	To discuss the prediction of EVs market shares and to suggest a method that combines a diffusion model with advanced discrete choice models	BEVs	ICEVs and BEVs	Bass diffusion model
Kieckhäfer et al. (2016)	2016	Germany	To analyse the leverage of manufacturers to support the market diffusion of EVs	EVs	BEVs, PHEVs and ICEVs	ABM
Krause et al. (2016)	2016	US	To assess how consumer demand might change with various breakthroughs in PHEVs technology	PHEVs	HEVs, PHEVs, BEVs and ICEVs	Consumer choice models
Noori and Tatari (2016)	2016	US	To study the market penetration of EVs considering the inherent uncertainties involved	EVs	HEVs, PHEVs, BEVs, extended range EVs and ICEVs	ABM
Pasaoglu et al. (2016)	2016	European Union countries	To integrate a wider range of market, industry and technology dynamics compared to existent models	AFVs	HEVs, BEVs and FCVs	SD
Rasouli and Timmermans (2016)	2016	Netherlands	To investigate the effects of vehicle attributes, contextual and social network attributes on the latent demand for BEVs	BEVs	BEVs	Consumer choice models
Shafiei et al. (2016)	2016	Iceland	To examine the capacity expansion strategies of biofuels supply and the potential for the market development of biofuel vehicles	AFVs	BEVs, PHEVs, HEVs, FCVs, biogas and biodiesel	SD
Benvenutti et al. (2017)	2017	Brazil	To investigate the impact of public policies in the long-term diffusion dynamics of AFVs in Brazil	AFVs	BEVs and HEVs	Bass-based diffusion model and SD

Study	Year	Country	Goal	Scope	Vehicles included in the analysis	Modelling method
Brand et al. (2017)	2017	UK	To examine the timing, scale and impacts of the uptake of PHEVs in the heterogeneous UK car market from a consumer perspective	PHEVs	ICEVs, BEVs, HEVs, PHEVs and FCVs	Consumer choice models
Jansson et al. (2017)	2017	Sweden	To analyse if the social system and interpersonal factors influence the adoption of AFVs	AFVs	AFVs and ICEVs	Innovation diffusion model
Kangur et al. (2017)	2017	Netherlands	To explore how policies for EVs may interact with consumer behaviour over such a long time period	EVs	BEVs, PHEVs and ICEVs	ABM
Liu and Cirillo (2017)	2017	US	To propose a generalized dynamic discrete choice approach that models purchase behaviour and forecasts future preferences	EVs	BEVs, HEVs and ICEVs	Consumer choice models
Liu et al. (2017)	2017	US	To understand the adoption of AFVs considering the uncertainties of consumer purchase behaviour, technology development and government regulation	BEVs	ICEVs, HEVs, FCVs, BEVs and PHEVs	SD
Ma et al. (2017)	2017	China	To investigate the potential impact of purchase subsidies and charging facilities on demand for EVs	BEVs	ICEVs, PHEVs and BEVs	Consumer choice models
Shafiei et al. (2017)	2017	Iceland	To evaluate how and if Iceland can achieve a near carbon-neutral transport system	AFVs	BEVs, PHEVs, HEVs, FCVs and biogas	SD
Sheldon et al. (2017)	2017	US	To estimate demand for PHEVs relative to BEVs and to explore heterogeneity in demand for these vehicles	PHEVs and BEVs	PHEVs, BEVs and ICEVs	Consumer choice models
Weiss et al. (2017)	2017	Germany	To assess the effects of increments of EVs on the German fleet	EVs	BEVs	ABM
Wolinetz and Axsen (2017)	2017	Canada	To improve understanding of market penetration forecasts of plug-in electric vehicles	BEVs and PHEVs	ICEVs, HEVs, PHEVs and BEVs	Consumer choice models
Liu and Cirillo (2018)	2018	US	To forecast households' future preferences on vehicle type, quantity and use, and to estimate greenhouse gas emissions	EVs	ICEVs, HEVs and BEVs	Consumer choice models
Shafiei et al. (2018)	2018	Iceland	To evaluate how the transition to EVs can be achieved through fiscal policy incentives	EVs	PHEVs, BEVs, HEVs and ICEVs	SD
Soto et al. (2018)	2018	Canada	To evaluate the influence of policies, attitudes and perceptions when incentivizing AFVs	AFVs	ICE, Natural Gas Vehicles, BEV and HEV	Consumer choice models

Table 2.3 - Innovation diffusion studies of AFVs.

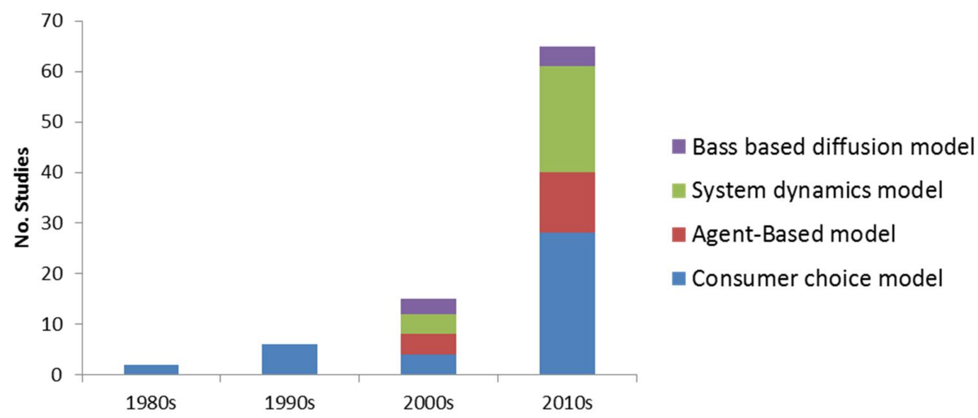

Figure 2.3 - Timeline distribution of innovation diffusion methods used for AFVs.

2.2.1. Consumer choice models

Al-Alawi and Bradley (2013) and Plötz et al. (2014) concluded that consumer choice models were amongst the most used methods to analyse the diffusion of AFVs. As these models are used in 44% of the reviewed modelling studies, this review corroborates their findings. The main reason pointed out to this extensive use of consumer choice models is related to the data collection method that they commonly use, i.e. SP methods (Plötz et al., 2014). As these surveys allow collecting information about vehicles and vehicle characteristics that do not exist in the market yet, they are extremely appealing to forecast studies of innovative vehicle technologies, as AFVs. The use of SP methods supported the use of these models to analyse the diffusion of AFVs since the 1980s, when few AFV models were available in the market. The constant evolution of consumer choice models has kept them as the most used models to forecast the AFVs diffusion until today (Figure 2.3). When the study´s scope was a specific type of vehicle, BEVs were the most frequently analyzed vehicles (33%).

2.2.2. System Dynamics models

SD was developed by Jay Forrester in 1961 and it consists in a modelling approach focused on the dynamic feedback and interactions within systems (Sterman, 2000). This method is used to simulate the dynamic behaviour of complex systems, in particular changes in the system behaviour over time (Keles et al., 2008; Park et al., 2011). SD combines nonlinear dynamics, diffusion models and system feedbacks, the latter being the most distinctive and relevant characteristic of the method (Shepherd et al., 2012). The feedback structure is related to a closed circuit that comes from the interconnection of the causal sequences of the variables (Sterman, 2000).

According to the studies reviewed, the use of SD to model the diffusion of AFVs has been growing over the years, representing 28% of the used modelling choices. This can be justified by its ability to represent complex networks between the selected market players for the analysis and the dependencies of the market penetration process (Janssen et al., 2006). Its ability to forecast the market penetration of AFVs considering the feedback effect of market shares on vehicle attributes also supports its use (Lee et al., 2013). The main scope of SD studies has been FCVs followed by BEVs. SD studies for AFVs diffusion analysis have become more prevalent since 2010 (figure 2.3) and the main scope of SD studies is EVs.

2.2.3. Agent Based models

ABM is a computer simulation method that aims to model complex social dynamic behaviours that emerge from autonomous and heterogeneous agents belonging to the market (Cui et al., 2010; Pellon et al., 2010; Eppstein et al., 2011). These agents can be buyers, dealers, governments or other relevant players acting in the market. The ABM starts with agents' preferences and behaviour rules that, by allowing them to interact, projects these behaviours into the future looking for collective responses, such as, for instance, the market penetration of a product (Mcmanus and Senter, 2009). As agent heterogeneity increases, the more effective and representative an ABM becomes.

In AFVs diffusion studies ABM creates a virtual environment to model the interactions of the different agents, such as new and used car-consumers, manufacturers, fuel-suppliers and governments, all making decisions in that common virtual environment (Sullivan et al., 2009; Noori and Tatari, 2016). ABM was the third most used method to analyse the diffusion of AFVs (20%), more prevalent since 2010, and it has focused mainly the diffusion of PHEVs and BEVs.

2.2.4. Bass and Bass-based diffusion models

Bass (1969) developed an innovation diffusion model that not only contributed to a better understanding of the adoption process of new products, but also to support the forecast of such product. The Bass model describes the diffusion of innovative products as a result of the social interaction between adopters and potential adopters of those products and it is a mathematical model frequently used to predict sales of new technology-based products (Jeon, 2001). This model predicts aggregate market outcomes based on parameters that were estimated on aggregate data (Mcmanus and Senter, 2009).

In the reviewed studies, there were some authors that used the Bass model to estimate the vehicle market shares (Becker et al., 2009; Lee et al., 2013), while others chose to use modified versions of the Bass model. Jeon (2001) used an extended version of the Bass Model, the Norton-Bass model, which consisted in applying the Bass model to successive generations of new technology products. Cao and Mokhtarian (2004) also used an extended version that incorporated a variable market potential to model the vehicles diffusion. Mcmanus and Senter (2009) used a Generalized Bass Model which extends the original model by accommodating marketing mix variables. This model allows identifying the effect of pricing and advertising on the diffusion of new products (Higgins et al., 2012).

Bass models have been used only a few times to analyse the diffusion of AFVs (8%) and they were mainly applied to EVs technologies.

2.3. Factors influencing consumer preferences for AFVs

The individual adoption highly influences the diffusion of an innovation in the market. Therefore, it is important to understand not only how consumers form their preferences but also which factors are behind the decision-making process (Dutschke et al., 2011). The adoption of AFVs, as innovative technologies, depends on a large variety of factors. For this thesis, a literature review was carried out to identify the most relevant factors. This review categorizes the influence factors in three main groups. The first group concerns technology-related factors. As there are several types of AFVs that have specific technical characteristics and limitations, for the sake of simplicity the technology-related factors concern only to the technical limitations of BEVs in particular, the most disruptive technology of the three AFVs technologies focused on this work (HEVs, PHEVs and BEVs). The second group of factors pertains to the influence of specific characteristics of consumers on general AFVs adoption. The third and last group is focused on the external factors that influence AFVs adoption, i.e. context-related factors. The influence of each group and the interlinkages between them brings complexity to the task of anticipating demand of AFVs. Therefore, a more detailed analysis of each group is presented below.

2.3.1. Influence of technology-related factors

Consumers continue to have several concerns about the adoption of new technologies in the transports field, most of them technical and investment related (Potoglou and Kanaroglou, 2007a; Hidrue et al., 2011). Among these concerns are the technological barriers to BEVs adoption (their innovative system demands different habits in comparison with the use of conventional vehicles). These barriers inhibit a larger market penetration within the current market conditions (Hacker et al., 2009). Three main BEVs characteristics have been pointed out as the main consumer concerns. Sustaining the assumption that the vehicle price plays a prominent role in the adoption of new vehicle technologies, one concern is the **purchase cost** (Eggers and Eggers, 2011). Several studies focused on identifying the most critical characteristics for BEV acceptance found that the purchase cost is one of its major obstacles (Horne et al., 2005; Caulfield et al., 2010; Hidrue et al., 2011; Lieven et al., 2011; Egbue and Long, 2012; Axsen et al., 2013; Chorus et al., 2013). The importance of price differential from BEVs to conventional vehicles comes from the fact that most of consumers do not discount the savings provided by their efficiency, which are distributed in a multiple year time span (Fontaine, 2008; Sovacool and Hirsh, 2008; Hacker et al., 2009; Gadenne et al., 2011).

Another concern regarding BEV is the **battery limitation**. Several dimensions can be included in this limitation such as cost and technical support or low warranty (Nemry et al., 2009; Parag, 2010), but the most crucial one is the limited range that is responsible for the so-called “range anxiety”, i.e. the fear that a vehicle runs out of battery before reaching the final destination (Beggs et al., 1981; Eggers and Eggers, 2011; Hidrue et al., 2011; Ziegler, 2012; Egbue and Long, 2012; Graham-Rowe et al., 2012; Axsen et al., 2013; Chorus et al., 2013; Globisch et al., 2013; Jensen et al., 2013; Hoen and Koetse, 2014). The importance of the driving range and its specific consequences was highlighted in previous studies. Dagsvik et al. (2002) verified that BEVs will be fully competitive in the market only if the driving range increases substantially. Eggers and Eggers (2011) demonstrated that, within a ceteris paribus analysis, BEVs need a minimum range to be chosen, i.e. a range below that minimum is considered unacceptable. Jensen et al. (2013) verified that the importance of the driving range of BEVs increases after consumers experience the vehicle, confirming that consumer concerns are related to the current BEVs in the market. Finally, Graham-Rowe et al. (2012) highlighted another aspect of range anxiety: when BEVs drivers observe the battery depletion, they start to minimize the use of features that would consume battery power, such as air conditioning or sound systems, reducing the pleasure of the driving experience. The importance of limited range for BEVs adoption decreases in multi-car households, because they can rely on another vehicle (usually an ICEV) whenever they have to drive long distances (Kurani, Sperling, et al., 1996; Graham-Rowe et al., 2012; Jensen et al., 2013). This may leave BEVs suitable only as second vehicle to use in short journeys (Graham-Rowe et al., 2012).

The third and last main concern of BEVs is the **charging time**. As it takes several hours to fully charge BEVs, charging time has been considered an important barrier for consumers’ acceptance of BEVs (Beggs et al., 1981; Chéron and Zins, 1997; Ewing and Sarigöllü, 1998; Hidrue et al., 2011; Zhang, Yu, et al., 2011; Chorus et al., 2013; Hoen and Koetse, 2014). The time drivers spend waiting for the full vehicle charge is seen as "dead time" and as a restriction of freedom of movement (Graham-Rowe et al., 2012). Ewing and Sarigöllü (1998) highlight that if fast charging stations are available, comprising charging times of half an hour or less, this concern would not be a significant barrier for BEVs adoption.

2.3.2. Influence of consumer-related factors

The individual characteristics of consumers are one of the dimensions responsible for this diversity and can support the anticipation of demand for AFVs (Axsen et al., 2015). Understanding in which way individual characteristics influence consumer preferences allows to uncover the existent market segments (Hoen and Koetse, 2014) and to identify which consumers have higher propensity to buy AFVs (Potoglou and Kanaroglou, 2007a).

The list of demographic characteristics that might influence consumer preferences is extensive. Therefore, for this analysis, a selection was done considering the most relevant characteristics for innovative and environmental products that were found in previous studies (Laroche et al., 2001; Kaushik and Rahman, 2014), namely age, gender, income, level of education and family size. Moreover, two vehicle-related demographics were added, driving habits and number of vehicles owned per household, due to their relevance and frequent analysis in AFVs studies.

Age influence

The effort to understand consumer preferences, and consequent behaviour, of the market segments defined by the consumers age is very common (Laukkanen and Laukkanen, 2007). The relationship between age and the adoption of new environmental friendly products has motivated the development of several studies that started with the assumption that younger consumers have higher preference for innovative and/or environmentally friendly products (Leventhal, 1997; Lambert-Pandraud and Gilles, 2010; Straughan and Roberts, 2011).

Regarding the influence of consumers' age on preferences for AFVs no consistency across studies has been found so far. Concerning BEVs, on one hand there were studies concluding that younger consumers preferred these vehicles more (Dagsvik et al., 2002; Hidrue et al., 2011; Ziegler, 2012; Hackbarth and Madlener, 2013; Parsons et al., 2014; Cirillo et al., 2017; Sheldon et al., 2017; Liao et al., 2018) or that older consumers have lower preferences for BEVs or prejudice against these vehicles (Bunch et al., 1993; Achtnicht et al., 2012; Bahamonde-birke and Hanappi, 2016). On the other hand, some studies concluded that older consumers are more likely to purchase BEVs (Zhang, Yu, et al., 2011; Shin et al., 2015) possibly because they can afford the higher initial cost to buy these vehicles and are less concerned about the limited range (Zhang, Yu, et al., 2011; Shin et al., 2015). Focused on FCVs, Ziegler (2012) found that younger consumers have higher propensity to purchase these vehicles. Concerning HEVs, Şentürk et al. (2011) verified that older consumers prefer these vehicles over gasoline ones, which can be justified by their higher sensitivity to the factors that affect negatively their health, whereas Hackbarth and Madlener (2013) found that younger consumers are more likely to adopt HEVs. Additionally, there were studies that analyzed the effect of age on AFVs in general where one concluded that preferences for these vehicles increase with age (Caulfield et al., 2010; Ma et al., 2017) whereas others concluded that age affects negatively the preferences for AFVs (Ewing and Sarigöllü, 1998; Potoglou and Kanaroglou, 2007a; Qian and Soopramanien, 2011; Hackbarth and Madlener, 2016).

As contradictory results were found regarding almost all vehicle technologies and as cultural differences can lead to variations of consumers level of innovativeness (Tellis et al., 2009)an analysis of the age influence on consumers preference for AFVs considering the consumers location (continent) was made. Studies developed in North America (Bunch et al., 1993; Ewing and Sarigöllü, 1998; Brownstone et al., 2000; Potoglou and Kanaroglou, 2007a; Hidrue et al., 2011; Cirillo et al., 2017; Liu and Cirillo, 2017; Sheldon et al., 2017) and Europe (Dagsvik et al., 2002; Ziegler, 2012; Hackbarth and Madlener, 2013, 2016; Bahamonde-birke and Hanappi, 2016; Liao et al., 2018) reported that younger consumers are more willing to buy greener vehicles (with the exception of Caulfield et al.(

2010)). On the other hand, Asian studies, with the exception of Qian and Soopramanien (2011), found that older consumers have higher propensity to buy AFVs (Zhang, Yu, et al., 2011; Şentürk et al., 2011; Shin et al., 2015; Ma et al., 2017). This analysis unveiled the geographical scope of the studies as a potential explanation for the contrast of preferences for AFVs.

Gender influence

Consumer behaviour varies according to gender, mainly due to role differences in cultural and social contexts (Kim et al., 2011). A significant impact of gender in the consumption of sustainable products (Pinto et al., 2014) and innovative products (Kim et al., 2011) has been observed.

Regarding BEVs several studies found that men preferred less these vehicles than women (Dagsvik et al., 2002; Mabit and Fosgerau, 2011; Krause et al., 2016; Cirillo et al., 2017; Ma et al., 2017; Huang and Qian, 2018; Liao et al., 2018) while one study found that men preferred BEVs (Liu and Cirillo, 2017). On the other hand, there were two studies where no interaction between gender and BEVs preferences was found (Zhang, Yu, et al., 2011; Ziegler, 2012). The studies of Mabit and Fosgerau (2011) and Ziegler (2012) differ on their results about FCVs: the first found that men have lower preferences for FCVs than women while the second concluded the opposite. Concerning HEVs, several studies found that it is less likely that men will purchase these vehicles (Caulfield et al., 2010; Qian and Soopramanien, 2015; Liu and Cirillo, 2017; Ferguson et al., 2018). Considering AFVs in general, Qian and Soopramanien (2011) verified that men are not keen to adopt a green vehicle.

Summing up, with the exception of FCVs, previous studies revealed that women are more willing than men to prefer sustainable vehicles. This can be explained by the different ways that women and men face the technical limitations of AFVs, as women are less sensitive to limited range (Bunch et al., 1993) and men have more concerns about the driving range and fuelling infrastructure for BEVs in the short-term (Dagsvik et al., 2002).

Income influence

Income is considered a strong predictor of the adoption of innovative products even though no influence between income and consumer innovative behaviour has been verified in some studies (Verlegh and Steenkamp, 1999; Im et al., 2003).

High levels of income are commonly assumed to be related to high levels of education (Zhang, Yu, et al., 2011). It is thus expected that wealthy consumers are better informed about the advantages of AFVs and are more likely to prefer them (Dagsvik and Liu, 2009; Şentürk et al., 2011; Shin et al., 2015), by valuating more their operation cost savings (Hevelston et al., 2015). However, this relation cannot be generalized to all AFVs, due to the presence of contradictory results in the studies reviewed. Some studies concluded that consumers with higher income present higher preferences for BEVs (Zhang, Yu, et al., 2011; Tanaka et al., 2014; Shin et al., 2015) but other studies concluded that consumers with higher earnings are more opposed to BEVs (Hevelston et al., 2015; Cirillo et al., 2017). Hidrue et al. (2011) and Ferguson et al. (2018) concluded that income did not influence consumers' choice for BEVs. Regarding HEVs, on one hand some studies concluded that wealthy consumers have stronger preferences for these vehicles (Potoglou and Kanaroglou, 2007a; Caulfield et al., 2010; Qian and Soopramanien, 2011; Cirillo et al., 2017; Fernández-Antolín et al., 2018; Soto et al., 2018) whereas others found that consumers who earn more have lower intentions to adopt HEVs (Hevelston et al., 2015; Shin et al., 2015) or that consumers with lower income prefer HEVs (Hahn et al., 2018). Bunch et al. (1993) reported that as consumer income increases the level of environmental concerns decreases and, for that reason, preferences for gasoline vehicles are higher.

In summary, regarding the influence of income on consumer preferences for AFVs no trend can be found so far as no consensus has been verified regarding the studied vehicle technologies.

Level of education influence

It is expected that education affects positively the adoption of innovative products, because it gives consumers a broader perspective and renders them more into new ideas and products (Tellis et al., 2009).

Concerning AFVs, it was found that environmental concerns increase according to level of education (Bolduc et al., 2008; Alvarez-Daziano and Bolduc, 2013). Therefore, almost all the reviewed studies are consistent in their findings regardless of the type of vehicle analyzed: consumers with a higher level of education are more likely to prefer and buy BEVs (Bunch et al., 1993; Brownstone et al., 2000; Hidrue et al., 2011; Hackbarth and Madlener, 2013; Tanaka et al., 2014; Krause et al., 2016; Ferguson et al., 2018; Fernández-Antolín et al., 2018; Soto et al., 2018); HEVs (Potoglou and Kanaroglou, 2007a; Liu and Cirillo, 2017; Fernández-Antolín et al., 2018) and PHEVs (Hackbarth and Madlener, 2013; Tanaka et al., 2014; Ferguson et al., 2018). In line with these findings, Sheldon et al. (2017) and Huang and Qian (2018) found that less educated consumers have less preference for BEVs and PHEVs. Zhang, Yu, et al. (2011) are the only authors presenting contrary results by finding that well-educated consumers are unwilling to buy BEV in a short-term. A possible explanation pointed out in this study is that the less developed sector of EVs industry in China leads to consumers with higher knowledge levels to be more familiar with these vehicles disadvantages and consequently do not purchase them in the short-term.

Family size influence

The influence of the number of family members on the purchase of innovative products is expected to be negative because parents' attention is more focused inward rather than outward to innovations (Tellis et al., 2009). On the other hand, families who have children are more willing to pay more for environmental products due to their concerns about the negative impact of a ruined environment on their children's future (Laroche et al., 2001). Therefore, the impact of the family size on environmentally friendlier vehicles preferences it is not easily predictable. However, literature reveals that studies addressing the influence of the number of family members in the preferences for BEVs reached the same conclusion: larger families are more willing to purchase these vehicles (Brownstone et al., 1996; Qian and Soopramanien, 2011, 2015; Zhang, Yu, et al., 2011; Krause et al., 2016; Huang and Qian, 2018) or PHEVs (Sheldon et al., 2017; Huang and Qian, 2018). These findings suggest that perceived environmental benefits of purchasing a more sustainable vehicle may be significant for larger families.

Vehicle-related demographics influence

Two vehicle-related influences were analyzed, driving habits and number of vehicles owned per household.

Driving habits are mainly expressed by the average vehicle mileage driven annually, weekly or daily (Kavalec, 1999; Şentürk et al., 2011; Beck et al., 2013; Hoen and Koetse, 2014; Hevelston et al., 2015; Shin et al., 2015) or by the type of routes that consumers use more often, city or intercity routes (Potoglou and Kanaroglou, 2007a; Qian and Soopramanien, 2011; Hackbarth and Madlener, 2013). On one hand, the influence of driving more kilometres or long distances on preferences for AFVs may favour these vehicles over diesel or gasoline vehicles as the running costs of AFVs are usually lower. On the other hand, it may influence consumers to not prefer AFVs as the owners of these vehicles face more often limited range and fuel availability problems (Hoen and Koetse, 2014). Potoglou and Kanaroglou (2007) and Qian and Soopramanien (2011) concluded that consumers that drive long distances present lower preferences for AFVs which was justified by their limited range and the limited availability of fuel. On the other hand, Dimatulac and Maoh (2017) found that long-distance consumers are more likely to purchase HEVs in order to save on gas. Considering consumers that undertake mainly city routes, Hackbarth and Madlener (2013) concluded that these consumers are more willing to buy BEVs due to the suitable range of these vehicles to city journeys. In this sense, it is possible that the influence of driving habits on preferences for AFVs is highly related with the technical limitations of these vehicles.

The number of vehicles owned per household is expected to affect positively the willingness to buy AFVs because these vehicles are considered to be fuel efficient (Şentürk et al., 2011) and also because households with more than one vehicle can manage the limitations of some AFVs. The low range of BEVs, for instance, is less of a concern as they have other vehicles for their long-distance journeys.

Some studies concluded that families that own more vehicles are more willing buy a BEVs (Zhang, Yu, et al., 2011) or a biofuel vehicle (Ziegler, 2012). One explanation pointed out for these results is the assumption that households that own more vehicles are wealthier and for that reason can more easily afford the higher purchase price of AFVs (Zhang, Yu, et al., 2011). On the other hand, Senturk et al. (2011) concluded that households with more vehicles present lower preference for HEVs. Therefore, the results show that the influence of the number of vehicles might be dependent on the type of vehicle or may be related with the families' wealth.

2.3.3. Influence of context-related factors

As mentioned before, preferences for innovative products are context-dependent, meaning that if the market conditions change the willingness to purchase new products may be affected. The context-related factors are external elements to both vehicle and consumer that have been found to influence the vehicles adoption (Sierzchula et al., 2014). Considering the AFVs, this section describes the influence of two external factors specific of AFVs, the influence of fuel price and of the development of fuelling/charging infrastructure, as well as two broad factors that may influence other products than AFVs, the influence of government policies and of social exposure. These factors were identified among the main context determinants for the consumer preferences of AFVs (Coffman et al., 2017).

Fuel price

Fuel prices have always been inherently volatile, but since 2008 this volatility was markedly high (Cambridge Econometrics, 2016). This context of high instability has consequences on the consumer behaviour, which is easier to observe when fuel price increases. Contexts of fuel price increments improve the relative competitiveness of AFVs due to their lower running costs (Graham-Rowe et al., 2012). Consumers' reactions to fuel price increments differ in the short-term and in the long-term. In the short-term, in order to reduce fuel expenses, the immediate reaction of consumers is to change their daily behaviour, such as choosing the most fuel efficient vehicle at their disposal (if they have multiple vehicles), using cheaper fuel types and reducing unnecessary journeys (Goodwin et al., 2004; Bomberg and Kockelman, 2007). On the other hand, in the long-term, consumers tend to change their transportation modes and, most importantly, they may change their non-fuel-efficient vehicles (Eltony, 1993; Jeihani and Sibdari, 2010; Sikes et al., 2010; Brown, 2013). Acknowledging that fuel prices have a direct impact on vehicle choice several studies have analyzed this relationship. Jeihani and Sibdari (2010), through the analysis of fuel price and HEVs sales evolution over the years, verified that they present the same trend. A two year time lag was identified between the increment of fuel prices and the purchase of fuel-efficient vehicles. This finding is in line with other studies that concluded that fuel price is one of the most important predictors of HEVs adoption (Gallagher and Muehlegger, 2007; Diamond, 2009; Eppstein et al., 2011). Similarly, Hsu et al. (2013) found that fuel price is determinant for HEVs market penetration, by observing that, without a significant increment in fuel prices, the HEVs market will not took off as result of its high initial cost. Focused on BEVs, Zhang, Yu, et al. (2011) and Hidrue et al. (2011) found that the probability of consumers buying a BEV increases when fuel prices also increase. Studies addressing the impact of high fuel prices on PHEVs sales followed the same trend of BEVs and HEVs studies (Sikes et al., 2010; Eppstein et al., 2011; Cirillo et al., 2017), revealing that increments of fuel price favour the adoption of AFVs.

Development of fuelling/charging infrastructure

In parallel with AFVs technical limitations, the limited fuelling/charging infrastructure has been considered a critical factor for a transition from conventional vehicles to AFVs (Segal, 1995; Greene, 1998; Shafiei et al., 2014; She et al., 2017). Therefore, the lack of a wide network of fuelling/charging infrastructures may constitute a barrier to the AFVs diffusion (Achtnicht et al., 2008). The solution for this problem consists in the increment of alternative fuels availability through the expansion of fuelling/charging infrastructures. This expansion requires a high investment and it will only be profitable for service station owners if the number of AFVs considerably increases (Achtnicht et al., 2008). This complementarity between vehicle demand and charging infrastructure is often called a “chicken-and-egg problem”, i.e. a lock-in effect where potential consumers would not consider purchase AFVs without an established charging infrastructure network and the suppliers of charging infrastructure would not set up those facilities without demand (Janssen et al., 2006; Achtnicht et al., 2008; Gnann and Plötz, 2015).

Policy makers recognize that building infrastructures to supply alternative fuels is essential to overcome the aforementioned “chicken-and-egg problem” and, therefore, to induce the market penetration of AFVs (Bakker and Trip, 2013). A possible strategy would consist in building some initial refuelling infrastructure until the system reaches a tipping point and expect that, from that point on, it will become self-sustaining (Gnann and Plötz, 2015). Another strategy, applied specifically for BEVs, would be to direct consumers towards the already available charging facilities at home or at their workplace in order to reduce the concerns about charging a BEV (Dutschke et al., 2011). Therefore, although the existence of public infrastructure is important for the visibility of the technology, investments in those infrastructures should not be overestimated to promote the market penetration of BEVs (Dutschke et al., 2011; Bakker and Trip, 2013). In fact, some cities prefer that consumers charge their vehicle at home in order to avoid the occupancy of existing parking spaces (Bakker and Trip, 2013).

Due to the dominance of petroleum fuels the relationship between fuel availability and vehicle choice received little attention in the past (Greene, 1998). However, with the market introduction of different types of AFVs, several studies analysed the influence of fuelling infrastructure on vehicle choice by consumers. Apart from Zhang, Yu, et al. (2011) that did not find a clear relation between fuelling/charging infrastructure and consumer preferences for AFVs, namely BEVs, all other studies reached a different conclusion. It was found that a large fuelling/charging infrastructure would have a positive impact on consumer preferences for BEVs (Achtnicht et al., 2008; Struben and Sterman, 2008; Daziano and Chiew, 2012; Egbue and Long, 2012; Sierzchula et al., 2014; Lieven, 2015; Shin et al., 2015; Zhang et al., 2016; Kangur et al., 2017; She et al., 2017), FCVs (Achtnicht et al., 2008) and Liquefied Petroleum Gas vehicles/Compressed Natural Gas vehicles (Achtnicht et al., 2008; Dutschke et al., 2011). The reduction of search costs (when searching for a charging infrastructure), the increment of convenience for drivers and the reduction of range anxiety (Achtnicht et al., 2012) explain this positive impact. However, according to Achtnicht et al. (2008), the impact of the infrastructure development on consumer's vehicle adoption is not linear, but it occurs with a diminishing marginal utility, i.e. when the fuelling/charging infrastructure density is above a certain level increasing its density would not have an impact in the same proportion on consumer preferences. This conclusion corroborates the findings of Greene (1998), consumer concerns about fuel availability are lower at density levels above 20%.

Government policies

Government policies are among the most frequently analyzed causes of influencing consumer preferences, because governments, as supporters of sustainable development, want to foster the rapid diffusion of environmental friendly technologies in the markets (Soete and Arundel, 1995). The motivations that drive governments to implement measures to increase the circulation of more environmental friendly vehicles are, among other: to increase the local air quality, to promote industrial development (Garling and Thogersen, 2001; Boyle, 2005), to achieve greenhouse gas emissions reduction targets and to reduce the dependence of foreign oil (Boyle, 2005; Ahman, 2006).

For some authors government support is acknowledged as a key feature of technical change and diffusion of new technologies in order to increase the number of consumers who are knowledgeable of these innovations (Soete and Arundel, 1995). Other authors rely on the governments the role of accelerating the adoption of AFVs (Fontaine, 2008; Parag, 2010; Borthwick, 2012). However, there are some uncertainties about the effectiveness of government policies on the shift of consumer purchase behaviour from more polluting vehicles to AFVs.

Government policies can be divided in two groups depending on whether they involve a financial incentive for consumers, i.e. monetary and non-monetary policies respectively. Monetary policies are among the most commonly studied since one of the drivers' main focuses is the financial burden associated to the vehicles ownership. Therefore, monetary measures have the potential to influence consumers' vehicle purchase decisions (Borthwick, 2012). Among the monetary policies, purchase subsidies and tax incentives are the most commonly analyzed. **Purchase subsidies** consist in an up-front "discount" of the total vehicle purchase price. However, the effectiveness of such subsidies is not easier to predict as consumers may consider that AFVs remain too expensive even with a price reduction (Bakker and Trip, 2013; Byun et al., 2018). Ewing and Sarigöllü (2000), Hidrue et al. (2011) and Hevelston et al. (2015) found that subsidizing BEVs purchases was effective in Canada, China and US, respectively. Focused on PHEVs, Musti and Kockelman (2011) and Kangur et al. (2017) verified that there was a positive effect of subsidies in the adoption of these vehicles in US and Netherlands, respectively. Regarding HEVs in US, while Diamond (2009) concluded that purchase subsidies were more effective to stimulate HEVs adoption than other delayed financial incentives, Riggieri (2011) found that purchase subsidies had little or no effect on AFVs purchases. Therefore, studies that analyse the influence of subsidies on BEVs, PHEVs or HEVs demand generally reached the same conclusion: subsidies have been effective on influencing demand towards AFVs. On the supply side, the existence of subsidies may have a negative effect as manufacturers may not feel the urgent need of lowering vehicle prices to increase demand (Bakker and Trip, 2013).

Regarding **tax incentives**, there are three incentives that can be implemented according to the targeted vehicle's lifetime stage. At the moment of vehicle purchase, the government can provide an exemption of the purchase or registration tax, consisting in an up-front release of value for consumers (Gass et al., 2011; Borthwick, 2012). As the exemption of this tax is considered to have the greatest potential to influence vehicle purchase decisions (Borthwick, 2012), the effect of this tax has been the most studied in the literature. When HEVs, BEVs or AFVs, in general, were the focus, the exemption of the purchase or registration tax had a positive effect in the purchase of targeted vehicles in the US (Gallagher and Muehlegger, 2007; Diamond, 2009), Canada (Potoglou and Kanaroglou, 2007a; Chandra et al., 2010), Denmark (Mabit and Fosgerau, 2011), Ireland (Caulfield et al., 2010) and China (Zhang, Yu, et al., 2011). As a periodic charge tax exemption, the government can provide the release of the circulation tax that is charged throughout the duration of the vehicle ownership (every 6 or 12 months). This tax is independent of the usage degree of the vehicle as it corresponds to the vehicle itself and it takes into account the released CO_2 emissions to compute its final value (Gass et al., 2011; Borthwick, 2012). Focusing on AFVs in general, while Whitehead et al. (2014) verified that the exemption of this tax increased the demand for these vehicles, Borthwick (2012) and Benvenutti et al. (2017) concluded that the influence of the circulation tax exemption was small. Ozaki (2011) found that circulation tax incentives affected positively the demand of HEVs in UK, whilst Shafiei et al. (2018) found that these taxes would only slightly increase the market penetration of BEVs and PHEVs in Iceland. Additionally, Borthwick (2012) and Sierzchula et al. (2014) verified that a combination of the exemption of the purchase or registration tax and the circulation taxes would be more effective to increase the circulation of AFVs. The third tax incentive is the exemption of fuel taxes, which is related with the degree of vehicle usage (Borthwick, 2012). As the charge of this tax is a regular visible expense it has the potential to influence the vehicle usage decisions. However, its impact on vehicle purchase decisions has been considered to be small. Ewing and Sarigöllü (2000) and Musti and Kockelman (2011) concluded that the exemption of fuel tax did not change drivers' preferences for PHEVs in US and for EVs in Canada, respectively.

While monetary policies are characterized by a direct investment of the government or municipalities, non-monetary policies are considered regulatory measures that have a low or no impact on public budgets (Bakker and Trip, 2013). Besides the development of fuelling/charging infrastructure addressed in the previous section, the second most popular non-monetary policy allows AFV owners to travel in high occupancy lanes. Gallagher and Muehlegger (2007) and Diamond (2009) studied the effect of this policy on HEV purchases in US and concluded that, outside the most congested locations, it does not affect the adoption of these vehicles. However, if this policy is applied in congested areas the HEVs share increases (Riggieri, 2011). Studies focused on AFVs did not find a significant influence of faster lane privileges on consumers' adoption for these vehicles in Canada (Potoglou and Kanaroglou, 2007a) and in Scotland (Borthwick, 2012). Regarding BEVs, while Ewing and Sarigöllü (2000) found that this policy was insufficient to influence consumers' purchase decisions in Canada, Zhang et al. (2016) verified that access to high occupancy lanes had a negative impact on consumers' purchases, possibly due to concerns about future congestions in these lanes. Another non-monetary measure consists in giving free parking privileges to AFVs owners. Two studies focused on AFVs found that this policy had no influence on consumers' vehicle decisions, possibly because the parking cost in the area was low (Potoglou and Kanaroglou, 2007a; Borthwick, 2012). On the other hand, studies focused specifically on BEVs found a positive effect of free parking on BEVs adoption (Cherchi, 2017; Wolbertus et al., 2018) although recognizing that a combination of this measure with other policies would help to compensate the major BEV technical limitations. Providing toll waivers for BEV owners in Norway proved to be effective on encouraging consumers to buy BEVs due to high toll expenses in that country (Bjerkan et al., 2016; Zhang et al., 2016).

In summary, it can be observed that monetary policies that imply up-front incentives were proved to be more effective on influencing consumers' purchase decisions because they represent an immediate incentive in comparison to other incentives that are dispersed over a multiple year time span (Diamond, 2009; Borthwick, 2012). The main barriers pointed out to explain the ineffectiveness of some government policies are the technical limitations of AFVs, related to range, acceleration and recharging, that have to be removed before other measures are applied (Ewing and Sarigöllü, 2000; Ahman, 2006; Hidrue et al., 2011).

Social exposure

Consumers are social beings, and therefore the development of their perceptions and purchase decisions are part of a social process (Axsen and Kurani, 2012). Social exposure has been shown to be determinant for consumers' adoption of new vehicle technologies (Al-Alawi and Bradley, 2013). Evidence was found that consumer preferences for emerging pro-environmental technologies can be formed through learning and exposure. The social exposure involves an interaction of internal and external factors that, by influencing consumers' adoption decisions, affects the diffusion of new products (Delre et al., 2010). Ignoring or underestimating these factors will affect the potential for understanding the consumers' decision-making process.

Internal factors correspond to the Word-of-Mouth (WOM), i.e. interpersonal influences of consumers' thoughts, feelings or actions that are affected by other consumers (Axsen et al., 2013). In market research WOM is described by the influence of advice from other consumers (East et al., 2007). WOM has been considered an important contributor for consumers' final purchase decision, in some cases more influential than other promotional methods (Bayus, 1985). This high influence can be explained by the absence of commercial bias (East et al., 2007) and from the search of consumers for social support for product adoption or no adoption (Arndt, 1967). WOM can affect positively or negatively consumers decisions, depending on whether it is favourable or unfavourable, respectively (Arndt, 1967).

In an electronic era, the transmission of WOM does not have to occur in a direct manner, face-to-face. In fact, there is evidence that opinions and references through electronic bulletin boards or social networks work analogously to traditional face-to-face WOM

(Buttle, 2011; Thorbjørnsen et al., 2015). The effect of WOM on AFVs diffusion has been considered as one of the most important factors to boost the perceived reliability and safety of innovative vehicle technologies (Dutschke et al., 2011). Studies that analyzed the influence of WOM on AFVs adoption found a significant and positive impact. Focused on AFVs, consumers were found to be more willing to adopt an AFV after reading favourable reviews (Nixon and Saphores, 2011; Zhang, Gensler, et al., 2011) and other studies focusing specific vehicles reached the same conclusion. Zhang, Yu, et al. (2011) concluded that the positive opinion of peers affects positively the BEVs purchase, and Hsu et al. (2013) concluded that WOM through social media significantly influences the HEVs market share. These results support that WOM is an influential factor to a fast diffusion of innovations.

There are several **external factors** that may influence consumer preferences for innovative technologies. Two of them, the so-called “neighbour effect” and marketing, are analyzed next. “Neighbour effect” is a term employed by Mau et al. (2008), that defined this effect as the tendency for consumer preferences to change as the technology becomes more prevalent in the market, at the time of diffusion of new technologies. The purpose of the quantification and analysis of this effect is to understand the preference dynamics involved in simulation models. If a positive relation is found additional motivation will be provided for governments to support the diffusion of vehicle new technologies (Mau et al., 2008). A study carried out by Grinblatt et al. (2007) in Finland, found that vehicle purchases by neighbours significantly influence the consumer`s decisions when they purchase a vehicle. This influence was dominated by the nearest neighbours and it lasted for short periods of time. A study focused on FCVs found that consumer preferences show different social needs on their purchase decision which are influenced by neighbours (Schwoon, 2006). This study underlined that consumers take into account their neighbours’ decisions more seriously because vehicles are considered prestige goods. Later, Mau et al. (2008) developed a study in Canada focused on the analysis of the absence or presence of this effect on HEVs and FCVs demand. This study verified that consumer preferences between HEVs and conventional technologies changed with market conditions. Consequently, they reported that an increase in a new technology market share led to higher preferences for that new technology while the consumer preferences for FCVs did not support the neighbour effect.

Two studies focused on HEVs corroborated Mau et al. (2008)'s findings. Axsen et al. (2009) developed a study to assess the "neighbour effect" in Canada and the US and found the consumers' willingness to pay for an HEV increases with the market penetration of these vehicles. Heutel and Muehlegger (2009) found that HEVs penetration rates significantly influence new HEVs purchases but for different reasons. They argue that consumers link high market penetration of HEVs to the development of more complementary services for these vehicles. Jansson et al. (2017) verified a neighbour effect on AFVs adoption, where AFVs would be more likely purchased if neighbours would have also purchased one.

Finally, marketing has been explored as one possible strategy that may influence the penetration rate of AFVs (Kurani and Turrentine, 2002). The absence of a skilled and committed marketing plan may compromise the effectiveness of appropriate policies that aim at increasing the market penetration of AFVs. This is mainly because consumers have to be aware of the vehicle characteristics before being persuaded with incentives to purchase new vehicle technologies (Garling and Thogersen, 2001). However, an appropriate marketing plan should not be limited to advertising and product descriptions, as it may not be considered enough to provide the information that consumers need to make vehicle purchase decisions. Therefore, this plan should also provide information from consumer magazines reporting the reliability of the AFVs (Urban et al., 1996). This information was corroborated by Axsen et al. (2013) that concluded that purchase of BEVs was influenced by media sources such as television programs of vehicles, magazines and newspapers.

2.4. Concluding remarks

The literature focused on consumer preferences for AFVs is extensive and since the early 80s it has been an active area of research. From the reviewed studies some remarks can be made:

- CA methods are the most common methodologies to assess individual consumer preferences for AFVs;
- Demographic characteristics influence consumer preferences for AFVs although the direction of that influence is not always clear;
- Preferences of Portuguese consumers were never analyzed at the individual or aggregated level;
- Consumer choice models, ABM and SD are the three methods most commonly used to analyse AFVs diffusion;
- Purchase price, range and charging time are the main technology-related factors that influence BEVs demand;
- Context-related factors have a significant impact on the AFVs diffusion, e.g. fuel price, charging infrastructure, government policies and social exposure.

The definition of the research approach of this thesis had these remarks into account in order to ensure that the developed analyses contribute to the literature on the consumer preferences field, at the empirical and at the methodological level. At the methodological level an alternative preference method was applied to assess consumer preferences for AFVs in order to corroborate the use of the traditional approach (CA) or to suggest an alternative approach. At the empirical level the analysis of Portuguese consumers' preferences was made and the influence direction of demographics characteristics on their preferences was assessed.

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CHAPTER 3

Preference data collection

The research strategy defined for this study, by involving the implementation of preference elicitation methods, required the collection of data from consumers of the targeted market, i.e. consumer preferences for EVs in Portugal. The implementation of a survey is the most common approach to collect preference information from consumers when the product to be studied is not available in the market or when its presence is scarce. As this is the case of EVs in Portugal, a survey was used as a data collection tool. This survey had to be designed from scratch in order to collect the required data to elicit preferences for the consumer preference models from CA and MCDA methodologies.

The survey design is a time-consuming process that frequently involves trials or pre-tests that allow identifying which adjustments are required before the design of the final survey. As CA methods have well-established survey design processes, with available software designed for this purpose (e.g. XLSTAT®, Sawtooth®, Survey Analytics®), several trials were focused on selecting the most appropriate strategy to collect MCDA preference data.

As mentioned in subsection 2.1.1, SP surveys are the most common and appropriate tool to collect preference data for non-introduced or non-established products in the market. Therefore, this study applied a SP survey to collect the required preference data.

This chapter presents the data collection process (§3.1), the description of the survey trials concerning the MCDA methodology (§3.2), the selection process of the alternatives and attributes required for the final survey design (§3.3) and the description of the tasks included in the implemented final SP survey (§3.4).

3.1. Data collection

The sample was drawn on a convenience basis, considering two selection criteria: consumers should be older than 18 years old and should be potentially vehicle buyers in the short-medium term. The use of convenience samples allows gathering data from a group of consumers with more interesting characteristics for the study purposes, but it has the drawback of potentially not being representative. However, as mentioned in subsection 2.1.2, very few studies sought representative samples.

The survey was implemented through face-to-face interviews. This data collection process, although demanding more time, had several advantages when compared with email or online surveys, namely allowing the interaction with the interviewer in real time and to ensure that respondents understood the questions. These underlines why several studies chose to gather data about consumer preferences through personal interviews (Mills, 2008; Dagsvik and Liu, 2009; Zhang, Yu, et al., 2011; Achtnicht et al., 2012) instead of using some available online data collection software.

3.2. MCDA data selection process

Considering the diversity of MCDA methodologies, MAUT was selected as it is one of the most widely used multicriteria methodologies (Belton and Stewart, 2002), namely in preference assessment in the environment-related field (see further in subsection 4.1.1.1). A review of MAUT applications in energy and environmental modelling shows that, under the analyzed application areas, MAUT was applied more often to assess preferences about energy utility operations and management, and energy-related environmental control (Zhou et al., 2006). MAUT has been also applied to analyse preferences regarding natural resource management problems (Bell, 1975; Teeter and Dyer, 1986; Pukkala, 1998; Prato, 1999; Ananda and Herath, 2005). Another reason to choose MAUT is that it allows trade-offs among the attributes in a way that is similar to CA approaches also used in this research.

MAUT rests on the assumption that a decision maker maximizes a function that aggregates all the attribute utilities[5] of each alternative into a global evaluation for that alternative (Bous et al., 2010). MAUT assumes that there exists a utility function that represents the consumer preferences, often considering an additive aggregation. Considering the commonly used additive MAUT model, the global utility of an alternative a for each consumer c, $U_c(a)$, is a weighted sum of the attribute utilities according to the following equation (Keeney and Raiffa, 1993):

$$U_c(a) = \sum_{k=1}^{n} w_{kc} u_{kc}(a) \tag{3.1}$$

Where,

n is the number of attributes

w_{kc} is the weight (scaling constant) of attribute k for consumer c;

$u_{kc}(a)$ is the single-attribute utility of alternative a in the attribute k for consumer c.

The utility function model (Keeney and Raiffa, 1993) assumes that, for any two alternatives a_i and a_j (for simplicity the index *c* relative to the consumer is omitted henceforth):

a_i is preferred to $a_j \Leftrightarrow U(a_i) > U(a_j)$

a_i is indifferent to $a_j \Leftrightarrow U(a_i) = U(a_j)$

When assuming the existence of an additive utility function, MAUT also requires the assumption of preferential independence among the attributes. This means that the preference of one alternative over another does not depend on the value they have in some of the attributes, if both alternatives have the same performance level in these common attributes (Keeney and Raiffa, 1993).

[5] The word utility is used in this work in a generic way, not distinguishing between value functions and utility functions (this work does not involve lotteries).

Let $g_k(a_s)$ denote the performance of the alternative a_s (s = 1,2, … , m) on the attribute k (k = 1,2, … , n). A performance table (Table 3.1) summarizes the performance measures of the alternatives being analyzed according to the selected attributes.

	$g_1(.)$	$g_2(.)$	…	$g_n(.)$
a_1	$g_1(a_1)$	$g_2(a_1)$	…	$g_n(a_1)$
a_2	$g_1(a_2)$	$g_2(a_2)$	…	$g_n(a_2)$
…	…	…	…	…
a_m	$g_1(a_m)$	$g_2(a_m)$	…	$g_n(a_m)$

Table 3.1 - Performance table.

The preference elicitation process can be performed using different methods. After selecting and applying an elicitation method for the single-attribute utility functions one obtains the utility of each alternative for each attribute, $u_k\big(g_k(a_s)\big)$, which for simplicity can be written as $u_k(a_s)$. Table 3.2 summarizes these utilities, where $u_k(a_s)$ is the single-attribute utility of the attribute value k of alternative s. Similarly, a weights elicitation method allows obtaining the other input of equation (3.1), w_k. Afterwards a global utility for each alternative is computed and the ranking of the alternatives set according to the MAUT method is obtained.

	$u_1(.)$	$u_2(.)$	**…**	$u_n(.)$
a_1	$u_1(a_1)$	$u_2(a_1)$	…	$u_n(a_1)$
a_2	$u_1(a_2)$	$u_2(a_2)$	…	$u_n(a_2)$
…	…	…	…	…
a_m	$u_1(a_m)$	$u_2(a_m)$	…	$u_n(a_m)$

Table 3.2 - Table summarizing the single-attribute utilities for each attribute of each alternative.

Following these basic concepts of MAUT, a survey design was progressively adapted (variants A to D), in order to conceive a MAUT elicitation procedure that would allow gathering suitable preference data for analysis. The suitability of each preference dataset was analyzed through different criteria explicitly described below for each survey.

While the first two surveys (A and B) allowed setting the basic definitions of the performance table, i.e. alternatives and attributes, the last two surveys (C and D) allowed defining the techniques to elicit single-attribute utilities and weights. Each of these surveys is described in the following paragraphs, which also explain the factors that were taken into account in designing the subsequent survey.

3.2.1. Survey A

In Survey A consumers were not given a performance table to assess a set of alternatives. Instead, they were asked to build their own performance table. With that purpose they were asked to point out at least five attributes to distinguish the vehicles set, which comprised eight specific existing vehicles in Portugal: Nissan Leaf (BEV), Opel Ampera (BEV), Renault Fluence ZE (BEV), Renault Fluence 1.5 dci (ICE), Toyota Auris 1.4 D-4D (ICE), Toyota Auris 1.6 valvematic (ICE), Toyota Auris 1.8 hybrid (HEV) and Toyota Prius. After the attributes were chosen, the performance of each attribute for each of these vehicles was displayed by the analyst resulting on the construction of a performance table for each consumer. Direct rating, was chosen to elicit single-attribute utilities. It consists in defining a numerical value to assess the utility of each alternative performance of each attribute. These performances are rated on the given attribute's scale reflecting the value of an alternative in relation to the defined reference points (Belton and Stewart, 2002; Goodwin and Wright, 2010). The Swings method was used in order to elicit weights. In this method, weights are derived by asking to each consumer to compare a change from the worst value to the best value on one attribute to a similar change in another attribute (Belton and Stewart, 2002; Goodwin and Wright, 2010).

Two main problems with Survey A data were identified. First, based on some comments from consumers, such as "*I would never buy this ugly car*", "*All my life I had Opel cars*", "*I would never buy a Toyota*", etc., the existence of a bias was observed regarding the brands of the vehicle set, where affect for a brand can be an overwhelming factor for consumers. And second, the use of a customized performance table for each consumer brought difficulties in the comparison of data, i.e. the obtained ranking of the alternatives cannot be directly compared between consumers because the elicited preferences were based in different attributes among consumers. Nevertheless, this survey was useful to identify which attributes are more relevant to consumers.

3.2.2. Survey B

In order to solve the two main identified problems in Survey A, two main changes were implemented in Survey B. The first change was the a priori definition of the attributes' set (its selection is described later in this chapter, in subsection 3.3), which allowed providing the same performance table to all consumers. The second change was a vehicle set that comprised anonymous vehicles instead of specific ones, namely BEV, PHEV, HEV, Diesel and Gasoline, in order to avoid any bias regarding the alternatives' brands. Respondents were instructed to consider all the vehicles were similar except for their powertrain. As the performance table design was re-structured from Survey A to Survey B the elicitation methods used in the previous survey were not changed.

This survey succeeded in focusing the respondents' attention on the powertrain attributes. However, the single-attribute utilities obtained through direct rating were not satisfactory to use in this work, because consumers tended to provide round ordinal scores, e.g. assigning a utility of 10 for the best vehicle on a given attribute, a utility of 9 for the second best vehicle, etc.

3.2.3. Survey C

In survey C the performance table was kept the same as in Survey B but, due to the elicitation problems identified in Survey B, the method used to elicit single-attribute utilities was changed and the bisection method was used instead. This method is suitable for continuous attributes and it is simple to apply, allowing nonlinear functions. The bisection method is an indirect assessment of the attributes' utility functions and it assumes that these functions are monotonically increasing or decreasing, if the attribute is to maximize or minimize respectively (Belton and Stewart, 2002). As the bisection method builds a utility function for each attribute, consumers could visualize the utility function graphs, giving them the opportunity to revise the assigned values when they did not agree with the shape of the function. The Swings method remained as the weights elicitation technique.

One question was added in this survey about whether consumers agree or not with the ranking obtained by the MAUT model elicited according to their preferences. In case of disagreement, consumers were allowed to adjust the MAUT ranking to obtain a Final Reference Ranking that represents their preferences regarding the vehicles set. Thus, the Final Reference Ranking is the ranking obtained through the MAUT elicitation process, if the consumer agrees with it, otherwise it is a modification of the raking that better represents the consumer's holistic preferences.

In order to derive conclusions about the quality of preference data, a preference disaggregation method, UTA (Utility Theory Additive), was applied. UTA is a preference disaggregation (Jacquet-Lagrèze and Siskos, 2001) (or ordinal regression (Greco et al., 2008)) approach, which assumes that the consumer attempts to maximize an additive utility function that aggregates all the attributes utilities of each alternative into a global evaluation (Bous et al., 2010). As the method used to elicit preferences assumes that preferences are additive, the UTA inference enables to analyse if an additive utility function could reconstitute the Final Reference Ranking, here considered as the representation of consumers holistic preferences.

The UTA inference consisted in verifying if single-attribute utilities and attribute weights could be inferred in order to achieve the Final Reference Ranking of each consumer (the mathematical formulation is given in Appendix VI). The inference results showed that UTA was able to successfully reproduce the Final Reference Ranking of 90% of consumers. Although the inference results can be considered satisfactory, the inability of representing preferences by an additive utility function for all the consumers might be a matter of concern. By analysing further the survey data, it became clear that many consumers clearly did not understand the swings method, even though the instructions had been improved since the first survey that applied this method (Survey A). Consumers commonly confounded the scaling weights with the intuitive importance of each attribute by for instance giving the highest score to the attribute they considered more relevant, the second higher to the attribute they considered the second most relevant attributes and so on, but disregarding the ranges represented by the swings. Hence, these data were excluded from further analysis and a new survey (D) was developed.

3.2.4. Survey D

Considering the good inference results from the Survey C, the design of the Survey D was kept unchanged with the exception of the elicitation method for the attributes' weights. In this new survey, the trade-offs method was used instead. According to this method, given a pair of alternatives that differ in only two attributes, consumers were asked to perform a matching task consisting in the adjustment of one attribute level of one of the alternatives such that the alternative became as attractive as the other one (Keeney and Raiffa, 1993). The purpose of this approach is to find pairs of values of two attributes such that these outcomes are indifferent for the consumer, i.e., these outcomes are equal in utility, from which the attribute weights ratio (trade-off rate) is derived.

Also using the Final Reference ranking of each consumer, the analysis of the quality of the preference data was again assessed through an UTA inference of the single-attribute utilities and weights, using the same inference formulation. By having a 100% of UTA inference success, the results showed the possibility of representing the consumer holistic preferences for all consumers. For this reason, the consumers' preference data collected with this survey (219 respondents) was selected for further analysis in the next two chapters.

3.3. Description of alternatives and attributes selection

As this study is focused on EVs, the selected alternatives included all the EVs types currently available in the Portuguese market, namely BEVs, PHEVs and HEVs. For comparison purposes two ICEVs vehicles were also included, Diesel and Gasoline vehicles. The inclusion of vehicles that are at consumers' disposal in a purchase context allows collecting data in a similar framework to a real purchase experience. The final alternatives set included two BEVs versions that differed only on price and range value, BEV1 is cheaper than BEV2 but it has a lower range. The reason for having two BEV versions was verifying whether a higher range but more expensive BEV would be preferred to the current version of BEV available in the Portuguese market.

The brand and model of the vehicles were kept anonymous to avoid the influence of brand loyalty on preference judgements. With the exception of Glerum et al. (2014), who focused their analysis on a specific single brand of vehicles, all the previous studies chose to use unbranded vehicles in their analysis.

In SP studies the appropriate selection of attributes and attribute values is an important feature. This choice is not arbitrary as it needs to account for several aspects, such as selecting a small number of attributes in order to minimize the estimation efforts, choosing realistic attribute levels and selecting attributes that are relevant and related to the chosen subject (Sattler and Hensel-Borner, 2007). In this context, there are several strategies to select a suitable attributes set. Previous studies focused on analysing consumer preferences for AFVs allowed identifying that the most common strategy to choose attributes is through a review of previous studies (Golob et al., 1993; Graham and Little, 2001; Potoglou and Kanaroglou, 2007b; Hensher and Greene, 2011; Mabit and Fosgerau, 2011; Chorus et al., 2013; Hoen and Koetse, 2014). On the other hand, surveys have not been frequently used to select attributes, because surveys are a more time consuming process, from the design, to data collection and data analysis.

For this study, attributes were selected through the free elicitation procedure included in Survey A as this procedure is considered to produce good results (Steenkamp and van

Trijp, 1997). The consumers' answer to the question "*Point out at least five attributes that allow you to distinguish the vehicles comprised in the alternatives set*" was used as dataset. This data was further analyzed in order to identify the main attributes across the sample. Consumers were told that the attributes did not have to be directly related to the specific vehicles involved, referring, for instance, the possibility of having reserved parking spots for electrics or hybrids was allowed. Afterwards, in order to identify the main attributes, simple linguistic categorization techniques were applied, where verbal data collected by open questioning allowed categorizing the mentioned attributes by merging different designations for the same category (characteristic). If a consumer mentioned two or more attributes that were categorized inside the same category they were only counted once. In total around 1800 attributes were mentioned that were organized in eighteen categories (Table 3.3).

The analysis of the frequency of each attribute revealed that the most mentioned attribute categories were "vehicle design" (17% of the mentioned attributes), "purchase price" (16%), "fuel/electricity consumption" (13%) and "performance" (11%) (Figure 3.1). However, considering the purpose of differentiating vehicle technologies and the frequency with which each attribute was mentioned the following attributes were selected:

- Purchase price: cost to acquire a vehicle;
- Fuel/electricity consumption (hereafter abbreviated to fuel consumption): cost to drive 100 km;
- Range: distance that can be driven without fuelling/charging the vehicle;
- CO_2 emissions: quantity of CO_2 emissions released to the environment during the usage phase of the vehicle.

Previous studies corroborate that the selected attributes are among the most used in studies that assess consumer preferences for electric vehicles, showing that the attributes selection was within the scope of the related studies in this field (e.g. (Bunch et al., 1993; Ewing and Sarigöllü, 2000; Potoglou and Kanaroglou, 2007a; Hidrue et al., 2011; Qian and Soopramanien, 2011; Hackbarth and Madlener, 2013; Jensen et al., 2013). The type of engine was added to the list of attributes in order to distinguish the vehicle technology of each alternative.

Category	**Attributes mentioned in the interviews**						
Purchase price	price	relation equipment/price					
Performance	engine capacity	power	horsepower	acceleration	top speed	fast	etc.
Dimension	trunk capacity	big	length	family vehicle	dimensions for cities	small cars to park	etc.
CO_2 Emissions	cars that are not pollutants	ecologic	environmental friendly	environmental advantages	environmental performance	carbon emissions	etc.
Comfort	comfortable	interior space	interior quality	big inside	Cabin	upholstery	etc.
Maintenance costs	exploitation costs	running costs	maintenance and technical assistance	maintenance price	price of service	extra expenses	etc.
Design	body type	exterior design	modern design	nice design	attractive	elegance	etc.
Fuel/electricity consumption	economy	average consumption	economy of consumption	very good consumption	low consumption of fuel	consumption of cars	etc.
Range	availability for large journeys	battery range					
Brand visibility	notoriety of brand	specialty magazines	brand reputation	status	brand prestige	extras (quality/status)	etc.
Safety	stability	ABS	extra equipment	assisted driving			
Warranty	warranty extension	warranty duration	warranty years	warranty and brand support			
Number of charging stations	ease of supply	some reservations regarding EV purchases	few places to charge cars which affects the purchase	charge points	absence of places to charge hybrid cars	access to refuelling	etc.
Existence of incentives	tax incentives	government aid	state incentives	taxes (circulation, insurance)			
Fuel price	monthly bill	savings fuel/electricity	operation costs	daily costs	lower price of fuel	global costs (or costs/km)	etc.
Reliability	high reliability	technical aspects	proven market	functionality	longevity	accessories	etc.
Innovation	innovative technology	existing technology in the vehicle	automatic gearbox	technology (accessories)	additional features (parking sensors)	technology (GPS, remote control)	etc.
Brand loyalty	trusted brand	brand sympathy	technical assistance of brand	I don't like brand X	brand credibility	my family always bought brand Y	etc.

Table 3.3 - Examples of the categorization process of the mentioned attributes.

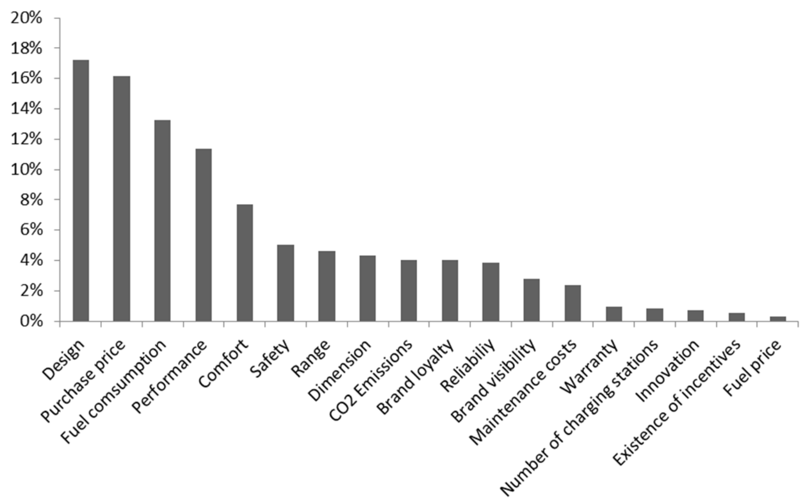

Figure 3.1 - Frequency of each attribute category.

3.4. Description of the SP survey

As explained in subsection 3.2, the dataset used to model consumer preferences was collected by Survey D. The specific survey design was defined in order to collect stated preference data that would enable to fulfil the research goals described in Chapter 1. The outlined scenarios and tasks in Survey D are described below.

3.4.1. Scenarios definition

As one of the goals of this research is to analyse the influence of dynamic preferences on EVs diffusion, future preference data was collected in addition to current preference data. This type of data collection can follow one of two commonly used strategies. One consists in tracking consumers' preferences over a short-medium period of time. This approach proved to be useful for low-investment products, such as a packaged good (Lachaab et al., 2006) or high technology products with short life cycles, such as mobile phones (Meeran et al., 2017). The other strategy consists in simulating future market conditions in order to collect preferences that may be revealed when that hypothetical market conditions are in place. According to this strategy, current and future preferences are collected in the same time period. This strategy was used in several studies applied to AFVs. Mau et al. (2008) and Axsen et al. (2009) used several resources to simulate future market conditions, such as future manufacturers' brochures, fictional appraisals of AFVs from different users and information of fictional market penetration of AFVs. Musti and Kockelman (2011) used two future scenarios in order to analyse the evolution of the fleet composition, namely a scenario with higher fuel prices and a scenario with environmental impact information.

Acknowledging the long life cycle of vehicles and the frequent use of the second strategy in the transportation field, future consumer preferences were collected in Survey D by simulating future market conditions, i.e. a hypothetical future scenario was designed. This scenario assumed that EVs sales take off and, as a consequence, manufacturers of fuelled vehicles try to mitigate ICEVs disadvantages in order to still be competitive with EVs. This context led to the following specific changes to the vehicle characteristics: more affordable BEVs price, higher fuel prices, lower CO_2 emissions of fuelled vehicles and lower fuel consumption (as result of more fuel efficient engines), and a higher BEVs range.

Regarding the current scenario, the characterization of each vehicle was based on real attribute values from vehicles that exist in the Portuguese market. These vehicles were chosen ensuring that they were similar in the attributes not included in this study (e.g. size, body, and comfort).

Considering the attributes and alternatives selection a performance table was built for the current and future scenarios, Table 3.4 and Table 3.5, respectively.

Type of engine	Price (€)	Range (km)	Fuel consumption (€/100km)	CO_2 Emissions (g/km)
BEV1	29,000	180	2	50
BEV2	31,000	250	2	50
HEV	27,000	1100	5	110
Gasoline	24,000	800	9	150
Diesel	27,000	1200	6	120
PHEV	34,000	1200	3	90

Table 3.4 - Performance table for the current scenario.

Type of engine	Price (€)	Range (km)	Fuel consumption (€/100km)	CO_2 Emissions (g/km)
BEV1	25,000	250	2	40
BEV2	30,000	600	2	40
HEV	27,000	1200	7	80
Gasoline	24,000	900	12	120
Diesel	26,000	1200	8	90
PHEV	29,000	1200	4	70

Table 3.5 - Performance table for the future scenario.

3.4.2. Survey tasks

The survey comprised six main tasks to be performed by each consumer (Appendix VIII):

1. Task 1: Demographic data collection
2. Task 2: Initial ranking of vehicles
3. Task 3: CBC exercise
4. Task 4: MAUT exercise
5. Task 5: Final ranking of vehicles
6. Task 6: Repetition of CBC exercise

Data was collected in two different interviews. Data for Tasks 1, 2 and 3 was collected in the first meeting. In the second meeting, data for the last three tasks was collected. A more detailed description of each task is presented below.

Task 1 – Demographic data collection

This task collected data about consumers' characteristics and their vehicles. Consumers were asked about the following information:

a. Age;
b. Gender;

c. Level of Education, among the options "No higher education", "College degree", "Master's degree" and "PhD degree";
d. Current vehicle brand/model and age;
e. Main use of the vehicle, choosing between "City" and "Intercity" routes;
f. Number of kilometres driven per trip and per year;
g. Knowledge about EVs (BEVs, PHEVs and HEVs);

Task 2– Initial ranking of vehicles

Based on the specific alternatives of each scenario (performances table) and on a more extensive description of each vehicle (Appendix VII) consumers were asked to rank the vehicles set (six vehicles in total) according to their preferences. Consumers were instructed to consider that these vehicles were equal on all the attributes not listed (brand, size, etc.). This ranking is hereafter called *Initial Reference Ranking*.

Task 3 – CBC exercise

The design of CBC questions encompasses several steps that were followed in this study, namely the selection of attributes; the assignment of attribute levels (values); the choice of a preference elicitation method; the choice of experimental design and, finally, the definition of SP questions (Kotri, 2006; Kuhfeld, 2010). As the attributes were already selected, the first step was the definition of levels. This definition had to consider several aspects (Hanley et al., 2001; Kotri, 2006) such as being realistic, i.e. close as possible to real products values; non-linearly spaced and allowing to capture non-linear utility functions within attributes by defining more than two levels for each attribute. As specific alternatives sets were considered (alternatives for current scenario and future scenario in Table 3.4 and Table 3.5, respectively), the attribute levels were defined in order to be as similar as possible to the alternatives' attributes values. This procedure ensured that the chosen levels were close to the real-life context that consumers face when purchasing a vehicle (Kotri, 2006). The attribute levels are depicted in Table 3.6 and Table 3.7, for the current and future scenario respectively.

Attribute	*Levels*
Type of engine	BEV / PHEV / HEV / Diesel / Gasoline
Price	24,000€ / 27,000€ / 30,000€ / 32,000€ / 34,000€
Range	150 km / 250 km / 350 km / 900 km/ 1200 km
Fuel consumption (per 100 km)	2€ / 4€ / 6€ / 8€ / 10€
CO_2 emissions (per km)	50 g / 90 g / 110 g / 130 g / 150 g

Table 3.6 - Attribute levels for the current scenario.

Attribute	*Levels*
Type of engine	BEV / PHEV / HEV / Diesel / Gasoline
Price	22,000€ / 24,000€ / 26,000€ / 28,000€ / 30,000€
Range	250 km / 400 km / 600 km / 900 km/ 1200 km
Fuel consumption (per 100 km)	2€ / 4€ / 7€ / 9€ / 12€
CO_2 emissions (per km)	40 g / 60 g / 80 g / 100 g / 120 g

Table 3.7 - Attribute levels for the future scenario.

Regarding the choice of the elicitation method, among CA elicitation methods, CBC was chosen because the data collection, by consisting in simulated purchase decisions, is considered to be more realistic and simple than providing product ratings (Jaeger et al., 2001; Borghi, 2009) and also due to extensive use in the literature to analyse consumer preferences for AFVs (see subsection 2.1.1). However, instead of asking to choose only the most preferred alternative, consumers were also asked to choose the least preferred alternative among a set of three, i.e. a Best-Worst choice analysis was applied and, as a result, a ranking of the three vehicles in each choice set was obtained. This type of questions have been considered easier to answer than complete rankings of all the alternatives and, therefore, considered to elicit more reliable preference data (Smith et al., 2017). This elicitation approach has been common in previous studies in the field (Dagsvik et al., 2002; Train, 2008; Dagsvik and Liu, 2009; Hensher and Greene, 2011; Hoen and Koetse, 2014; Smith et al., 2017).

The experimental design of CA studies can take one of two forms, a full factorial design (or full profile design) or a fractional factorial design. A full factorial design consists in presenting the consumer with all the possible combinations of the attribute levels, and therefore entails a tedious and cost-prohibitive process by having consumers considering so many combinations (Kotri, 2006). If a full-factorial design was considered in this study, each consumer would have to assess $3125=5^5$ product profiles (different combinations of attribute levels), which would be impossible to achieve. Therefore, this study applied the second form of experimental design, the fractional factorial design, where only a few products are assessed by each consumer. The number of products is computed according to the minimum necessary to estimate efficiently preferences of different attributes on the dependent variable, i.e. the SP of purchase a product (Kotri, 2006; Kuhfeld, 2010). As possible unrealistic combinations might occur in this process, some prohibitions were defined in order to make this task as realistic as possible (Appendix IX). When fractional design is selected the constructed product combinations have to be grouped before being presented to consumers. As consumers generally have limits on their ability to process information the number of questions should not be too high or too difficult because it may compromise the acquisition of quality data (Carson et al., 1994). Fatigue or boredom from consumers due to answering to a lot of questions will increase the probability that their answers exhibit high levels of randomness (Day et al., 2012). As this is a highly complex process, the definition of SP questions was made through Sawtooth® software. The final design comprised 8 versions of SP surveys with 9 CBC questions each, which were randomly assigned to each consumer. Each CBC question comprised three vehicles to indicate which one was the most and which one was the least preferred alternative in each triplet according to his or her preferences. Consumer preferences obtained through this exercise were elicited through CBC/HB (see further subsection 4.1) that had as output a ranking hereafter called *CBC Initial ranking*.

Task 4 – MAUT exercise

After an analysis of the performance table (Table 3.4 or Table 3.5 according to the assigned scenario) consumers underwent an elicitation process to derive single-attribute utilities (the utility functions), and then the weight for each attribute. The single-attribute utilities were obtained through the bisection method. With this purpose, the maximum and minimum performance utilities of each attribute were defined, so that all attributes have performance utilities within the same interval. Next, consumers had to define which performance value would split the full range interval in two in terms of utility (Table 3.8), such that when the performance value changes from the minimum performance (utility=0) to the midpoint performance the added utility is the same as changing from that midpoint performance value to upper performance (=10). This performance corresponded to the utility of 5. Then, the same process was repeated to bisect the interval values [0, 5] and [5, 10] (Fishburn, 1967; Belton and Stewart, 2002).

Level	Range
10	1300 Km
7.5	?
5	?
2.5	?
0	150 Km

Table 3.8 - Bisection method for range attribute.

Regarding the computation of the attribute weights, the trade-off method was used. The attribute weights task consisted in the adjustment of pairwise comparisons in order to obtain the mentioned equalities between attribute values. For the example in Figure 3.2 the following question would be asked: *"Would you prefer a vehicle costing 30,000€ with a range of 1000km or a vehicle costing 25,000€ but with a lower range of 800km"*. If the consumer preferred the alternative on the left, then the question would be repeated considering a lower price for the alternative on the right. Otherwise, the price of the alternative on the right would increase. The process continues by trial-and-error until the consumer is indifferent between the two alternatives. This defines a ratio between two weights, per equation (3.1.), since if the consumer states that ($u_{price}(x), u_{range}(x)$) is indifferent to ($u_{price}(y)$, $u_{range}(y)$) then it must hold that

$$w_{price}u_{price}(x) + w_{range}u_{range}(x) = w_{price}u_{price}(y) + w_{range}u_{range}(y),$$

$$\text{i.e., } w_{price} = w_{range}\left[\frac{u_{range}(y)-u_{range}(x)}{u_{price}(x)-u_{price}(y)}\right]$$

After the process of elicitation of preference data was over, the Excel template computed the global utility for each vehicle, resulting in a ranking of the six vehicles, hereafter called *MAUT Ranking*.

	Price €	Range Km		Price €	Range Km
Trade-off Price vs Range	30,000	1000	⟺	**25,000↑↓**	800

Figure 3.2 - Example of trade-off task between attributes price and range.

Task 5 – Final ranking of vehicles

After a ranking of the six vehicles set was obtained in the previous task, the consumer was given the opportunity of revising the obtained ranking according to his/her preferences. This ranking is hereafter called *Final Reference Ranking*.

Task 6 – Repetition of CBC exercise

After completing the MAUT exercise, each consumer was asked to answer again to the same CBC questions set (nine questions) of the Task 3 of the survey that had been asked in the first meeting. Consumer preferences obtained through this exercise were elicited through CBC/HB (see further subsection 4.1) that had as output a ranking hereafter called *CBC Final ranking.*

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CHAPTER 4

Analysis of consumer preferences

Consumer preferences can be modelled through aggregation, segmentation and individual-level models. The selection of the model is dependent on the specific goals of each research and/or on the preference pattern that may emerge from the consumers included in the analysis (Kotler, 2000). In this context, aggregation models are more suited when the research goal is to define a global marketing strategy for a specific market. Segmented models should be selected when the segmentation of the market is of interest to marketeers. Individual-level models are appropriate when the variance among consumers is large, i.e. when there are high levels of heterogeneity among consumer preferences (Kotler, 2000).

According to the defined research goals of this study, two models were applied: individual-level models (subsection 4.1) and aggregation models (subsection 4.2).

4.1. Individual preferences

The analysis of preferences at the individual level allows the consideration of different consumer preferences sensitivities (Rossi et al., 2005), provides the identification of consumption patterns (Arora et al., 1998) and usually has high validity levels of individual-level preferences (Moore, 2004).

Considering individual preference data three specific analyses were performed addressing specific goals:

1. Comparison of preference models: to provide a novel comparison between CBC and MAUT in order to verify which method better represents the consumer preferences for EVs (§4.1.1)

2. Learning effects on preferences: to understand the potential impacts of using a MAUT preference elicitation method on elicitation of preferences through CBC (§4.1.2)
3. Influence of demographics on preferences: to identify if preferences for EVs are influenced by consumer demographics (§4.1.3)

The analysis of individual preferences was performed through two preference elicitation methods, CBC/HB approach and a MAUT based approach.

CBC/HB was selected because it allows analyzing data at the individual level, by considering each consumer as random sample from an underlying population (Borghi, 2009). As the preference data derived from these two methods was used in the three analyses, and considering that the MAUT elicitation was described in Chapter 3, the description of CBC/HB model and its elicitation procedures is presented next.

CBC/HB models consumer preferences as a function of an upper-level model (pooled across consumers) and a lower-level model, at the individual level (pooled within-consumer) (Orme and Howell, 2009). The upper-level model gives the variation of consumer's preferences and the variation in their part-worths over the population (Lenk et al., 1996):

$$Y_c = X_c \beta_c + \epsilon_c \tag{4.1}$$

$$\beta_c = \Theta z_c + \omega_c \tag{4.2}$$

In equation (4.1), Y_c represents a vector of m_c metric responses for consumer c (c = 1,2, ... l) to the profiles described by a given design matrix X_c. β_c is the p-dimensional vector of regression part-worths for consumer c. Equation (4.2) represents the heterogeneity of each consumer by giving individual-level part-worths via multivariate regression model with q-dimensional covariates, z_c, and Θ, a p by q matrix of regression coefficients. The error terms ϵ_c and ω_c are assumed to be mutually independent (Lenk et al., 1996). To allow a fair comparison between the two methodologies it was decided to use as model inputs only the SP answers from the surveys excluding other inputs, namely demographic variables, unless otherwise stated. Therefore, the analysis of consumer preferences considered the simplest case of equation (4.2) where z_c is equal to 1, which transforms this equation in the standard random-effects distribution for β_c (Allenby and Ginter, 1995) and Θ in the mean vector for the part-worths.

At the lower-level model, the consumer is assumed to choose the alternative that yields the maximum utility. The global utility of an alternative for the consumer c, $U_c^{CBC}(a)$, is obtained by adding up the part-worths β for the attribute levels j that describe that alternative according to the following equation (Malhotra, 2008):

$$U_c^{CBC}(a) = \sum_{k=1}^{n} \sum_{j=1}^{p} \beta_{kjc} X_{kj}(a) \tag{4.3}$$

Where,

β_{kjc} is the part-worth utility of level j (j = 1,2 ..., p) of attribute k (k = 1,2, ..., n) for consumer c (c = 1,2, ..., l);

$X_{kj}(a)$ is a dummy variable, equal to 1 if the level j of the attribute k is present in alternative a, and 0 otherwise.

4.1.1. Comparison of preference models

CA has become the most frequently used method to assess consumer preferences and it has been considered one of the major contributions of marketing science to marketeers practice (Netzer et al., 2008). There are several explanations for the widespread use of CA. First, it has the ability to deal with a crucial question for marketeers, to analyze why consumers choose one product, brand or service over another one (Green et al., 2001). Second, CA is a good approximation of the purchase process in a competitive market where consumers face a range of products which they have to screen and select (Orme, 2009b). Finally, the introduction of efficient and user friendly software, e.g. Sawtooth®, has simplified not only the usually complex survey design of SP surveys but also the estimation procedures at an individual level that are appealing in marketing studies (Halme and Kallio, 2011).

Several studies have focused on testing other preference elicitation methods against CA. These studies have been performed to assess the efficacy of other methods on eliciting preferences, often motivated by CA limitations, such as the difficulty of CA in dealing with a large number of attributes (Srinivasan and Park, 1997; Meißner et al., 2008; Netzer and Srinivasan, 2011), or because CA survey design is a complex and time consuming process. The main goal of these studies was to evaluate which method better assesses consumer preferences, and under which conditions (Agarwal and Green, 1991; Mulye, 1998; Helm and Steiner, 2004). The comparison of preference elicitation methods also allows understanding whether they reach the same conclusion and, if not, which one is more adequate in a specific context (Mulye, 1998). These comparisons are usually done under the dichotomy of decompositional (CA method) versus compositional approaches, a common classification of preference elicitation methods (Green et al., 1972; Huber et al., 1993).

In this context, the main goal of this subsection is to provide a novel comparison between two preference models, CBC (as a decompositional approach) and MAUT (as a compositional approach), in order to verify which method better represents the consumer preferences for AFV. Three main reasons support the use of MAUT in a comparative study with CBC. The first reason is the existence of a comparability basis between these methods: CBC and MAUT share a linear additive preference model, the concept of trade-offs to determine the attributes' weights and they are equivalent in the absence of risk (Bleichrodt et al., 2011). The second reason is that, within the MCDA methods used to assess consumer preferences, MAUT is an aggregation (compositional) approach that has been frequently used to assess consumer preferences, mainly within energy-related subjects (§4.1.1.1.2). The third reason, and knowing that the Self-Explicated Method (SEM) (further explained in subsection 4.1.1.2) is the most prominent compositional approach (Eggers and Sattler, 2001), is that MAUT elicitation overcomes one of the disadvantages of SEM. MAUT, contrarily to SEM that is not able on capturing nonlinearities in the attribute part-worth utility functions (Sattler and Hensel-Borner, 2007;

Rao, 2014), offers the potential of capturing such nonlinearities within each attribute while. In the end of this analysis three main questions are to be answered:

1. Which method has higher validity on predicting individual preferences?
2. Which method better predicts the market penetration of the vehicles set?
3. Are the inferred preferences similar between methods?

A brief literature review about studies focused on the main applications of MCDA methods in preference assessment (§4.1.1.1) and on the comparison of preference elicitation methods (§4.1.1.2), followed by the methodological approach used to address the questions above (§4.1.1.3). Finally, the main results (§4.1.1.4) and concluding remarks (§4.1.1.5) are presented.

4.1.1.1. Previous studies on MCDA applications for consumer preference assessment

MCDA methods have different applications in the preference analysis field. These applications depend on their aggregation paradigm, i.e. if the MCDA method is a disaggregation (or decompositional) or aggregation (or compositional) method.

MCDA disaggregation methods (Jacquet-Lagrèze and Siskos, 2001) involve the inference of preference models from knowledge about holistic preferences of decision makers. Two popular disaggregation methods are UTA (Utility Theory Additive) and MUSA (Multicriteria Satisfaction Analysis), where an ordinal regression formulation is used to measure consumer preferences and satisfaction, respectively (Siskos et al., 1998; Jacquet-Lagrèze and Siskos, 2001; Grigoroudis and Siskos, 2002; Greco et al., 2008).

UTA has been applied to identify the most determinant criteria that could explain consumers' choices about several agricultural products (Baourakis et al., 1996; Matsatsinis et al., 1999; Siskos et al., 2001) and to understand the impact of some attributes on brand preferences (Ghaderi et al., 2015). MUSA has assessed the consumer satisfaction mainly in the services sector, such as banking (Mihelis, 2001; Grigoroudis et al., 2002), transportation-communication (Grigoroudis and Siskos, 2004), internet services (Kyriazopoulos and Spyridakos, 2007), tourism (Arabatzis and Grigoroudis, 2010) and public services (Manolitzas et al., 2013).

MCDA aggregation approaches start with a separate assessment of preferences for each product attribute in order to achieve a global preference relation (a global utility value or, in some methods, a system of relations accepting incomparability) through an aggregation rule (Jain et al., 1979; Eggers and Sattler, 2011). There are two aggregation methods that are used more often in the consumer preference analysis field, namely Analytical Hierarchy Process (AHP) and MAUT. AHP involves an importance-ratio assessment procedure based on hierarchies of attributes (Dyer et al., 1992). This method has been used with different purposes within the preferences field, such as to incorporate preferences into regional forest planning (Ananda and Herath, 2003), to analyze preference shifting applied to wooden furniture (Scholz and Decker, 2007), to elicit preferences for health technologies (Danner et al., 2011), or to test if AHP was a good representation of preferences for chocolate boxes (Ishizaka et al., 2011). AHP has been also applied in studies where its ability to represent consumer preferences is compared with CA to assess preferences in the marketing field (Table 4.1).

MAUT (see description in Chapter 3) has been often applied in environmental-related fields. A review of MAUT applications in energy and environmental modelling shows that, under the analyzed application areas, MAUT was applied more often to assess preferences about energy utility operations and management, and energy-related environmental control (Zhou et al., 2006). MAUT has been also applied to analyze preferences regarding natural resource management problems (Bell, 1975; Teeter and Dyer, 1986; Pukkala, 1998; Prato, 1999; Ananda and Herath, 2005).

4.1.1.2. Previous studies on comparison of preference elicitation methods

In a compositional approach (or buildup approach) consumers assess the product attributes separately and the global utility of each product can be computed using a simple linear aggregation rule, for instance a weighted sum of the product's perceived attribute utilities (Jain et al., 1979; Eggers and Sattler, 2011). This approach uses direct questions on each attribute in order to estimate the consumer's preferences for each product (Green et al., 1972).

In a decompositional approach, consumers assess the whole product, by taking into account the product's attributes jointly (Eggers and Sattler, 2011). In this approach consumers are asked for general judgements on multiattribute products, by examining a set of profiles (alternatives) from which consumers have to choose from, according to their preferences (Green et al., 1972; Jain et al., 1979). The standard decompositional approach is CA, where consumers overall preferences are collected and then decomposed into individual contributions of each attribute, reflecting the relevance of the product's characteristics to consumers (Molin et al., 1997). Statistical methods can be used to decompose preferences (Eggers and Sattler, 2011).

Studies focused on the comparison of preference elicitation methods are summarized in Table 4.1. The two pairs of methods compared the most are SEM vs CA and AHP vs CA. The first pair consists of the standard compositional and decompositional approaches. SEM collects the consumers' evaluation of each attribute level in a desirability scale and it also asks consumers to allocate a score to each attribute in order to reflect their relative importance. At the end, attributes part-worths are obtained through the product of weights with the attribute-level desirability ratings (Sattler and Hensel-Borner, 2007). The comparison of CA with SEM was the first to emerge and it was addressed in several studies (see an in-depth review in Sattler and Hensel-Borner (2007)). The ultimate goal of most studies was to compare the predictive validity of the methods (Green et al., 1972, 1983; Akaah and Korgaonkar, 1983; Green and Helsen, 1989; Agarwal and Green, 1991; Huber et al., 1993).

The comparison between CA and AHP is more recent as it started to be addressed only in the last decade. AHP belongs to the MCDA field, which has the primary purpose of suggesting how the consumer should select his/her preferred alternative rather than trying to predict his preferences (as in CA) (Currim and Sarin, 1984). Table 4.1 also shows which CA methods were used the most: ratings and rankings are the CA types most frequently used before 2007, but since then the use of CBC is more common.

	Compositional approach		Decompositional approach – CA		
	SEM	AHP	Traditional conjoint (Rating or Ranking)	CBC	Adaptive Conjoint Analysis
Huber et al. (1971)	✓		✓		
Green et al. (1972)	✓		✓		
Akaah and Korgaonkar (1983)	✓		✓		
Green et al. (1983)	✓		✓		
Leigh et al. (1984)	✓		✓		
Green and Helsen (1989)	✓		✓		
Agarwal and Green (1991)	✓				✓
Green et al. (1993)	✓		✓		✓
Huber et al. (1993)	✓		✓		✓
Mulye (1998)	✓	✓	✓		
Duke and Aull-Hyde (2002)		✓	✓		
Helm and Steiner (2004)		✓	✓		
Moran et al. (2007)		✓		✓	
Dagher and Petiot (2008)		✓	✓		
Ijzerman et al. (2008)		✓		✓	
Meißner et al. (2008)		✓			✓
Meißner and Decker (2009)		✓		✓	
Perini et al. (2009)		✓	✓		
Koo and Koo (2010)		✓	✓		
Kallas et al. (2011)		✓	✓		
Netzer and Srinivasan (2011)	✓			✓	
Ijzerman et al. (2012)		✓		✓	
Sönmez and Haciköylü (2012)		✓	✓		
Nikou et al. (2015)		✓	✓		

Table 4.1 - Compositional and decompositional approaches used in previous studies.

4.1.1.3. Methodological approach

The assessment of the validity of preference elicitation methods on representing consumer preferences requires information about the real preferences of consumers against which elicited preferences are compared. However, when the scope of decision-making problems is a product or a service that is not available or is too recent in the market it is not possible to capture real consumer preferences in order to compare with the methods' predictions (Nikou et al., 2015). To partially overcome this problem one of two strategies can be implemented. One consists in including a method to be used as a reference to compare the predictions of the preference elicitation methods (Helm and Steiner, 2004). The other consists in including holdout questions, i.e. choice tasks that are not included in the utility estimations of CBC and that are used to compare the methods' results (Meißner et al., 2008). For this analysis the first strategy was chosen, where the "Initial Reference ranking" was used (Task 2) to compare with the CBC preference data (Task 3) (analysis 1) and the MAUT preference data (Task 4) (analysis 2) (Figure 4.1).

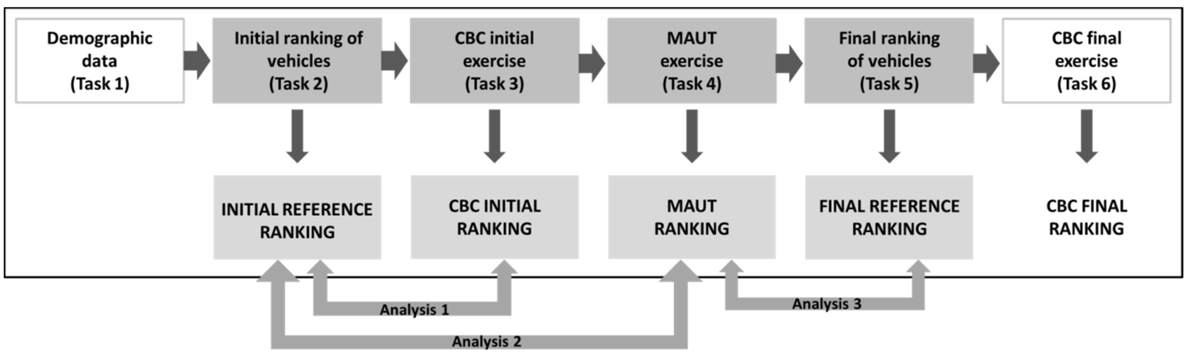

Figure 4.1 - Data research strategy for comparison of preference models with the three comparisons performed in this analysis identified.

The methods were then compared using validity measures that are common in consumer preference studies, namely predictive and convergent validities (e.g. Green et al., 1972; Akaah and Korgaonkar, 1983; Leigh et al., 1984; Huber et al., 1993; Mulye, 1998; Helm and Steiner, 2004; Meißner et al., 2008). Predictive validity assesses the ability of a method in modelling real preferences by comparing elicited preferences with real/stated preferences (Helm and Steiner, 2004; Nikou et al., 2015). This validity has been frequently used to measure ranking disagreements (Can, 2014) and it has also been considered the most common performance measure applied within CA (Akaah and Korgaonkar, 1983). The convergent validity consists in testing if two independent methods of eliciting preferences lead to the same results (Mulye, 1998). Therefore, a high convergent validity is found if the two methods lead to similar results (Helm and Steiner, 2004).

After the validity tests were performed, analysis 3 was done where MAUT Ranking and the Final Reference Ranking were compared. As the Final Reference Ranking consists in a revision of the MAUT Ranking results when consumers did not agree with the MAUT method results, this comparison is valuable to complement the findings regarding the ability to represent preferences through validity tests.

4.1.1.4. Results

For this analysis the consumers from the two scenarios (current and future) were jointly considered, as the market context in which preferences were collected is not expected to influence the validity of the elicitation methods.

The validity of the CBC and MAUT approaches was analyzed based on the comparison of the elicited individual rankings of the vehicles set, CBC Initial ranking and MAUT ranking respectively, with the stated Initial Reference Ranking.

The predictive validity was analyzed through three specific measures, two at the individual level and one at the aggregate level. At the individual level the predictive validity was measured through the Kemeny distance and Hit Rates. The Kemeny distance measures the number of pairwise disagreements between strict preferences, i.e., linear rankings (Kemeny, 1959). A Kemeny distance was computed between CBC Initial and Initial Reference Ranking, as well as between MAUT and Initial Reference Ranking. Figure 4.2 depicts the cumulative results of these distances. The results show that CBC Initial ranking outperforms the MAUT ranking regarding the proximity to the Initial Reference Ranking. It can be observed that, for instance, considering the CBC ranking 80% of consumers have at most 5 permutations. However, if the MAUT ranking is considered, that percentage drops to 50% for the same number of permutations. The average distance is 3.75 for CBC and 5.25 for MAUT.

These results confirm the better performance of CBC over MAUT since with a 95% confidence level the distance between the Reference and CBC ranking is within [3.3,4.2] while the distance between Initial Reference Ranking and MAUT ranking is within [4.65,5.7].

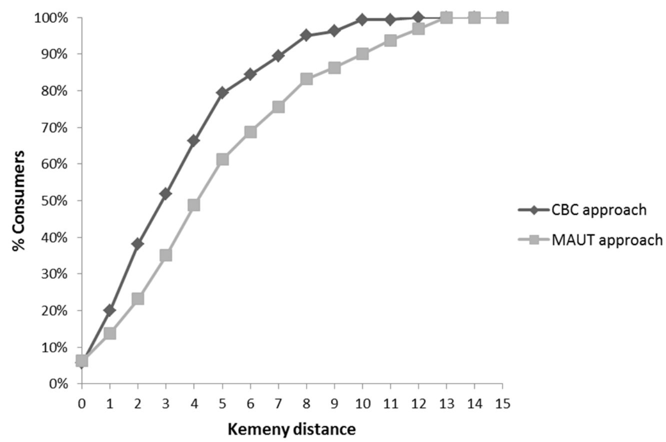

Figure 4.2 - Cumulative results of the Kemeny distance between CBC Initial and Initial Reference Ranking and MAUT and Initial Reference Ranking.

The second measure computed at the individual level was the Hit Rate. In this study, Hit Rate is defined as the percentage of times that a method predicts correctly each consumer's first choice (Huber et al., 1993), i.e., the vehicle placed at the top of the Initial Reference Ranking. Hit rates are a frequent measure to compare the predictive validity of different methods (e.g. Leigh et al., 1984; Green and Helsen, 1989; Agarwal and Green, 1991; Green et al., 1993; Huber et al., 1993; Helm and Steiner, 2004). Based on Helm and Steiner (2004), four hit rates were computed:

- First-choice Hit rate (HR1): frequency of getting the same first-ranked vehicle as the Initial Reference Ranking;
- First-second-choice hit rate (HR12): frequency of getting the same first-and second-ranked vehicles as the Initial Reference Ranking;

- First-second-third choice hit rate (HR123): frequency of getting the same first, second and third-ranked vehicles as the Initial Reference Ranking;
- All in hit rate (HRall): frequency of having exactly the same ranking as the Initial Reference Ranking.

The results showed that CBC ranking had a better performance than MAUT ranking on HR1 and HR12 while MAUT performed better in HR123 and HRall, however only the HR1 results are statistically significant (Table 4.2).

	CBC	MAUT
HR1*	47%	36%
HR12	21%	19%
HR123	11%	15%
HRall	5%	6%

* Difference statistically significant at a significance level of 0.05.

Table 4.2 - Hit rates for CBC and MAUT.

Given the predictive validity results at the individual level, CBC clearly outperforms the MAUT based approach in predicting the consumers SP. Several reasons can be pointed out to explain this result. One reason is related to the direct manner in which the preferences components are collected for the compositional approach. This characteristic of data collection has the advantage of demanding less effort from consumers to analyze the alternatives (one attribute at a time) but it has at the same time the downside of making the elicited preferences more susceptible to the control of consumers. Namely, this control can lead consumers to overrate or underrate attribute weights according to what is more or less socially desirable, as for instance underrate the importance of price (Sattler and Hensel-Borner, 2007; Meyerding, 2016). In the sample used this effect can be observed regarding the CO_2 emissions. Society expects that the value of CO_2 emissions has a significant contribution in the consumers purchase process of a vehicle, as it is better for the social welfare that consumers drive low polluting vehicles. The results show that the direct value of this attribute elicited through the MAUT based approach was higher than the elicited value through CBC for 73% of consumers. The overrating of the importance of some attributes may draw attention for features that are not that important in real purchasing decisions, making it more difficult to predict preferences (Meyerding, 2016).

Regarding the utility functions, it is more likely that the decompositional approach captures more easily potential nonlinearities in the utility functions as the utility values are elicited by the method and not by the consumers (Green and Srinivasan, 1990). Following the same reasoning, a compositional approach is potentially less able in detecting such nonlinearities as there is a natural instinct from consumers to assign an intermediate attribute value for intermediate utilities (Sattler and Hensel-Borner, 2007). For example, given the purchase price scale of 20,000€ to 35,000€, consumers may assign more frequently the mid-value of the scale, i.e. 27,500€, to the mid-utility value. In order to examine if this effect was influencing the MAUT results the distribution of utilities for each attribute level was computed to compare with the attribute values that would be part of a linear utility function (Figure 4.3). This figure allows verifying that the elicited utility functions were almost linear, mainly for the purchase price and range where the linear values (red dots) overlap the center of the distribution plots. These results suggest that the lower predictability of MAUT based approach may be related not only with underrating or overrating some attribute weights but also with the consumers' tendency to choose attribute utilities that lead to almost linear attribute utility functions.

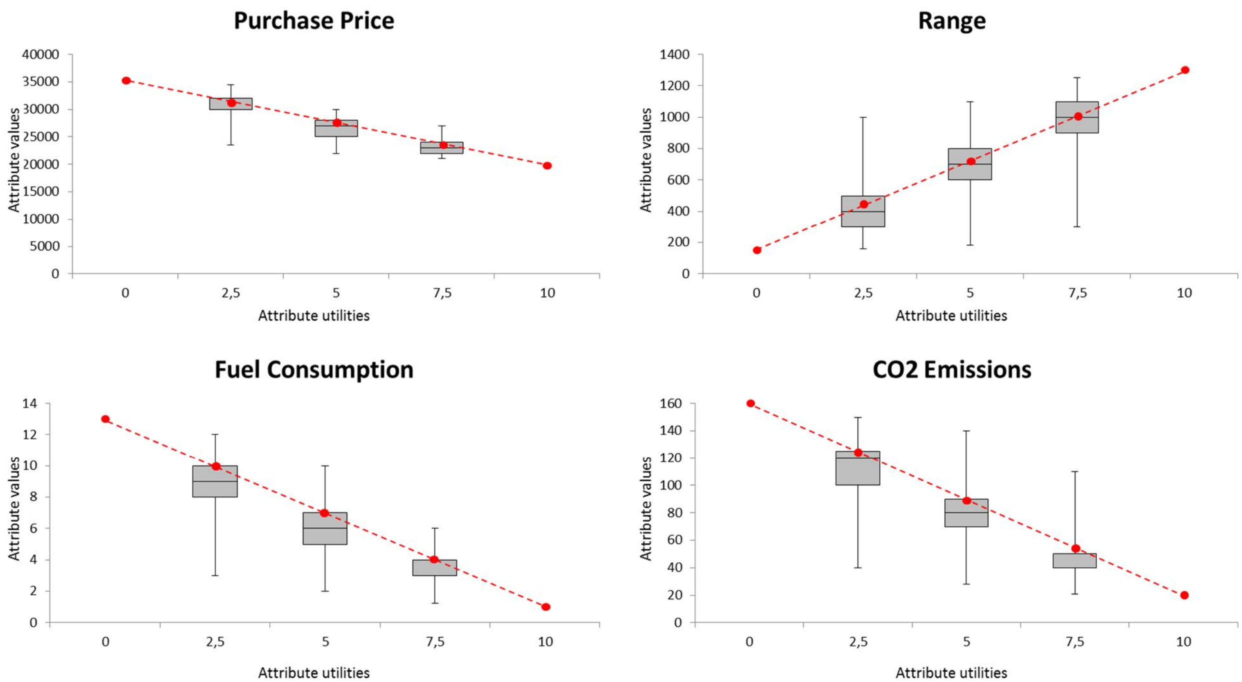

Figure 4.3 - Distribution of MAUT utilities for each attribute. The dashed line represents a linear utility function (red dots).

The third analysis (analysis 3 in Figure 4.1) compared MAUT Ranking and the Final Reference Ranking to verify if they corroborate that MAUT Ranking did not represent preferences of consumers. First, the Kemeny distance between the two rankings was computed and found to be statistically different, meaning that consumers significantly changed (through ranking revisions) the ranking from MAUT (Figure 4.4). Another analysis consisted in identifying how many consumers agreed with the vehicle placed in the first position by MAUT and therefore kept that result in the Final Reference Ranking. The same analysis was done for the first two positions (1^{st} and 2^{nd} places) and for the first three positions (1^{st}, 2^{nd} and 3^{rd} places). The results showed that:

- Half of consumers kept the vehicle that MAUT placed at the first position;
- One third of consumers agreed with the vehicles placed in the 1^{st} and 2^{nd} positions;
- Less than one quarter of consumers kept the vehicles placed in the first three positions by MAUT.

These results revealed that most of consumers revised the MAUT Ranking by not agreeing that it represented their preferences.

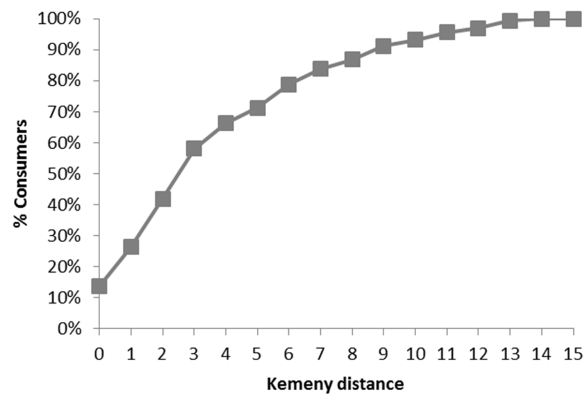

Figure 4.4 - Cumulative results of the Kemeny distance between MAUT Ranking and Final Reference Ranking.

Although CBC appears to outperform MAUT at the individual level, whether this pattern also occurs in the prediction of aggregate choice shares remains to be shown. Therefore, the third and last predictive measure is an aggregate level measure, the computation of market shares. The share of each vehicle was computed according to the maximum utility criterion, assuming that the alternative with the highest predicted utility, within the alternatives set, is chosen, i.e. the highest global utility $U(a)$. Afterwards, the Root Mean Square Error (RMSE) was used to assess the difference between the percentages of consumers predicted to choose an alternative and those who actually did so (Huber et al., 1993). Table 4.3 presents the predicted market shares according to the two methods and the respective RMSE value. Regarding the differences of market shares obtained between the Reference and the CBC ranking and the Reference and MAUT ranking, two observations can be made. First, the maximum deviation between vehicles shares is presented by the MAUT ranking regarding the PHEV, +24%, whilst the maximum deviation of CBC ranking is of +13% also for the PHEVs. And second, the RMSE computation showed that choice shares obtained through CBC deviate less from the real/stated choice shares (Initial Reference ranking) (8%) in comparison to MAUT (13%). Therefore, at the aggregate level, although the predictive results showed that none of the methods provide a good prediction of the market shares, the lower RMSE of CBC implies that its aggregate predictions are less distant from the SP than MAUT.

	Initial Reference ranking	CBC ranking	MAUT ranking
Diesel	27%	26%	6%
Gasoline	4%	4%	1%
HEV	12%	3%	13%
PHEV	29%	42%	53%
BEV1	17%	23%	16%
BEV2	11%	2%	11%
RMSE		0.08	0.13

Table 4.3 - Market share of the Reference, CBC and MAUT ranking.

The test for convergent validity was based on the comparison between the CBC and MAUT rankings of the alternatives set. Results showed that both methods placed the same vehicle in the first position for 41% consumers. In addition, 67% of those common first positions were PHEVs. On the other hand, exactly the same ranking of the six vehicles was observed in only 4% of all cases. For the remaining consumers the Spearman's rank-order coefficient was used in order to quantify the rank correlation. This coefficient has values within the range [-1,1] and the correlation is considered strong if its absolute value is close to 1. An average of Spearman's coefficient of 0.48 was obtained, which can be interpreted as a low correlation between CBC and MAUT rankings. The use of different elicitation formats of preferences, i.e., either a choice set comparing three alternatives or individual analysis of each attribute (Voelckner, 2006; Novemsky et al., 2007), also may explain the low correlation between methods.

The importance order of the selected attributes was also addressed to assess if CBC and MAUT reached convergent or divergent results. An important difference between MAUT and CBC exercises should be noted first. For MAUT, the type of engine is used in the identification of the vehicles but it is not an attribute under evaluation, since in MAUT one assumes alternatives are assessed solely by their performances. In CBC, the type of engine can be considered as an attribute to which might influence the consumer's choice independently of the performances (e.g. capturing prejudice against some technology).

The results showed that both methods found that fuel consumption was the most important attribute to consider in a future vehicle purchase decision (Figure 4.5).

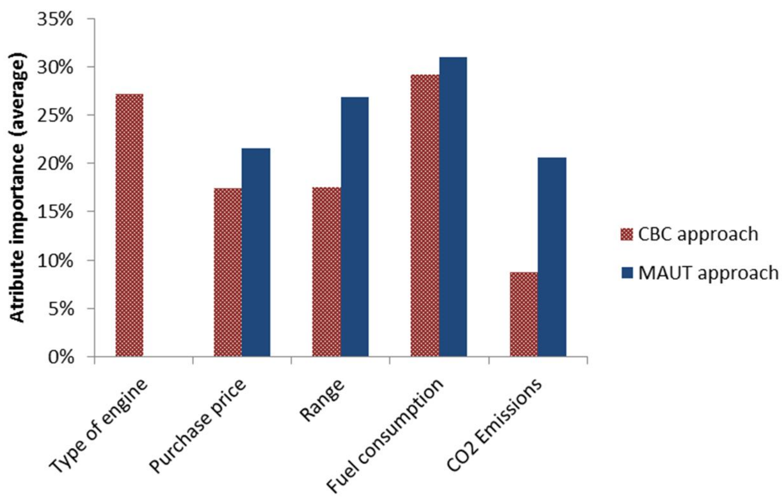

Figure 4.5 - Relative importance of each attribute.

4.1.1.5. Concluding remarks of preference models comparison

Previous comparisons between CBC and other preference elicitation methods from MCDA do not allow deriving a definitive conclusion. Regarding the predictive validity, at the aggregate level, while Meißner and Decker (2009) concluded that AHP outperforms CBC, Kallas et al. (2011) found that the differences between methods were not statistically significant. At the individual level, (Netzer and Srinivasan, 2011) found that an adaptative version of SEM performed better than CBC while Meißner and Decker (2009) and Kallas et al. (2011) did not found a clear conclusion if AHP method predicts better consumer preferences than the CA version. Regarding the convergent validity, the results are also contradictory. Moran et al. (2007) concluded that the resulted rankings were divergent whilst Meißner and Decker (2009) found a high convergence between AHP and CBC rankings. In this context, this analysis contributes to the literature with statistically significant results in favor of CBC at the individual level, but considering MAUT as the alternative approach. At the aggregate level, it seems that CBC has more ability in predicting market shares than MAUT.

Although the inferred preferences between CBC and MAUT did not converge, both methods reached the same conclusion regarding the most relevant attribute, i.e. fuel consumption.

Considering that CBC was found to better represent consumer preferences, CBC elicited preferences were, from this point forward, used to develop the analysis that follows this subsection.

4.1.2. Learning effects on preferences

When a company has to predict the product sales of innovative products, consumers are asked to express their preferences for the innovation in comparison to the competing products. The measurement of those preferences is highly dependent on the assumptions made about how they are expressed (Payne et al., 1999). One point of view is based on the standard economics theory, assuming an individual's preferences are stable and well-defined for most of the objects (Rabin, 1998). According to this theory, individuals know their preferences and they rationally maximize those preferences (Freeman, 1995; Payne et al., 1999). Therefore, the measurement task consists in uncovering the pre-existent preferences (Gregory et al., 1993; Payne et al., 1999). Another point of view based on behavioral theory is that individuals construct/learn their preferences during the evaluation task and that the process of preferences construction is influenced by the interactions between stored information and the information provided along the decision task (Bettman et al., 1998; Payne et al., 1999). The measurement of such constructive preferences rests on building a robust and defensible value or set of values instead of uncovering the pre-existent values (Gregory et al., 1993). In this context, there are situations when the expression of preferences reflects well-defined memorized values, for instance when the focused issues are familiar, simple and that were directly experienced, and there are other situations in which preferences have to be built/learned, such as when the targeted objects are novel and complex and there are no memorized preferences to retrieve (Payne et al., 1999).

Preferences for EVs, as other innovative technologies, tend to not pre-exist because, as several attributes are novel, consumers did not experience or thought about them before (Axsen et al., 2013). When consumers face a new product category they need to construct their preferences due to the limited knowledge and absence of experience with those products (Hoeffler and Ariely, 1999). Previous studies that used elicitation methods concluded that constructed preferences are dependent on several factors, such as the type of elicitation task (Novemsky et al., 2007), task order (Swait and Adamowicz, 2001; Day and Prades, 2010), task complexity (Swait and Adamowicz, 2001; Deshazo and Fermo, 2002), and cognitive burden (Swait and Adamowicz, 2001).

Acknowledging that previous studies focused on assessing the existence of a learning effect on preferences used only one preference elicitation method (see further subsection 4.2.1.1), the main goal of this analysis is to understand the potential learning impacts of using a MAUT preference elicitation method on preferences elicitation with CBC: the impact of MAUT on learning of preferences elicited through CBC and the impact of MAUT on improving the ability of CBC to predict consumer preferences. In this study, the methodological strategy (presented with more detail in subsection 4.1.2.2) consisted in the analysis of a sequence of elicitation tasks that included two different elicitation methods, CBC and MAUT, where CBC tasks were performed before (Task 3) and after (Task 6) the MAUT task (Task 4).

The analysis of learning effects on preference data was done in order to answer the outlined research questions:

1. Do CBC elicited preferences change after MAUT elicitation?
2. Do CBC rankings change after MAUT elicitation? Are those changes aligned with the MAUT elicitation?
3. Does the MAUT approach improve the ability of CBC to predict individual and/or aggregated preferences?

This subsection is organized as follows. First it presents a brief literature review of studies that assessed learning effects on preferences (§4.1.2.1), followed by the applied methodological approach (§4.1.2.2), the main results (§4.1.2.3) and the concluding remarks (§4.1.2.4).

4.1.2.1. Previous studies on identifying preference learning effects in surveys

The collection of consumer preferences is commonly done through SP surveys which comprise a set of choice tasks (rating or ranking tasks are also possible, but are currently less used). A sequence of choice-based tasks has a high potential for providing rich data about consumer preferences. However, it also raises concerns about the stability of preferences, as the accuracy of choices and the underlying decision strategies may change during the survey answering process (Czajkowski et al., 2014). These phenomena are known as ordering effects and they have several possible explanations. One explanation is institutional learning: since most consumers never answered to SP surveys before, it is expected an increase of accuracy of responses as they become more familiar with the mental mechanism to answer the choice questions. A second explanation is preference learning or value learning: as the consumer becomes more familiar with its own preferences and with the decision environment the decisions become more coherent. A third explanation is fatigue or boredom: as consumers can get tired by answering to several choice tasks, after some time their responses may exhibit high levels of randomness. Lastly, there is the starting point effect, as consumers anchor their preferences to features included in the initial SP question (Day et al., 2012). The literature focused on analyzing order effects is extensive (see Czajkowski et al., 2014). However, as in this study the focus is on the potential effect of value or preference learning on preferences the review was centered on studies focused on analyzing this effect (Table 4.4).

Studies focused on learning effects usually have SP surveys with specific design characteristics to identify such effects. The literature reports three main survey designs. One corresponds to the traditional SP survey data collection through a set of different questions (Desarbo et al., 2004; Holmes and Boyle, 2005; Savage and Waldman, 2008; Hess, Hensher, et al., 2012; Czajkowski et al., 2014) and the other two involve repetition of questions. Some studies have repeated trials of questions in different time periods (Morrison, 2000; Shiell et al., 2000; Carlsson et al., 2012) or at the same time (Carlsson and Martinsson, 2001). Other studies repeat at least one question in the beginning and in the end of a sequence of questions (Johnson and Bingham, 2001; Brouwer et al., 2010). A common characteristic to all the surveys is the use of only one type of elicitation method in the survey and the most used type of questions is choice (Carlsson and Martinsson, 2001; Swait and Adamowicz, 2001; Brouwer et al., 2010; Carlsson et al., 2012; Hess, Hensher, et al., 2012; Czajkowski et al., 2014).

Regarding the results, all the studies found learning effects on preferences with the exception of Johnson and Bingham (2001) and Savage and Waldman (2008).

Study	Goal	Subject	SP survey design	Results
Morrison (2000)	To examine willingness to pay and willingness to accept responses while controlling for substitutability, learning, and imprecise preferences	Mugs and chocolates	5 repeated trials of the same group of questions	Consumers learned their preferences over the trials
Shiell et al. (2000)	To test whether people have complete preferences over health states or whether the process of eliciting values forces influences preferences	Health services	Interviews in three time periods	Respondents constructed their preferences during the elicitation tasks
Carlsson and Martinsson (2001)	To analyze the existence of differences between a hypothetical choice and an actual choice experiments	Donations for environmental projects	Answer to sixteen different choice sets (two sequences of 8 choices)	The elicitation task influences the construction of consumer preferences
Johnson and Bingham (2001)	To evaluate the validity of SP estimates for health valuation research	Health state	Repeated questions from the beginning and end of the SP question sequence	Preferences were almost consistent across the questions
Swait and Adamowicz (2001)	To test if preferences change with choice complexity and task order	Food choice (Frozen concentrate orange juice)	Answer to sixteen different choice sets	Aggregate preferences change as choice complexity changes and as the task progresses
Desarbo et al. (2004)	To capture structural changes that may affect the elicitation of consumer preferences	Student apartment	Thirty rating profiles	The structure of preferences changes significantly over the sequence of profile responses
Holmes and Boyle (2005)	To test whether preferences are stable across a sequence of policy packages	Forest management	4 profiles to vote	People learn about their preferences for attribute based environmental goods by comparing attribute levels across choice sets
Savage and Waldman (2008)	To investigate the survey mode on respondent learning and fatigue	High speed internet service	8 questions of paired comparisons	Respondents answer questions consistently throughout a series of choice experiments
Brouwer et al. (2010)	To examine how repeated choice affects preference learning in SP experiments	Water scarcity	Five choice cards with repetition of the first card in the end	Results indicate that learning occurs
Carlsson et al. (2012)	To understand how learning processes potentially affect respondents' SP in a sequence of choice sets	Food choice (chicken breast filets)	2 trials of eight choice sets	Preference learning can be of significant structural importance when conducting choice experiment surveys
Hess et al. (2012)	To investigate evidence of respondent fatigue across a larger number of different surveys	Transport (route choice)	8 choice tasks	Possibility of learning of true preferences as a respondent proceeds through the survey
Czajkowski et al. (2014)	To analyse the presence or fatigue on preferences taking into account unobservable preference and scale heterogeneity	Environmental protection	Twenty six choice sets (order randomized for each respondent)	Evidence of learning on consumer preferences

Table 4.4 - Studies focused on learning effects on preferences.

4.1.2.2. Methodological approach

The strategy for this analysis used the MAUT data (Task 4) and two CBC results (Initial and Final), Task 3 and Task 6. The use of repeated elicitations is a common approach on studies focused on analyzing the influence of elicitation tasks on learning/construction of preferences in economics and behavioral experiments studies (see Table 4.4). The rational basis behind this strategy is to give consumers the opportunity to revise their answers in order to obtain, in the end, more accurate representations of their preferences for the targeted product studies (Morrison, 2000).

In this study the analysis of learning effects was performed through ranking analysis techniques. Two pairs rankings were compared (Figure 4.6):

- CBC Initial and CBC Final ranking (analysis 4)
- MAUT ranking and CBC Final Ranking (analysis 5)

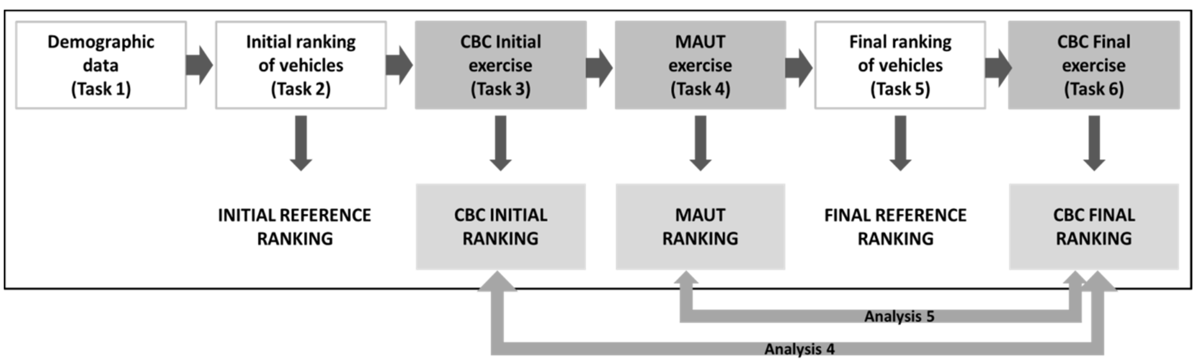

Figure 4.6 - Strategy of data analysis: tasks and data analyzed are in grey and the arrows represent the performed rankings comparison.

4.1.2.3. Results

Similarly to the analysis of the subsection 4.1.1, the consumers from the two scenarios were jointly considered, as the market context in which preferences were collected is not expected to influence the analysis of the learning effect on preferences.

The results of two analyses are presented. The first analysis (analysis 4) aimed at finding out if the preference data collected in the two CBC trials was significantly different. The analysis of differences between the CBC Initial and CBC Final tasks was based on the Kemeny distance. The results showed that only 8% of consumers gave exactly the same answers to the CBC Initial and Final questions (Figure 4.7). The average distance between the two sets of answers was found to be statistically different from 0 (at a significance level of 0.05).

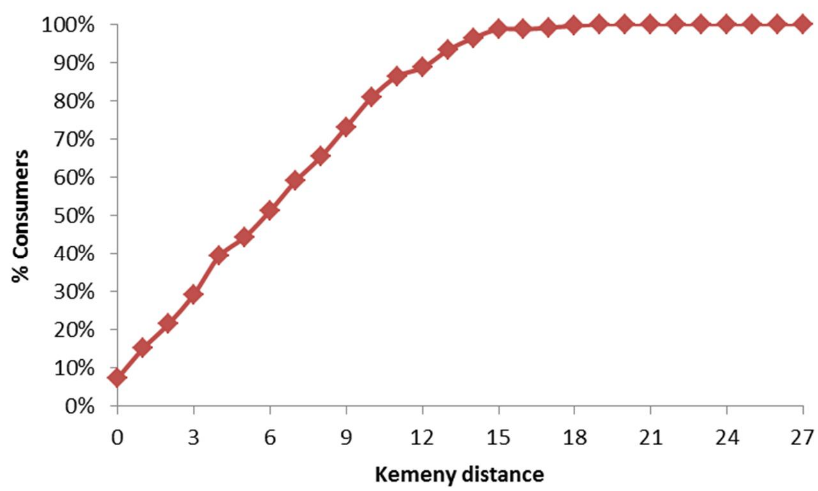

Figure 4.7 - Cumulative results of the Kemeny distance between CBC Initial and Final answers.

The differences between the resulting CBC Initial and CBC Final Rankings were also assessed using the Kemeny distance. Results showed that 15% of consumers had the same derived rankings (CBC Initial ranking=CBC Final ranking) (Figure 4.8) and that the average distance between the rankings was statistically different from 0 (at a significance level of 0.05).

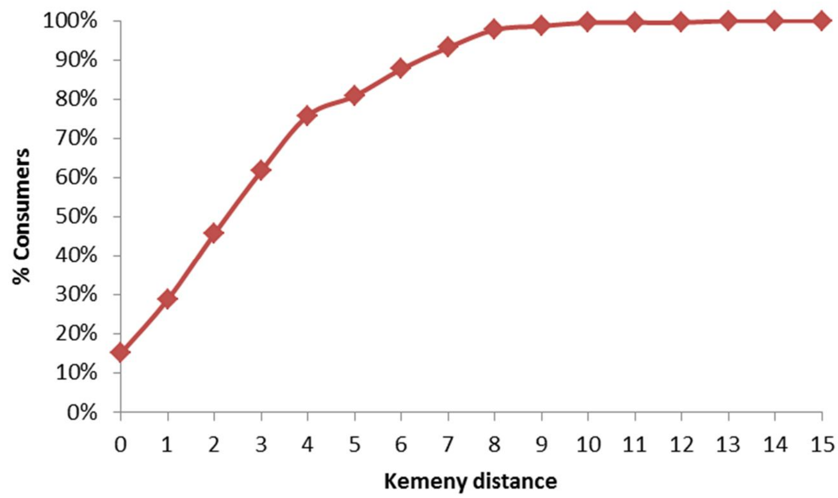

Figure 4.8 – Cumulative results of the Kemeny distance between CBC Initial and Final rankings.

The second analysis (analysis 5) aimed at assessing how much were the reversals of the CBC-derived rankings aligned with the MAUT task. This analysis, based on the 85% of consumers that had different CBC Initial and Final rankings, was made in three steps. First, a matrix with elements $HD_c(a,b)$ (equation (4.4)) indicating the rank reversals from CBC Initial ranking to CBC Final ranking between pairs of alternatives, a and b, was built for each consumer c (c = 1,2, … , l). The second step consisted in building a second matrix $AD_c(a,b)$ (equation (4.5)) with elements indicating for each consumer c the preference relation between pairs of alternatives, a and b, according to the MAUT ranking. The third and final step consisted in the combination of the two matrices (from step 1 and 2) according to equations (4.6) and (4.7), where SA_c represents the sum of all the reversals for each consumer c that agree with MAUT preference relations, and SD_c represents the sum of all the disagreeing reversals for each consumer c.

$$HD_c(a,b) = \begin{cases} 1, & if\ b \succ_c a\ in\ CBC\ Initial\ ranking \wedge a \succ_c b\ in\ CBC\ Final\ ranking \\ 0, & otherwise \end{cases} \tag{4.4}$$

$$AD_c(a,b) = \begin{cases} 1, & if\ a \succ_c b\ in\ MAUT\ ranking \\ -1, & otherwise \end{cases} \quad (4.5)$$

$$SA_c = \sum_{i \neq j: AD_c(a,b)=1} HD_c(a,b) = \#\{(a,b): HD_c(a,b) = 1 \wedge AD_c(a,b) = 1\} \quad (4.6)$$

$$SD_c = \sum_{i \neq j: AD_c(a,b)=-1} HD_c(a,b) = \#\{(a,b): HD_c(a,b) = 1 \wedge AD_c(a,b) = -1\} \quad (4.7)$$

In this step, the percentage of aligned reversals for each consumer c was computed as $A_c = SA_c / (SA_c + SD_c)$,. The results are depicted on Figure 4.9, from which the following observations can be made:

- Approximately 50% of the consumers have more than 60% of their reversals aligned with MAUT rankings.
- For 25% of the consumers the reversals between the CBC rankings were totally aligned with their MAUT rankings.
- For 23% of consumers all the reversals between the CBC rankings occurred in the opposite direction of the MAUT ranking.

The analysis of the structure of preferences of the consumers that had a complete alignment with MAUT ranking allowed observing that for 11% of the consumers the ranking reversals led to a perfect match between CBC Final ranking and MAUT ranking. Additionally, it was noted that the three main ranking reversals of these consumers led to an EV being preferred to fossil vehicles, namely, HEV $\succ$ Diesel; PHEV $\succ$ Diesel; and BEV1 $\succ$ Gasoline.

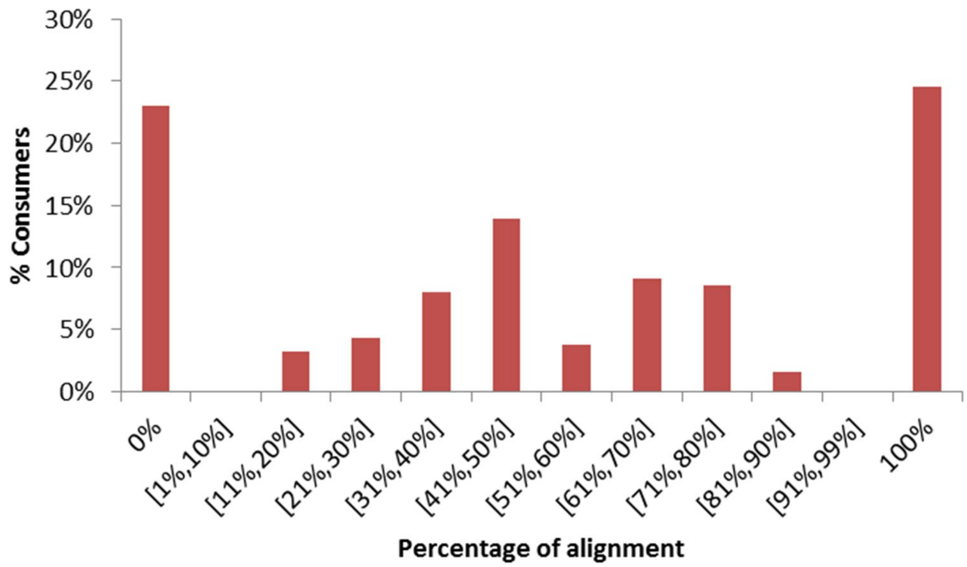

Figure 4.9 - Percentage of reversals aligned between CBC-derived rankings and MAUT ranking.

Analyzing the most frequent reversals between the CBC elicited rankings and the MAUT ranking, independently of the reversal direction (Figure 4.10), allowed identifying that consumers reversed the position of three pairs of vehicles more often, namely Diesel-HEV, BEV1-BEV2 and HEV-BEV1, which represent 10.2%, 9.2% and 8.6% of the total reversals, respectively. On the opposite, the three most stable preferences between two pairs of vehicles were Gasoline-PHEV, Gasoline-HEV and Diesel-Gasoline, accounting for 4.2%, 4% and 3.3% of total reversals, respectively.

Looking at the reversal direction between EVs and fossil vehicles (Figure 4.11), one can observe the general trend that the reversals favoring an EV over a fully fossil fuel vehicle (Diesel or Gasoline) tend to be aligned with the MAUT ranking (83% of these cases), whereas the opposite reversals tend to be in disagreement with MAUT (76% of these cases). In the MAUT rankings, a fossil fuel vehicle is at the top in only 5% of the cases. Concerning the least stable pair, there was a potential preference construction between

HEVs and Diesel vehicles as the reversal from Diesel to HEVs, aligned with MAUT, occurred for a majority of the consumers (Table 4.5).

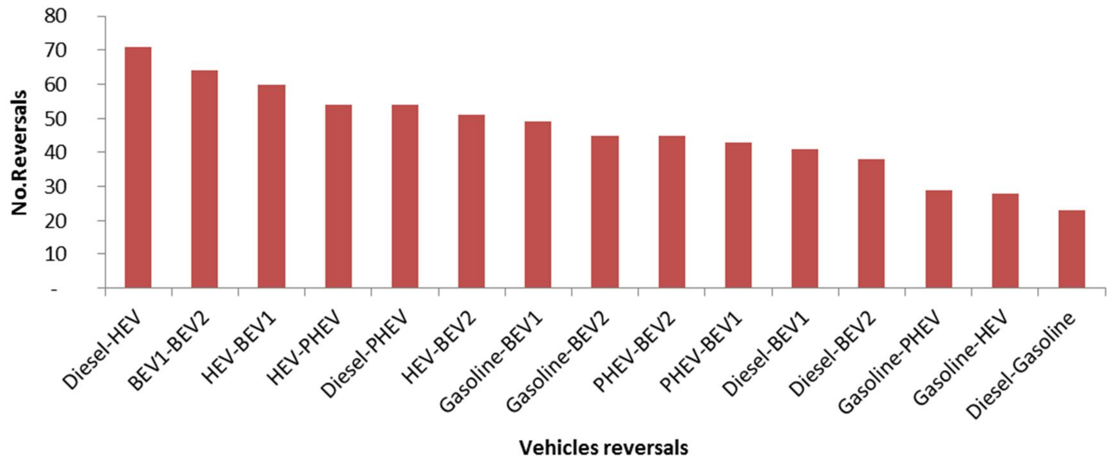

Figure 4.10 - Number of total reversals, by decreasing order.

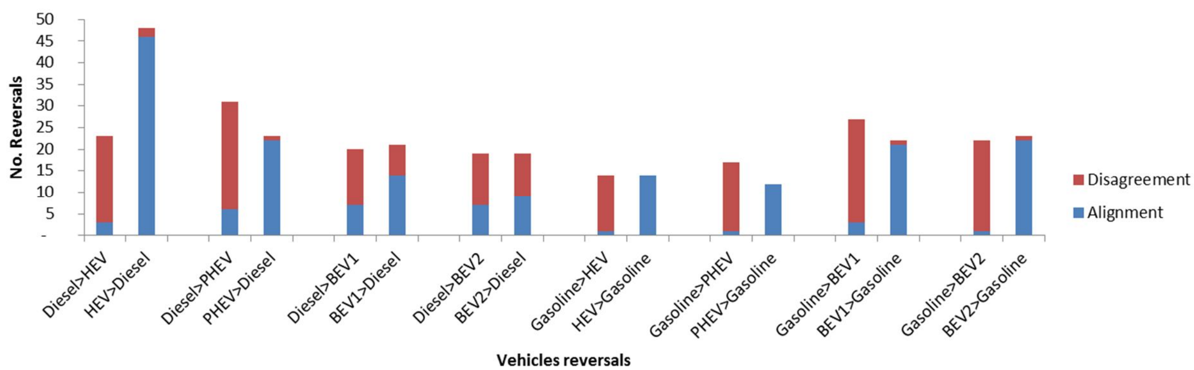

Figure 4.11 - Number of aligned and disagreed reversals between EVs and ICEVs according to the preference direction.

	Alignment	Disagreement	
Diesel>HEV	3 (4%)	20 (28%)	23 (32%)
HEV>Diesel	46 (65%)	2 (3%)	48 (68%)
	49 (69%)	22 (31%)	

Table 4.5 - Potential preference construction for the least stable pair.

Regarding the analysis of the ability of the MAUT approach on improving the predictive power of CBC, the three measures of predictive validity described and computed in the subsection 4.1.1 were considered again in order to analyze if there were significant differences between the CBC Initial and CBC Final rankings. At the individual level, the predictive measures did not show significant differences between CBC Initial and Final ranking. However, at the aggregate level, the computation of market shares showed that the two CBC rankings were statistically different (Table 4.6). Additionally, the RMSE between the market shares computed with CBC and the reference ranking decreased when the CBC Final ranking was considered.

	Reference ranking	CBC Initial ranking*	CBC Final Ranking*
Diesel	27%	26%	31%
Gasoline	4%	4%	4%
HEV	12%	3%	13%
PHEV	29%	42%	38%
BEV1	17%	23%	14%
BEV2	11%	2%	2%
RMSE		0.08	0.06

* Difference between Reference ranking shares and CBC shares are statistically significant at any significance level.

Table 4.6 - Market share of the Reference, CBC Initial and CBC Final ranking.

4.1.2.4. Concluding remarks of learning effects on preferences

This study analyzed the potential of MAUT on leveraging the learning of preferences elicited through CBC.

In line with previous findings, significant differences were found between the two CBC elicited rankings. As mentioned earlier, these results may have several explanations, such as institutional learning, preference learning, fatigue or starting point effect. As the number of CBC questions was small (fatigue usually appears in surveys with more than 10 questions (Caussade et al., 2005) and the set of CBC questions was displayed at the same time (to mitigate the starting point effect), these two possible causes were excluded from possible explanations for the differences found between the two preference elicitation CBC trials. Therefore, the potential differences in elicited preferences can be a result of institutional learning and/or preference learning. It is unclear how to separate the effects of these two types of learning and it is usually expected that institutional learning takes place in the initial questions and preference learning emerges later (Bateman et al., 2008; Czajkowski et al., 2014). Therefore, learning effects occurred but it was not possible to specify which one. Consumers may have constructed/learned their preferences at the time of preference elicitation, possibly because their preferences were not well formed at the time they stated their preferences as the vehicles set included three innovative technologies that may be unfamiliar for most of the consumers. Furthermore, as the aggregated predictive results of CBC improved after the detailed procedure of the MAUT task, results suggest that consumers learned about their preferences throughout the MAUT procedure.

In order to corroborate the role of MAUT on the learning process verified above, the alignment between the preference reversals from the CBC Initial to the CBC Final ranking, and the elicited MAUT preference model, was analyzed. The outcome of this analysis revealed a strong influence of the MAUT task on CBC Final results for one quarter of consumers (100% of preferences alignment) and a relative influence for another quarter of consumers (>60% of preferences alignment).

4.1.3. Influence of demographics on preferences

Preferences for different vehicles vary between market segments, so it is expected that different types of consumers respond differently to AFVs (Ewing and Sarigöllü, 1998). As described in Chapter 2, demographic characteristics have been extensively analyzed in consumer-based research (Kaushik and Rahman, 2014). Demographics are already considered to be one of the major influences for the adoption of new vehicle technologies (Potoglou and Kanaroglou, 2008; Al-Alawi and Bradley, 2013; Li and Loo, 2014). In this context, the main goal of the analysis of demographic data is to identify if preferences for EVs are influenced by consumers demographics. Three research questions are to be answered, namely:

1. Which demographics are more likely to influence preferences for EVs?
2. What is the influence of demographics on preferences for vehicle attributes?
3. Does the influence of demographics on preferences change with different market conditions?

This subsection is organized as follows. A brief review of the analyses of demographics influence on consumer preferences for AFVs is presented (4.1.3.1) followed by description of the methodology used to understand the impact of demographics on preferences (§4.1.3.2) and the main results (§4.1.3.3). Finally, the concluding remarks are presented (§4.1.3.4).

4.1.3.1. Previous preferences studies for AFVs that analyzed the influence of demographic variables

A review of consumer preference studies was made in order to understand how commonly demographic data is included in these studies and which goals have been defined for collecting such data. With this purpose the studies presented on Tables 2.1 and 2.3, (Chapter 2) that used choice modelling techniques to collect and analyze consumer preferences data, were analyzed. The reason for reviewing only of studies that used the same methodological techniques is to further allow the comparison of results. Table 4.7 presents the studies included in this review depicting the demographic variables collected and the purpose of collecting this data.

Study	Collection of demographic data?	Demographic variables collected						Collected to:		
		Age	Gender	Income	Level of education	Driving habits	Other variables	Analyse the sample representativity	Interact with type of vehicle	Interact with vehicle attributes
Beggs et al. (1981)	Yes	✓	✓	✓	✓		Family size		✓	
Calfee (1985)	No									
Bunch et al. (1993)	Yes	✓	✓	✓	✓		Family size		✓	
Golob et al. (1993)	Yes		✓				Family size, no. vehicles		✓	
Brownstone et al. (1996)	Yes	✓		✓						
Kurani, Turrentine, et al. (1996)	Yes				Not mentioned					
Chéron and Zins (1997)	Yes				Not mentioned					
Ewing and Sarigöllü (1998)	Yes	✓	✓	✓			Home language		✓	Acceleration, range, emissions
Tompkins and Bunch (1998)	Yes	✓	✓	✓	✓		Family size, no. vehicles	✓		Body type and size
Kavalec (1999)	Yes	✓				✓	Family size	✓		
Brownstone et al. (2000)	Yes	✓		✓	✓		Family size		✓	
Ewing and Sarigöllü (2000)	Yes	✓		✓				✓		
Dagsvik et al. (2002)	Yes	✓	✓						✓	Price, top speed, range, fuel consumption
Horne et al. (2005)	Yes	✓	✓	✓	✓		Region, vehicle type, commuting habits	✓		
Hess et al. (2006)	No									

Study	Collection of demographic data?	Demographic variables collected						Collected to:		
		Age	Gender	Income	Level of education	Driving habits	Other variables	Analyse the sample representativity	Interact with type of vehicle	Interact with vehicle attributes
Potoglou and Kanaroglou (2007a)	Yes	✓	✓	✓	✓		No. vehicles		✓	Acceleration, price
Achtnicht et al. (2008)	Yes	✓					Region	✓	✓	
Ahn et al. (2008)	No									
Bolduc et al. (2008)	Yes	✓	✓	✓	✓		Mode of transportati on			
Mau et al. (2008)	Yes	✓		✓			Family size	✓		
Axsen et al. (2009)	Yes	✓	✓	✓	✓		House location	✓		
Dagsvik and Liu (2009)	Yes	✓	✓	✓			Family size			
Caulfield et al. (2010)	Yes	✓	✓	✓	✓			✓	✓	
Eggers and Eggers (2011)	Yes	✓	✓				Current car (type, brand, age)	✓		
Hensher and Greene (2011)	Yes	✓	✓	✓						Price, fuel consumption, engine capacity, seating capacity
Hidrue et al. (2011)	Yes	✓	✓	✓	✓		Family size, no. vehicles, type of residence	✓	✓	
Kudoh and Motose (2011)	Yes	✓	✓				Current vehicle	✓		
Mabit and Fosgerau (2011)	Yes	✓	✓				Family size	✓	✓	Acceleration, range, price
Qian and Soopramanien (2011)	Yes	✓		✓		✓	Family size, no. vehicles, distance from home to workplace, no. of working members		✓	

Study	Collection of demographic data?	Demographic variables collected						Collected to:		
		Age	Gender	Income	Level of education	Driving habits	Other variables	Analyse the sample representativity	Interact with type of vehicle	Interact with vehicle attributes
Şentürk et al. (2011)	Yes	✓	✓	✓	✓	✓	No. vehicles		✓	
Zhang, Gensler, et al. (2011)	No									
Zhang, Yu, et al. (2011)	Yes	✓	✓	✓	✓		Family size, no. vehicles, no. of family members with driver's license		✓	
Achtnicht et al. (2012)	Yes	✓	✓	✓	✓			✓		
Hess, Fowler, et al. (2012)	Yes			✓			Family size, no. vehicles, house location, no. of workers	✓		
Lebeau et al. (2012)	Yes	✓	✓		✓		Region	✓		
Ziegler (2012)	Yes	✓	✓		✓	✓	Family size, no. vehicles, habitation location (rural or urban)		✓	
Alvarez-Daziano and Bolduc (2013)	Yes	✓	✓	✓	✓		Mode of transportation to commute		✓	
Axsen et al. (2013)	Yes	✓		✓	✓		Family size, type of residence and housing ownership			
Beck et al. (2013)	Yes	✓	✓	✓		✓	Family size, employment status, no. of hours worked, no. of years with a driver's license			
Chorus et al. (2013)	No									

Study	Collection of demographic data?	Demographic variables collected						Collected to:		
		Age	Gender	Income	Level of education	Driving habits	Other variables	Analyse the sample representativity	Interact with type of vehicle	Interact with vehicle attributes
Hackbarth and Madlener (2013)	Yes	✓		✓	✓		Place of residence	✓	✓	
Ito et al. (2013)	Yes	✓		✓			No. vehicles	✓		Vehicle size
Jensen et al. (2013)	Yes	✓	✓				No. vehicles		✓	
Glerum et al. (2014)	Yes	✓	✓				Language	✓		
Hoen and Koetse (2014)	Yes	✓	✓		✓	✓	Family size, possibility of charging vehicle at home, current vehicle type	✓		Price
Parsons et al. (2014)	Yes	✓	✓	✓	✓		No. vehicles			
Tanaka et al. (2014)	Yes	✓	✓	✓	✓		Marital status, house dwelling, interest in AFV	✓	✓	
Axsen et al. (2015)	Yes	✓	✓	✓	✓		Residence type, own residence, previous familiarity with PHEV	✓		
Hevelston et al. (2015)	Yes	✓	✓	✓	✓	✓	Family size, marital status, access to vehicle charging	✓		
Lieven (2015)	Yes	✓	✓			✓		✓		Range
Qian and Soopramanien (2015)	Yes	✓	✓			✓	No. children	✓	✓	
Shin et al. (2015)	Yes	✓	✓	✓		✓	Family size, dwelling size		✓	
Valeri and Danielis (2015)	Yes		✓	✓	✓		Family size, current employment and car expertise level	✓		Price, acceleration, range, annual operating cost

Study	Collection of demographic data?	Demographic variables collected						Collected to:		
		Age	Gender	Income	Level of education	Driving habits	Other variables	Analyse the sample representativity	Interact with type of vehicle	Interact with vehicle attributes
Axsen et al. (2016)	Yes	✓		✓			Family size	✓		
Bahamonde-birke and Hanappi (2016)	Yes	✓	✓	✓	✓		No. vehicles	✓		Engine size
Braz da Silva and Moura (2016)	Yes	✓	✓	✓	✓	✓	Family size, neighbourhood, employment status	✓		
Hackbarth and Madlener (2016)	Yes	✓	✓	✓	✓		Family size, no. vehicles	✓	✓	
Jensen et al. (2016)	Yes	✓	✓	✓		✓	Family size, no. vehicles, no. children	✓		
Krause et al. (2016)	Yes		✓	✓	✓		No. children, race	✓	✓	
Rudolph (2016)	Yes	✓	✓	✓	✓		Type of employment	✓		
Beck et al. (2017)	Yes	✓	✓	✓			Family size	✓	✓	
Cherchi (2017)	Yes	✓	✓	✓		✓	Family size, no. vehicles, profession			Charging time, fuel/electricity cost
Cirillo et al. (2017)	Yes	✓	✓	✓	✓		Work status, home type	✓	✓	
Dimatulac and Maoh (2017)	Yes		✓	✓	✓		Family size, type of occupation		✓	
Higgins et al. (2017)	Yes	✓	✓	✓	✓		Family size, language, marital status, dwelling type, dwelling tenure	✓		vehicle size and body
Liu and Cirillo (2017)	Yes	✓	✓	✓	✓			✓	✓	

Study	Collection of demographic data?	Demographic variables collected						Collected to:		
		Age	Gender	Income	Level of education	Driving habits	Other variables	Analyse the sample representativity	Interact with type of vehicle	Interact with vehicle attributes
Ma et al. (2017)	Yes	✓	✓	✓			No. vehicles, region	✓	✓	
Sheldon et al. (2017)	Yes	✓		✓	✓		Family size, no. vehicles		✓	
Smith et al. (2017)	Yes	✓		✓	✓		No. vehicles		✓	
Byun et al. (2018)	Yes	✓	✓	✓	✓			✓		
Costa et al. (2018)	Yes	✓	✓		✓		Job	✓		
Ferguson et al. (2018)	Yes	✓	✓	✓	✓		Family size, marital status, dwelling type, dwelling tenure	✓	✓	
Fernández-Antolín et al. (2018)	Yes			✓	✓		Family size, no. vehicles		✓	
Hahn et al. (2018)	Yes	✓	✓	✓			Family size, driving experience, housing type, occupation		✓	
Huang and Qian (2018)	Yes	✓	✓	✓	✓		Family size, car use experience		✓	
Liao et al. (2018)	Yes	✓	✓	✓	✓		Family size		✓	
Liu and Cirillo (2018)	Yes	✓	✓	✓	✓			✓		
Soto et al. (2018)	Yes	✓	✓		✓		Family size, no. vehicles		✓	
Wolbertus et al. (2018)	Yes	✓	✓	✓	✓		No. vehicles, full employment	✓	✓	

Table 4.7 - Demographic analysis of consumer preference and demand studies for AFVs.

The review allowed verifying that demographic data collection is a common procedure in consumer preferences studies of AFVs with 95% of the reviewed studies collecting data about individual characteristics of consumers. Age and gender are the demographics collected more often, followed by income. Regarding the purpose of collecting such data, the main reasons identified were the analysis of sample representativity (52%), analysis of the interaction of individual characteristics with vehicle preferences (41%) and with vehicle attributes (15%) (Figure 4.12). Only one study (Mabit and Fosgerau, 2011) covered these three analyses.

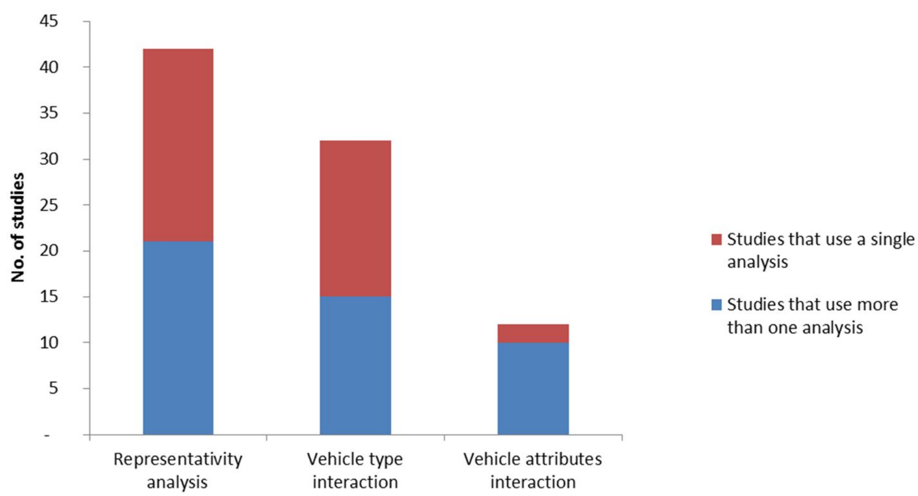

Figure 4.12 – Purpose of collecting demographic data.

As a review of the influence of demographics on preferences for type of vehicle was already presented in Chapter 2, only a brief review about the influence of demographics on consumer preferences for vehicle attributes is presented here. The vehicle attributes analyzed more often were purchase price, range, acceleration and vehicle size (Figure 4.13), whilst the influence of age and gender on preferences was tested with more frequency.

Only a few studies found a statistically significant influence of demographics on preferences for vehicle attributes. Regarding the influence of gender and age on preferences for range previous studies found that women (Ewing and Sarigöllü, 1998; Lieven, 2015) and younger consumers (Ewing and Sarigöllü, 1998; Mabit and Fosgerau, 2011) are more sensitive to range. On the other hand, Valeri and Danielis (2015) concluded that women are less sensitive to range. Additionally, women were also found to be less sensitive to purchase price (Valeri and Danielis, 2015), acceleration (Ewing and Sarigöllü, 1998; Potoglou and Kanaroglou, 2007a; Valeri and Danielis, 2015), fuel consumption (Valeri and Danielis, 2015) and top speed (Dagsvik et al., 2002) than men. Concerning the vehicle size, women and younger consumers have higher preferences for midsize vehicles, while men and older consumers prefer large vehicles (Tompkins and Bunch, 1998; Ito et al., 2013).

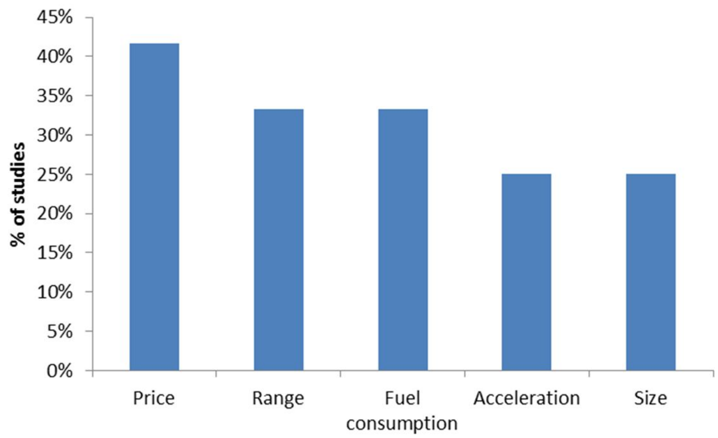

Figure 4.13 – Frequency of vehicle attributes analyzed more often.

4.1.3.2. Methodological approach

The data strategy for this analysis was to cross the demographic data with the preferences elicited through CBC in order to assess if any significant relations could be identified. Between the two sets of data, CBC Initial and CBC Final rankings, CBC Final ranking was used due to its higher predictive found in subsection 4.1.1 (analysis 6 in Figure 4.14).

The relation between demographics and preferences was analyzed through counting analysis from Sawtooth® software. This analysis consists on computing the percent of times that each level is chosen, when available, for each demographic group (Orme and Howell, 2009).

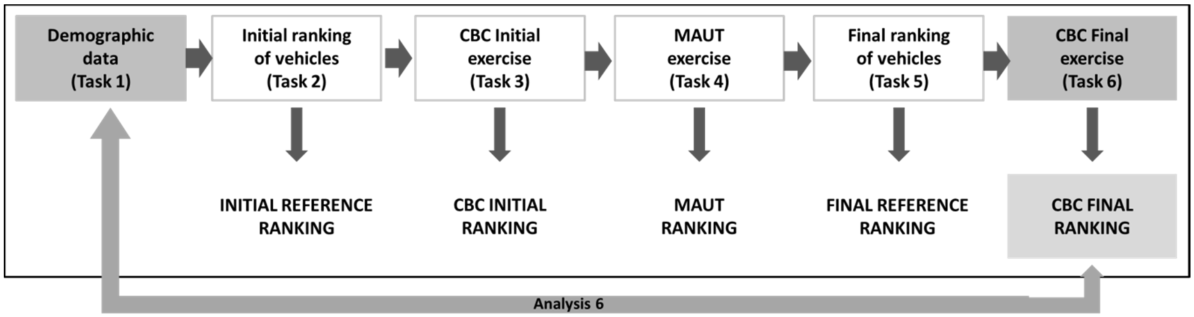

Figure 4.14 - Strategy of data analysis: tasks and data analyzed are in grey and the arrows represent the performed rankings comparison.

4.1.3.3. Results

Analysis of sample representativity

According to Statistics Portugal from Census 2011 (INE, 2012), the sample used in this survey is not representative of the Portuguese population, as young adults, males and consumers with higher education were overrepresented (Table 4.8). The misrepresentation of Portuguese population is a downside of selecting a convenience sample that fit the selection criteria for the study, presented in the subsection 3.1. However, as previously mentioned, the absence of representativity is not a major concern if it allows gathering data from a group of consumers with more interesting characteristics for the study purposes (e.g. (Potoglou and Kanaroglou, 2007a; Caulfield et al., 2010; Zhang, Yu, et al., 2011; Achtnicht et al., 2012)). Table 4.9 presents the statistics of demographic variables per scenario.

Variable	Sample (%)	INE (2011 National statistics) (%)
Age		
<45	61	43
≥45	39	57
Gender		
Female	44	53
Male	56	47
Level of education		
No higher education	27	84
College degree	40	13
Master/PhD degree	33	3

Table 4.8 - Demographics of consumers.

Variable	Current Scenario (%)	Future Scenario (%)
Age		
<**45**	68	74
≥45	32	26
Gender		
Female	51	34
Male	49	66
Level of education		
No higher education	26	31
College degree	45	31
Master/PhD degree	28	38
Type of route		
City	55	52
Intercity	45	48
Vehicle age		
[0-5]	30	31
]5-10]	24	30
>10	45	39
Annual distance		
<30000	87	89
>=30000	13	11
Knowledge		
Low	53	37
Medium/high	47	63

Table 4.9 - Demographics of consumers per scenario.

Analysis of attributes importance for demographic groups

As the goal of this study is to identify differences (if there are any) between demographic groups, a series of “Between group Chi-Square” tests was performed to verify if the differences among results are statistically significant. This test consists in identifying if the levels of one attribute significantly differ in their choice frequency between demographic groups, for example if women are more likely to prefer a BEV than men.

The counting analysis results are depicted on Table 4.10 and 4.11, for the current scenario, and on Table 4.12 and 4.13, for the future scenario, along with the respective Chi-Square results. Considering only the results that were found to be statistically significant for the “Between group Chi-Square” test, some conclusions were derived for each scenario.

In the current scenario, the results showed that preferences for the type of engine are frequently influenced by demographic characteristics of consumers. BEVs are more likely to be preferred by older consumers, similarly to Zhang, Yu, et al. (2011) and Shin et al. (2015); by consumers that drive less annually and by city drivers, in line with Hackbarth and Madlener (2013). On other hand, younger consumers, drivers of intercity routes and consumers that drive less have higher preferences for gasoline vehicles. In line with Dimatulac and Maoh (2017) findings, consumers that drive long-distances more often have higher preferences for HEVs.

About the influence of demographics on vehicle attributes relations were found, such as:

- Consumers with higher education are more price sensitive;
- City drivers are less sensitive to range;
- Older consumers and consumers that drive less are more sensitive to fuel consumption;
- Lower knowledge consumers are less sensitive to lower emission values.

Among the above relationships found between demographics and vehicle attributes preferences, there were two which had an unexpected direction, namely the higher price sensitivity from high educated consumers and the higher sensitivity to fuel consumption from consumers that drive less. Concerning the first relationship, it can be considered counterintuitive because higher educated consumers tend to be wealthier and therefore less sensitive to price (see subsection 2.3.2.3). It is conjectured that this might not be the case among the convenience sample of this study, which included many young Portuguese with college degrees, but who nowadays often earn less than older consumers without a degree. Another possible explanation is that better numeracy leads higher educated consumers to be more attentive to cost implications. Concerning the second relationship, one would expect that consumers driving less can afford a higher cost per km. A possible explanation for the relationship found is that consumers avoid driving, or drive less, when fuel price is higher due to their higher sensitivity to higher driving costs, but this relationship should be further examined in future studies.

In the future scenario, less conclusions could be derived due to the existence of fewer statistically significant relations. Regarding the influence on vehicle choice, city drivers are more likely to prefer BEVs and less likely to choose PHEVs and Diesel vehicles. Focusing the influence of demographics on vehicle attributes preferences, men are more sensitive to low prices and city drivers are more sensitive to range, fuel consumption and to lower CO_2 emissions.

Attribute	Demographic variables									
	Age			Gender			Level of education			
	< 45	≥ 45	Dif.	M	F	Dif.	No higher education	College degree	Master/PhD degree	
Type of engine										
BEV	19%	25%	-6%	22%	20%	+2%	23%	22%	17%	
PHEV	40%	44%	-4%	42%	40%	+2%	46%	42%	35%	
HEV	40%	38%	+3%	40%	38%	+2%	35%	36%	49%	
Gasoline	33%	18%	+15%	24%	33%	-9%	18%	31%	33%	
Diesel	49%	46%	+3%	48%	49%	-1%	50%	46%	50%	
Sig. between groups			0.05			Not Sig.				Not Sig.
Price										
24,000	45%	38%	+7%	41%	45%	-4%	40%	42%	49%	
27,000	50%	49%	+1%	50%	50%	0%	46%	47%	59%	
30,000	28%	28%	-1%	29%	27%	+3%	29%	30%	24%	
32,000	25%	23%	+1%	26%	22%	+4%	21%	25%	26%	
34,000	17%	22%	-5%	18%	19%	-1%	26%	20%	9%	
Sig. between groups			Not Sig.			Not Sig.				0.05
Range										
150	15%	19%	-3%	17%	16%	+2%	20%	17%	13%	
250	21%	28%	-7%	25%	22%	+2%	27%	25%	19%	
350	20%	32%	-12%	25%	24%	+1%	25%	26%	20%	
900	35%	28%	+7%	34%	32%	+1%	30%	33%	35%	
1200	45%	44%	+1%	43%	46%	-3%	44%	44%	46%	
Sig. between groups			Not Sig.			Not Sig.				Not Sig.
Fuel consumption										
2	28%	30%	-2%	30%	27%	+2%	28%	29%	28%	
4	34%	41%	-7%	38%	34%	+4%	43%	38%	26%	
6	42%	48%	-6%	43%	44%	-1%	45%	43%	45%	
8	34%	22%	+12%	29%	32%	-3%	26%	31%	34%	
10	25%	15%	+10%	19%	24%	-6%	15%	20%	31%	
Sig. between groups			0.05			Not Sig.				Not Sig.
CO_2 Emissions										
50	28%	33%	-5%	32%	28%	+3%	32%	31%	26%	
90	31%	33%	-2%	30%	32%	-2%	35%	32%	27%	
110	34%	34%	0%	31%	36%	-5%	33%	32%	38%	
130	45%	41%	+3%	45%	42%	+3%	43%	42%	47%	
150	29%	23%	+6%	27%	27%	0%	21%	29%	29%	
Sig. between groups			Not Sig.			Not Sig.				Not Sig.

Table 4.10 - Counting analysis for the current scenario and the significance between groups for each attribute.

	Demographic variables								
	Route			Km per year			Knowledge		
Attribute	City	Intercity	Dif.	≤30,000	>30,000	Dif.	Low	Medium/ High	Dif.
Type of engine									
BEV	25%	16%	+9%	21%	16%	+6%	19%	23%	-4%
PHEV	41%	41%	0%	42%	34%	+8%	38%	45%	-6%
HEV	36%	43%	-7%	40%	38%	+2%	44%	35%	9%
Gasoline	21%	36%	-15%	25%	49%	-24%	29%	27%	2%
Diesel	49%	48%	+1%	48%	50%	-2%	52%	45%	6%
Sig. between groups			0.01			0.05			Not Sig.
Price									
24,000	40%	47%	-7%	42%	53%	-11%	45%	41%	+3%
27,000	47%	53%	-6%	49%	52%	-2%	54%	45%	+10%
30,000	32%	23%	+10%	28%	25%	+3%	25%	31%	-6%
32,000	24%	25%	-1%	25%	17%	+8%	22%	26%	-4%
34,000	20%	17%	+3%	19%	14%	+5%	17%	21%	-4%
Sig. between groups			Not Sig.			Not Sig.			Not Sig.
Range									
150	21%	12%	+9%	17%	13%	+4%	13%	20%	-7%
250	28%	18%	+10%	24%	20%	+4%	22%	25%	-3%
350	27%	21%	+6%	27%	10%	+17%	24%	24%	0%
900	30%	36%	-6%	31%	45%	-13%	33%	32%	+1%
1200	42%	46%	-4%	45%	42%	+2%	46%	43%	+3%
Sig. between groups			0.05			Not Sig.			Not Sig.
Fuel consumption									
2	32%	24%	+8%	29%	25%	+4%	26%	32%	-6%
4	38%	34%	+5%	38%	23%	+15%	33%	39%	-6%
6	41%	47%	-5%	43%	48%	-5%	46%	41%	+5%
8	26%	35%	-9%	29%	43%	-15%	32%	28%	+4%
10	22%	22%	0%	21%	28%	-7%	25%	18%	+7%
Sig. between groups			Not Sig.			0.05			Not Sig.
CO_2 Emissions									
50	33%	27%	+6%	31%	25%	+5%	25%	35%	-10%
90	32%	31%	+1%	31%	36%	-5%	31%	31%	0%
110	30%	38%	-7%	34%	34%	0%	37%	30%	+7%
130	44%	43%	+2%	44%	40%	+5%	43%	44%	-1%
150	26%	29%	-3%	26%	32%	-6%	31%	23%	+7%
Sig. between groups			Not Sig.			Not Sig.			0.05

Table 4.11 - Counting analysis for the current scenario and the significance between groups for each attribute. (cont.)

	Demographic variables									
	Age			Gender			Level of education			
Attribute	< 45	≥ 45	Dif.	M	F	Dif.	No higher education	College degree	Master/PhD degree	
Type of engine										
BEV	31%	27%	4%	30%	30%	1%	26%	31%	32%	
PHEV	53%	55%	-1%	52%	56%	-4%	52%	53%	56%	
HEV	37%	35%	2%	39%	33%	6%	35%	36%	38%	
Gasoline	9%	9%	0%	10%	8%	2%	11%	10%	6%	
Diesel	35%	42%	-7%	35%	40%	-5%	45%	36%	32%	
Sig. between groups			Not Sig.			Not Sig.				Not Sig.
Price										
22,000	48%	44%	4%	43%	55%	-12%	50%	47%	45%	
24,000	29%	34%	-5%	28%	33%	-5%	29%	32%	29%	
26,000	34%	35%	-1%	35%	32%	3%	37%	33%	33%	
28,000	27%	24%	2%	31%	17%	14%	23%	24%	30%	
30,000	33%	32%	1%	31%	35%	-4%	31%	34%	32%	
Sig. between groups			Not Sig.			0.01				Not Sig.
Range										
250	23%	24%	-1%	23%	24%	-1%	20%	17%	13%	
450	35%	22%	13%	32%	33%	-1%	27%	25%	19%	
600	21%	20%	1%	23%	18%	5%	25%	26%	20%	
900	33%	33%	0%	33%	32%	2%	30%	33%	35%	
1200	43%	47%	-4%	43%	46%	-3%	44%	44%	46%	
Sig. between groups			Not Sig.			Not Sig.				Not Sig.
Fuel consumption										
2	42%	39%	2%	42%	40%	2%	36%	43%	43%	
4	51%	53%	-2%	49%	55%	-6%	52%	49%	53%	
7	32%	29%	3%	32%	30%	2%	32%	34%	27%	
9	22%	29%	-7%	25%	22%	3%	28%	21%	22%	
12	10%	11%	-1%	9%	13%	-3%	12%	9%	10%	
Sig. between groups			Not Sig.			Not Sig.				Not Sig.
CO_2 Emissions										
40	40%	37%	3%	37%	41%	-4%	35%	39%	41%	
60	45%	50%	-5%	47%	44%	3%	46%	46%	46%	
80	24%	25%	0%	26%	21%	4%	25%	25%	23%	
100	29%	28%	1%	30%	28%	2%	31%	26%	30%	
120	25%	24%	1%	24%	27%	-3%	28%	27%	21%	
Sig. between groups			Not Sig.			Not Sig.				Not Sig.

Table 4.12 - Counting analysis for the future scenario and the significance between groups for each attribute.

Demographic variables									
	Route			Km per year			Knowledge		
Attribute	City	Intercity	Dif.	≤30,000	>30,000	Dif.	Low	Medium/ High	Dif.
Type of engine									
BEV	37%	23%	+14%	30%	31%	-1%	28%	31%	-3%
PHEV	51%	56%	-5%	55%	48%	+7%	52%	55%	-3%
HEV	36%	37%	-1%	36%	43%	-8%	39%	35%	+4%
Gasoline	8%	10%	-2%	9%	7%	+2%	8%	9%	-1%
Diesel	30%	44%	-14%	37%	36%	+1%	41%	35%	+7%
Sig. between groups			0.01			Not Sig.			Not Sig.
Price									
22,000	48%	47%	1%	46%	51%	-5%	47%	47%	0%
24,000	31%	29%	2%	31%	23%	+7%	29%	31%	-2%
26,000	36%	33%	3%	34%	37%	-3%	36%	33%	+3%
28,000	25%	27%	-2%	27%	23%	+4%	24%	27%	-3%
30,000	31%	34%	-4%	33%	34%	-2%	33%	32%	+1%
Sig. between groups			Not Sig.			Not Sig.			Not Sig.
Range									
250	32%	16%	+16%	23%	24%	-1%	24%	23%	+1%
450	34%	30%	+4%	32%	34%	-3%	28%	34%	-7%
600	24%	18%	+6%	21%	22%	-1%	18%	23%	-5%
900	32%	34%	-2%	33%	29%	+4%	33%	33%	+1%
1200	39%	48%	-9%	44%	45%	-1%	46%	43%	+3%
Sig. between groups			0.01			Not Sig.			Not Sig.
Fuel consumption									
2	48%	34%	+14%	41%	40%	+2%	41%	41%	0%
4	48%	55%	-7%	52%	50%	+2%	48%	53%	-5%
7	27%	35%	-8%	31%	30%	+1%	32%	31%	+1%
9	23%	24%	-1%	24%	24%	-1%	27%	21%	+6%
12	11%	10%	+1%	10%	14%	-4%	11%	10%	+1%
Sig. between groups			0.01			Not Sig.			Not Sig.
CO_2 Emissions									
40	46%	32%	+14%	39%	36%	+3%	38%	39%	-1%
60	43%	49%	-5%	45%	53%	-7%	46%	46%	-1%
80	24%	25%	-1%	25%	21%	+4%	22%	26%	-4%
100	28%	30%	-3%	28%	32%	-4%	31%	28%	+3%
120	21%	28%	-7%	26%	20%	+6%	26%	24%	+1%
Sig. between groups			0.05			Not Sig.			Not Sig.

Table 4.13 - Counting analysis for the future scenario and the significance between groups for each attribute (cont.)

Comparison between scenarios

The analysis of the demographic variables influence on type of engine and vehicle attributes allowed identifying changes in different directions between scenarios. First, there were demographic variables that significantly influenced preferences for some attributes in the current scenario but they no longer influenced preferences in the future scenario, and vice versa; second, there were variables that were significant in both scenarios (Table 4.14).

Regarding the variables that influenced preferences in the current scenario, but not in the future scenario, three can be pointed out: age, annual distance and knowledge. The context of the future scenario, where EVs are more affordable and familiar to consumers and where the vehicle set is more fuel efficient and has less emissions, may explain why these variables lost their influence in the future scenario. On the other hand, in the future scenario gender started to significantly influence preferences for vehicle price while type of route, in addition to type of engine and range, also influenced preferences for fuel consumption and CO_2 emissions. This broader influence of type of route on vehicle attributes preferences underlines the importance and influence of consumer driving habits on future vehicle purchases in a more competitive market as the one defined in the future scenario.

Regarding the relationships that were statistically significant in both scenarios, the same preference direction was observed, namely city drivers are more likely to prefer BEVs and are less sensitive to range.

	CURRENT SCENARIO	FUTURE SCENARIO
AGE	**Type of engine** Young (+) Gasoline Young (-) BEVs **Fuel consumption** Young less sensitive to fuel consumption	-
GENDER	-	**Price** Men more price sensitive
EDUCATION	**Price** Higher education more price sensitive	-
TYPE OF ROUTE	**Type of engine** City drivers (+) BEVs City drivers (-) HEVs (-) Gasoline **Range** City drivers less sensitive to range	**Type of engine** City drivers (+) BEVs City drivers (-) Diesel (-) PHEVs **Range** City drivers less sensitive to range **Fuel consumption** City drivers more sensitive to fuel consumption **CO_2 emissions** City drivers more sensitive to emissions
ANNUAL DISTANCE	**Type of engine** Drive less (+)BEVs (+) PHEVs Drive less (-) Gasoline **Fuel consumption** Drive less more sensitive to fuel consumption	-
KNOWLEDGE	**CO_2 emissions** Low knowledge less sensitive to emissions	**-**

Table 4.14 – Influence of demographic variables on attribute preferences for each scenario.

4.1.3.4. Concluding remarks on the influence of demographics on preferences

This analysis provided several insights about the influence of demographic variables on vehicle choice and on preferences for vehicle attributes. The results showed that demographic variables frequently influenced preferences for the type of vehicles, mainly, age, type of route and annual distance driven by consumers.

Regarding the influence of demographics on vehicle attributes, the relevance of type of route should be highlighted not only because it influenced a broader range of attributes, considering the two scenarios, but also because its influence on vehicle attributes was consistent in both scenarios revealing a robust impact on preferences that was independent of the market conditions.

4.2. Aggregated preferences

Although models that compute utility functions at the individual level are a better fit to SP data of consumers, for purposes such as to make managerial decisions based on large samples, it is useful to have one set of utilities that represent the whole group of consumers. Therefore, this subsection is centered on preferences at the aggregate level.

This subsection contributes to the literature by providing aggregate utility functions that represent preferences for EVs for the analyzed sample. The main goal of this analysis is to obtain an aggregated structure of preferences for Portuguese consumers in order to provide insights about which policies would have a higher impact on consumer preferences for EVs. In this context, and considering the two defined scenarios, four specific questions are to be answered through this analysis:

1. Do the consumers’ part-worth utility functions change within different market conditions?
2. Which attributes consumers’ value the most in a vehicle purchase decision in the current market conditions? And in a future context?
3. What are the consumer preferences for the vehicles set?
4. What is the sensitivity of consumer preferences to attributes variation?

4.2.1. Previous studies on analysing preferences in the Portuguese market

Consumer preferences have been extensively analyzed over the years worldwide. Those analyses have been targeting some countries more than others. For instance, US, Canada and Germany are among the most analysed countries. However, Portugal is among the least analyzed countries regarding the analysis of preferences for AFVs or market penetration of AFVs studies. Only two studies addressed the Portuguese market, namely Fazeli et al. (2012), that aimed at understanding the interaction between the refuelling network and the AFVs vehicle sales and Braz da Silva and Moura (2016), that aimed at estimating the environmental impact of LDVs fleet. Both studies had the final purpose of analysing a AFVs diffusion model applied to the Portuguese market, but only Braz da Silva and Moura (2016) collected preference data from Portuguese consumers. However, this study used preference data only to compute the required utility coefficients for the model and, therefore, the preferences structure was not analyzed. For instance, the identification of the most relevant attributes, the ranking of vehicles according to consumer preferences or the sensitivity of Portuguese consumers to changes in attributes values were not addressed.

4.2.2. Methodological approach

The computation of aggregated preferences was based on CBC elicited preferences. However, as this study performed two preference elicitations based on CBC questions (task 3 and task 6), a decision had to be made about which CBC elicited results to consider to compute the aggregated preferences. Consistent with the previous selection, this decision was based on CBC results that had higher predictive validity of consumer preferences, i.e. which better represent consumer preferences (considering the Initial Reference Ranking). Therefore, the CBC data used for the computations of aggregate preferences was from task 6, CBC Final exercise (Figure 4.15).

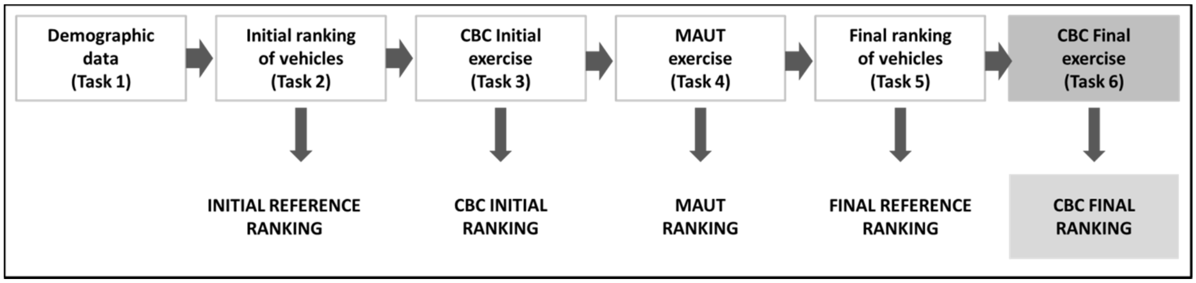

Figure 4.15 – Strategy of data analysis: task and data analyzed in grey.

In order to address the outlined questions, and similarly to previous studies (e.g. Decker and Trusov, 2010; Lüthi and Wüstenhagen, 2011; Şentürk et al., 2011; Hoen and Koetse, 2014; Hevelston et al., 2015), the average of the CBC/HB individual utilities was computed in order to obtain aggregated utility functions for each attribute. The resulting output was a single set of part-worth utility function for all consumers for each scenario.

4.2.3. Results

As averaged utilities were used, the distribution of each attribute level is presented in order to analyze the variability of the attribute utilities across consumers. The aggregated part-worth utilities (values presented in Appendix X and XI for the current and future scenario) were plotted for each scenario (Figure 4.16 and Figure 4.17 for current and future scenario).

The current scenario results show a higher heterogeneity of preferences for the type of engine, purchase price and fuel consumption attributes (higher standard deviations) and homogenous preferences regarding the CO_2 emissions attribute (lower standard deviations). The utility results for the future scenario reveal an overall more homogenous set of preferences than in the current scenario. The higher heterogeneity of preferences is observed in the extreme values of the fuel consumption attribute, namely for 2€/100km and 12€/100km. Similarly to the current scenario, homogenous preferences are observed for CO_2 emissions.

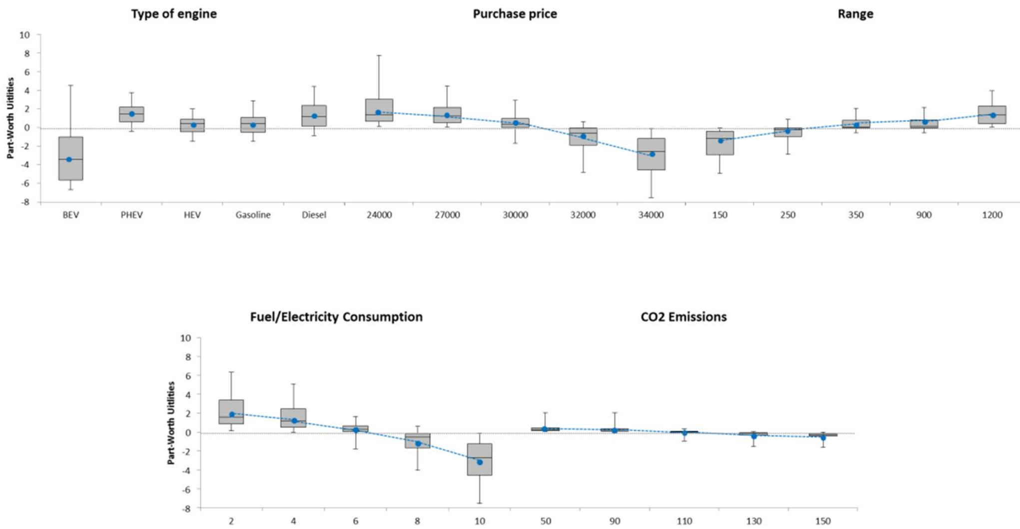

Figure 4.16 - Preference distribution of each attribute (blue dots represent the average utility value of each attribute level and blue dashed line represent the part-worth utility function for each continuous attribute) for the current scenario.

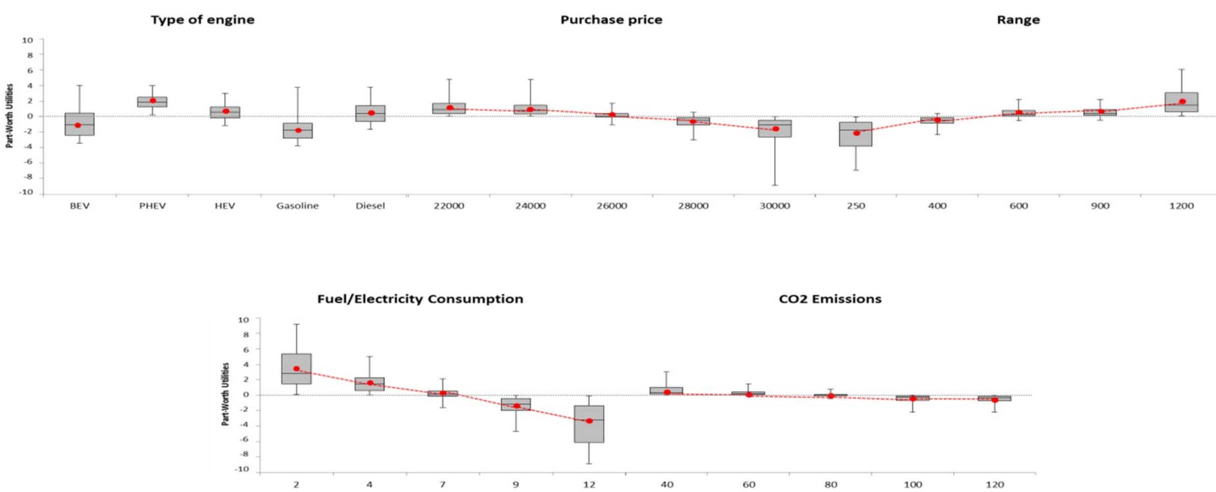

Figure 4.17- Preference distribution of each attribute (red dots represent the average utility value of each attribute level and red dashed line represent the part-worth utility function for each continuous attribute) for the future scenario.

In order to highlight the main differences regarding the consumer preferences in different market conditions, the results of the aggregated preferences that follow are presented and analyzed in a comparative basis regarding the part-worth utilities, relative importance of each attribute and vehicles ranking (§4.2.1.1-4.2.1.3). A sensitivity analysis of the most important attributes of each scenario is then presented (§4.2.1.4).

4.2.3.1. Part-worth utilities

In order to perform a comparative analysis between scenarios the average part-worth utility functions of both scenarios were plotted in the same graph (Figure 4.18). The analysis of the slope of these utility functions allowed verifying how sensitive consumers are to changes in attribute levels in each scenario. Therefore, the following was observed:

- Purchase price: consumers are more price sensitive in the future scenario than in the current scenario conditions (in terms of slope between 24000€ and 30000€);
- Range: increments of range have higher impact on consumers' utility in the future scenario, mainly between 400km and 600km;
- Fuel consumption: consumers are more sensitive to increments of fuel consumption when the consumption is higher in the current scenario, namely between 8€/100km and 10€/100km, while in the future scenario they are more sensitive to increments of fuel consumption when its value is low, between 2€/100km and 4€/100km;
- CO_2 emissions: consumers are more sensitive to changes in CO_2 emissions in the future scenario mainly between 50g/km and 100g/km.

Regarding the type of engine attribute, as a non-quantitative attribute, its analysis was based on the comparison between the utility values of each type of vehicle displayed in the Figure 4.19. PHEVs and HEVs have similar preferences in both scenarios and the highest increment of preferences from current to future scenario belongs to BEV (+2.152). In opposition, the preferences regarding the Gasoline vehicle were the ones that decreased more (-1.927).

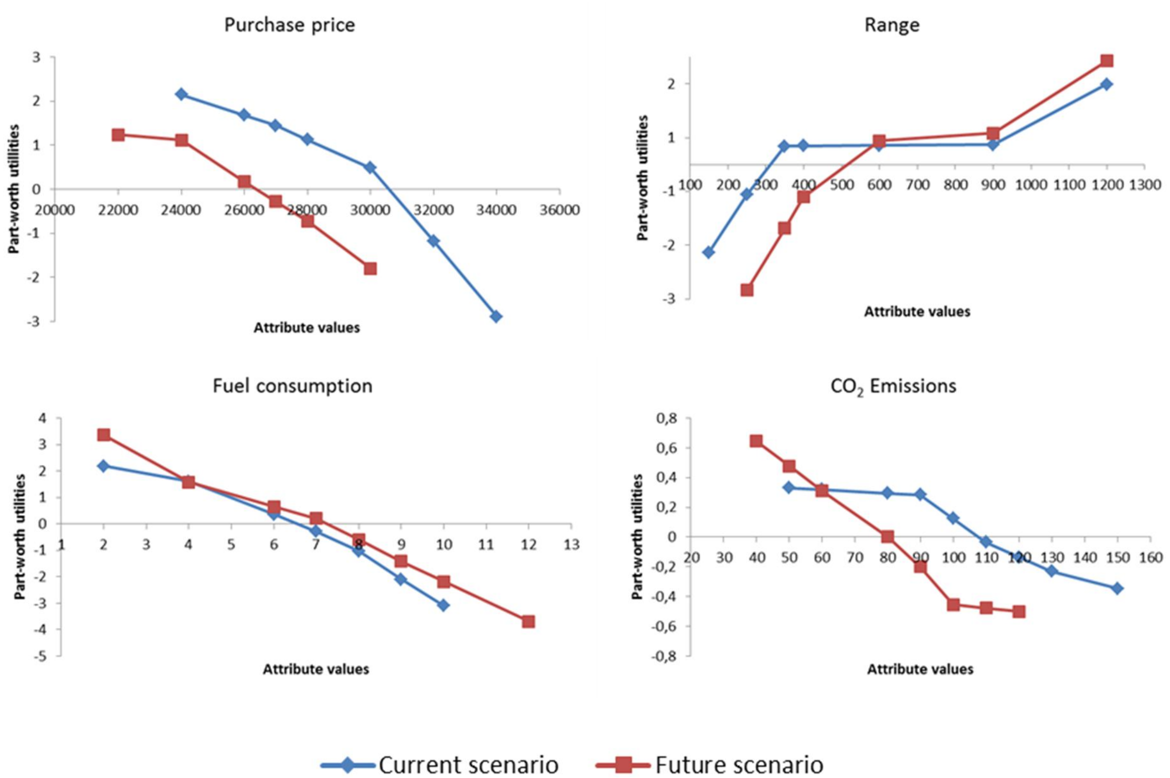

Figure 4.18 – Part-worth utility functions for current and future scenarios.

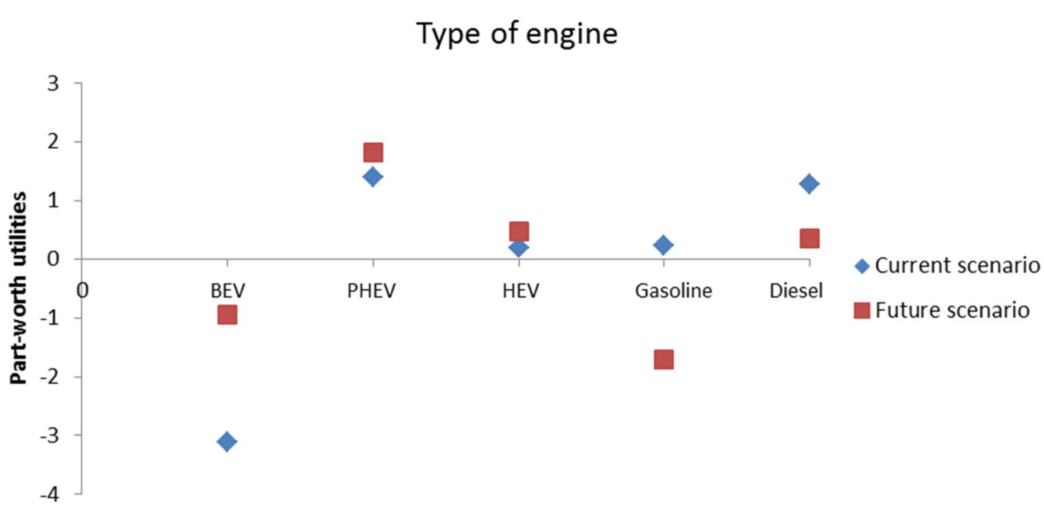

Figure 4.19 – Part-worth utilities of each type of engine for each scenario.

4.2.3.2. Relative importance of attributes

The relative importance of each attribute k, W_k, was assessed considering the aggregated part-worth utility functions for each scenario. The part-worth range of each attribute is normalized so that the k attribute importances add up to unity (Malhotra, 2008):

$$W_k = \frac{I_k}{\sum_{k=1}^{n} I_k} \tag{4.8}$$

$$I_k = \{\max(\beta_{kj}) - \min(\beta_{kj})\}, \text{ for each attribute } k \tag{4.9}$$

So that,

$$\sum_{k=1}^{n} W_k = 1$$

where,

I_k is the difference between the highest and lowest part-worth utility of attribute k

The results depicted in the Figure 4.20 allowed identifying fuel consumption and CO_2 emissions as the most and the least important attribute in both scenarios, respectively. Regarding the second most important attribute it differs between scenarios. While consumers value more the purchase price in the current scenario, in the future scenario range is the second most important attribute.

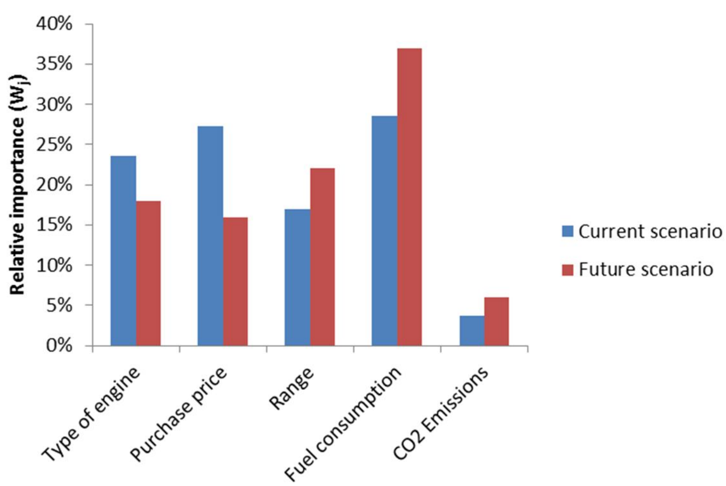

Figure 4.20 – Relative importance of each attribute according to each scenario.

4.2.3.3. Ranking of vehicles

The vehicles were ranked by decreasing order of their global utility, according to equation (4.3). The aggregated ranking that represents the preferences for the whole sample obtained for each scenario is plotted in Figure 4.21, which depicts the magnitude of the utility differences between ranking positions. Through the analysis of the rankings some comments can be made. First, both scenarios have the same top three vehicles (Diesel, HEV and PHEV). Second, although BEV1 did not change its position in the final ranking and BEV2 only rose one position from current to future scenario, they achieved global utilities markedly closer to the other EVs (higher competition among EVs in the future scenario) and close to the Diesel vehicle. Third, the Gasoline vehicle decreased two positions and became the least preferred vehicle in the future scenario, far from the remaining ones. And fourth, the utilities range (difference between the utility of the vehicle placed at first and last) in the future scenario is more than the double of the range in the current scenario, but the position of the vehicles in the ranking is more concentrated with only the Gasoline vehicle being placed with a higher distance from the other vehicles. This shows that, considering the defined future market conditions, the Gasoline vehicles are markedly considered the less preferred vehicles from the vehicles set.

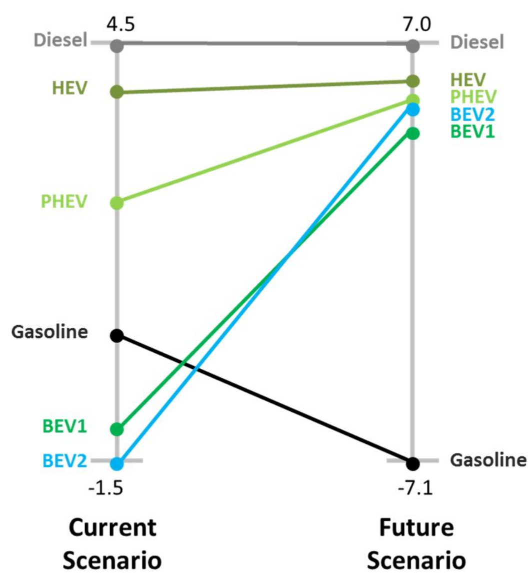

Figure 4.21 – Plot of the aggregated ranking of the vehicles set for each scenario.

4.2.3.4. Sensitivity analysis

A sensitivity analysis of the attributes with higher relative importance in each scenario was performed (see Figure 4.20). The goal of this analysis was to provide insights regarding the policies design that aim at increasing the market penetration of BEVs. The sensitivity analysis is thus focused on variations of attribute values that would lead to higher preferences for BEVs. This analysis considered only one BEV from the vehicles set, namely BEV1, because this vehicle was based on an existent BEV in the Portuguese market.

- **Current scenario**

As the purchase price and fuel consumption are the two most important attributes for consumers in this scenario the sensitivity of consumers' utility to changes in these attributes was analyzed. The first analysis consisted in the reduction of the purchase price of BEVs, testing the potential effect of a purchase subsidy for these vehicles. The results showed a slight impact of a price reduction on BEVs utilities when the reduction was equal or above 6,000€, with BEVs rising one position in the final ranking (Figure 4.22).

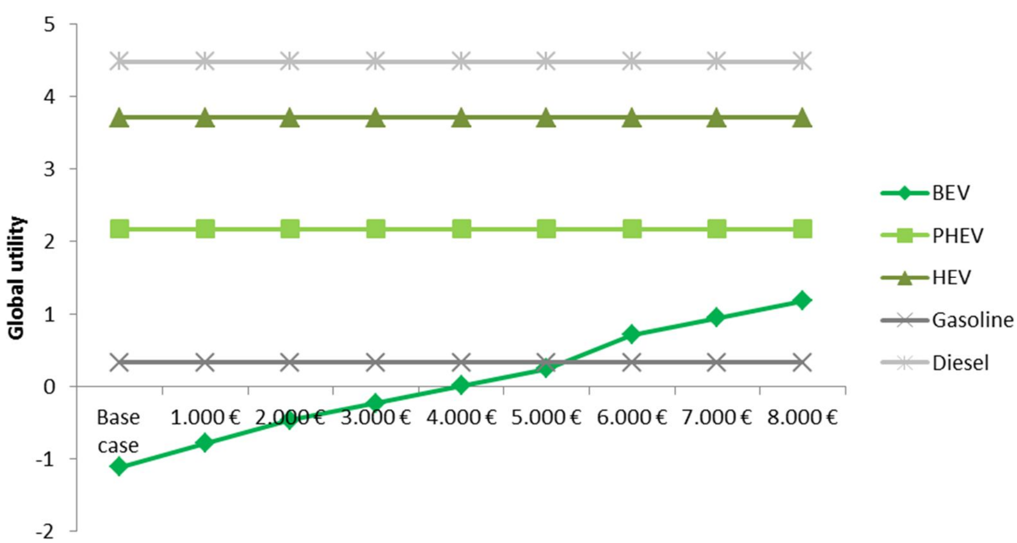

Figure 4.22 – Evolution of vehicle utilities considering the price reduction of BEVs.

The second analysis concerned to an increase in the fuel prices (gasoline and diesel) testing, for instance, the potential effect of a fuel price tax increment in order to encourage the purchase of non-fueled vehicles. Results showed that increments of fuel prices under 90% of their value have a small impact on BEVs position in the final ranking (Figure 4.23). When the fuel price increment reaches 100%, 3.16€/l and 2.78€/l for Gasoline and Diesel respectively, BEVs rose to the second position in the vehicles ranking. This result showed that, although the low cost of energy is one of the main advantages of BEVs, this characteristic is significant for vehicle purchase decisions only in a scenario where the gasoline and diesel prices are considered unbearable for consumers. The impact of the fuel price increments on vehicle global utilities also shows that preferences for Gasoline vehicles are the ones that decrease the most.

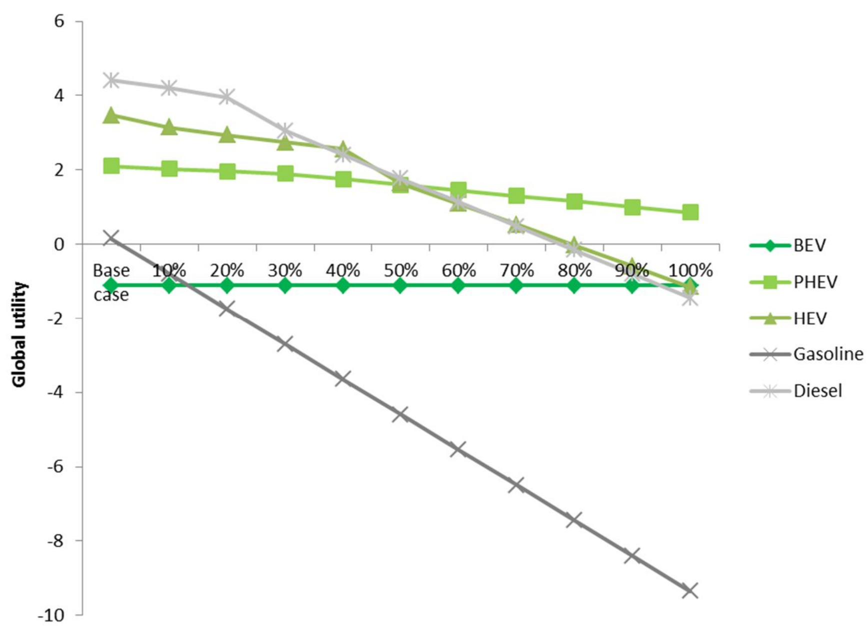

Figure 4.23 – Evolution of vehicle utilities considering the variation of fuel prices.

- **Future scenario**

In the future scenario the sensitivity analysis focused the fuel consumption and range attributes. The analysis of the fuel consumption was similar to the one performed for the current scenario. The results unveil a significant effect on BEVs ranking position when the fuel price increment is equal to or above 40%, 2.8€/l and 2.38€/l for Gasoline and Diesel respectively (Figure 4.24). Additionally, these increments also favored the preferences for PHEVs that reached the first position in the ranking from the fuel increment of 20% onwards, due to the small impact that fuel increments had on PHEVs global utility.

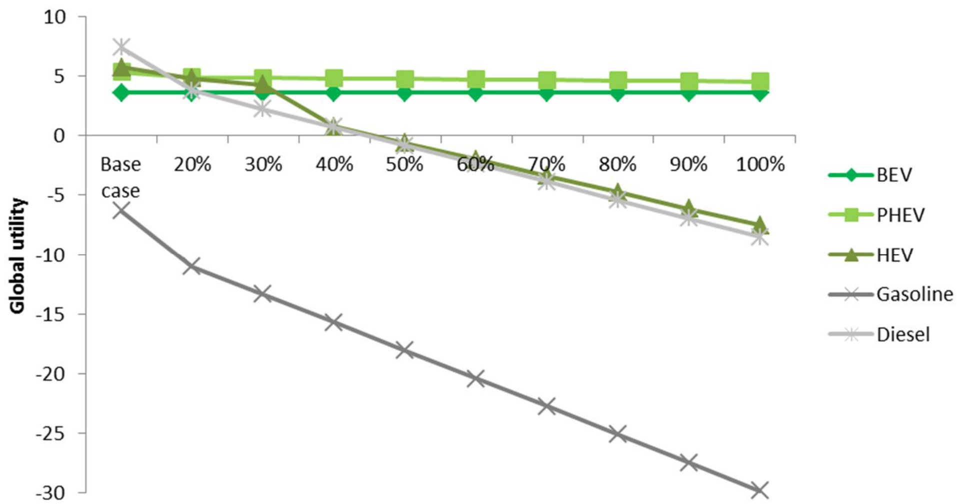

Figure 4.24 – Evolution of vehicle utilities considering the variation of fuel prices in the future scenario.

The sensitivity analysis of range attribute was made through increments from 200km to 1100km for BEVs. This analysis allows understanding what could be the effect on BEVs preferences of stimulating automotive companies to increase R&D investments in order to improve BEVs batteries. Results showed that a minimum range of 400km is necessary to place BEVs as the most preferred vehicle (Figure 4.25). The significant increment of BEVs global utility, as a result of range improvements, explains the higher preferences for these vehicles.

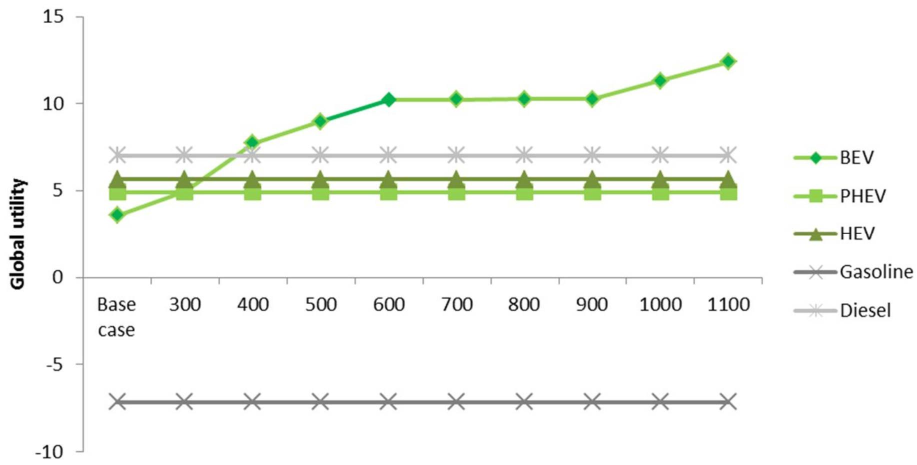

Figure 4.25 – Evolution of vehicle utilities considering the variation of BEV range in the future scenario.

4.2.4. Concluding remarks concerning aggregated preferences

The analysis of the most relevant attributes for consumers highlighted the importance of the fuel consumption on consumer preferences in both scenarios. This high relevance of fuel consumption can be linked to the progressive increase of fuel prices in recent years, which motivates consumers' concern and, consequently, could contribute to its higher relevance on future choice decisions in a purchase context.

The analysis of the consumers' sensitivity to attribute values change allowed verifying that consumers were generally more sensitive to variations in attribute values when future market conditions were considered. Along with the closer global utility of EVs with Diesel vehicles in the future scenario, this suggests a higher competition among vehicle technologies in the future, as consumers become more familiar with EVs and the characteristics of these vehicles become more similar to the existent conventional vehicles.

The sensitivity analysis provided interesting insights about which policies should be tested, and in what magnitude, in order to increase the circulation of EVs through increasing the consumer preferences for BEVs, namely:

- Purchase subsidies revealed to have a small impact in the short-term;
- Potential of fuel tax increments on increasing BEVs circulation in the short-term that increases in the medium-term;
- R&D incentives, by increasing batteries range, with a significant impact on consumer preferences for BEVs in the medium-term.

This analysis provided interesting insights about consumer preferences that are useful not only for managers to outline strategic plans but also for policy-makers to design policies.

CHAPTER 5

Diffusion model of Electric Vehicles

Diffusion is a stage of the innovation process that consists in the spread of a new product in the market (Schumpeter, 1939). Diffusion was defined by Rogers (1962) as "*the process by which an innovation is communicated through certain channels over time among the members of a social system*" and considered a special type of communication where the message consists in new ideas widespread through mass media and interpersonal communications. Later, Bass (1969) developed a model that outlined the main theoretical basis of diffusion of innovations described by Rogers according to the timing of adoption in order to forecast the demand growth of new consumer durable products. Since the development of the Bass diffusion model, several innovation diffusion models have followed in order to predict the future permanence of products in the market and to provide decision support for managers to outline marketing strategies for new products (Li and Sui, 2011).

The diffusion of technological innovations has been considered the most important within innovation diffusion research (Li and Sui, 2011). In particular, the diffusion of AFVs, as technological innovation products, has been focused in several studies in order to understand the market penetration of these vehicles and predict consumer behaviour in face of their introduction in the market (Lee and Cho, 2009). These studies were already summarized in sub-section 2.2, where the main methods used to develop AFVs diffusion models were identified: ABM, consumer choice models, Bass and Bass-based diffusion models, and SD. Among these methodologies, SD was chosen to develop the diffusion model. The circular analysis of the relationship among several variables (feedbacks) the basic mathematical formulation and the ability to overcome the limitations of conventional statistical methodologies focused on the correlation among variables are among the advantages of SD that justify its choice for this study (Sterman, 2000; Keles et al., 2008).

The SD model developed by Struben and Sterman (2008) was chosen to be the core model for the analysis in this thesis due to being considered a reference model to understand the influence of consumer awareness on AFVs diffusion. The relevance of this model comes from the included behavioural dynamics that allow understanding the key factors that could determine the adoption of AFVs by individual consumers.

A review on dynamic consumer preferences (subsection 5.1) along with a review based on how consumer preferences has been modelled in SD diffusion studies (subsection 5.2) supported the definition of the main contribution of the EVs diffusion model presented in this chapter, namely the incorporation of dynamic consumer preferences on an EVs diffusion model. The main goal of this model is to assess the impact of considering dynamic preferences on the market penetration of EVs and on the definition of incentive policies for these vehicles. Through this chapter, the following questions are to be answered:

1. What is the impact of considering dynamic preferences on EVs diffusion analysis?
2. Are market penetration incentive policies adapted to consumer dynamic preferences more effective than “traditional” policies?
3. What would be the impact of lower production costs on BEVs market penetration?

This chapter is organized as follows. Subsections 5.1 and 5.2 present a review about dynamic consumer preferences and preferences modelling in SD diffusion studies. In subsection 5.3 an overview of the SD model is given and in subsection 5.2 the process of incorporation of dynamic preferences is described. The calibration of the model is presented in section 5.5. The main results and conclusions are presented in sections 5.6 and 5.7, respectively.

5.1. Review on dynamic preferences literature

In the past few years several studies aimed at verifying if consumer preferences were dynamic. Lachaab et al. (2006) analysed the evolution of preferences regarding an unnamed packaged good. Using panel data of household purchases they concluded that preferences for product attributes changed over time, e.g. consumers became more price sensitive over time. Mau et al. (2008) focused on preferences for HEVs and FCVs and manipulated market conditions in order to verify if preferences changed accordingly. They used a web-based environment to reproduce HEVs or FCVs experiences such as providing consumers with brochures with information about these technologies, comments about HEVs or FCVs from fictional owners and fictional information about different market penetration of the assessed technologies. Results from the HEVs study supported that changes in market conditions affect consumer preferences and, considering a scenario with high market penetration of HEVs, the propensity for buying these vehicles increased. Axsen et al. (2009) followed a similar approach but focused only in HEVs. Besides the different HEVs market penetration scenarios, three sources of information were provided to consumers in order to simulate word-of mouth and learning: a newspaper article, a brochure from vehicle manufacturers and opinions from other consumers. Findings showed that preferences for these vehicles were higher in scenarios with higher penetration. In order to investigate future consumer preferences for AFVs, Maness and Cirillo (2012) used an innovative survey design, where the attributes values changed dynamically during six years. Results showed that consumer preferences for AFVs, mainly BEVs, changed with time. Focused on several products with different life-cycles, such as fan heater, laptop, mobile phone and TV, Meeran et al. (2017) aimed at verifying if consumer preferences change with time. They tracked consumer preferences over a six months period and verified that consumer preferences varied significantly.

There are several reasons explaining what drives dynamic preferences and in which circumstances they change. Meeran et al. (2017) pointed out three main explanations for dynamic preferences. First, the existence of *cognitive biases* that can occur when consumers evaluate a product based on only a subset of all the available attributes. If this subset changes over time, for instance because some of those attributes are not as relevant as before, preferences change accordingly to the modifications in the relative importance of the analyzed attributes. This is consistent with the concept of constructed preferences, which assumes consumers usually do not have well defined preferences, but instead they construct those preferences when they face a choice decision (Bettman et al., 1998). In this sense, if consumers face the same decision in different contexts or different times this may lead to different preference constructions and, consequently, to different choices. The second cause is *familiarity*. If a consumer is unfamiliar with product characteristics, less information is available to support a decision. Therefore, the learning process about the product is followed by changes in consumer preferences or revising choices. Third, preference changes may result from *external factors* such as changes in the economic environment or may be driven by social interactions. These interactions have been highlighted by other studies as potential explanation for dynamic preferences (Janssen and Jager, 2001; Lachaab et al., 2006; Axsen et al., 2013; Cojocaru et al., 2013). Preferences for a product can then be influenced by interactions with friends, family or peers that may not have direct experience with the product (Axsen et al., 2013) or that currently use that product (Janssen and Jager, 2001).

5.2. **Review on consumer preferences modelling on AFVs diffusion studies**

The vehicle market comprises three main players: automotive industry and services, consumers and governmental institutions (Janssen et al., 2006; Struben and Sterman, 2008). Their interplay determines the success or failure of the penetration of new vehicle technologies. In the last decade several diffusion studies used SD to address this topic, where usually one of the market players was the main focus. The studies that addressed the automotive industry analyzed different vectors, namely the impact of infrastructure (Meyer and Winebrake, 2009; Köhler et al., 2010; Fazeli et al., 2012; Shafiei, Davidsdottir, et al., 2015; Guðmundsdóttir, 2016), the strategies of vehicle manufacturers (Walther et al., 2010; Keith, 2012; Kieckhäfer et al., 2016), and the fuel supply requirements (Leaver et al., 2009; Shafiei et al., 2014, 2016) to a transition to AFVs. Studies targeting consumers focused their analysis on AFVs in general (Struben and Sterman, 2008; Shafiei, Leaver, et al., 2015), FCVs (Keles et al., 2008; Park et al., 2011), BEVs (Liu et al., 2017) and EVs (Shepherd et al., 2012; Molina, 2013; Pasaoglu et al., 2016). In general, the main objectives of these studies were to forecast the market penetration of AFVs and to understand the dynamics involved in the transition to more sustainable vehicles. Some of these were studies had more specific aims. Struben and Sterman (2008) analyzed the dynamics of a broad behavioural model for a future transition to AFVs, considering the consumer awareness and learning. Molina (2013) developed a model to analyse how the interplay of uncertainties influences the transition towards HEVs and BEVs without a specific country context. Shafiei, Leaver, et al. (2015) aimed at understanding the cost-effectiveness and emissions mitigation of a transition to AFVs. Finally, other studies mainly centred on the role of government institutions to support the adoption of AFVs. These studies aimed at identifying suitable policies to overcome the market barriers of new vehicle technologies and therefore to enable a smooth transition to AFVs (Janssen et al., 2006; Harrison and Shepherd, 2014; Shafiei et al., 2017, 2018).

The consumers sector was included and analyzed in all the reviewed studies with the exception of Park et al. (2011) and Kwon (2012). The specifications of how consumer preferences were modelled in each study are presented in Table 5.1 and allow highlighting some trends regarding preferences modelling in AFVs diffusion literature, namely:

- Discrete choice models are the most frequently used models to compute the probabilities of vehicles choice;
- The most common attributes used to incorporate consumer preferences in the model are the purchase price, fuel/running costs, range and number of filling/recharging stations;
- Previous studies were the main source of consumer preferences data;
- All studies used fixed attribute coefficients for each attribute, as consumer preferences were considered static over time.

Study	Consumer model specification		
	Vehicle attributes	Estimation procedure	Data source
Janssen et al. (2006)	Fuel price, purchase price	MNL model	Brownstone et al. (2000)
Keles et al. (2008) Köhler et al. (2010)	Purchase price, performance, range, fuel costs, share of hydrogen filling stations	Not mentioned	Not mentioned
Struben and Sterman (2008)	Not included	Logit model	Not mentioned
Leaver et al. (2009)	Fuel economy, purchase price	Logit model	Not mentioned
Meyer and Winebrake (2009)	Fuel cost, purchase price, station density	Logit model	Not mentioned
Walther et al. (2010)	Range, purchase price, recharging stations	Discrete choice model (not specified)	Brownstone et al. (1996)
Park et al. (2011)	Did not include a consumer model		
Fazeli et al. (2012)	Purchase price, fuel cost, range, performance, refuel station	Logit model	Obtained through calibration process
Keith (2012)	Purchase price, emissions, operation cost, acceleration, range	Logit model	Brownstone et al. (2000)
Kwon (2012)	Did not include a consumer model		
Shepherd et al. (2012)	Purchase price, operation costs, maximum speed, fuel availability, emissions, range	MNL model	Batley et al. (2004)
Molina (2013)	Purchase price, operational cost, driving range , carbon footprint	Not mentioned	Data from sampling through Latin Hyper Cube method
Harrison and Shepherd (2014)	Range, purchase price, recharging stations	Discrete choice model (not specified)	Brownstone et al. (1996)
Shafiei et al. (2014) Shafiei, Davidsdottir, et al. (2015) Shafiei, Leaver, et al. (2015) Shafiei et al. (2016) Shafiei et al. (2017) Shafiei et al. (2018)	Purchase price, maintenance cost, range, emissions , battery replacement cost, fuel cost, fuel availability	MNL model	Calibration (adapted from Greene (2001))
Braz da Silva and Moura (2016)	Fuel technology, purchase price, operational costs, maximum velocity, range, refuelling time	Nested Logit model	Stated preference survey
Guðmundsdóttir (2016)	Purchase price, acceleration, top speed, range, operation costs, fuel search cost	MNL model	Brownstone et al. (2000) for all the attributes except emissions Brownstone et al. (1996) for emissions attribute
Pasaoglu et al. (2016)	Performance, reliability, safety, popularity, ownership cost, purchase price, emissions	Multinomial Logit model	Not mentioned
Kieckhäfer et al. (2016)	Purchase price, range performance, annual mileage , environmental awareness infrastructure supply	Nested logit model	Achtnicht et al. (2008)
Liu et al. (2017)	Purchase price, operation cost, environmental impact, range	Multinomial Logit model	Set according to scenarios

Table 5.1 - SD specifications of the consumers' models in previous studies.

5.3. SD model

5.3.1. Basic notions of SD methodology

SD is a modelling approach that enhances learning about complex systems behaviour. Most of the complex behaviours usually arise from the interactions among the variables that are part of the system, i.e. feedbacks, and not from the individual complexity of the variables themselves. The purpose of SD modelling is the analysis of systems that are characterized by dynamics in the long-term, interdependencies, nonlinearity and feedback processes. The core basis of SD is a set of basic concepts, which are the feedbacks, stocks and flows, described next (Sterman, 2000):

- **Stocks** are accumulations or integrations that characterize the state of the system and generate the information based on which decisions and strategies are based. They provide inertia and memory to the system. Stocks create delays through the accumulation between the inflow to a process and its outflow.
- **Flows** are the rates that change the amount accumulated in the stocks. There are two types of flows, inflow if the flow increases the stock value and outflow if it decreases the stock value. Only they are responsible for changes in the stock values.
- **Feedback** is a circular chain of causality that “feeds back” to itself and it is the base of the dynamic of the system. In a feedback system, each variable is cause and effect at the same time. There are two types of feedback loops, the positive or self-reinforcing feedback loop, and the negative or self-correcting feedback loop. The positive feedback loop tends to reinforce or amplify the effect on a variable, i.e. it occurs if an increment in a variable, after a delay, leads to a further increment in the same variable. The negative feedback loop counteracts and is opponent to change, i.e. if an increment in a variable leads to a decrease in the same variable. Therefore, while positive loops represent the processes that generate their own growth negative loops represent processes that seek balance and equilibrium.

There are several stages in the process of building a SD model, namely the boundary selection of the system, the formulation of the dynamic hypothesis to be analyzed, the formulation of the simulation model, the testing of the behaviour of the working model and, finally, the policy design (for more detail see Sterman (2000), Chapter 3).

5.3.2. Model overview

Struben and Sterman's (2008) model, which is based on innovation diffusion models and their applications to the automotive industry, was chosen to incorporate this study's contribution on AFV diffusion modelling (Figure 5.1). The model is centred on a set of feedbacks that influence AFV diffusion, namely the consumers' adoption of vehicles depends on their consideration of AFV through feedback from driving experience, WOM and marketing.

Struben and Sterman's model included two main elements, a social diffusion process and a fleet turnover model. The <u>social diffusion process</u> was then modelled by a "social exposure loop" in which consumers' willingness to consider (WtC) a specific vehicle depends on the exposure level to that vehicle, through marketing, spread of word from drivers or non-drivers of that vehicle. WtC vehicle j by drivers of vehicle i, W_{ij}, it is computed through equation (5.1), where η_{ij} represents the impact of social exposure of vehicle j by drivers of vehicle i on the increase in familiarity of vehicle j and ϕ_{ij} is the average fractional decay of W_{ij}. W_{ij} increases when social exposure of vehicle j increases and, as consumers will forget what they saw and heard unless marketing and social exposure are refreshed, WtC decays over time.

$$\frac{dW_{ij}}{dt} = \eta_{ij}\left(1 - W_{ij}\right) - \phi_{ij}W_{ij} \qquad (5.1)$$

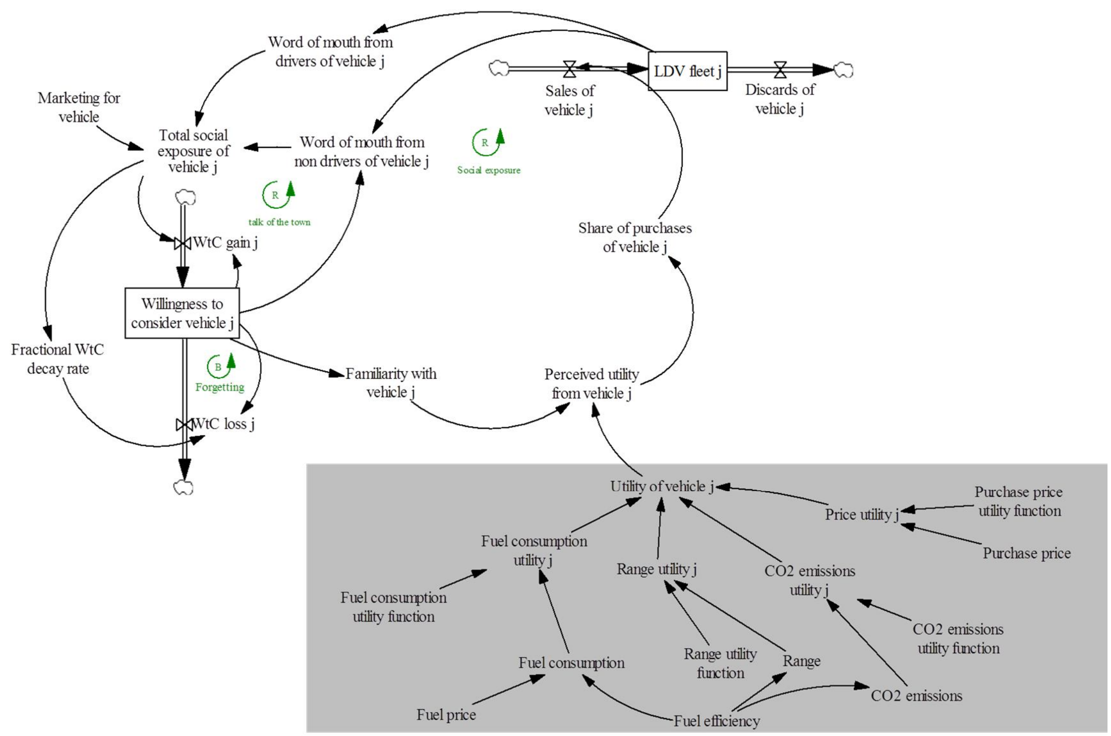

Figure 5.**1** - Core model of AFV diffusion from Struben and Sterman and model extensions (in grey).

If a vehicle's exposure decays under a minimum level, consumers will forget that vehicle and, consequently, it will not be considered in future purchases. This mechanism is modelled through the "forgetting loop". When the dominant technology is considered, ICEVs, the forgetting rate should approach zero. The whole second term $\phi_{ij}W_{ij}$ will go to zero by letting $f(\eta_{it})$ follow a logistic form (equation (5.2)).

$$\phi_{ij} = \phi_0 f(\eta_{ij}); f(0) = 1, f(\infty) = 0, f'(.) \leq 0$$

$$f(\eta_{ij}) = \frac{\exp[-4\varepsilon(\eta_{ij}-\eta^*)]}{1+\exp[-4\varepsilon(\eta_{ij}-\eta^*)]} \tag{5.2}$$

As represented in equation (5.3), the total exposure to a vehicle is a sum of three components: marketing effectiveness; WOM from drivers of that vehicle; and WOM about that vehicle among those not driving it. The "Talk of the town" loop models the diffusion of information about AFV among non-drivers of AFVs.

$$\eta_{ij} = \alpha_j + c_{ijj} W_{jj} \frac{V_j}{N} + \sum_{k \neq j} c_{ijk} W_{kj} \frac{V_j}{N} \quad (5.3)$$

Where:

α_j is the marketing effectiveness of vehicle j

c_{ijj} is the contact effectiveness between drivers of i and j about vehicle j

c_{ikj} is the contact effectiveness between drivers of i and k about vehicle j

V_j/N is the fraction of the installed base of drivers of vehicle j

Additionally to this process, Struben and Sterman also included a fleet turnover model which consisted in an update of LDVs fleet through sales, generated by familiarity and consumer preferences for each vehicle, and vehicles scrappage, dependent on the vehicle life. Therefore, the total number of vehicle j (j = $\{1,2,\ldots,n\}$ in the fleet, V_j, accumulates new vehicle sales, s_j, minus vehicle discards, d_j through equation (5.4).

$$\frac{dV_j}{dt} = s_j - d_j \quad (5.4)$$

Discards are age dependent and sales are a sum of initial and replacement purchases of vehicles, where σ_{ij} represents the drivers share of vehicle i that replace their vehicle with vehicle j and g is the fractional growth of the installed base (equation (5.5)).

$$s_j = \sum_i \sigma_{ij}(d_i + gV_i) \tag{5.5}$$

The share switching from vehicle i to j depends on perceived utility for vehicle j, u_{ij}^p, a population-aggregated utility effect (equation (5.6)). The perceived utility is dependent on the awareness and knowledge about vehicle j (W_{ij}) and on the expected utility of vehicle j regarding the attributes that characterize that vehicle, i.e. the global utility of vehicle j (U_j) (equation (5.7)).

$$\sigma_{ij} = \frac{u_{ij}^p}{\sum_j u_{ij}^p} \tag{5.6}$$

$$u_{ij}^p = W_{ij} * U_j \tag{5.7}$$

Similarly to Shepherd et al. (2012), Struben and Sterman's model was used as a starting point and a discrete choice model to compute vehicle utilities that would determine the perceived utility of each vehicle was added.

The diffusion model of this study is focused on EVs and the following extensions and adaptations were applied:

- The consideration of five specific vehicles (BEVs, HEVs, PHEVs, Gasoline and Diesel) instead of two generic sets (AFVs and ICEVs). All electric powertrains considered are already available in the Portuguese market;
- The disaggregation of vehicle utilities into attribute utilities: price, fuel consumption, range and CO_2 emissions;
- The inclusion of choice model utility functions for each attribute;
- The inclusion of dynamic preferences, by including two sets of utility functions for each attribute.

Regarding the parameters values for social diffusion process, values from Struben and Sterman (2008) were used with the exception of the social exposure rate and the effective contact rate drivers that was defined in the calibration process (see further in 5.5.2). The data for the fleet turnover model came from the Automotive Association of Portugal (ACAP, 2013), namely for the installed base of each vehicle type and the average scrappage time of vehicles (Appendix XII). The discrete choice model consisted in the aggregated part-worth utility functions for each attribute presented in subsection 4.2.

5.4. Incorporation of dynamic consumer preferences on the EVs diffusion model

This study's approach involves the inclusion of dynamic preferences in a reference diffusion model. Therefore, data collected through two defined scenarios was used.

As the goal of this model was to verify the impact of considering dynamic preferences on EVs diffusion, two models were simulated where the only difference was the computation of the utilities of each attribute (Figure 5.2). The Static Preferences Model (Model SP) is a EVs diffusion model where the consumer preferences are fixed over time and, therefore, uses only a set of utilities for each attribute. Within this model the utility of each attribute k for vehicle j reflects the utility functions corresponding to the initial/current preferences. The Dynamic Preferences Model (Model DP) incorporates dynamic preferences by using two sets of utilities for each attribute. One set of utilities represents the initial/current preferences whereas the other set represents the final/future preferences.

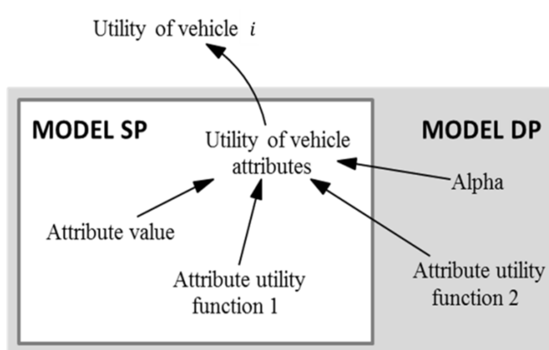

Figure 5.2 - Model SP and model DP.

Studies that incorporate preferences evolution have to define how the transition between current and future preferences occurs. Previously, Janssen and Jager (2001), using a multi-agent simulation model, simulated the dynamics of adoption of new products with a model that assumed a constant rate of change to adjust preferences over time. In another study, In order to model the evolution of consumers' preferences for new versions of already established products, Cojocaru et al. (2013) considered that the velocity of adjustment of consumers' preferences depended on the distance from the product identified as more attractive.

In this study, two model DP variants were implemented that differed on the computation of the preferences transition in order to verify if results were robust regarding to this modelling option. The first variant of model DP, Model DP1, performs a linear transition between current and future preferences through a constant rate of change α:

$$\alpha = \frac{1}{(t_{final} - t_{initial})}$$

$$\beta_{kjt} = \lambda_t * \beta_{kjI} + (1 - \lambda_t) * \beta_{kjF} \tag{5.8}$$

with $\lambda_t = \left(t_{final} - t\right) * \alpha$, for $t = t_{initial}, t_{initial+1}, \dots, t_{final}$

Where,

β_{kjt} is the part-worth utility of attribute k for the vehicle j at time t

λ_t is the relative amount of change at time t, from 1 (current scenario) to 0 (future scenario).

β_{kjI} is the part-worth utility of attribute k for the vehicle j considering the initial utility function I.

β_{kjF} is the part-worth utility of attribute k for the vehicle j considering the final utility function F.

The second variant of model DP, Model DP2, was similar to Cojocaru et al. (2013). Since the limited range of BEVs has been pointed out as one of the major barriers to its diffusion (see subsection 2.3.1), a higher battery range was defined as the most attractive attribute. Thus, the transition of preferences from the current situation to the future scenario is measured by the evolution in the BEVs range. A 600km range was defined as very attractive value that BEVs range could reach in a future scenario (e.g., allowing to travel from Porto in the North of Portugal to Algarve in the South). This value was considered as the most attractive BEVs range, $Range_{AT}$. The computation of the (nonlinear) transition of preferences was computed through equation (5.8) but the value of λ_t was obtained through the following computation:

$$\lambda_t = \frac{Range_{AT} - Range_t}{Range_{AT} - Range_0}$$

Where,

$Range_{AT}$ is the value of the attractive range for consumers

$Range_t$ is the value of the BEV range at time t

$Range_0$ is the BEV range at $t_{initial}$ (first year of simulation)

Considering the specifications of each model, the vehicle overall utility for Model SP was computed through equation (4.3) whilst the overall vehicle utility for Model DP1 and Model DP2 was computed through equation (5.9), a combination of equation (4.3) and (5.8):

$$U_t(j) = [\lambda_t * \beta_{PricejI} + (1 - \lambda_t) * \beta_{PricejF}] + [\lambda_t * \beta_{RangejI} + (1 - \lambda_t) * \beta_{RangejF}] +$$
$$+ [\lambda_t * \beta_{FCjI} + (1 - \lambda_t) * \beta_{FCjF}] + [\lambda_t * \beta_{EmissionsjI} + (1 - \lambda_t) * \beta_{EmissionsjF}] \quad (5.9)$$

Where,

$\beta_{Price\,jI}$ and $\beta_{Price\,jF}$ represent the part-worth utilities of level j of attribute Price considering the utility function I or the utility function F, respectively, and similar notation is used for attributes Range, FC (fuel consumption) and Emissions.

5.5. Calibration of the model

5.5.1. Attributes modelling

5.5.1.1. Modelling attribute values

In AFV diffusion studies, the most common approach is to model vehicle purchase price as dependent on the industry learning effect, i.e. purchase price decreases as a result of lower production costs from learning by doing and scale of economies (Leaver et al., 2009; Walther et al., 2010; Guðmundsdóttir, 2016; Pasaoglu et al., 2016; Shafiei et al., 2018). In the base-case scenario, purchase price was kept constant over time (similarly to Meyer and Winebrake (2009) and Fazeli et al. (2012)) in order to better identify the effects of dynamic preferences and the impacts of purchase subsidies on vehicles demand. Further ahead, a learning effect scenario is considered to analyse its impact on EVs demand.

The cost of fuel consumption, measured in €/100km, is affected by two variables, fuel price at time t (FP_t) and fuel efficiency rate at time t (FE_t), that influences the fuel consumption at time t (FC_t, measured in l/100km). These variables are related because when fuel price increases there is an effort by manufacturers to increase fuel efficiency (Klier and Linn, 2008). Therefore, by defining this relationship, a lower fuel consumption of fuelled vehicles is obtained when fuel price increases. Considering the evolution of the fuel consumption presented on the European Vehicle Market Statistics (ICCT, 2013) as fuel efficiency increased, on average, 2.1% per year, the same increment was considered in the model (similarly to the approach applied by Guðmundsdóttir (2016)). On the other hand, when fuel price decreases, it was considered that the fuel efficiency increases 0.21% (i.e., ten times less) (equation (5.10)). The fuel consumption of ICEVs and HEVs was computed by equation (5.11).

$$FE_t = \begin{cases} 0.021, \text{ if } FP_t > FP_{t-1} \\ 0.0021, \text{ if } FP_t \leq FP_{t-1} \end{cases} \tag{5.10}$$

$$Fuel\ consumption_{\,t} = FP_t * FC_t * (1 - FE_t) \tag{5.11}$$

In the case of PHEVs, driver behaviour influences the consumption of fuel or electricity through the driving pattern, i.e. how many kilometres are driven in an electric mode (Karabasoglu and Michalek, 2013). The impact of the driver behaviour through driving patterns on PHEVs consumption was considered through a constant, η, which represents the fraction of travelled distance that is powered by the electric engine. Therefore $(1 - \eta)$ represents the distance powered by liquid fuel (Samaras and Meisterling, 2008). In the absence of Portuguese data, a value for η computed from real driving patterns of US PHEVs drivers presented in Samaras and Meisterling (2008) was used, which gathered data for three PHEVs: PHEV30, PHEV60 and PHEV90. As the PHEV defined in this study has an electric range of 25km, the value for PHEV30, η = 0.47, was chosen. The fuel consumption of PHEVs is given by the following equation:

$$Fuel\ consumption\ \ PHEV_t =$$

$$(1 - \eta) * ICEV\ consumption + \eta * Electric\ engine\ consumption$$

$$= (1 - \eta) * FP_t * FC_t * (1 - FE_t) + \eta * BEV consumption \tag{5.12}$$

Regarding the non-fuelled vehicle BEV, running costs were defined as constants.

The computation of <u>CO_2 emissions</u> may account for one or several phases of vehicles life cycle (Adams and Schmidt, 1998). The use phase comprises two main components, namely the “Well-to-Tank” (WtT) that accounts for the emissions released from the fuel production and electricity generation, and the "Tank-to-Wheels" (TtW) that accounts for emissions released while driving a vehicle, i.e., use phase emissions from fuel combustion (Bicer and Dincer, 2016). However, as this study is designed from a consumer perspective, and according to a European Commission directive (European Comission, 2000) CO_2 emissions from fuel extraction and distribution are not included in the vehicle labelling available for consumers, only TtW emissions were considered. Therefore, BEVs have zero emissions in the model (and indeed, car manufacturers market them as zero-emission vehicles). Nevertheless, a scenario where all the use phase emissions are taken into account is presented further (subsection 5.6.4) to assess the differences, if any, of not considering BEVs as zero emission vehicles.

Regarding fuelled vehicles, the emissions from fuel combustion depend on several factors, such as vehicle fuel efficiency, fuel consumption and driver behaviour (Karabasoglu and Michalek, 2013). The emissions were assumed to depend only on fuel consumption and fuel efficiency. The computation of CO_2 emissions depends on two constant variables, fuel combustion stoichiometry (FCS) and fuel density (FD) measured in g/l, which differ according to the considered fuel, and depend on the fuel consumption at time t *(FC_t),* that varies over time. Therefore, TtW CO_2 emissions at time *t*, measured in g CO_2/km, were computed through the following equation:

$$TtW\ CO_2Emissions_t = FCS * FD * FC_t / 100 \tag{5.13}$$

The fuel consumption at time *t* *(FC_t)* is a function of the effective fuel efficiency rate at time *t*, FE_t:

$$FC_t = FC_t * (1 - FE_t) \tag{5.14}$$

For PHEVs, consistent with the fuel consumption computation, the same driving pattern was considered for the computation of PHEVs emissions:

$$CO_2Emissions_t = (1 - \eta) * FCS * FD * FC_t \tag{5.15}$$

Range was modelled differently for fuelled and non-fuelled vehicles. For the progression of range for fuelled vehicles (HEVs, Diesel, Gasoline and PHEVs) a standard approach was applied. Range was computed taking into account the progress of fuel efficiency (Shafiei et al., 2014; Guðmundsdóttir, 2016), which, as mentioned before, is assumed to depend on the evolution of fuel prices. Therefore, the range of these vehicles, measured in km, was computed according the following equation:

$$Range_t = Range_{t-1} * (1 + FE_t) \tag{5.16}$$

Considering the system boundaries, the range modelling of non-fuelled vehicles, namely BEVs, can be performed endogenously or exogenously. As BEVs range can evolve as result of R&D investment that allow to increase battery capacity (Walther et al., 2010; Guðmundsdóttir, 2016; Liu et al., 2017), a manufacturer module could be included in the model in order to add the feedback loop that brings those interactions to the system. However, as the model presented in this study is focused on consumer demand and its main goal is verify the impact of dynamic preferences, BEVs range[6] was modelled exogenously, similarly to Fazeli et al. (2012) and Shepherd et al. (2012). This model considers that, independently of other factors, there will always be some improvement of the range over time coming from the automotive industry in order to make BEVs more attractive. In 2012, lithium-ion batteries, with an average capacity of 25 kWh, provided a range of 150 km (for a 240 kg pack of batteries) (Gerssen-Gondelach and Faaij, 2012). For a given battery size, increment of range is dependent on how fast technological advances improve the batteries specific energy (Scrosati and Garche, 2010). For the first time period, 2013 until 2015, following Gerssen-Gondelach and Faaij (2012), the increment projected was 6.67%/year, i.e. $increment_t$ = 0.0667. According to battery performance projections for the medium-term, the increment of the specific energy[7] of lithium-ion batteries (from 200 to 250 Wh kg^{-1}) until 2025 will provide a range of 240km (for

[6] BEVs range was defined considering a given battery size.
[7] Total energy storage per unit mass.

a 330 kg batteries pack) (Gerssen-Gondelach and Faaij, 2012). This range matches a variation of 3.3%/year (i.e., $increment_t$ = 0.033 between 2015 and 2025). In the absence of further projections, assumptions had to be made concerning the range increment between 2025 and 2053. As it is expected that manufacturers will invest in R&D as a strategy to solve one of the main technical limitations of BEVs, an $increment_t$ = 0.04 during this period was considered. Considering the above, the computation for BEVs range was made according to the following equation:

$$Range\ BEV_t = Range_{t-1} * (1 + increment_t) \qquad (5.17)$$

The initial values for each attribute were based on characteristics of vehicles available in the Portuguese market (Table 5.2).

	Purchase price (€)	Range (km)	Fuel consumption l/100km and €/100km	CO_2 Emissions (g/100km)
BEV	29.000	160	0 and 1.7	0
PHEV	34.000	1400	2.9 and 3.2	36.6
HEV	27.000	1200	3.6 and 5.7	85.8
Diesel	27.000	1200	4.45 and 6.2	116.9
Gasoline	24.000	800	5.8 and 9.2	138.2

Table 5.2 - Attribute values in 2013.

5.5.1.2. Modelling attribute utilities

The aggregated part-worth utility functions obtained in subsection 4.2 were used to compute the attribute utilities in the SD model. However, since the attribute values vary over time, the range of the part-worth utility function of each attribute (for instance fuel consumption in the current scenario varies between 2€/100km and 10€/100km) may not include all the values reached during the simulation time. Therefore, in order to determine part-worth values outside the estimation range, a function that could approximate the utility function for each attribute, resulting from curve fitting, was used. Observing that for some attributes (purchase price and fuel consumption in both scenarios) the function was an almost perfect fit (R^2>0.99), this function was used as utility function. An example is given in Figure 5.3 (graph on the left). For the attributes in which the computed function was a less satisfactory fit (range and CO_2 emissions) the part-worth utility function was used within the attribute levels range and the values of the computed function were used only outside that range. An example is given in Figure 5.3 (graph on the right) (see all the functions in Appendix XIII). For the latter cases, the utilities for the intermediate values of the part-worth utility function were obtained through linear interpolation (Green and Srinivasan, 1978).

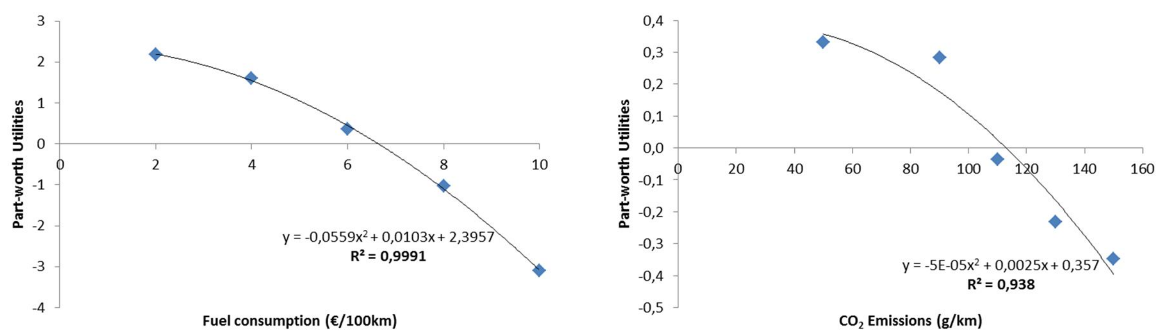

Figure 5.3 - Function for fuel consumption (left) and CO_2 emissions (right) attributes. The blue diamonds are the computed utility values for each attribute level.

5.5.2. Calibration of the LDVs trajectory

The model validation was based on Model SP and entailed performing several procedures. First, “reality check” tests were carried out to verify that the model behaved as expected when extreme conditions were applied. Additionally, as these model simulations started in the year of 2013, real data (ICCT, 2018) is already available for comparison with simulated results until 2017. The comparison allowed verifying that the simulated market penetration of EVs was similar to real adoption of these vehicles (Figure 5.4).

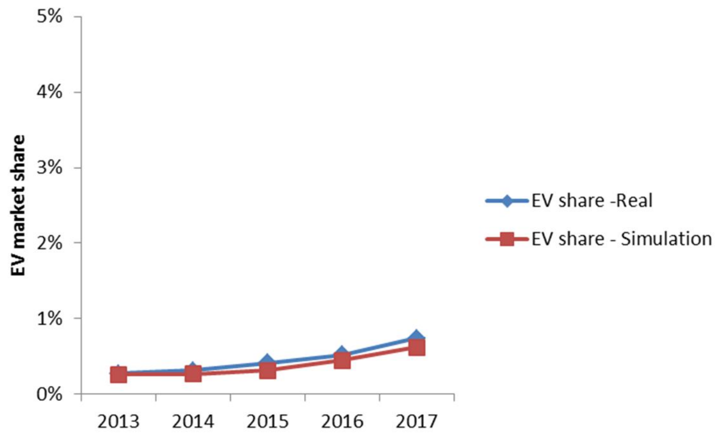

Figure 5.4 - Real vs simulated EVs market share.

Although the behaviour of the model was satisfactory during the analyzed period, the time range is too short to have robust conclusions about how this model predicts data for the Portuguese market. Therefore, a calibration of the model was done. Similarly to Shepherd et al. (2012), it consisted in defining a mid-point of the model timeline in order to verify if the model projections were in line with the projections of other studies focused on the same market. As the work of Fazeli et al. (2012) was applied to the diffusion of AFVs in Portugal and it was calibrated to fit historic Portuguese data, their model projections were used as a reference point. The specifications defined for the calibration were the following:

- The comparison was based on AFVs share because the AFVs set considered in Fazeli et al.'s model and this model differ (Fazeli's model comprised HEVs, PHEVs and ethanol E85). Thus, the predicted value that was compared between the two models was the total share of AFVs in the LDVs fleet instead of a share of a specific type of AFV;
- The mid-point chosen to perform the comparison was 2030 (the last year of Fazeli et al.'s simulation and an intermediate year of this model);

After observing that this model predicted a higher EVs share for 2030 (12.5%) than the predicted EVs share of Fazeli et al.'s model (approx. 7%), the model was tuned in order to obtain a similar EVs share by adjusting the constant values of "social exposure rate" parameter and the “type of engine utilities” (see calibrated values in Appendix XII). The model adjustment to real data (Figure 5.4) was not affected by this calibration.

Afterwards, a sensitivity analysis of the most uncertain parameters of the model was performed to analyse the model robustness. The sensitivity analysis comprised the definition of two scenarios with extreme values of each variable, scenario 1 and 3, and a scenario with “mid-values”, scenario 2. The considered values are depicted on Table 5.3 and the resulting impact on EVs market share is depicted in Figure 5.5. The EVs market share variations revealed that the model is more robust regarding the “growth rate” (parameter g in equation 5.5) and “effective contact rate of drivers” (parameter c_{ijj} in equation 5.3). The “effective contact rate of non-drivers” (parameter c_{ikj} in equation 5.3) and “marketing” (parameter α_j in equation 5.3) variables present higher variation regarding the scenario 1. However, the Vensim® sensitivity graphs (see Appendix XIV), which display the variable behaviour in terms of confidence bounds, allowed observing that most of the simulation results of the “effective contact rate of non-drivers” and “marketing” variables, mainly marketing, have low impact on results.

	Scenarios			
Variables	Base-case scenario	Scenario 1	Scenario 2	Scenario 3
Marketing	1.5%	0.1%	50%	95%
Effective contact rate drivers	25%	1%	50%	95%
Effective contact rate non-drivers	15%	1%	50%	95%
LDV growth rate	0%	-2%	5%	20%

Table 5.3 – Values set for each scenario.

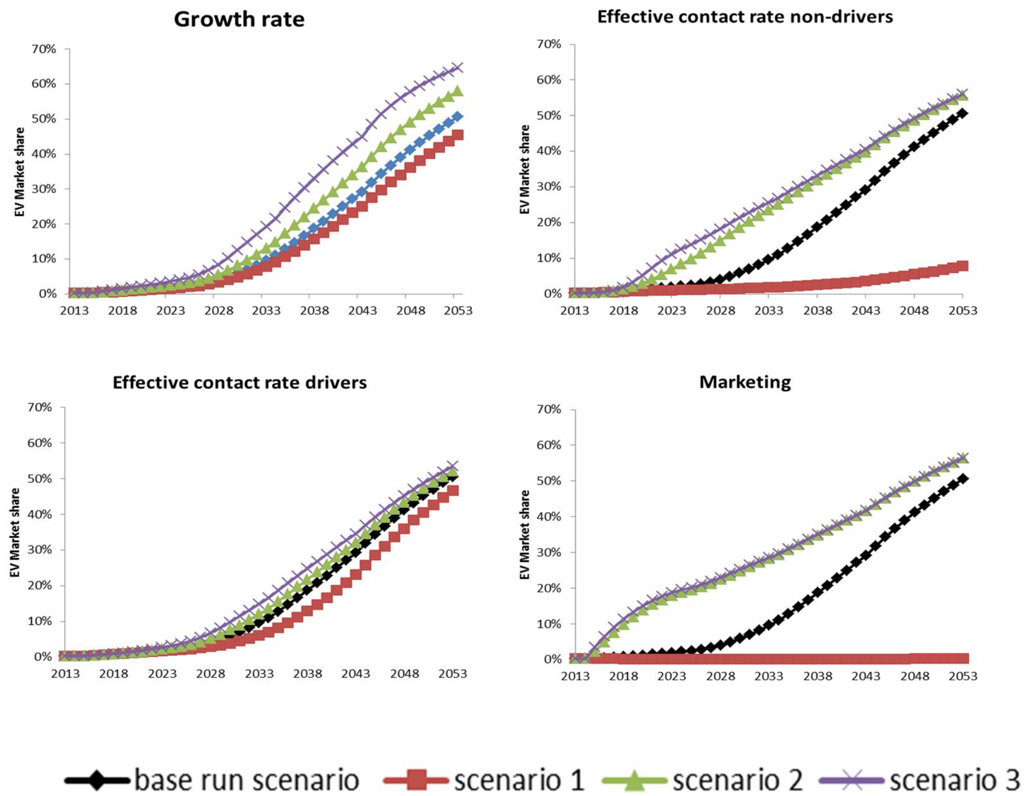

Figure 5.5 – Market share of EVs considering the defined scenarios.

5.6. Results

5.6.1. Robustness analysis of the transition preference models

Two DP models (Model DP1 and Model DP2) were implemented to verify if the models' outputs were robust. Observing the transition of preferences over time of each model allows verifying that the transition in Model DP1 occurs by design linearly through the simulation period, while the transition in Model DP2 ends in 2046, when the value defined as attractive range is reached (Figure 5.6). Figure 5.7 and Figure 5.8 depict the evolution of the LDVs fleet and of the EVs market share for each DP model, respectively. The results show not only a similar evolution of the LDVs fleet in both models but also similar EVs shares. Therefore, it can be concluded that the results are robust regarding the computation of the preferences transition. For this reason, only Model DP2 was used to compute the results henceforward, as it represents a more dynamic transition of preferences that is dependent on the BEVs range.

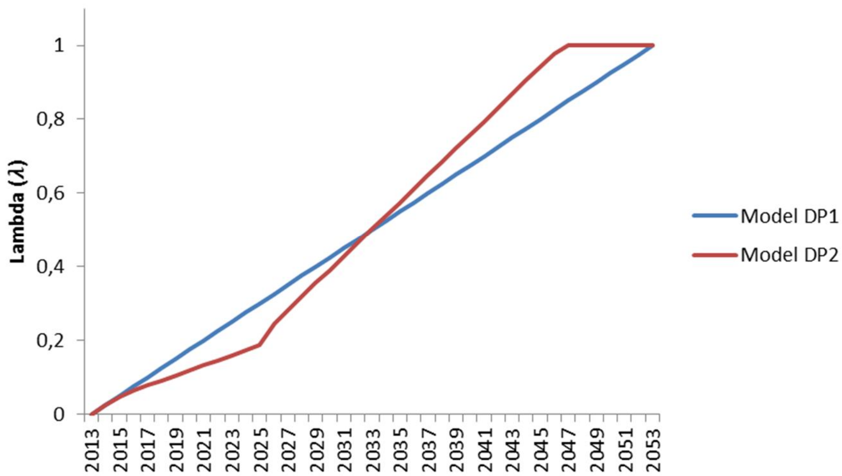

Figure 5.6 - Transition of preferences values over time for each DP model.

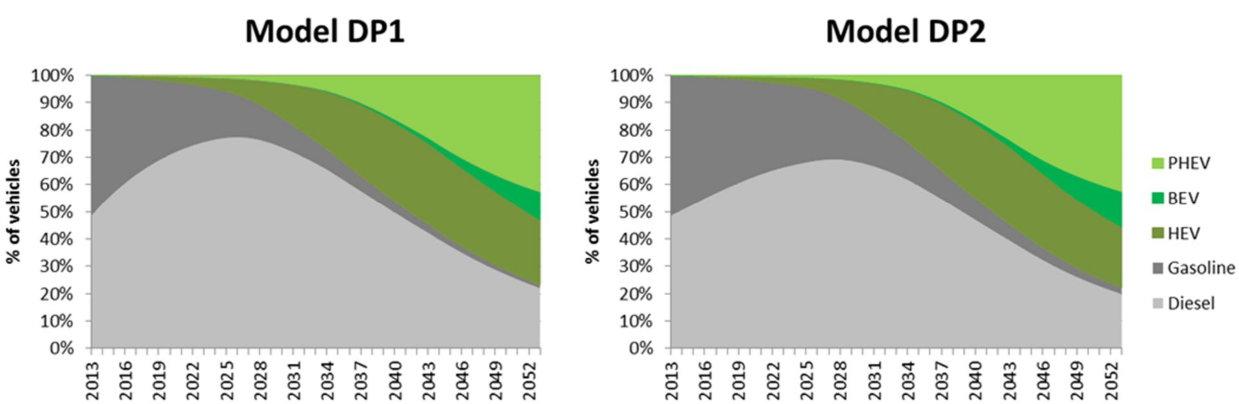

Figure 5.7 – Evolution of LDV fleet in Models DP1 and DP2.

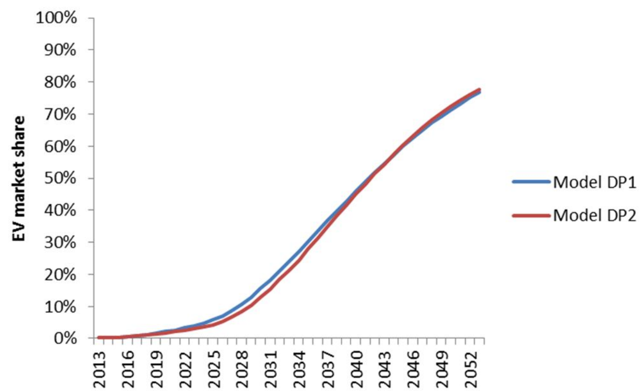

Figure 5.8 – Evolution of EVs market shares in models DP1 and DP2.

5.6.2. Impact of dynamic preferences on EVs diffusion

The impact of considering dynamic preferences on the EVs diffusion model was made through the comparison between the Model SP and the Model DP2. This comparison was made regarding three results depicted in Figure 5.9. The results showed substantial differences between the outputs of the two models, namely:

- LDV fleet: preferences for Diesel vehicles predominate in Model SP, while Model DP2 presents a more diversified fleet mainly after 2042;
- EVs market share: in Model DP2 the EVs market share is almost the double of AFVs share in Model SP in the medium term (2033) and 26 pp (percentage points) higher in the long-term (2053);
- Vehicle utilities: the preferences structure regarding the ranking of vehicles in Model SP dos not change much over time. The main change is that PHEVs preferences that surpass Gasoline preferences in 2031 and HEVs and surpass Diesel around 2043. On the other hand, Model DP2 presents more changes. For instance, PHEV starts to be preferred to Gasoline, Diesel and HEVs earlier, 2025, 2035 and 2039 respectively; HEVs preferences surpass Diesel preferences in 2027 and BEVs preferences surpass Diesel and HEVs preferences in 2043 and 2047, respectively. At the end of the simulation period the final ranking of vehicles obtained with Model DP2 differs more from the initial one than the ranking obtained through Model SP.

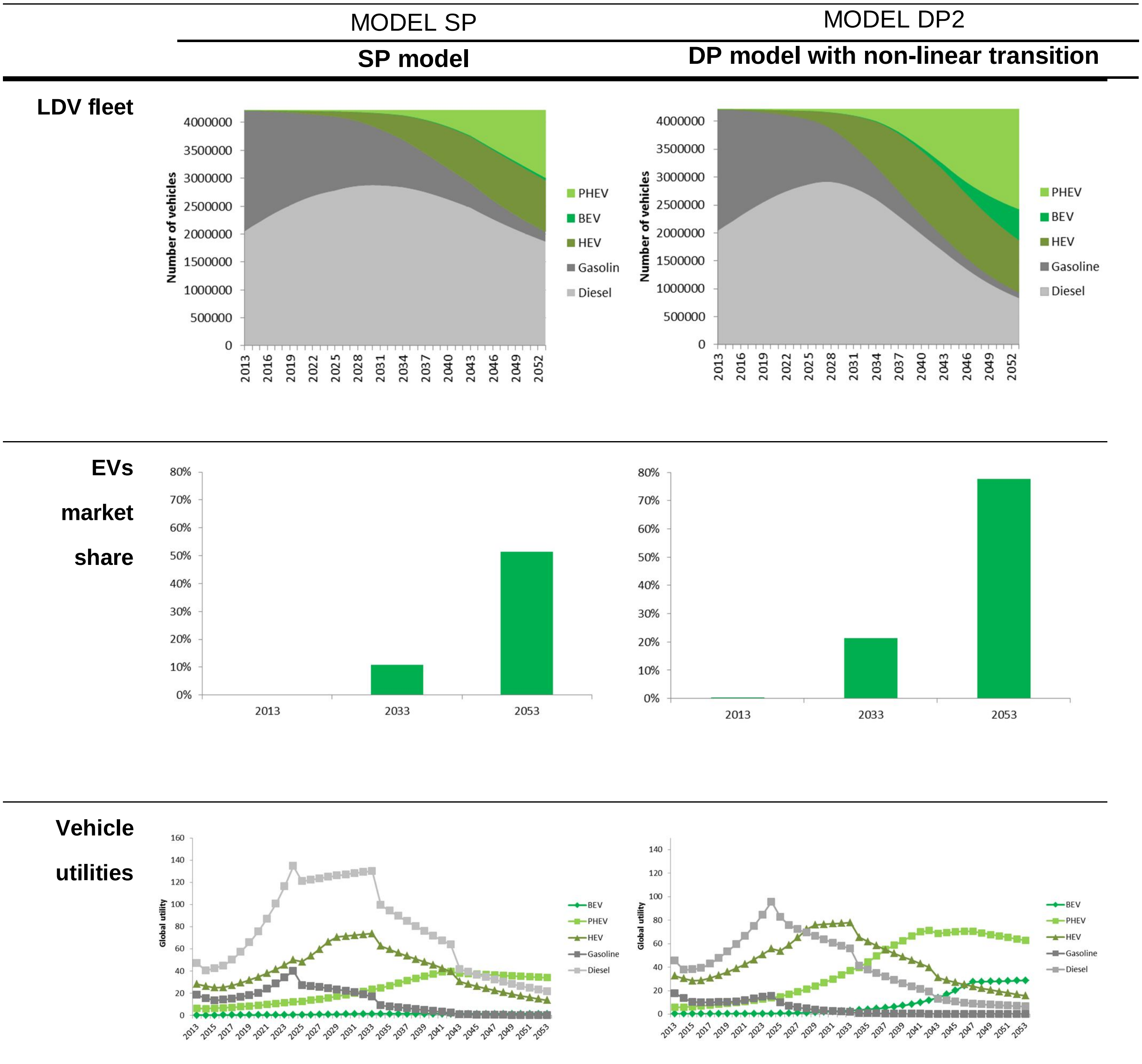

Figure 5.9 – Comparison between Model SP and DP1 regarding the LDVs fleet, EVs market share and vehicle utilities.

A result that is common to both models is the declining share of Gasoline vehicles in the fleet, as a result of low utility values of these vehicles. On one hand this result may seem extreme because it is difficult to understand why consumers have such low preferences for

Gasoline vehicles. On other hand the results seem to be in line with the historic downward trend of Gasoline sales in the last years (ICCT, 2018), whereas Gasoline vehicles sales share has been markedly decreasing and it was surpassed by Diesel vehicle sales share since 2005 (Figure 5.10). Since 2014 the sales of Gasoline vehicles started to increase over Diesel vehicles. The Dieselgate in 2015 might explain the increasing share of Gasoline vehicles more marked since 2015.

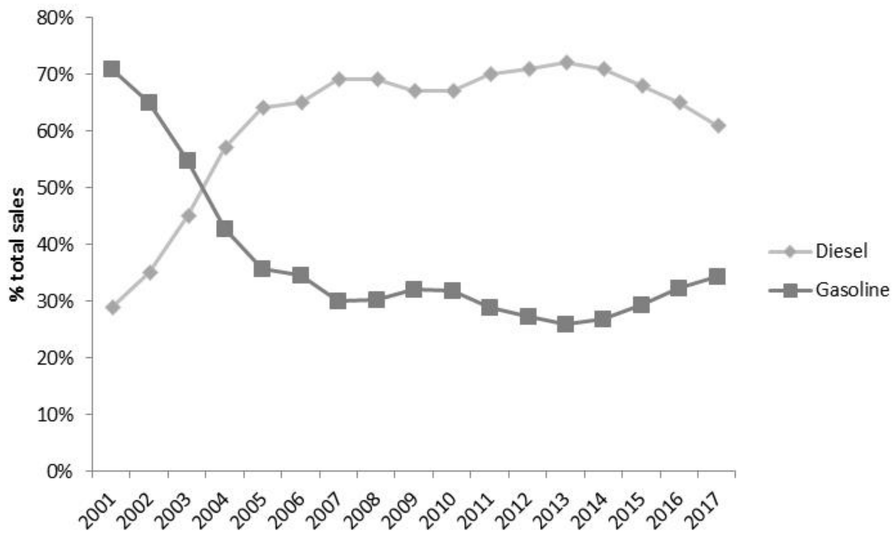

Figure 5.10 - Gasoline and Diesel vehicle sales share evolution from 2001 to 2017.

5.6.3. Learning effect scenario

Learning curves allow to model technological change as a result of accumulation of experience by reducing costs from cumulative investments in a specific technology (Kettner et al., 2008). This cost reduction leads to a decrease of the product price over time. In this sense, the learning effect is an explanation of how the increase in experience and know-how of all the players in the product production and distribution can result in costs reduction when the production increases (Sterman, 2000). So, costs decrease with increments of cumulative experience with the products, where, in a manufacturing setting, the cumulative experience is represented by cumulative production (Sterman, 2000). Unit costs usually fall by a fixed amount every time the experience doubles, depending on the type of industry and the considered products. Cost reductions of 10% to 30% per doubling of cumulative experience/production have been reported in several industries (Argote and Epple, 1990).

Decreasing product costs, through production increments, enables lower purchase prices which leads to a higher market share and industry demand that boosts sales even more. This reinforcing feedback loop of the learning effect reveals the relevance of making the product price endogenous to the model through the incorporation of a learning curve (Sterman, 2000). However, as this study reports to a specific (and small) market, modelling endogenously a learning curve according to which the vehicles purchases of Portuguese consumers would boost the worldwide production of vehicles would be unrealistic. Therefore, in this model, the learning effect was modelled exogenously.

The modelling of learning effect was made accordingly to Sterman (2000). However, in this study's model, as mentioned above, the cumulative production was not affected endogenously by the adoption rate of the vehicle and, consequently, was treated as an exogenous variable, i.e. its values did not depend on the model outputs.

Similarly to Weiss et al. (2012) the production costs of vehicles were considered to be approximately the retail price, once the production costs are usually confidential of manufacturers. As part of the production costs are fixed and consequently do not depend of the production volume, the "effect of learning on price" does not affect the whole product price but just a part of it. Therefore, following Weiss et al.'s (2012) work, the price was divided into two components. One component that concerned to the ancillary costs that comprised the non-engine related costs of the vehicle (vehicle chassis, the suspension, the interior, and the retailers' mark-up). This component accounts for $82\mp4\%$ of the total vehicle price for ICEVs (Lipman and Delucchi, 2003). The second component comprehended the engine-related costs that, in the case of BEV, comprised all the costs related to the electrification of the vehicle (battery costs, electric motor and auxiliary components). Therefore, the engine-related costs accounts for the remaining part of the price after deducting the ancillary costs ($18\mp4\%$). As the engine-related costs are the target of the technological innovation the effect of learning on price was affected only to this price component (Weiss et al., 2012) according to the following equation:

$$Price = Ancillary\ costs + Engine\ costs * Effect\ of\ Learning\ on\ Price \tag{5.18}$$

The Effect of Learning on Price was computed by equation (5.19). The cumulative production values were taken from Weiss et al. (2012) till 2035 and extrapolated till 2053 based on the slope between the last two years available (2034-2035). The same source was used to define the value of the initial cumulative production.

$$Effect\ of\ Learning\ on\ Price = \left(\frac{Cumulative\ Production}{Initial\ Cumulative\ Production}\right)^{s} \tag{5.19}$$

$$s = Log_2(1-f) \tag{5.19}$$

The variable s determines the strength of the learning curve and the variable f is the fractional cost reduction per doubling production (equation (5.20)). The f value for each EV was defined according to the reduction of the electrification costs related to the lithium-ion batteries, i.e. 17% (Nagelhout and Ros, 2009).

According to the definitions above the BEVs price decreased to a minimum of 20,920 € and higher BEVs utilities were obtained (Figure 5.11). The LDVs fleet composition under scenario 2 showed that the increment of BEVs utility led to a higher penetration of these vehicles in the market (53% in 2053) over PHEVs and HEVs, as can be observed on (Figure 5.12). The ICEVs share between the base case and learning effect scenarios was similar, 22% and 19% respectively, meaning that the lower price of BEVs due to learning effects of lower production costs led consumers to choose BEVs over other EVs.

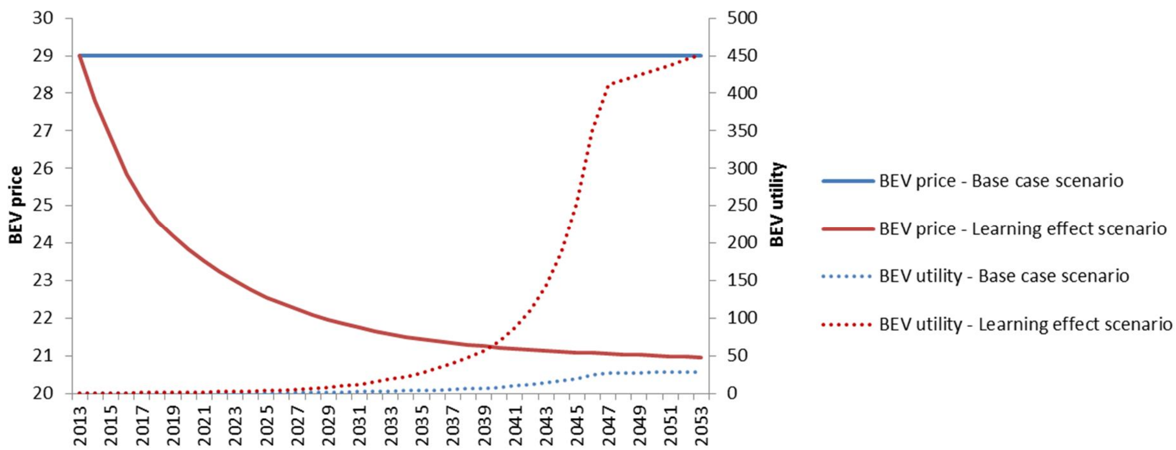

Figure 5.11 - Evolution of BEVs price and BEVs utility under the base case and leaning effect scenario.

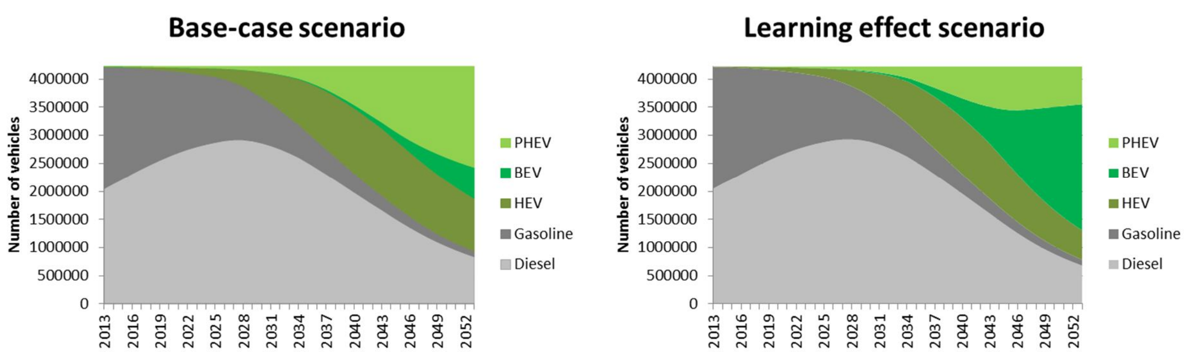

Figure 5.12 - LDVs fleet composition under base-case and learning effect scenario.

5.6.4. Scenario with BEVs emissions

In this scenario BEVs are assumed as non-zero emission vehicles in order to understand the impact of taking into account BEVs usage phase emissions in the market penetration of these vehicles. In this context, the "Well-to-Wheels" (WtW) approach was used to compute CO_2 emissions where, in addition to the CO_2 emissions from the component TtW already computed, the emissions from the WtT component, i.e. fuel production (FPE)

measured in g CO_2/km were also included. Therefore, the total WtW was computed through equation (5.21), where the already computed TtW CO_2 emissions (recall equation (5.13)) were summed to the now computed WtT CO_2 emissions.

$$WtW\ CO_2 emissions_t = WtT\ CO_2 emissions_t + TtW\ CO_2\ emissions_t$$
$$= (FCS + FPE) * FD * FC_t / 100 \quad (5.21)$$

The WtT emissions for BEVs are the emissions released from the electricity production required to charge these vehicles' batteries. Therefore, these emissions depend on the energy sources used to produce electricity (wind, solar, coal, natural gas…), i.e. emissions depend on the averaged electricity mix in each year. The WtT emissions for BEVs were then computed through the observed (until 2017) and predicted electricity mix evolution (DGEG, 2015; EDP, 2017) considering a consumption of 0.14 kWh (Figure 5.13).

The WtT emissions for PHEVs have to take into account emissions from fuel and electricity production, in a proportion computed according to the driving pattern considered in previous PHEVs emissions computations (equation (5.22)). The evolution of the electricity mix for PHEVs is presented in Figure 5.13, where a consumption of 0.087 kWh was considered.

$$WtW\ CO_2\ emissions_t = (1 - \eta) * (FCS + FPE) * FD * \frac{FC_t}{100} + \eta * EM_t \quad (5.22)$$

Where EM_t is the electricity mix at time t.

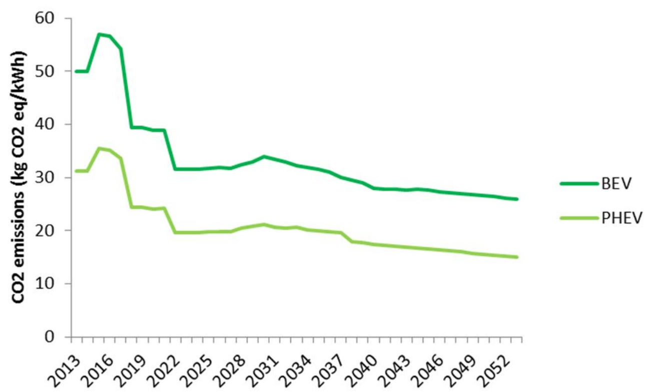

Figure 5.13 – Evolution of electricity mix emissions for BEVs and PHEVs.

The results of this scenario showed that considering all the use phase emissions had a higher impact on PHEVs and BEVs utilities which decreased significantly comparing with the base-case scenario (Figure 5.14). As the reduction of these vehicles utilities was more marked from 2030 upwards, the impact on BEVs and PHEVs market shares was negligible in the medium-term but pronounced in the long-term (Figure 5.15). However, the market share of EVs was very similar in both scenarios (Figure 5.16), as the lower preferences for PHEVs and BEVs due to higher CO_2 emissions were compensated by higher adoption of HEVs.

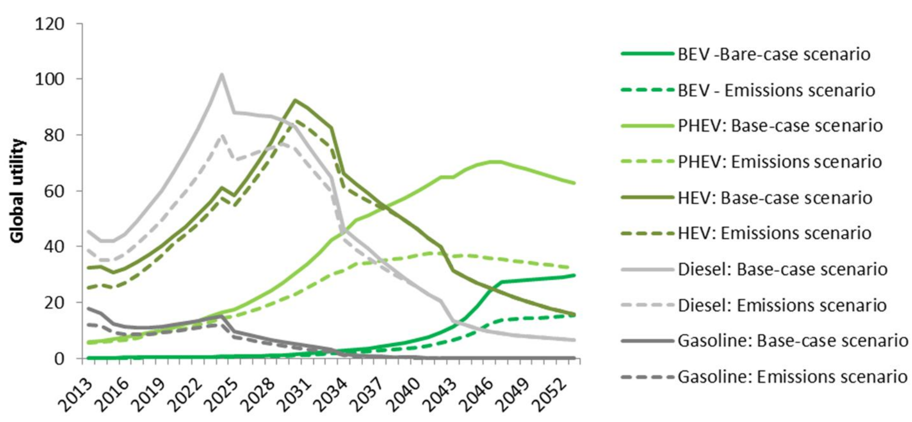

Figure 5.14 – Evolution of utilities in both scenarios.

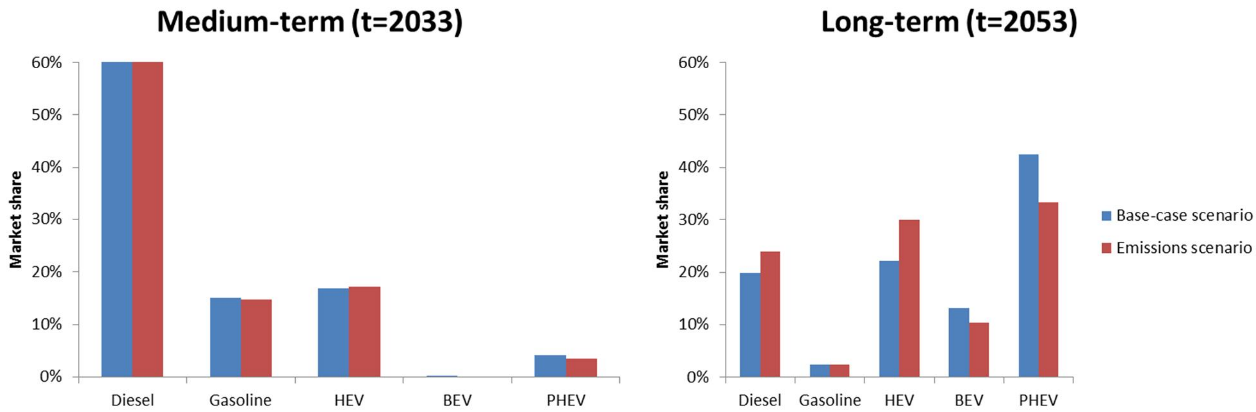

Figure 5.15 - Vehicles market share in the medium (left) and long (right) term considering the base run and emissions scenario.

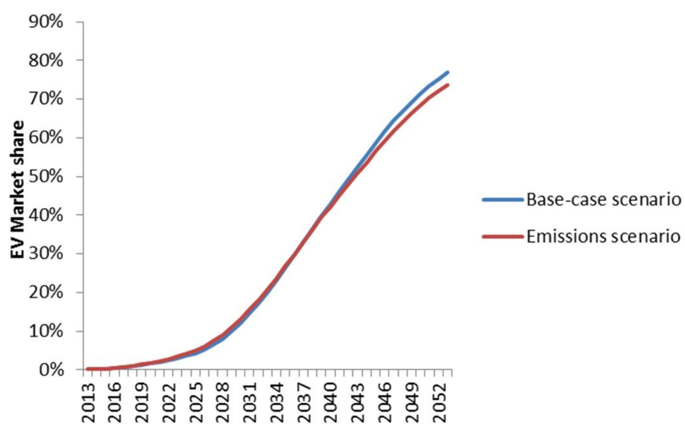

Figure 5.16 - Evolution of market share of EVs considering both scenarios.

5.6.5. Analysis of subsidies scenarios

Along the past few years there have been several attempts by the Portuguese government to implement policies that would be effective on increasing the purchase of EVs (Appendix I). As the government policies have been mainly focused on BEVs and knowing that BEVs, as a more disruptive technology in comparison with HEVs and PHEVs, face more challenges and barriers on penetrating the market, the policy scenarios considered in this thesis are mainly focused on these vehicles. The subsidy scenarios were applied to the Model DP2.

Acknowledging the importance of designing subsidy policies that are time and cost-effective policies adapted to the dynamic preference of consumers were simulated. Three specific scenarios were defined:

- Scenario 1: Implementation of BEVs subsidies to achieve a 5% market share of BEVs
- Scenario 2: Implementation of PHEVs subsidies to achieve 10% market share of PHEVs
- Scenario 3: Implementation of BEVs subsidies considering a 5 million € budget

The final price of the vehicles targeted with the subsidy was computed through the equation (5.23) in all scenarios:

$$Final\ vehicle\ price\ = Vehicle\ Price_t - subsidy_t \tag{5.23}$$

Scenario 1 was based on a target defined by the Portuguese government for BEVs, i.e. a BEVs share of 5% to be achieved until 2020 (IEA, 2015). Two subsidy policies were applied and compared to analyse which one would achieve the defined target earlier. The first policy, policy 1, consisted in a standard subsidy of 5000€ that remains constant over time. The policy 2 was defined as a degressive incentive which starts as a percentage of the initial purchase value (a specific absolute value could have been defined instead) and then decreases at a specific rate. The reason behind this policy rests on the dynamic preferences that underlie the model presented in this study. Consumers may need a higher subsidy in the short-term as an incentive to buy BEVs, but in a medium-long term that incentive could eventually be lower as the BEVs utility increases over time due to the evolution of preferences (Figure 5.17). The initial subsidy value for this policy was 30% of the purchase price that decreases at a rate of 1%/year (policy 2). The results of both policies are depicted in Table 5.4, which presents the time needed to achieve the defined goal and the Net Present Value (NPV) of the total cost involved. The discount rate used to compute the NPV was the inflation rate in place in 2013 (0.3%). The results showed that the implementation of a degressive subsidy (policy 2) will allow achieving the 5% BEVs share two years earlier and with a lower cost when compared with a constant subsidy (policy 1). The better results from policy 2 are explained by the preferences evolution for BEVs. Policy 2 has higher subsidy values than Policy 1 over modelling time that allows BEV sales to benefit of the increment of BEVs utility.

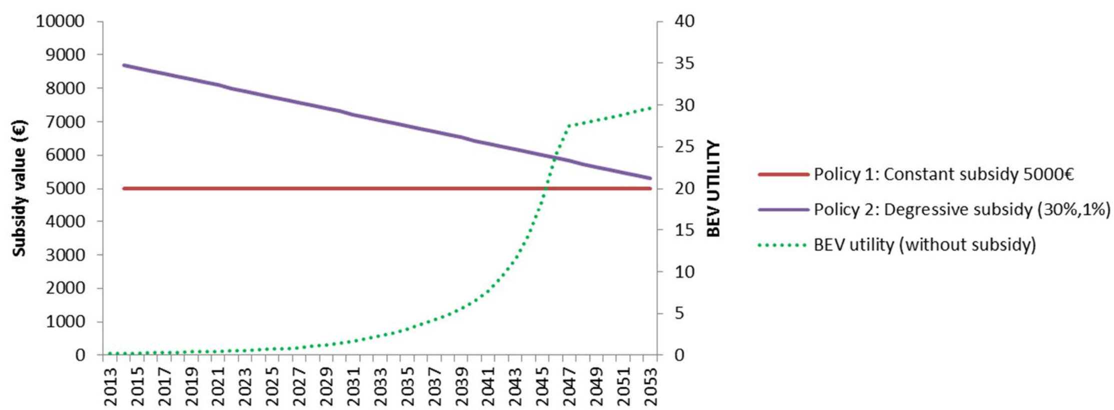

Figure 5.17 – Subsidies policies in scenario 1 and the evolution of the utility of BEVs over time.

Scenario 1 – Target 5% BEVs			
	Target achieved	Cost (NPV)	Δ (cost)[1]
Base-case scenario	2047	-	
Policy 1: Constant BEV subsidy	2040	1,415 M€	
Policy 2: Degressive BEV subsidy (30%, 1%)	**2038**	1,203M€	**-0,212 M€**

[1] Cost differential in relation to policy 1

Table 5.4 – Results of the designed policies in the scenario 1.

Scenario 2 was defined to verify if a degressive subsidy would be more effective than a constant subsidy for a PHEV. The same two policies applied in the scenario 1 were implemented for PHEVs purchase price. In this scenario the results were more divergent between policies. When a degressive subsidy is implemented the targeted 10% share of PHEVs is achieved 3 years earlier with a significant lower investment (approx. 1,725 million € less) (Table 5.5). These results are due to the more favourable evolution of PHEVs preferences (Figure 5.18).

Scenario 2 – Target 10% PHEVs			
	Target achieved	Cost (NPV)	Δ (cost)[1]
Base-case scenario	2037		
Policy 3: Constant PHEV subsidy	2020	6,944 M€	
Policy 4: Degressive PHEV subsidy (30%, 1%)	**2017**	5,220 M€	**-1,725 M€**

[1] Cost differential to policy 4.

Table 5.5 – Results of the designed policies in the scenario 2.

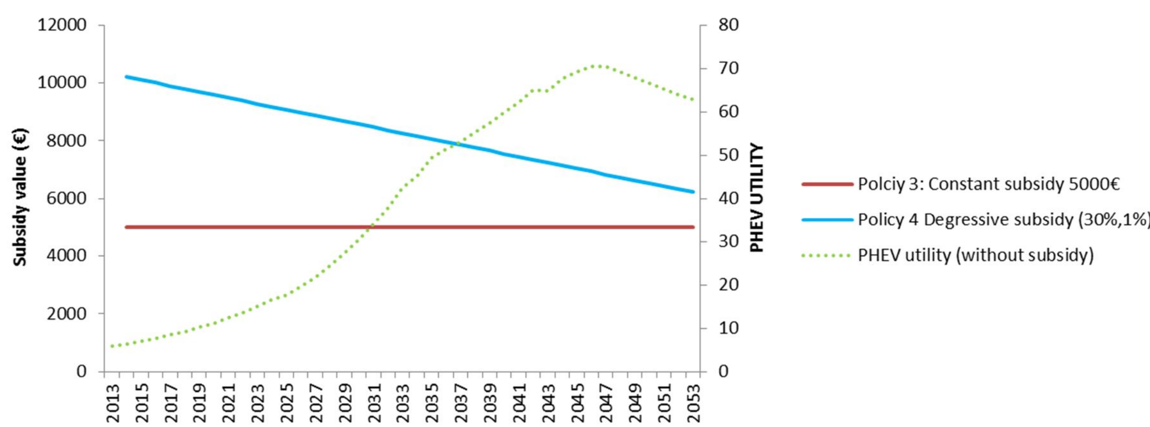

Figure 5.18 – Subsidies policies in scenario 2 and the evolution of the utility of PHEVs over time.

In **Scenario 3** several subsidies were implemented to increase BEVs share, under a budget restriction of 5 million €. Two policies with a constant subsidy (policy 5 and 6) and three policies with degressive subsidies (Policies 7 to 9) were applied. Figure 5.19 presents the evolution of BEVs subsidy according to each policy and budget restriction, allowing to verify that policies with constant subsidies are in place less time than degressive subsidies.

Subsidies results are displayed in Table 5.6, where the BEV share is presented for the medium-term (2033), for the year in which the subsidy ends and for the end of simulation (2053). Analysing the market share increments of each policy relative to the base-case scenario, it is possible to observe that, in the medium-term, the BEVs share increments are small, with the highest increment belonging to the policy 6 (+1.8%) where a constant 10,000€ subsidy is applied. Regarding the long-term results, the most effective policies were two degressive subsidies, Policies 7 and 9 where a 24.7% and 24.2% BEVs share were achieved, respectively (11.7 pp and 11.2 pp higher than the base-case scenario share). The effectiveness of these policies is due to the adaptation of the subsidies to the consumer preferences dynamics and to a high permanence of these subsidies in the market. BEVs share continued to increase after the subsidy ends, meaning that the subsidies were able of stimulating a self-sustaining increment of BEVs share.

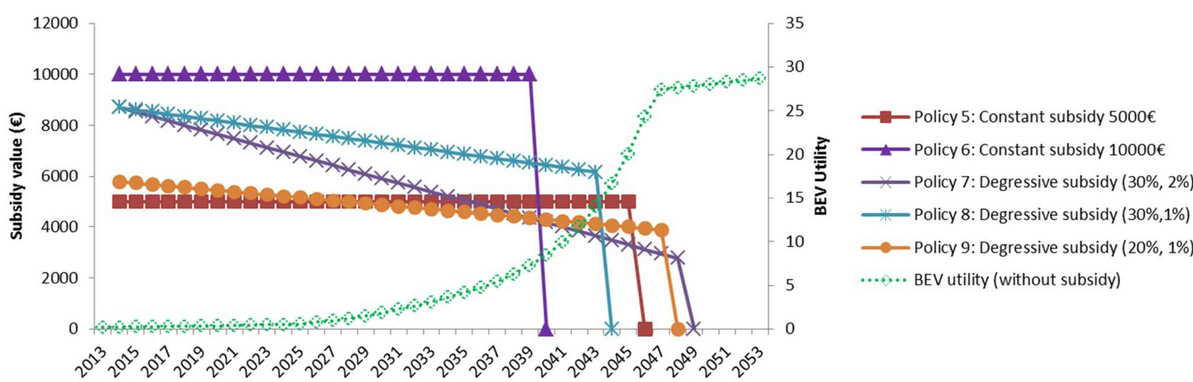

Figure 5.19 – BEVs subsidy according to each policy and the evolution of BEVs utility.

Scenario 3 – Target highest BEVs share with 5M€ budget			
	BEV share in 2033	BEV share when subsidy ends[1]	BEV share in 2053
Base-case scenario	0.2%		13%
Policy 5: Constant subsidy 5000€	0.8%	17% (2045)	21%
Policy 6: Constant subsidy 10000€	1.8%	9.6% (2039)	16.3%
Policy 7: Degressive subsidy (30%, 2%)	0.9%	22.6% (2048)	24.7%
Policy 8: Degressive subsidy (30%, 1%)	1.2%	13.4% (2043)	19%
Policy 9: Degressive subsidy (20%, 1%)	0.76%	21.3% (2047)	24.2%

[1] In brackets is the time when the subsidy ends due to the budget restriction.

Table 5.6 – BEVs market share results of the designed policies in the scenario 3.

5.7. Concluding remarks

When dynamic consumer preferences were considered, the impact on EVs diffusion was significant. This result corroborates Meeran et al. (2017)'s findings and it is highly relevant for future studies aiming to predict market shares, showing that not including dynamic preferences when performing forecasts may lead to less accurate predictions of EVs diffusion.

Based on the evolution of consumer preferences for EVs with a dynamic preferences model, several policies were designed accordingly in order to verify if they will allow achieving the defined targets with higher time and cost effectiveness. The results showed that adapting subsidies policies to consumer dynamic preferences produces more effective results on stimulating EVs adoption. In all the considered scenarios, the implementation of degressive subsidies stimulated AFVs adoption more effectively leading to the requirement of a lower investment to achieve the defined market penetration targets. The results of the purchase incentives applied to PHEVs reveal that purchase price is the major barrier for the market penetration of these vehicles as even a standard incentive of 5000€ was able to achieve a 10% share of the market almost two decades earlier than when the full PHEVs price was considered.

Two scenarios that waived the base-case assumptions were tested. The learning effect scenario showed that BEVs market penetration took off in the medium-long term as a result of a purchase price reduction. The scenario with BEVs emissions led to lower preferences mainly for BEVs and PHEVs as it considered these vehicles not as green as they were in the base-case scenario and higher preferences for HEVs instead. This showed that HEVs absorbed the consumers that were no longer choosing PHEVs and BEVs due to higher emissions.

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CHAPTER 6

Conclusions

6.1. Key findings and contributions

Given the environmental burden and significant energy demand from road transportation, EVs are seen as potential solutions to mitigate the consequences of a high circulation of fuelled vehicles. However, the difficult market penetration of EVs in Portugal along with the ineffectiveness of the implemented policies to stimulate consumers demand for these vehicles reveals that a more comprehensive analysis of the market was lacking. Acknowledging the relevance that consumer preferences have in the long-term viability of EVs demand, this work was centred on modelling consumer preferences for these vehicles. The main goal of this thesis was to identify the preferences structure of Portuguese consumers under different market contexts and verify the impact of such preferences on the market dynamics of EVs diffusion. The complexity of this goal required a "multimethodology". Two preference elicitation methods, CBC and MAUT, were applied to elicit individual preferences and to assess which method better represented consumer preferences. Afterwards, the individual preferences collected from CBC, the method that better approximated the elicited values to the stated consumer preferences, were aggregated and included in the diffusion model of EVs using SD. In this model preferences were incorporated as being dynamic, i.e. preferences were allowed to change according to different market conditions.

Hence, the main contribution of this work is the modelling of consumer preferences for EVs and their use to assess the impact of incentive policies on stimulating EVs demand through diffusion analysis. Previous studies usually focused on either consumer preferences' modelling or diffusion analysis of EVs. However, only a comprehensive approach that interlinks both analyses would allow achieving a deeper knowledge of how demand for EVs could be increased.

The contribution of this work is enhanced by the inclusion of dynamic preferences in the diffusion model of EVs. Diffusion studies applied to AFVs have been modelling static consumer preferences which do not allow to accurately predicting the market penetration of EVs, since it has been verified in several studies that consumers value products differently when the market conditions change. Therefore, the diffusion model for EVs that includes a transition of preferences over time developed in this research can be further applied to the diffusion of other vehicles or other durable products.

In summary, this work contributed with:

- A novel comparison between two preference elicitation methods regarding the representation of consumer preferences of EVs;
- The analysis of the potential learning effect of MAUT on preferences elicited through CBC;
- Insights about individual and aggregated preferences of Portuguese consumers;
- Insights about the impact on EVs diffusion of considering dynamic preferences;
- Insights about policies design to stimulate EVs adoption based on dynamic preferences.

The findings from this thesis were derived in the process of answering to the research questions outlined in Chapter 1. The answers and related findings are following presented.

RQ1: What is the appropriate survey design to elicit consumer preferences considering the methodological strategy applied in this study?

The attributes set considered consisted of purchase price, fuel consumption, range and CO_2 emissions.

One of the challenging processes when analysing how consumers choose among products is the selection of the appropriate attributes that characterize those products and, therefore, understand their purchase decisions. A survey allowed identifying vehicle design, purchase price, fuel consumption and performance as the most relevant attributes in a purchase context of an EV. However, crossing the purpose of distinguishing different vehicle technologies with the relevance of the attributes for consumers led to the selection of range and CO_2 emissions instead of vehicle design and performance.

The preference data collection of MAUT was made through the bisection and the trade-offs methods.

In the context of this study, a suitable survey design is a survey that allows obtaining similar (comparable) outputs from the two applied elicitation methods in order to compare the elicited preference data. The elicitation of preferences through CBC provides, for each consumer, a part-worth utility function and the relative importance of each attribute. Therefore, several trials of surveys were developed in order to identify the appropriate design for a MAUT elicitation process that would provide comparable data with CBC without compromising the consumer data reliability. The final design comprised the bisection method to elicit utility functions for each attribute, where consumers could visualize the utility function of each attribute and adjust it if they considered that it does not correctly represent their preferences. The elicitation of attributes importance was performed through the method of trade-offs that was found to be easier for consumers to assess the attributes importance as it consisted in the comparison of only two attributes at a time.

RQ2: Which preference elicitation method better represents consumer preferences?

CBC represents consumer preferences for EVs better than MAUT.

This question arose from a methodological trend identified in consumer preference studies: CA methods, such as CBC, were found to be amongst the most used methodologies to elicit consumer preferences. In this context, CBC and MAUT were compared at the individual and aggregated level on their ability to represent consumer preferences for EVs. The results were clear at the individual level, where CBC was found to better represent consumer preferences. At the aggregated level, CBC tends to outperform MAUT on predicting vehicle shares.

CBC and MAUT preference results did not converge but provided similar insights for managerial decisions.

The correlation analysis between CBC and MAUT methods showed that the elicited data was poorly correlated. However, the insights for managerial decisions from these methods were similar. PHEVs were found to be the most preferred vehicle by presenting the highest market share in both methods. Concerning the vehicle attributes relevance, fuel consumption was found to the most determinant attribute in vehicle purchase decisions.

RQ3: Is there a learning effect from the preference elicitation process?

A potential learning process occurred along the elicitation process of consumer preferences.

The SP survey was designed to analyse the impact of a sequence of elicitation procedures on the consumer preferences. The analysis revealed significant differences on CBC elicited data before and after MAUT. These differences can be explained by the existence of several phenomena such as institutional learning, preference learning, fatigue or starting point effect. Fatigue and starting point effect were excluded as the set of questions was small and displayed at the same time. Therefore, the changes on CBC preferences can be interpreted as a result of a process of learning that occurred along the elicitation process.

The MAUT elicitation process influenced the elicited preference data through CBC.

The differences between CBC elicited data before and after MAUT allowed verifying that the final CBC elicitation (after MAUT) predicted the vehicles market share better, i.e. CBC Final ranking represented consumer preferences better at an aggregated level. MAUT; by demanding a higher cognitive and conscious process of preferences elicitation, it may have improved the quality of preference elicited data. This supposition was corroborated through the observation that there was a strong/moderate influence of MAUT elicited preferences on the CBC final preferences, i.e. MAUT preferences influenced the position reversals of vehicles in the CBC rankings.

RQ4: What is the influence of individual characteristics of Portuguese consumers on their preferences for EVs? Does it change with different market contexts?

Age, type of route and annual distance driven are the most influent characteristics on consumer preferences for EVs.

The influence of the individual characteristics on consumer preferences was not always consistent with different market conditions. Consumer´s age and the annual distance driven influenced only preferences in the current market conditions, where older consumers and consumers that drive less per year have higher preferences for EVs. The influence of type of route on consumer preferences was consistent across different market conditions and in a similar way: consumers that drive city routes are more willing to choose an EV.

Sensitivity for EVs attributes was mainly influenced by the type of route driven more often by consumers.

A broader influence of the type of route on vehicle attributes sensitivity was observed in the future market conditions. In the current scenario only the sensitivity for range was influenced by the type of route, with city drivers being less sensitive to range. In the future scenario, in addition to range, the type of route influenced the sensitivity to fuel consumption and CO_2 emissions, where city drivers were more sensitive to both.

RQ5: What is the preference structure of Portuguese consumers at the aggregated level? Does it change within different market conditions?

Fuel consumption was the most relevant attribute for consumers in both scenarios.

From the attributes selected to differentiate the vehicles set, the cost of fuel consumption was the attribute that most influenced consumers' willingness to choose a vehicle in both scenarios, although more markedly in the future scenario. The high relevance of fuel consumption for consumers can be due to the context of market volatility of fuel prices that has been experienced since the economic crisis started. This may motivate consumers' concern and, consequently, could contribute to its higher relevance on future purchase decisions.

Consumers were generally more sensitive to variations in attribute values when future market conditions were considered.

Considering the current market conditions, consumers were more sensitive to small variations of price and fuel consumption values. When future market conditions were assumed, the impact of fuel consumption variations increased and the impact of range variations revealed to be markedly effective to increase consumers propensity to choose an EV. This higher sensitivity of consumers to attributes in the future suggests a higher competition among vehicle technologies, as consumers become more familiar with EVs and their characteristics.

The sensitivity results allowed identifying which policies could be more effective to stimulate EVs demand in the short and medium term. For instance, in the short term purchase subsidies and fuel tax increments policies could support an increment of EVs circulation and, in addition to fuel tax increments, R&D incentives to manufacturers companies could boost EVs demand in the medium term.

RQ6: What is the impact of considering dynamic preferences on EVs diffusion? And what would be the expected impact of incentive policies?

The inclusion of dynamic preferences on EVs diffusion affects significantly the market penetration results.

The comparison between a diffusion model with static and dynamic preferences allowed identifying a clear difference regarding the EVs market penetration results and preference structure for EVs. For instance, when dynamic preferences were considered, the EVs market share doubled in the medium term (vs. the EVs share considering static preferences) and the preferences for PHEVs overpass preferences for Diesel vehicles sooner and with a larger difference than when preferences were considered to be static.

Purchase subsidies adapted to dynamic preferences are more time and cost effective on increasing EVs market diffusion.

In order to give a higher incentive for consumers to purchase an EV when their preferences were lower, degressive subsidies were designed and applied to stimulate earlier EVs purchases. The results showed that degressive subsidies, either applied to BEVs or PHEVs, produced always more time- and cost-effective results, in comparison to the standard constant subsidies, reaching the defined targets earlier and at a lower cost. The most significant results corresponded to the degressive subsidies applied to PHEVs, markedly reducing the time required to reach a defined share and at a lower cost. This highlights the higher purchase price of PHEVs as their main diffusion barrier.

The joint analysis of the specific conclusions allowed identifying two findings that were robustly supported by more than one analysis presented in this thesis. The first was the identification of the fuel consumption attribute as the most determinant attribute for consumers in a decision involving new vehicle technologies. This attribute was considered the most relevant considering different elicitation procedures and also different market contexts. The second finding was that PHEVs were the most preferred vehicle according to different elicitation procedures. In addition, their market penetration could rapidly and effectively increase when purchase subsidies are applied. As the fuel consumption of PHEVs is one of its higher advantages (2.1 l/100km) the purchase price is the attribute that influences the most these vehicles market penetration. These higher preferences for PHEVs along with their easier diffusion in the market shows that PHEVs may act as a transitional technology for BEVs and, therefore, boost the diffusion of these vehicles by attenuating the consumers' resistance to BEVs, similarly to the transitional role of HEVs for PHEVs adoption found in US (Keith, 2012).

The outcomes of this thesis are therefore relevant for car manufacturers and charging infrastructure suppliers, by proving insights about the relevance that fuel/charging costs have on consumer preferences for EVs; and for policy makers as they provide an overview of the Portuguese market dynamics of EVs adoption and also provide strong bases to support effective incentive policies to increase the demand of EVs.

6.2. Limitations and future research

The research developed within this thesis has some limitations that can be used as research opportunities and, therefore, to extend the work presented.

One limitation of this work is the use of a consumer sample that is not representative of the Portuguese consumers. As mentioned before, this is a common downside of aiming to collect preference data from a group of consumers that had to meet specific selection requirements, such as for instance to intend to purchase a vehicles in the near future. Another limitation about this sample is that the surveys were carried out in the first part of the work leading to this dissertation, before the Volksvagen *dieselgate* and the ensuing consequences (e.g., manufacturers planning to cease diesel engines production, cities banning diesel vehicles and even a Portuguese minister warning consumers that diesel vehicles will soon lose resale value). Preferences for diesel vehicles are not likely to reflect the current preferences.

Regarding the comparison of preference elicitation methods two limitations were identified. One limitation comes from the considered vectors in the comparison of methods, where only the numerical, and most relevant, facet was included leaving aside qualitative considerations. Future studies could, therefore, complement the comparison between CBC and MAUT with qualitative information such as for instance the practical applicability of the methods from the consumer's point of view (Helm and Steiner, 2004). This would allow understanding if consumers found the tasks realistic, how certain they were of their answers or if the decision problem was difficult or easy. The second limitation, which was beyond the scope of this research, regards to the comparison between CBC and MAUT being restricted to one type of products, vehicles. Therefore, this comparison should be addressed in future studies considering other products in order to analyse if the results of this study are corroborated or if they were context-dependent.

The consumers’ preference data was analyzed at the individual and aggregated levels, according to the aim of this thesis. However, the analysis of segmented data would be an interesting path to follow in future research. Clusters of consumers with similar preferences could be identified and, therefore, specific market penetration strategies could be designed according to the characteristics of those clusters. The findings of this research regarding the influence of demographic variables on consumer preferences for vehicles and their attributes could be a starting point for clustering Portuguese consumer in future studies.

The diffusion model of EVs had two limitations related with the defined system boundaries. The first limitation regards to the exclusion of the charging/fuelling infrastructure module. This module was not included due to not only to the scope of the diffusion model in this study, which focused mainly on the consumers’ dynamic preferences, but also because in the survey that collected the most determinant EVs attributes for Portuguese consumers this variable was not considered relevant (Chapter 3). Nevertheless, as the charging/fuelling infrastructure has been considered relevant for AFVs diffusion in previous studies (subsection 2.3.3) their inclusion should be further addressed in future studies in order to analyse its impact on EVs diffusion. The second limitation is the absence of a feedback loop that would represent the learning effect for battery range or costs, i.e. range was modelled as an exogenous variable. The modelling of range endogenously is further suggested to be analyzed in future research in order to infer if it would accelerate the EVs diffusion.

In addition to the above suggestions, the diffusion model developed in this research can be also extended in several vectors. Given the effective results on increasing EVs share through subsidies adapted to dynamic preferences, one suggestion is to test other policies designed in a way that would also take into account the transition of preferences. The goal would be to verify if other policies would be similarly effective.

Another suggestion is the inclusion of market segments or clusters of consumers in the EVs diffusion model. The identification of market segments of consumers with similar preferences has been addressed in recent studies focused on consumer preferences of AFVs (Axsen et al., 2015; Hackbarth and Madlener, 2016; Ferguson et al., 2018) but it was never considered in diffusion models of these vehicles. This extension would allow to analyse the specific market penetrations for each market segment and to test customized policies according to the each cluster's characteristics.

Additionally, the EVs diffusion model can also be extended to account for impacts related to a mass integration of EVs in the transportation system, such as the environmental and distribution network impacts. The environmental benefits of increasing EVs circulation, in comparison to ICEVs impacts, are heterogeneous, i.e. they depend on several factors (Holland et al., 2016). Therefore, factors such as the electricity mix used to charge EVs, the technological improvements (e.g. increment of vehicles fuel efficiency), and the consumers driving habits (e.g. distance travelled per year) are among the factors that should be taken into account in order to have a comprehensive comparison between the environmental burden of EVs and ICEVs (Hawkins and Gausen, 2012; Garcia et al., 2015; Holland et al., 2016). As high penetration levels of EVs influence not only emissions release but also the load capacity of distribution networks (Habib et al., 2015) it is relevant verifying if the distribution network is prepared for a high penetration scenario of these vehicles. For instance, the charging pattern, where and when BEVs/PHEVs are plugged, has been identified as determinant factor for analysing if the current grid capacity is able to accommodate the load demand from plug-in electric vehicles charges (Camus et al., 2009; Lopes et al., 2009). The inclusion of these analyses would provide a broader perspective of the consequences of a mass introduction of EVs in the market.

Finally, the challenging and continuously evolving market context of EVs also shed light about topics that can be addressed in future consumer preferences studies. One example is related with the collection and analysis of RP data of EVs if the EVs market penetration increase significantly. Therefore, future studies may address the consumer preferences of EVs through the analysis of actual purchases of consumers. Other example regards to the charging costs that consumers have to support to charge EVs after fast charging stations have been privatized, where the costs to drive an EV are not as distant from ICEVs fuel costs as they were before. Therefore, recalling the importance that the fuel consumption has on consumer preferences for EVs found in this study and knowing that consumers were found to be more sensitive to electricity prices than to fuel prices (Liu 2018) the analysis of the impact of such costs on consumers' willingness to choose EVs in future purchases can be a path for future research. The impact of batteries acquisition options in addition to buying, such as rent or switch, on consumers' willingness to choose EVs can also be addressed in future studies in order to understand if they can accelerate the adoption of these vehicles.

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Appendix I – Government incentives for EVs adoption

Year	Program	Specific measures for EVs: Purchase Subsidy	Specific measures for EVs: Circulation tax (IUC)	Specific measures for EVs: Purchase tax (ISV)	Specific measures for EVs: Infrastructure development	Legislation
2007			Exemption for BEVs	50% reduction for HEVs Exemption for BEVs		Law nº 22A-2007
2008	PNAEE 2008 - 2015					Resolution of the Council of Ministers nº80/2008
2009					Approval of Mobi.E	Resolution of the Council of Ministers n.º 20/2009
2010		5000€ for BEVs (first 5000 BEV sold) + 1500€ if an ICEVs is discarded			Development of 320 charging spots	Decree-law nº39/2010
2011					Development of 1000 charging spots	Decree-law nº39/2010
2012		Withdrawal of 5000€ subsidy for BEVs				Law n.º 64-B/2011
2013	PNAEE 2013-2016				Development of solutions for domestic charging	Resolution of the Council of Ministers nº20/2013
2015	Reform of Green Taxation Plan of Action for Electric Mobility			40% reduction for HEVs 75% reduction for PHEVs (min 25km electric mode) 4500€ reduction on a BEVs purchase if an ICEV was discarded 3250€ reduction on PHEVs purchase if an old ICEV was discarded	50 fast charging spots	Order n.º 1962/2014 Order nº8809/2015 Law n.º 82-D/2014
2016				2250€ reduction on a BEVs purchase if an ICEV was discarded 1125€ € reduction on PHEVs purchase if an old ICEVs was discarded		Law n.º 7-A/2016
2017	Environmental fund	Subsidy of 2250€ for the first 1000 BEVs and PHEVs sold		Reduction till 562.50€ for PHEVs	Investment of 715,000€ in the charging network company Mobi.E	Law n.º 42/2016 Decree-law n.º 42-A/2016

Table I.1 – Summary of programs and government measures to support EVs adoption.

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Appendix II – Evolution of number of EVs models

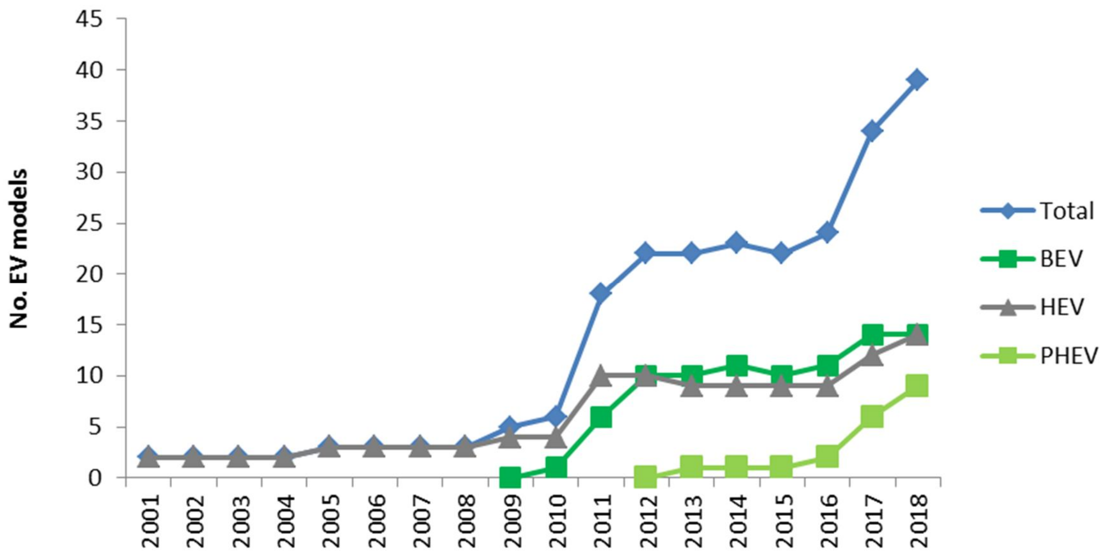

Figure II.1 - Number of EVs models available in the market in each year (source: author' own).

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Appendix III – EVs sales

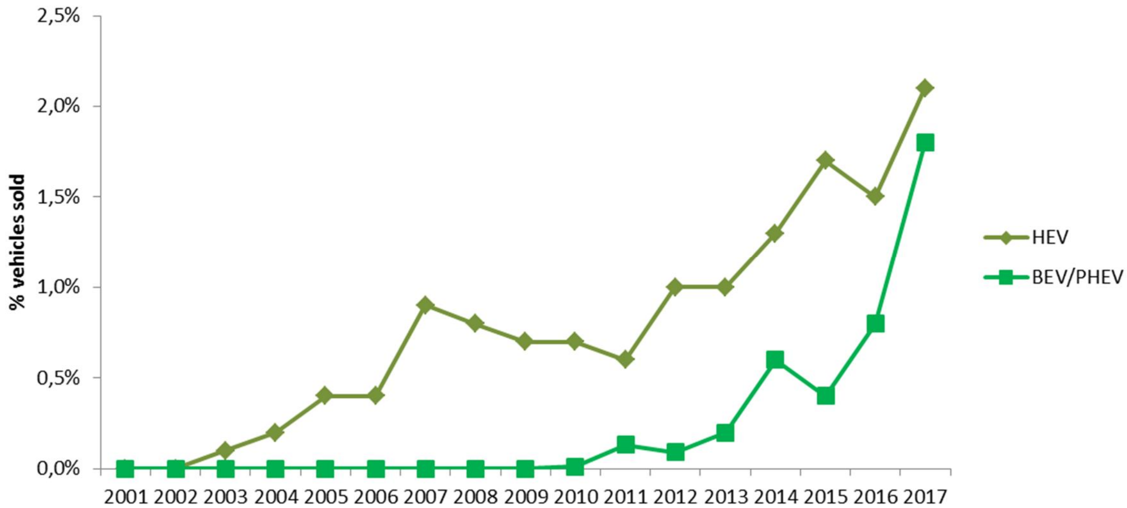

Figure III.1 - Evolution of HEVs and BEVs/PHEVs sales (source: ICCT (2018)).

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Appendix IV – Publications (abstracts)

Preference elicitation approaches for energy decisions

Gabriela Oliveira(a,b,c); Luis C. Dias(b,c); Luis Neves(c,d)

(a) DEM – Mechanic Engineering Department, University of Coimbra Pólo II da Universidade de Coimbra, Rua Luís Reis Santos, 3030-788 Coimbra, Portugal

(b) CeBER, Faculty of Economics, University of Coimbra, Av. Dias da Silva 165, 3004-512 Coimbra, Portugal

(c) INESCC - Institute for Systems Engineering and Computers at Coimbra, Rua Sílvio Lima, Pólo II, 3030-290 Pinhal de Marrocos Coimbra, Portugal

(d) School of Technology and Management, Polytechnic Institute of Leiria, Ap. 4163, 2411-901 Leiria, Portugal

Abstract:

Decision and planning problems are often informed by the preferences of the actors involved. This chapter aims at explaining what “elicitation of preferences” means for different decision support methodologies. Three elicitation approaches are presented: Multi-criteria Decision Analysis, Conjoint Analysis and Problem Structuring Methods. The potential of these approaches for structuring and supporting energy-related decisions is illustrated through several applications, namely the assessment of initiatives to promote energy efficiency through Soft Systems methodology and ELECTRE, the evaluation of policies to foster the development of smart grids using the Delphi method and ELECTRE TRI, and the modelling of consumer preferences for electric vehicles using Choice-Based Conjoint Analysis.

Key Words:

Preference elicitation; Problem structuring methods; Multi-criteria decision aiding; Conjoint Analysis; Energy behaviour

Influence of demographics on consumer preferences for Alternative Fuel Vehicles: A review of choice modelling studies and a study in Portugal.

Gabriela D. Oliveira [1,2,3,*] and Luis C. Dias [2,3]

[1] DEM - Mechanical Engineering Department, University of Coimbra, Coimbra 3030-788, Portugal;

[2] CeBER and Faculty of Economics, University of Coimbra, Coimbra 3004-512, Portugal;

[3] INESCC - Institute for Systems Engineering and Computers at Coimbra, Rua Sílvio Lima, Pólo II, 3030-290 Pinhal de Marrocos Coimbra, Portugal;

***** Corresponding author: gdoliv@fe.uc.pt

Abstract

The significant energy consumed by road transportation and the difficult market penetration of Alternative Fuel Vehicles (AFVs) has led to a substantial body of research aiming to understand consumer preferences and future demand for AFVs. The individual characteristics of consumers are one of the explanatory factors of these preferences. In this context, the main purpose of this work is to present a state-of-the-art review of how consumer demographics influence their preferences concerning AFVs. This review focuses on papers that applied Choice Modelling techniques to elicit individual consumer preferences for AFVs through stated preference surveys. Age, gender, income, level of education, family size, driving habits and number of vehicles per household were selected for analysis. This study also adds to the literature by analyzing the influence of demographic characteristics on preferences of Portuguese consumers. Very few studies addressed the influence of demographics on preferences for vehicle attributes. Considering the influence of consumers' income and age, no consistent results were found. However, when age and consumers' nationality were crossed, a potential trend of consumers' age influence was unveiled. Regarding gender, level of education and family size, it was observed that consumers with higher education levels, women and consumers with larger families have higher preferences for AFVs.

Keywords: consumer preferences; alternative fuel vehicles; electric vehicles; choice modelling; demographic influence; literature review

Modelling consumer preferences for electric vehicles in Portugal: an exploratory study.

Gabriela D. Oliveira [1,2,*], Luis C. Dias [2,3], Paula Sarabando[3,4]

[1] DEM - Mechanical Engineering Department, University of Coimbra, Coimbra 3030-788, Portugal;

[2] INESCC - Institute for Systems Engineering and Computers at Coimbra, Rua Sílvio Lima, Pólo II, 3030-290 Pinhal de Marrocos Coimbra, Portugal;

[3] Faculty of Economics, University of Coimbra, Coimbra 3004-512, Portugal;

[4] ESTGV – Superior School of Technology and Management of Viseu, Polytechnic campus 3504-510 Viseu.

***** Corresponding author: gdoliv@fe.uc.pt

Abstract

Purpose – The purpose of this paper is to understand consumer preferences concerning electric vehicles (EV) in Portugal, based on comparisons with other vehicles with different powertrains. **Design/methodology/approach** – The analysis incorporated two survey-based approaches: choice-based conjoint analysis (CBC) and multicriteria decision analysis (MCDA) based. The survey interviewed 252 respondents. The criteria characterizing each vehicle are purchase price, range, fuel consumption and CO2 emissions. Another criterion was added to verify the potential of EV privileges to influence consumer preferences. A sensitivity analysis on the influence of purchase price and fuel price in the global utility of the vehicles was performed. **Findings** – The results showed that monetary criteria are those influencing vehicle purchase decisions the most, whereas the existence of privileges for EV owners has little relevance. EV are chosen by the consumer only if their price decreases or if gasoline and diesel prices increase sharply. The position of PHEV in the rankings makes the promotion of this type of vehicle an interesting path to exploit as potential intermediates to the diffusion of EV. **Practical implications** – The results underline the need of improving technical barriers of EV that are responsible for consumers' relevant concerns and that a price subsidy could eventually be effective to increase EV sales at its current market price. **Originality/value** – This study compares a wide range of vehicles (conventional, hybrid and electric), addresses the Portuguese market and proposes an MCDA-based approach to obtain preference information, which is compared with a CBC approach.

Keywords: Consumer preferences, Electric vehicles, Choice-based conjoint analysis, Multicriteria decision analysis

The potential learning effect of a MCDA approach on consumer preferences for Alternative Fuel Vehicles

Gabriela D. Oliveira[a, b,c*], Luis C. Dias[b,c,d]

[a] DEM – Mechanic Engineering Department, University of Coimbra Pólo II da Universidade de Coimbra, Rua Luís Reis Santos, 3030-788 Coimbra, Portugal

[b] INESCC - Institute for Systems Engineering and Computers at Coimbra, Rua Sílvio Lima, Pólo II, 3030-290 Pinhal de Marrocos Coimbra, Portugal

[c] CeBER, University of Coimbra, Av. Dias da Silva 165, 3004-512 Coimbra, Portugal

[d] Faculty of Economics, University of Coimbra, Av. Dias da Silva 165, 3004-512 Coimbra, Portugal

Abstract

Despite efforts from governments to increase the diffusion of more sustainable vehicles, such Alternative Fuel Vehicles (AFV), the market penetration of these vehicles has been difficult. Eliciting consumer preferences may provide valuable information on how to increase AFV diffusion. Since these are unfamiliar and complex products for most consumers, preferences are usually learnt during the process of elicitation. Preference learning is dependent on several factors, which include the type of elicitation task and task complexity. In this work, a stated preference survey was designed to analyze the potential impact of more complex elicitation tasks, Multiattribute Utility Theory approach (MAUT), on the learning of preferences elicited through a traditional approach, Choice-Based Conjoint Analysis (CBC). The survey comprised two CBC sets of questions, one asked before and another asked after the MAUT. As a result three rankings of the vehicles set were obtained for each consumer, one derived from the initial set of CBC answers, a second one derived from the elicited MAUT model, and a third one derived from the second set of CBC answers. According to the results, there are significant differences from the first to the third ranking, possibly due to learning effects. Differences between the CBC-derived rankings were analyzed to assess if they were aligned with the MAUT model.

Keywords: Conjoint analysis; Multicriteria decision analysis; preference learning; elicitation task; alternative fuel vehicles.

Diffusion of Alternative Fuel Vehicles considering dynamic preferences

Gabriela D. Oliveira[a,b,c,*], Richard Roth[d], Luís C. Dias[c,e]

[a] DEM – Mechanical Engineering Department, University of Coimbra Pólo II da Universidade de Coimbra, Rua Luís Reis Santos, 3030-788 Coimbra, Portugal

[b] INESCC - Institute for Systems Engineering and Computers at Coimbra, Rua Sílvio Lima, Pólo II, 3030-290 Pinhal de Marrocos Coimbra, Portugal

[c] CeBER, Av. Dias da Silva 165, 3004-512 Coimbra, Portugal

[d] Engineering Systems Division, Massachusetts Institute of Technology, 77 Massachusetts Ave, E38-420,Cambridge, MA 02139-4301, USA

[e] Faculty of Economics, University of Coimbra, Av. Dias da Silva 165, 3004-512 Coimbra, Portugal

[*] Corresponding author: gdoliveira@student.dem.uc.pt

Abstract

Consumer preferences are a crucial element of models aimed at understanding and predicting the diffusion of Alternative Fuel Vehicles (AFVs). Previous AFVs diffusion studies have considered static preferences, but preferences for complex products such as AFVs are likely to change under different market conditions. Therefore, using static preferences for demand forecasts may compromise the accuracy of those predictions. This study aims at incorporating dynamic preferences on a reference AFVs diffusion model and analyzing if adapting subsidy policies according to those preferences will provide more cost-effective results on AFVs adoption.

Two system dynamics models are developed for comparative purposes: one considering static preferences and other one considering dynamic preferences. According to the results derived from these models, the model with dynamic preferences predicts a higher market penetration of AFVs, mainly due to the increment of Plug-in Hybrid Electric vehicles and Battery Electric Vehicle market shares. These results show that considering dynamic consumer preferences has a significant impact on AFVS diffusion predictions. The subsidies scenarios allow concluding that designing subsidies according to the evolution of preferences stimulated AFVs adoption more effectively.

Keywords: Dynamic Preferences; Alternative Fuel Vehicles; Diffusion Model; System Dynamics.

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Appendix V – Conference proceedings, communications and other publications

Papers in proceedings of international conferences

1. **Oliveira, G.**, Luis, L.C. (2015). Which criteria matter when selecting a conventional or electric vehicle? Energy for Sustainability 2015, Sustainable cities: Designing for people and the planet. May 14, Coimbra, Portugal.
2. **Oliveira, G.**, Luis, L.C., Sarabando, P. (2013). Modeling consumer preferences about electric vehicles: an exploratory survey. Energy for Sustainability 2013, Sustainable cities: Designing for people and the planet. September 8, Coimbra, Portugal

Communications and posters:

1. **Oliveira G.**, Dias L. (2018). Difusão de veículos de combustível alternativo considerando preferências dinâmicas. XIX Congress of APDIO 2018. University of Aveiro, September 5-7, Aveiro, Portugal. (communication)
2. Oliveira, G., Dias, L. (2016). Alternative Fuel Vehicles adoption considering dynamic consumer preferences: a system dynamics approach. MIT Portugal International conference, Braga, Portugal. (poster)
3. **Oliveira, G.**, Dias, L.C., Sarabando, P. (2013). Modeling consumer preferences about vehicles with multi-attribute additive models: survey-based experiments. 26th European Conference on Operation Research. July 3, Rome, Italy. (communication)
4. Dias, L.C., **Oliveira, G.**, Sarabando, P. (2013). Modeling consumer preferences about vehicles with multi-attribute additive models: survey-based experiments. 22nd International Conference on Multiple Criteria Decision Making. June 20, Málaga, Spain. (communication)

5. Sarabando, P., **Oliveira, G.**, Dias, L.C. (2013). Modelação das preferências dos consumidores sobre diferentes veículos: estudo baseado em experiências. XVI Congresso Associação Portuguesa de Investigação Operacional. June 4, Bragança, Portugal. (communication)

Publications not directly related to the PhD thesis:

1. Soares, N., Martins, A.G., Carvalho A.L., Caldeira C., Du, C., Castanheira, É., Rodrigues, E., **Oliveira, G.**, Pereira, G.I., Bastos, J., Ferreira, J.P., Ribeiro, L.A., Figueiredo, N.C., Šahović, N., Miguel, P., Garcia, R.. (2018). The challenging paradigm of interrelated energy systems towards a more sustainable future. Renewable and Sustainable Energy Reviews 95, pp. 171-193.

Appendix VI – Formulation of UTA inference

UTA aims at inferring one or more additive utility functions from a given ranking on a set of reference alternatives reflecting holistic evaluations by a decision maker (Jacquet-Lagrèze and Siskos, 1981; Siskos et al., 2005). Therefore, decision makers (in this case, consumers) are asked to provide a linear order (a ranking without ties) of a set *R* of n reference alternatives:

$$a_{[1]} \succ a_{[2]} \succ \ldots \succ a_{[n]}$$

where $\succ$ denotes the preference relation and $a_{[i]}$ denotes the i^{th} most preferred alternative in the consumer's Final Reference Ranking.

UTA uses linear programming to estimate a (possibly nonlinear) additive function that reproduces the ranking provided in (2) and, similarly to MAUT, it requires the assumption of preferential independence among the attributes. The inference consists in the computation of the weights w_k and single-attribute utilities u_{ki}. This is possible using linear programming by adopting variables U_{ki} representing the product $w_k u_{ki}$. There exists a utility function $U(.)$ that is compatible with the Final Reference Ranking if and only if the following linear program has a non-negative optimal value:

$$\max_{(U_{11},\ldots,U_{1m},\ldots,U_{n1},\ldots,U_{nm},\varepsilon)} \varepsilon$$

Subject to:

$$\sum_{k=1}^{n} U_{ki} - \sum_{k=1}^{n} U_{kj} - \varepsilon \geq \delta, \quad \forall (a_i, a_j): a_i \succ a_j$$

$$U_{ki} - U_{kj} - \varepsilon \geq \delta, \quad \forall k \in \{1, \ldots, n\}, (a_i, a_j): a_i \succ_k a_j$$

$$U_{ki} - U_{kj} - \varepsilon \geq 0 \ \wedge \ U_{kj} - U_{ki} - \varepsilon \geq 0 \ \forall k \in \{1, \ldots, n\}, (a_i, a_j): a_i \sim_k a_j$$

$$\sum_{k=1}^{n} U_{k[Best(k)]} = 1,$$

$$\left(U_{1[Worst(1)]}, \dots, U_{n[Worst(n)]}\right) = (0, \dots, 0)$$

Where,

δ is an arbitrarily small positive quantity (to enforce strict inequality).

$[Best(k)]$ and $[Worst(k)]$ denote respectively the index of best and worst performance in attribute *k* among the alternatives being compared.

From the optimal solution of linear programming presented above it is then possible to reconstitute weights (w_k=$U_{k[Best(k)]}$) and single-attribute utilities (v_{ki} = $V_{ki}/V_{k[Best(k)]}$).

Appendix VII – Vehicles description

Current scenario

Battery Electric Vehicle (BEV1):
Vehicle that has an electrical engine that moves using electricity accumulated on batteries that can be recharged in specific charging stations or on any regular electrical outlet. This vehicle costs 29000 €. It has 180 km range (distance that can be covered on a single battery charge). Each km travelled has an average cost of 0.02€ (cost of used electricity) and implies emissions of 50 grams of CO2. The CO2eq emissions produced during the entire life-cycle of the vehicle (total emissions from the manufacture of the vehicle to its end-of-life disposal, including emissions due to the electricity generated to run it, maintenance processes, etc., considering a useful life of 200 000 km) amount to 21 Ton. The maximum speed of this vehicle is 145 km/h and it accelerates 0-100 km/h in 8 seconds. The battery takes 8 hours for a full recharge.

Battery Electric Vehicle (BEV2):
This vehicle costs 31000 € and distinguishes itself from BEV1 by having a 250 km autonomy. In all other aspects it is similar to BEV1.

Hybrid Electric Vehicle (HEV):
Vehicle that has an electrical engine plus a gasoline internal combustion engine. It has a 2 km autonomy on fully electric mode. Batteries cannot be recharged at an electric outlet: they are recharged profiting from the kinetic energy of the vehicle when breaking or when descending on a route. The autonomy (considering the internal combustion engine) is 1100 km. This vehicle costs 27 000€. Each km travelled has an average cost of 0.05€, having a consumption of 3.8 l/100km of gasoline. There are emissions of 110 grams of CO2 per km. The CO2eq emissions produced during the entire life-cycle of the vehicle amount to 27 Ton. The maximum speed of this vehicle is 180 km/h and it accelerates 0-100 km/h in 10.9 seconds.

Gasoline Vehicle:
Vehicle that has a gasoline internal combustion engine. The autonomy of the internal combustion engine is 800 km. This vehicle costs 24 000€. Each km travelled has an average cost of 0.09€, corresponding to a consumption of 6.1 l/100km of gasoline. There are emissions of 150 grams of CO2 per km. The CO2eq emissions produced during the entire life-cycle of the vehicle amount to 36 Ton. The maximum speed of this vehicle is 175 km/h and it accelerates 0-100 km/h in 12.6 seconds.

Diesel Vehicle:
Vehicle that has a diesel internal combustion engine. The autonomy of the internal combustion engine is 1200 km. This vehicle costs 27 000€. Each km travelled has an average cost of 0.06€, corresponding to a consumption of 4.2 l/100km of diesel. There are emissions of 120 grams of CO2 per km. The CO2eq emissions produced during the entire life-cycle of the vehicle amount to 32 Ton. The maximum speed of this vehicle is 175 km/h and it accelerates 0-100 km/h in 14.7 seconds.

Plug-in Hybrid Electric Vehicle (PHEV):
Vehicle that has an electrical engine plus a gasoline internal combustion engine. It has a 60 km autonomy on fully electric mode and batteries can be recharged at any electric outlet. When the vehicle can no longer run on electricity, the autonomy is extended by the internal combustion engine up to 1200km. This vehicle costs 34 000 €. Each km travelled has an average cost of 0.03€. The consumption of gasoline using the combustion engine is 2.1 l/km. There are emissions of 90 grams of CO2 per km. The CO2eq emissions produced during the entire life-cycle of the vehicle amount to 25 Ton. The maximum speed of this vehicle is 180 km/h and it accelerates 0-100 km/h in 11.4 seconds. The battery takes 1.5 hours for a full recharge.

Future scenario

Battery Electric Vehicle (BEV1):
Vehicle that has an electrical engine that moves using electricity accumulated on batteries that can be recharged in specific charging stations or on any regular electrical outlet. This vehicle costs 25000 €. It has 250 km range (distance that can be covered on a single battery charge). Each km travelled has an average cost of 0.02€ (cost of used electricity) and implies emissions of 40 grams of CO2. The CO2eq emissions produced during the entire life-cycle of the vehicle (total emissions from the manufacture of the vehicle to its end-of-life disposal, including emissions due to the electricity generated to run it, maintenance processes, etc., considering a useful life of 200 000 km) amount to 19 Ton. The maximum speed of this vehicle is 145 km/h and it accelerates 0-100 km/h in 8 seconds. The battery takes 8 hours for a full recharge.

Battery Electric Vehicle (BEV2):
This vehicle costs 30000 € and distinguishes itself from BEV1 by having a 600 km autonomy. In all other aspects it is similar to BEV1.

Hybrid Electric Vehicle (HEV):
Vehicle that has an electrical engine plus a gasoline internal combustion engine. It has a 2 km autonomy on fully electric mode. Batteries cannot be recharged at an electric outlet: they are recharged profiting from the kinetic energy of the vehicle when breaking or when descending on a route. The autonomy (considering the internal combustion engine) is 1200 km. This vehicle costs 27 000€. Each km travelled has an average cost of 0.07€, having a consumption of 3.5 l/100km of gasoline. There are emissions of 80 grams of CO2 per km. The CO2eq emissions produced during the entire life-cycle of the vehicle amount to 23 Ton. The maximum speed of this vehicle is 180 km/h and it accelerates 0-100 km/h in 10.9 seconds.

Gasoline Vehicle:
Vehicle that has a gasoline internal combustion engine. The autonomy of the internal combustion engine is 900 km. This vehicle costs 24 000€. Each km travelled has an average cost of 0.09€, corresponding to a consumption of 5.8 l/100km of gasoline. There are emissions of 120 grams of CO2 per km. The CO2eq emissions produced during the entire life-cycle of the vehicle amount to 30 Ton. The maximum speed of this vehicle is 175 km/h and it accelerates 0-100 km/h in 12.6 seconds.

Diesel Vehicle:
Vehicle that has a diesel internal combustion engine. The autonomy of the internal combustion engine is 1200 km. This vehicle costs 26 000€. Each km travelled has an average cost of 0.08€, corresponding to a consumption of 3.8 l/100km of diesel. There are emissions of 90 grams of CO2 per km. The CO2eq emissions produced during the entire life-cycle of the vehicle amount to 26 Ton. The maximum speed of this vehicle is 175 km/h and it accelerates 0-100 km/h in 14.7 seconds.

Plug-in Hybrid Electric Vehicle (PHEV):
Vehicle that has an electrical engine plus a gasoline internal combustion engine. It has a 60 km autonomy on fully electric mode and batteries can be recharged at any electric outlet. When the vehicle can no longer run on electricity, the autonomy is extended by the internal combustion engine up to 1200km. This vehicle costs 29 000 €. Each km travelled has an average cost of 0.04€. The consumption of gasoline using the combustion engine is 2.1 l/km. There are emissions of 70 grams of CO2 per km. The CO2eq emissions produced during the entire life-cycle of the vehicle amount to 21 Ton. The maximum speed of this vehicle is 180 km/h and it accelerates 0-100 km/h in 11.4 seconds. The battery takes 1.5 hours for a full recharge.

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Appendix VIII – Survey tasks

Task 1 – Demographic data

a) Age:
b) Gender:
   F_
   M_
c) Brand/model current vehicle (e.g. VW Golf):
d) Current vehicle age:
e) Main use:
   City_
   Intercity_
f) Km per trip:
g) Km per year:
h) Garage:
   yes_
   No_
i) Knowledge about hybrid and electric vehicles:
   Low_
   Some_
   High_
j) Interest in this study:
   Low_
   Some_
   High_

Task 2 – Initial ranking of vehicles

Considering the vehicles presented on the table rank them according to your preferences:

Type of engine	Price (€)	Range (km)	Fuel consumption (€/100km)	CO_2 Emissions (g/km)	**Ranking**
BEV1	29,000	180	2	50	
BEV2	31,000	250	2	50	
HEV	27,000	1100	5	110	
Gasoline	24,000	800	9	150	
Diesel	27,000	1200	6	120	
PHEV	34,000	1200	3	90	

Task 3 – CBC exercise

Choose the best and worst vehicle in each question according to your preferences:

Question 1

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
BEV	27000	350	4	90	
PHEV	34000	1200	8	130	
Diesel	32000	1200	10	150	

Question 2

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
Gasolina	30000	900	10	110	
HEV	24000	900	6	130	
BEV	34000	250	2	50	

Question 3

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
PHEV	27000	900	2	150	
BEV	32000	350	6	50	
BEV	24000	150	4	110	

Question 4

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
Gasolina	34000	1200	10	90	
HEV	30000	1200	6	90	
Diesel	24000	1200	8	130	

Question 5

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
BEV	30000	350	2	110	
PHEV	27000	1200	4	50	
HEV	32000	900	8	110	

Question 6

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
Gasolina	34000	900	8	150	
BEV	34000	150	6	130	
HEV	30000	1200	4	90	

Question 7

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
BEV	30000	150	2	50	
HEV	27000	1200	6	110	
PHEV	34000	1200	4	90	

Question 8

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
Diesel	27000	1200	6	130	
BEV	30000	150	2	50	
PHEV	34000	1200	4	90	

Question 9

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
Gasolina	24000	900	8	150	
Diesel	27000	1200	6	130	
BEV	32000	250	2	50	

Task 4 – MAUT exercise

a) Which purchase price value would correspond to the level 5 so that changing from the level 0 to the level 5 has the same utility than changing from level 5 to level 10? Repeat the same reasoning to assign a purchase price value to 2.5 and 7.5. Repeat then the same procedure for range, fuel consumption and CO_2 emissions.

	€	km	€/100km	g/km
	Purchase price	Range	Fuel consumption	CO2 emissions
Level 10 (best level)	20000	1300	1	20
Level 7,5				
Level 5				
Level 2.5				
Level 0 (worst level)	35000	150	13	160

b) Adjust the following comparisons between attribute values in order to be indifferent between each pair of alternatives.

	Price €	Autonomy km		Price €	Range km
Tradeoff price vs range	20000	150	<=>	35000	1300

	Price €	Consumption €/100km		Price €	Consumption €/100km
Tradeoff price vs consumption	20000	13	<=>	35000	1

	Price €	Emissions g/km		Price €	Emissions g/km
Tradeoff price vs emissions	20000	160	<=>	35000	20

Task 5 – Final ranking of vehicles

According to your preferences, do you agree with the ranking of the vehicles set provided by the method MAUT? If no, adjust the vehicle positions in order to obtain a vehicles ranking that represent your preferences.

MAUT ranking	
1	
2	
3	
4	
5	
6	

Revised ranking	
1	
2	
3	
4	
5	
6	

Task 6 – Repetition of CBC exercise

Question 1

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
BEV	27000	350	4	90	
PHEV	34000	1200	8	130	
Diesel	32000	1200	10	150	

Question 2

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
Gasolina	30000	900	10	110	
HEV	24000	900	6	130	
BEV	34000	250	2	50	

Question 3

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
PHEV	27000	900	2	150	
BEV	32000	350	6	50	
BEV	24000	150	4	110	

Question 4

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
Gasolina	34000	1200	10	90	
HEV	30000	1200	6	90	
Diesel	24000	1200	8	130	

Question 5

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
BEV	30000	350	2	110	
PHEV	27000	1200	4	50	
HEV	32000	900	8	110	

Question 6

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
Gasolina	34000	900	8	150	
BEV	34000	150	6	130	
HEV	30000	1200	4	90	

Question 7

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
BEV	30000	150	2	50	
HEV	27000	1200	6	110	
PHEV	34000	1200	4	90	

Question 8

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
Diesel	27000	1200	6	130	
BEV	30000	150	2	50	
PHEV	34000	1200	4	90	

Question 9

	Purchase price	Range	Fuel consumption	CO_2 Emissions	**Ranking**
Gasolina	24000	900	8	150	
Diesel	27000	1200	6	130	
BEV	32000	250	2	50	

Appendix IX – Prohibitions defined in the CBC design

	Price					Range					Fuel consumption					CO_2 Emissions				
	24,000	27,000	30,000	32,000	34,000	150	250	350	900	1200	2	4	6	8	10	50	90	110	130	150
BEV																				
PHEV																				
HEV																				
Gasoline																				
Diesel																				

Figure IX.1 – Prohibitions for attribute values in the current scenario.

	Price					Range					Fuel consumption					CO_2 Emissions				
	22,000	24,000	26,000	28,000	30,000	250	400	600	900	1200	2	4	7	9	12	40	60	80	100	120
BEV																				
PHEV																				
HEV																				
Gasoline																				
Diesel																				

Figure IX.2 – Prohibitions for attribute values in the future scenario.

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Appendix X – Part-worth utilities for the current scenario

Attribute level	Part-Worth Utility	Standard Deviation
Type of engine		
BEV	-3.101	2.833
PHEV	1.402	1.239
HEV	0.203	0.959
Gasoline	0.227	1.273
Diesel	1.270	1.472
Purchase price		
24000€	2.149	2.034
27000€	1.446	1.118
30000€	0.479	0.802
32000€	-1.178	1.419
34000€	-2.895	2.076
Range		
150 Km	-1.642	1.348
250 Km	-0.562	0.817
350 Km	0.342	0.571
900 Km	0.371	0.589
1200 Km	1.491	1.124
Fuel consumption		
2€/100km	2.181	1.620
4€/100km	1.598	1.322
6€/100km	0.356	0.555
8€/100km	-1.030	1.227
10€/100km	-3.105	2.004
CO_2 Emissions		
50g/km	0.331	0.341
90g/km	0.283	0.332
110g/km	-0.035	0.177
130g/km	-0.232	0.294
150g/km	-0.347	0.287

Table X.1 – Part-worth utilities for each attribute level for the current scenario.

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Appendix XI – Part-worth utilities for the future scenario

Attribute level	Part-Worth Utility	Standard Deviation
Type of engine		
BEV	-0.950	2.025
PHEV	1.813	1.011
HEV	0.481	1.098
Gasoline	-1.701	1.623
Diesel	0.356	1.522
Purchase price		
22000€	1.236	1.134
24000€	1.115	1.097
26000€	0.171	0.512
28000€	-0.725	0.756
30000€	-1.796	1.854
Range		
250 Km	-2.343	1.865
400 Km	-0.606	0.608
600 Km	0.442	0.519
900 Km	0.581	0.523
1200 Km	1.926	1.503
Fuel consumption		
2€/100km	3.351	2.457
4€/100km	1.577	1.134
7€/100km	0.194	0.681
9€/100km	-1.426	1.192
12€/100km	-3.696	2.600
CO_2 Emissions		
40g/km	0.643	0.730
60g/km	0.310	0.351
80g/km	0.002	0.196
100g/km	-0.454	0.488
120g/km	-0.500	0.492

Table XI.1 – Part-worth utilities for each attribute level for the current scenario.

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Appendix XII – Definitions of the constant variables

Variable	Unit	Value	Source
Growth rate of LDV fleet	$Year^{-1}$	0	Struben and Sterman (2008)
Marketing effectiveness	$Year^{-1}$	0.025	Struben and Sterman (2008)
Effective contact rate drivers	$Year^{-1}$	0.2	Calibration (see subsection 5.5.2)
Effective contact rate non-drivers	$Year^{-1}$	0.15	Struben and Sterman (2008)
Social exposure rate	$Year^{-1}$	0.029	Calibration (see subsection 5.5.2)
Installed base LDV fleet	Vehicles	Gasoline: 2,160,000 Diesel: 2,051,000 HEV: 10,630 BEV: 286 PHEV: 296	ACAP (2013)
Average vehicle life	Years	11.1	ACAP (2013)

Table XII.1 – Values and sources for the constant variables.

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Appendix XIII – Curve fitting of attribute utility functions

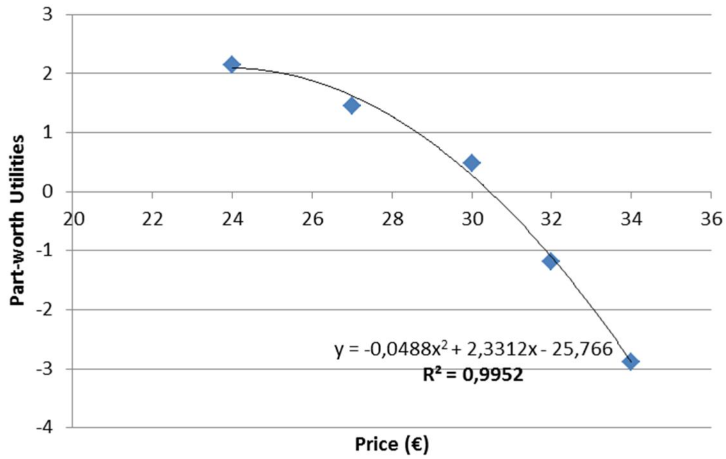

Figure XIII.1 – Part-worth utility function and fit curve for price in the current scenario.

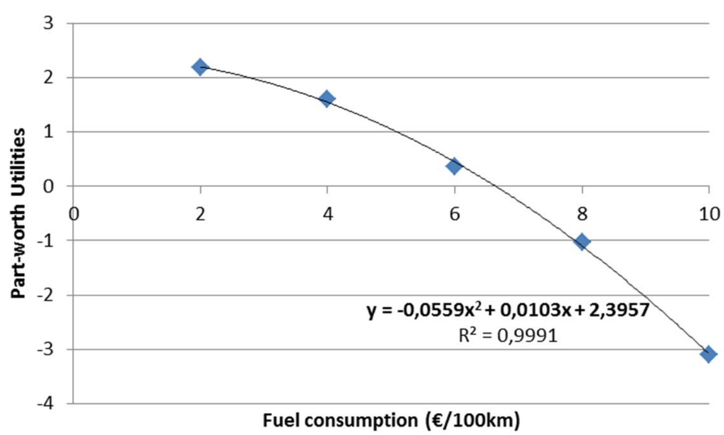

Figure XIII.2 – Part-worth utility function and fit curve for fuel consumption in the current scenario.

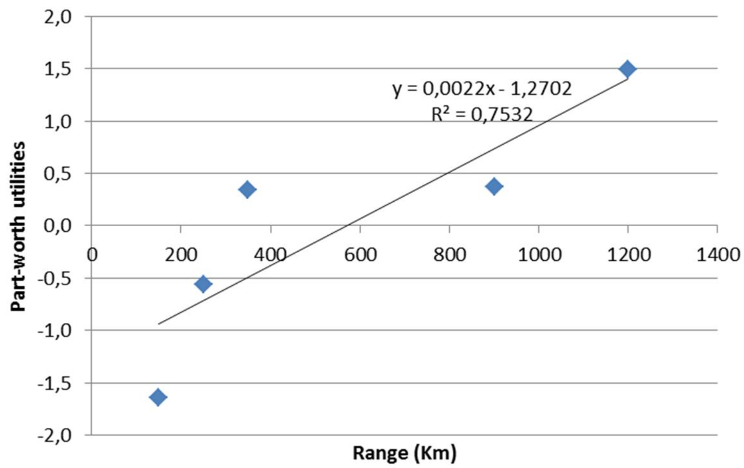

Figure XIII.3 – Part-worth utility function and fit curve for range in the current scenario.

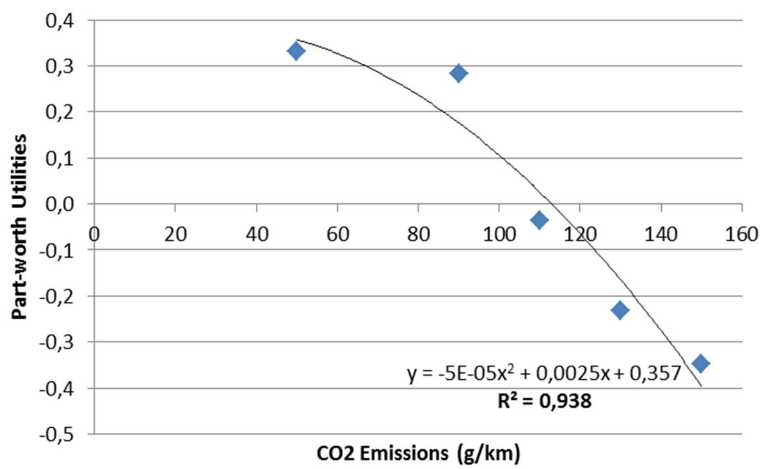

Figure XIII.4 – Part-worth utility function and fit curve for CO_2 emissions in the current scenario.

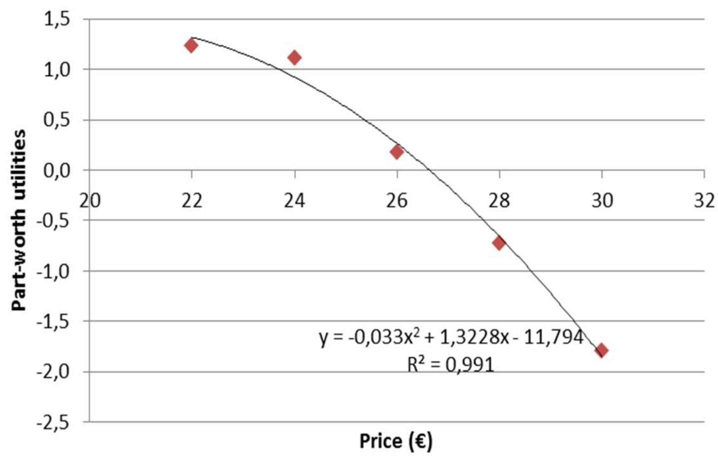

Figure XIII.5 – Part-worth utility function and fit curve for price in the future scenario.

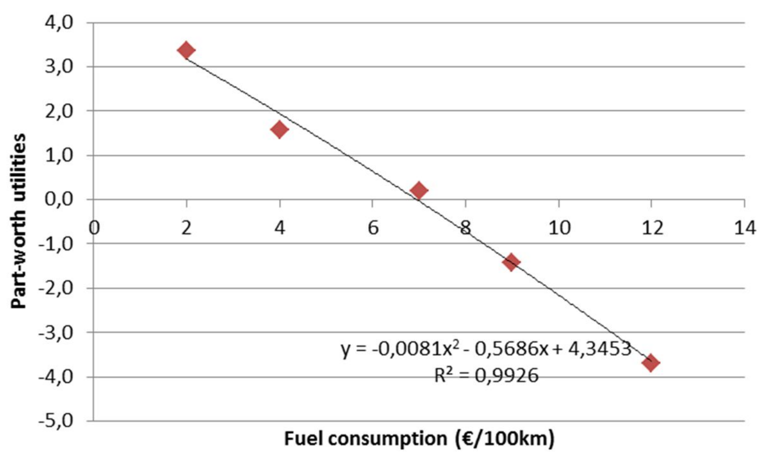

Figure XIII.6 – Part-worth utility function and fit curve for fuel consumption in the future scenario.

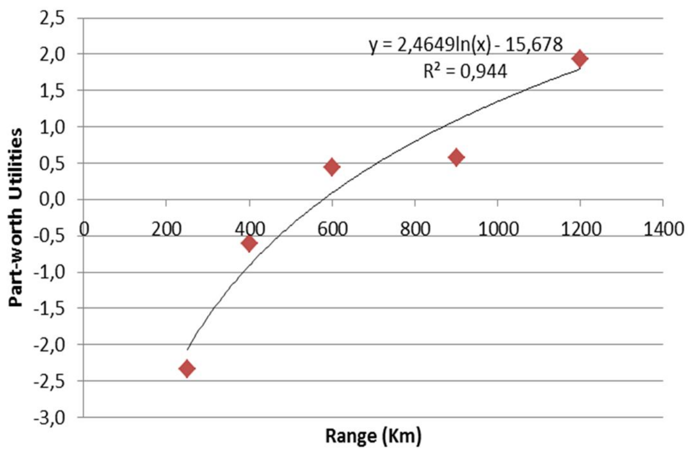

Figure XIII.7 – Part-worth utility function and fit curve for range in the future scenario.

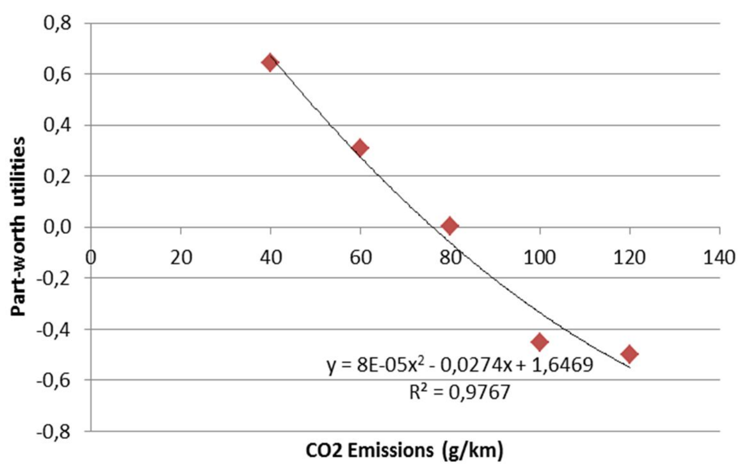

Figure XIII.8 – Part-worth utility function and fit curve for CO_2 emissions in the future scenario.

Appendix XIV - Sensitivity analysis graphs

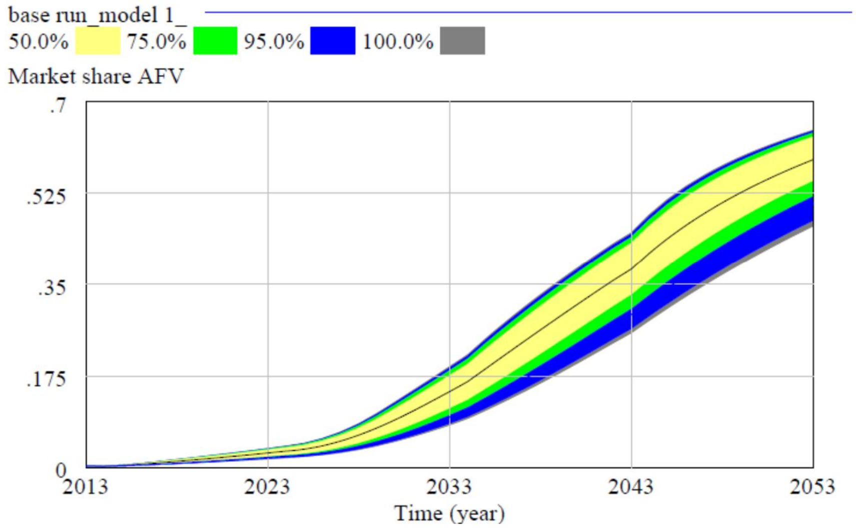

Figure XIV.1 – Sensitivity graph of EVs market share according to variations of "growth rate" variable.

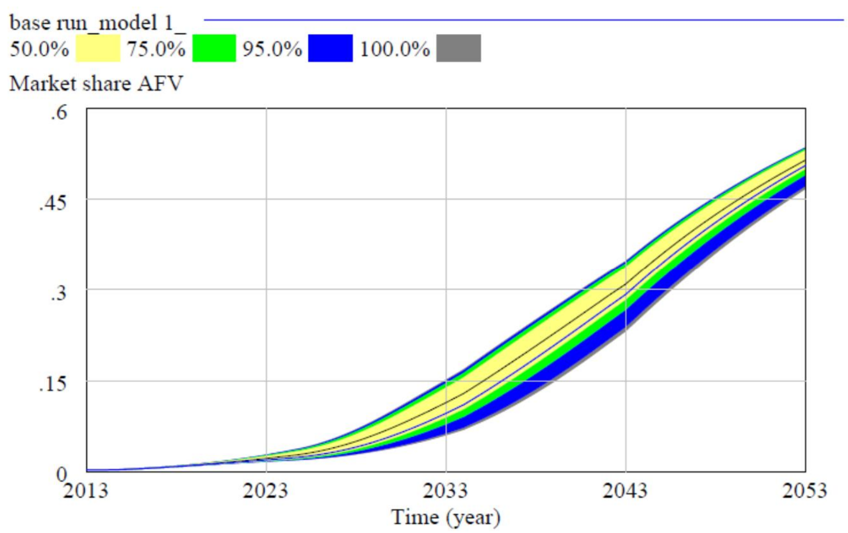

Figure XIV.2 – Sensitivity graph of EVs market share according to variations of "Effective contact rate drivers" variable.

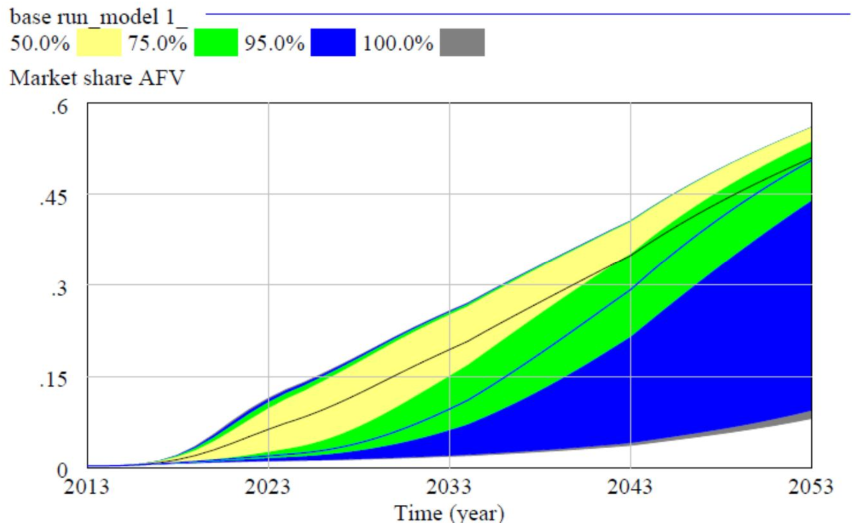

Figure XIV.3 – Sensitivity graph of EVs market share according to variations of "Effective contact rate non-drivers" variable.

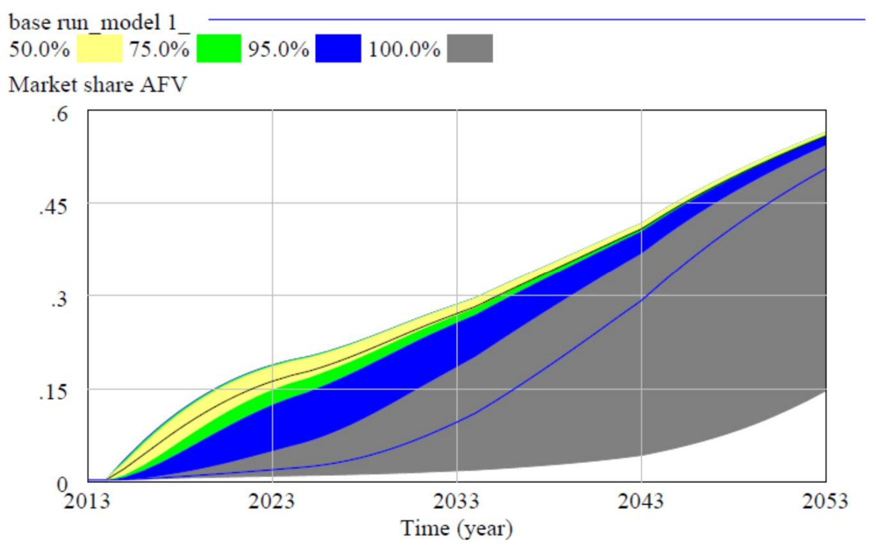

Figure XIV.4 – Sensitivity graph of EVs market share according to variations of "marketing" variable.