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Diffusion of Alternative Fuel Vehicles considering dynamic preferences

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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. A System Dynamics model adapted to the Portuguese market was developed to study the impact of considering dynamic preferences and several incentive policies adapted to such preferences.

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

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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.

Highlights:

- Alternative Fuel Vehicles (AFVs) diffusion model incorporates dynamic preferences.
- A Static Preferences model and a Dynamic Preferences model are compared.
- AFVs adoption results from Dynamic Preferences model are markedly different from the Static model.
- Degressive subsidies allow achieving higher market penetration of AFVs than constant subsidies.

1. Introduction

Road transportation is still a matter of great concern, accounting for more than a fourth of the total energy consumption and for two-thirds of the European Union final demand of oil and its derivatives (European Commission, 2018). Alternative Fuel Vehicles (AFVs) have been regarded as possible solutions for energy use and environmental problems, 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 conventional vehicles but also from the possibility of using renewable energy to charge electric batteries (Hacker et al., 2009). However, AFVs have had difficulties to penetrate the markets, as consumers continue to have technical and economic concerns about the adoption of new vehicle technologies (Potoglou and Kanaroglou, 2007; Hidrue et al., 2011). Indeed, several barriers strongly affect the transition from conventional vehicles to AFVs, such as their limited range and the (un)availability of charging infrastructures, not to mention consumers resistance to adopting innovative technologies (Leiby and Rubin, 2004).

Several diffusion studies have tried to understand AFVs market penetration in order to predict consumer behavior in face of the introduction of these vehicles. Diffusion analysis is particularly suited to identify measures to overcome market barriers, addressing the process of innovation diffusion (Rogers, 1962). One of the main purposes of the diffusion studies for AFVs is to forecast vehicles demand (e.g., Janssen et al., 2006; Keles et al., 2008; Köhler et al., 2010; Walther et al., 2010; Park et al., 2011; Kwon, 2012; Shepherd et al., 2012). In these studies consumers play a major role by providing the stated preferences required to support the prediction of that demand for new vehicle technologies (Ahn et al., 2008). Their preferences are considered a critical factor for the success of AFVs development (Struben and Sterman, 2008; Huijts et al., 2012). Traditionally, in the economics field, preferences were considered as static limiting analysis of the consequences of a given set of preferences (Janssen and Jager, 2001). Currently, economics joined the psychological and marketing fields, in which questions such as how the preferences are formed and how they change over time are addressed (Janssen and Jager, 2001; Lachaab et al., 2006).

As consumer preferences towards more complex products, such as AFVs, are less stable (Bettman et al., 1998), several researchers analysed the preferences for these vehicles and concluded that consumer preferences for AFVs were likely to change under different market conditions, i.e., they were dynamic (Mau et al., 2008; Axsen et al., 2009; Maness and Cirillo, 2012). Therefore, ignoring the evolution of preferences may lead to inaccurate predictions of vehicle market shares, especially when the measurement of preferences is done well ahead of the forecast period (Axsen et al., 2013; Meeran et al., 2017). Dynamic preferences are an important component of technological change that should not be left out from new vehicle technologies analysis (Axsen et al., 2009).

The literature on consumer preferences (reviewed in subsection 2.1) sustains that these preferences evolve in time, i.e., they are dynamic. However, only static preferences have been considered in AFVs diffusion studies literature (reviewed in subsection 2.2). Therefore, the main contribution of the present research is to incorporate dynamic consumer preferences on an AFVs diffusion model in order to assess their impact on the market penetration of these vehicles. This is an innovative approach on the diffusion analysis of AFVs as not only the attribute values change over time but the consumer preferences for each attribute also change. In this study, dynamic preferences are seen as a consequence of changes in the market conditions. This means that preferences change with different economic environments that imply changes in social interactions between consumers and their relatives or friends that may or not have experienced the product. The study addresses the Portuguese market, in which the penetration of AFVs has been particularly hard (section 4), and it is focused on the Electric Vehicles (EVs) already available in this market, namely Battery-Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs) and Hybrid Electric Vehicles (HEVs).

The implementation of government policies is a frequently analyzed strategy to influence consumer preferences, by which governments seek to foster the rapid diffusion of environmental friendly technologies (Soete and Arundel, 1995). Monetary policies are among the most commonly studied, since one of the consumer's main concerns is the financial burden associated with buying a vehicle. Therefore, monetary incentives consisting in an up-front discount on the vehicle purchase price have the potential to positively influence consumers' vehicle purchase decisions (Eggers and Eggers, 2011; Borthwick, 2012). However, the effectiveness of purchase subsidies is not easy to predict as consumers may consider that AFVs remain too expensive even with a price reduction (Bakker and Trip, 2013). The Portuguese government implemented several policies in order to stimulate the adoption of AFVs, including a BEV purchase subsidy of 5000€. However, sales were far below the initial projections (ACAP, 2013). Within this context, an interesting research question is how to design an incentive policy that would be adapted to the evolution of dynamic consumer preferences. Therefore, the second contribution of this study is to assess if adapting subsidies to dynamic consumer preferences can provide more cost-effective results. The analysis of the impact of subsidies adapted to dynamic preferences challenges the established practice of analyzing the impact of purchase subsidies on the diffusion of AFVs, as the impact of purchase incentives has always been analyzed assuming the implementation of constant subsidies.

A System Dynamics (SD) model adapted to the Portuguese market was developed to study the impact of considering dynamic preferences and several incentive policies adapted to such preferences.

The paper is organised as follows. The next section presents a review of studies that addressed the existence of dynamic preferences and the state-of-the-art of modelling consumer preferences in AFVs diffusion studies using SD. The SD model developed for this study is described and justified in section 3. Section 4 presents the SD diffusion model and its validation and calibration for Portugal. Results and main conclusions are reported on section 5 and 6, respectively.

2. Literature review

2.1. Review about dynamic consumer preferences

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 an eight year 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 Fuel Cell Vehicles (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 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 affected 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 on 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) tracked consumer preferences over a six months period and verified that consumer preferences changed significantly with time.

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 attributes. This is consistent with the concept of constructed preferences, where consumers usually do not have well defined preferences, but instead they construct those preferences when they face a choice decision (Bettman et al., 1998). Thus, 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 to 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 a 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).

2.2. Review about consumer preferences modelling

2.2.1. Consumer preferences modeling

Before reviewing how the consumer preferences have been modelled in AFVs diffusion studies, let us briefly recall how consumer preferences are modelled in general. Consumer preferences are usually modelled through disaggregation methods, such as Conjoint Analysis or Discrete Choice Models. These methods use as inputs the overall assessment of each product obtained through stated preference surveys, where each consumer states his/her preferences considering the attribute values for each product (Green et al., 1972). The collected preference data is then decomposed into individual utilities, called part-worth utilities, of each attribute reflecting the relevance of the product's characteristics for consumers (Molin et al., 1997). The overall utility of a product b, $U(b)$, is then obtained by adding the part-worth utilities β of the attribute levels l that describe that alternative according to the following expression (Malhotra, 2008):

$$U(b) = \sum_{k=1}^{m} \sum_{l=1}^{n} \beta_{kl} x_{kl} \qquad (1)$$

Where,

β_{kl} is the part-worth utility of level l ($l = 1,2 \dots, n$) of attribute k ($k = 1,2, \dots, m$);

x_{kl} is a dummy variable, equal to 1 if level l of the attribute k is present in product b, and 0 otherwise.

2.2.2. Consumer preferences modeling in AFVs diffusion studies using SD

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). 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 studies had more specific aims. Struben and Sterman (2008) analyzed the dynamics of a broad behavioral model for a future transition to AFVs, considering the consumer awareness and learning. Molina (2013) developed a model to analyze 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, some studies focused mainly 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 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 (β value of the equation 1), as consumer preferences were considered static over time.

Considering the modelling trends presented above, this study's model differentiates from all the previous literature by considering dynamic preferences in the diffusion analysis of AFVs. The collection of preference data also differs from most of the previous studies as it was collected through stated preference surveys.

				CONSUMER MODEL SPECIFICATIONS			
STUDY	**YEAR**	**SCOPE**	**FOCUS**	**Vehicle attributes**	**Estimation procedure**	**Data source**	**Dynamic or static preferences**
Janssen et al. (2006)	2006	Switzerland	Natural Gas Vehicles	Fuel price Purchase price	Multinomial Logit model	Brownstone et al. (2000)	Static Preferences
Keles et al. (2008) Köhler et al. (2010)	2008 2010	Germany	FCVs	Purchase price Performance Range Fuel costs Share of filling stations	NM	NM	Static Preferences
Struben and Sterman (2008)	2008	US	AFVs	NI	Logit model	NI	Static Preferences
Leaver et al. (2009)	2009	New Zealand	FCVs and BEVs	Fuel economy Purchase price	Logit model	NM	Static preferences
Meyer and Winebrake (2009)	2009	US	FCVs	Fuel cost Purchase price Station density	Logit model	NM	Static Preferences
Walther et al. (2010)	2010	US	BEVs, PHEVs and HEVs	Range Purchase price Recharging stations	Discrete choice model (not specified)	Brownstone et al. (1996)	Static Preferences
Park et al. (2011)	2011	South Korea	FCVs	Did not include a consumer model			
Fazeli et al. (2012)	2012	Portugal	HEVs, PHEVs and ethanol	Purchase price Fuel cost Range Performance Refuel station	Logit model	Obtained through calibration process	Static Preferences
Keith (2012)	2012	US	HEVs, PHEVs and BEVs	Purchase price Emissions Operation cost Acceleration	Logit model	Brownstone et al. (2000)	Static Preferences

				CONSUMER MODEL SPECIFICATIONS			
STUDY	**YEAR**	**SCOPE**	**FOCUS**	**Vehicle attributes**	**Estimation procedure**	**Data source**	**Dynamic or static preferences**
				Range			
Kwon (2012)	2012	US	AFVs		Did not include a consumer model		
Shepherd et al. (2012)	2012	UK	PHEVs and BEVs	Purchase price Operation costs Maximum speed Fuel availability Emissions Range	Multinomial Logit model	Batley et al. (2004)	Static Preferences
Molina (2013)	2013	US	HEVs and BEVs	Purchase price Operational cost Driving range Carbon footprint	NM	Data from sampling through Latin Hyper Cube method	Static Preferences
Harrison and Shepherd (2014)	2014	US	BEVs, PHEVs and HEVs	Range Purchase price Recharging stations	Discrete choice model (not specified)	Brownstone et al. (1996)	Static Preferences
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)	2014 2015 2015 2016 2017 2018	Iceland	BEVs, PHEVs, HEVs, FCVs, biogas, biodiesel BEVs, PHEVs, HEVs, FCVs and biogas BEVs, PHEVs and HEVs	Purchase price Maintenance cost Range Emissions Battery replacement cost Fuel cost Fuel availability	Multinomial Logit model	Calibration (adapted from Greene (2001))	Static Preferences
Guðmundsdóttir (2016)	2016	Iceland	PHEVs, BEVs, HEVs and FCVs	Purchase price Acceleration Top speed Range Operation costs Fuel search cost	Nested Logit model	Brownstone et al. (2000) and Brownstone et al. (1996)	Static Preferences
Pasaoglu et al. (2016)	2016	European Union countries	HEVs, PHEVs, BEVs and FCVs	Performance Reliability Safety Popularity Ownership cost Purchase price Emissions	Multinomial Logit model	NM	Static Preferences
Kieckhäfer et al. (2016)	2016	Germany	BEVs, PHEVs and HEVs	Purchase price Range Performance Annual mileage Environmental awareness Infrastructure supply	Nested logit model	Achtnicht et al. (2008)	Static Preferences
Liu et al. (2017)	2017	US	BEVs	Purchase price Operation cost Environmental impact Range	Multinomial Logit model	Set according to scenarios	Static Preferences
The present study	2019	Portugal	BEVs, PHEVs, HEVs, ICEVs	Purchase price Range Fuel costs Emissions	Choice Based Conjoint Analysis/Hierarchical Bayes	Stated preferences survey	Dynamic Preferences

Table 1 – Studies that used SD to model AFVs diffusion (NM: Not Mentioned; NI: Not included).

3. The model

As we were interested in the dynamic interaction among variables of the system, and considering the diffusion methods commonly used to analyse the diffusion of AFVs, there were two main dynamic simulation approaches from which we could choose from, SD and Agent Based Model (ABM).

SD is a modelling approach that enhances learning about complex systems behaviour. Most of these complex behaviours 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 (Sterman, 2000). 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).

The main difference between SD and ABM is related with the adopted perspective to model the system. While SD uses a "top-down" approach, i.e. it models a system by diving it into its main components and then models the component interactions, ABM models the system through a "bottom-up" perspective, i.e. by modelling the individual agents that are part of the system and their interactions (Macal, 2010). Moreover, while SD uses mostly continuous processes of the system variables, ABM uses mainly discrete time processes, i.e. it jumps from one event to another (Borshchev and Filippov, 2004).

Therefore, as SD provides a continuous analysis of the variables of the system, where a feedback effect provides a circular causality between those variables, a more realistic understanding of the demand dynamics for AFVs was considered to be provided through this methodology, underlining why SD was chosen to use in this study. Furthermore, SD has been frequently used in the diffusion of AFVs (it was used by all studies in table 1). The objectives that studies applying SD for AFVs diffusion aimed to fulfill include: to represent complex networks between the market players and the dependencies of the market penetration process (Janssen et al., 2006); to analyze the coevolution of AFVs and the corresponding infrastructure (Guðmundsdóttir, 2016); and to assess how the transition to electric vehicles can be achieved through fiscal policy incentives (Shafiei et al., 2018).

3.1. Model overview

An overview of our model is depicted in figure 1. The core of our model is the diffusion model of Struben and Sterman (2008), which is considered a reference to model the feedbacks that affect consumer awareness for AFVs and their diffusion. Considering our consumer-focused approach, this model is highly relevant as it includes relevant behavioural dynamics that allow understanding the key factors that influence the consumer adoption of AFVs. These dynamics were incorporated through a process that followed the social diffusion of AFVs, where willingness to consider an alternative vehicle and word of mouth were endogenously included (from drivers and non-drivers) and marketing was considered as exogenous. The social diffusion process was then modelled by the 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 (2), where η_{ij} represents the impact of social exposure of vehicle on the increase in familiarity 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.

$$\frac{dW_{ij}}{dt} = \eta_{ij}(1 - W_{ij}) - \phi_{ij}W_{ij} \tag{2}$$

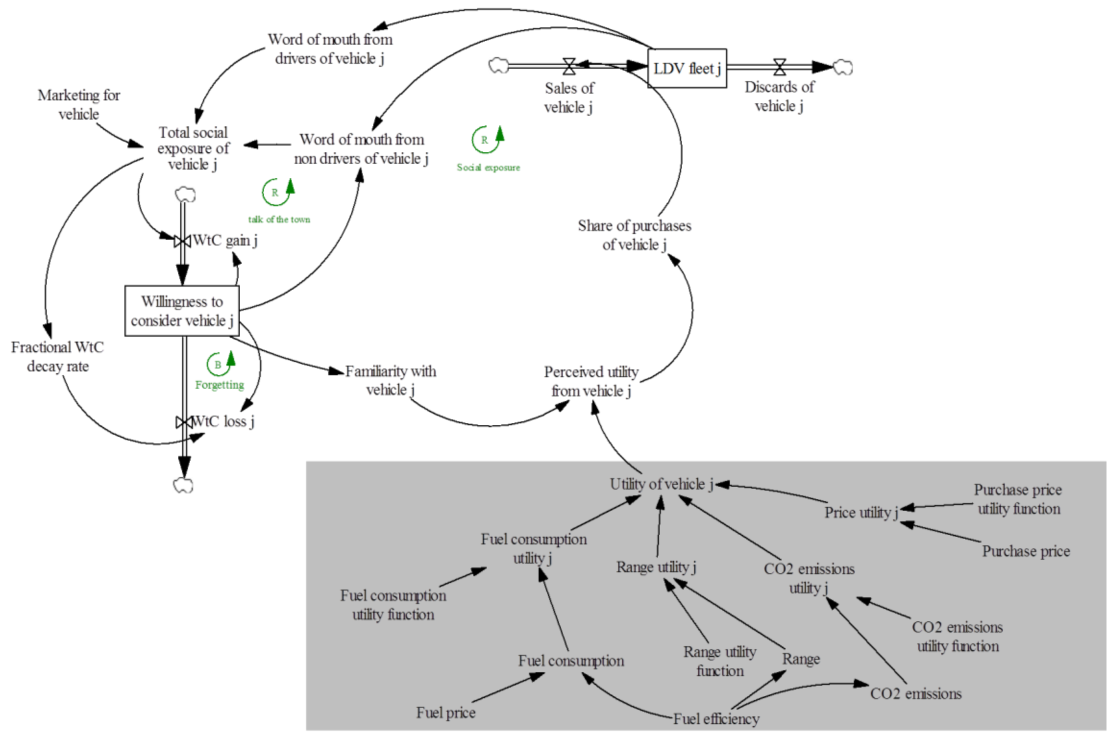

Figure 1 - Core model of AFVs diffusion from Struben and Sterman and model extensions (in grey).

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. When the dominant technology is considered, Internal Combustion Engine Vehicle (ICE), 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 (3)).

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

$$f(\eta_{ij}) = \frac{\exp[-4\varepsilon(\eta_{ij}-\eta^*)]}{1+\exp[-4\varepsilon(\eta_{ij}-\eta^*)]} \tag{3}$$

As represented in equation (4), the total exposure to a vehicle is a sum of three components: marketing effectiveness; word-of-mouth from drivers of that vehicle; and word-of-mouth about that vehicle among those not driving it.

$$\eta_{ij} = \alpha_j + c_{ijj} W_{jj} \frac{V_j}{N} + \sum_{k \neq j} c_{ijk} W_{kj} \frac{V_j}{N} \tag{4}$$

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 the Light Duty Vehicles (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 ($j = \{1,2, \dots, n\}$ in the fleet, V_j, accumulates new vehicle sales, s_j, minus vehicle discards, d_j through equation (5). 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 (6)). The share switching from vehicle i to j depends on perceived affinity/familiarity for vehicle j, a_{ij}^p, a population-aggregated utility effect (equation (7))

$$\frac{dV_j}{dt} = s_j - d_j \tag{5}$$

$$s_j = \sum_i \sigma_{ij}(d_i + gV_i) \tag{6}$$

$$\sigma_{ij} = \frac{a_{ij}^p}{\sum_j a_{ij}^p} \tag{7}$$

Similarly to Shepherd et al. (2012) we added a discrete choice model to compute vehicle utilities that would determine the share of purchases of each vehicle.

Considering the above, Struben and Sterman's model was used as a starting point to incorporate dynamic preferences in our study, where the main extensions or adaptations of their model were:

- The consideration of five specific vehicle sets (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/electricity costs, 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.

An overview of our model is depicted in figure 1. Regarding the parameters value for social diffusion process, we used the values from Struben and Sterman (2008). The data for the fleet turnover model comes from the Automotive Association of Portugal (ACAP, 2013), namely for the installed base of each vehicle type and the average scrappage time of vehicles (11.1 years). The discrete choice model data was computed through collected stated preference data, as described in the next section.

3.2. Incorporation of dynamic consumer preferences

The incorporation of dynamic preferences requires at least two set of preferences data in order to implement a transition of preferences over time. For this study two sets of preference data were collected: preferences for vehicles that currently exist in the market, i.e. current preferences, and preferences for vehicles that will be available in the future, i.e. future preferences. These preferences, here named “future preferences” for brevity, are used as an illustration for the model developed in this article, as it is not possible to warrant these will be the preferences that will be held 40 years after the survey.

In general, there are two strategies to collect future preferences data, in addition to the current preferences. One approach is to track consumer 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 those hypothetical market conditions are in place, i.e., current and future preferences are collected in the present. This strategy was used in several studies applied to AFVs (Mau et al., 2008; Axsen et al., 2009; Musti and Kockelman, 2011) where future preferences were collected by simulating a future environment, as described in Section 2.

Acknowledging the long life cycle of vehicles and the frequent use of the second strategy in the transportation field, we collected future consumer preferences by simulating future market conditions. The hypothetical future scenario assumed that electric vehicles sales take off and, as a consequence, manufacturers of fuelled vehicles try to mitigate ICEVs disadvantages in order to become more competitive with electric vehicles. This context led to the following specific changes in the vehicle characteristics (detailed in Section 5): 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.

Preference data was collected through a stated preferences survey, a common approach for collecting current preferences (Tompkins and Bunch, 1998; Ewing and Sarigöllü, 2000; Potoglou and Kanaroglou, 2007; Achtnicht et al., 2008; Caulfield et al., 2010) as well as future preferences (Mau et al., 2008; Axsen et al., 2009; Maness and Cirillo, 2012; Meeran et al., 2017).

As the main goal of this research is to assess the impact of considering dynamic preferences on AFVs diffusion, two models were simulated where the only difference was the computation of the utilities of each attribute (figure 2). The Static Preferences Model (Model SP) is an AFVs 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.

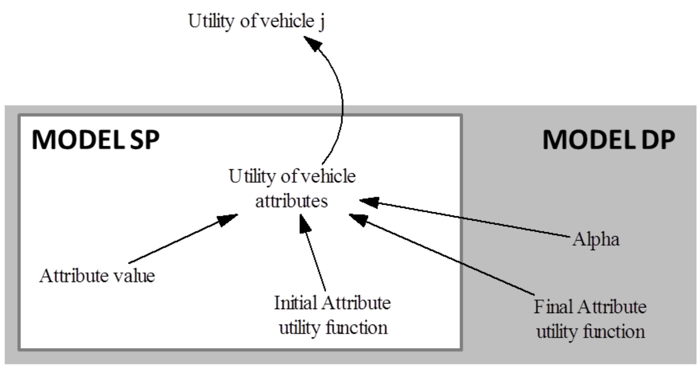

Figure 2 - Model SP and model DP.

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, Cojocaru et al. (2013), in order to model the evolution of consumers' preferences for new versions of already established products, considered that the velocity of adjustment of consumers' preferences depended on the distance from the product identified as more attractive.

In the present study, we implemented two model DP variants that differ on the computation of the preferences transition in order to verify if results are robust with regards 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:

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

$$\beta_{kjt} = \lambda_t * \beta_{kjI} + (1 - \lambda_t) * \beta_{kjF} \tag{8}$$

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 0 (current scenario) to 1 (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 (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), a higher range BEVs 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 BEV 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 BEV range, $Range_{AT}$. The computation of the (nonlinear) transition of preferences was computed through equation (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 (1) whilst the overall vehicle utility for Model DP1 and Model DP2 was computed through equation (9), a combination of equation (1) and (8):

$$U_t(j) = [\lambda_t * \beta_{PricejI} + (1-\lambda_t) * \beta_{PricejF}] + [\lambda_t * \beta_{RangejI} + (1-\lambda_t) * \beta_{RangejF}] + \\ +[\lambda_t * \beta_{FCjI} + (1-\lambda_t) * \beta_{FCjF}] + [\lambda_t * \beta_{EmissionsjI} + (1-\lambda_t) * \beta_{EmissionsjF}] \quad (9)$$

Where $\beta_{PricejI}$ and $\beta_{PricejF}$ represent the part-worth utilities of level j of attribute price considering the utility function I or the utility function F, respectively, and so on.

4. The Portuguese diffusion model

The Portuguese market was chosen as scope for the diffusion model developed in this study. The analysis of Portuguese market dynamics highlight why Portugal is an appealing context to address the diffusion of AFVs.

Targeting a 5% share of AFVs in 2020 (IEA, 2015), the Portuguese government has been implementing several incentive policies to favor the market penetration of AFVs (mainly BEVs). Purchase subsidies, exemption of purchase tax and circulation tax, and the development of charging infrastructures are among the main incentives implemented (see supplementary material Appendix A.1). The government efforts were followed by an increment of AFVs models in Portugal, i.e. in 2017 consumers had at their disposal a more diversified portfolio of AFVs to choose from (see supplementary material Appendix A.2). However, the efforts put in place to successfully mass introduce these vehicles in the market have not been as effective as expected, with AFVs share reaching only 0.74% of market share of LDVs (figure 3). Figure 3 shows that the financial crisis that headed the transport sector did not benefit the market penetration of AFVs, as the majority of the incentives from government and suppliers took place in the period where the crisis in the sector was stronger, i.e. between 2010 and 2012. Additionally, crossing the government incentives for AFVs penetration and the evolution of sales shows that that the sales dynamics did not respond to the incentives as would be expected; in fact, in some periods of time they behaved in the opposite direction (see supplementary material Appendix A.3).

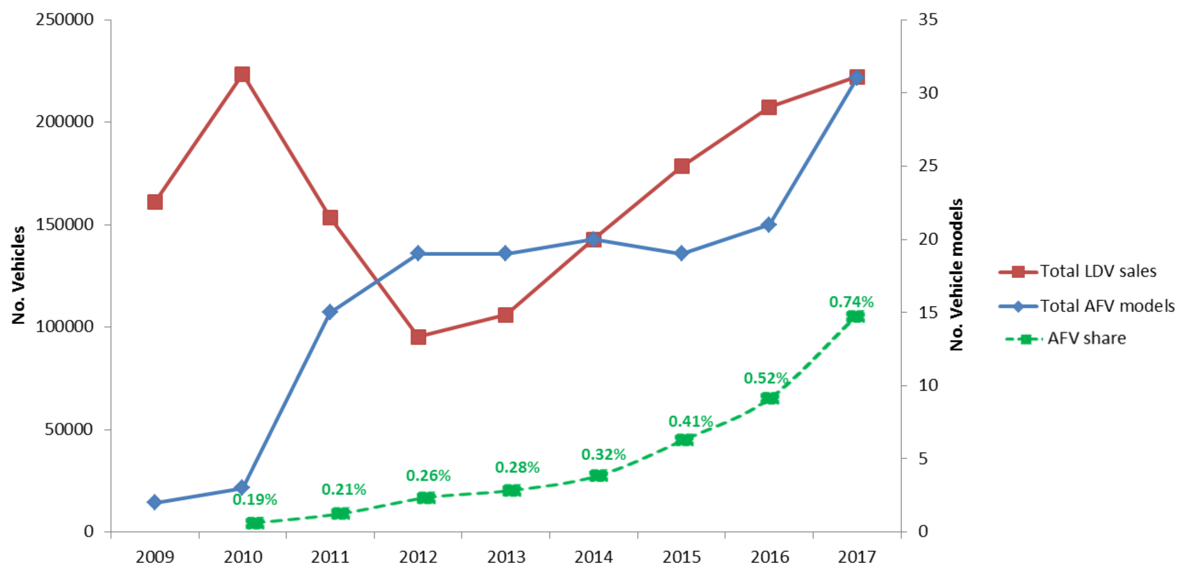

Figure 3 - Evolution of LDVs sales with AFVs models introduction and the achieved AFVs share.

4.1. Preference data collection

Consumer preferences data was collected using a Stated Preference survey in Portugal. Similarly to other studies, Choice-Based Conjoint Analysis (CBC) was chosen as the preference elicitation method (Chéron and Zins, 1997; Ahn et al., 2008; Eggers and Eggers, 2011; Lebeau et al., 2012; Kabaday et al., 2013; Wu et al., 2014).

The attributes selection was based on a previous study that aimed at finding out which attributes Portuguese consumers valued the most when purchasing a vehicle (Oliveira and Dias, 2015). This selection was corroborated by the most frequently used vehicle attributes in AFVs diffusion studies with SD, accordingly to the review presented in Section 3.2. Two different sets of levels (values) for each attribute were defined, one set for each scenario (table 2 and 3 for the current and future scenario respectively).

The choice questions were obtained through a fractional factorial design using Sawtooth® software. This design allowed reducing the total number of different combinations of the attribute levels in order to obtain a comfortable number of questions for consumers to answer. Each consumer was asked to select the best and worst option in each choice set according to their preferences.

Regarding the selection criteria for applying the survey, two criteria were defined for the data collection: consumers should be older than 18 years old and should be potentially vehicle buyers in the short-medium term. Previous experience driving AFVs can contribute to increased preferences towards these vehicles (Gyimesi and Viswanathan, 2011). However, due to the insufficient penetration of AFVs in Portugal, respondents were not required to have already driven all the types of vehicles in the choice set. The survey was implemented through face-to-face interviews, a process that allowed the interaction with the interviewer in real time and to ensure that consumers understood the questions.

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/electricity costs (per 100 km)	2€ / 4€ / 6€ / 8€ / 10€
CO_2 emissions (per km)	50 g / 90 g / 110 g / 130 g / 150 g

Table 2 - 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/elctricity costs (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 - Attribute levels for the future scenario.

4.2. Attributes modelling

4.2.1. Modelling attribute values

In AFVs diffusion studies, the most common approach is to model vehicle <u>purchase price</u> as dependent on 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 our 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 analyze its impact on AFVs demand.

The <u>fuel/electricity cost</u>, measured in €/100km, is affected by two variables, fuel price at time t (FP_t) and fuel efficiency rate at time t (FE_t). 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 (10)). The fuel consumption of ICEVs and HEVs was computed by equation (11).

$$FE_t = \begin{cases} 0.021, \text{ if } FP_t > FP_{t-1} \\ 0.0021, \text{if } FP_t \leq FP_{t-1} \end{cases} \tag{10}$$

$$Fuel/electricity\ cost_t = FP_t * FC_t * (1 - FE_t) \tag{11}$$

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). We considered the impact of the driver behaviour through driving patterns on PHEVs consumption 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, we used a value for η computed from real driving patterns of US PHEVs drivers presented on Samaras and Meisterling (2008), which gathered data for three PHEVs: PHEV30, PHEV60 and PHEV90. As the PHEV defined in our study has an electric range of 25km, the value for PHEV30, $\eta = 0.47$, was chosen. The fuel consumption of PHEV is given by the following equation:

$$Fuel/electricity\ \ cost\ \ PHEV_t = (1 - \eta) * ICE\ consumption + \eta * Electric\ engine\ consumption$$

$$= (1 - \eta) * FP_t * FC_t * (1 - FE_t) + \eta * BEVconsumption \tag{12}$$

Regarding the non-fuelled vehicle BEV, it was defined that the running costs are constant.

The CO_2 emissions of each vehicle type were computed following a "tank-to-wheels" approach, accounting for the emissions released while driving a vehicle, i.e., use phase emissions from fuel combustion (Bicer and Dincer, 2016). Although there are emissions in other life cycle stages of a vehicle, namely manufacturing and disposal (Adams and Schmidt, 1998), our SD model was designed from the consumer perspective. Thus, it made sense to consider only the CO_2 emissions that consumers have access and take into account during the purchase process. According to a European Commission directive (European Comission, 2000), CO_2 emissions from fuel production and distribution are not communicated to consumers in vehicle labelling. As BEV runs only on electric batteries no use phase emissions are considered. 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 differs according to the considered fuel, and depend on the fuel consumption at time t (FC_t), measured in l/100km, that varies over time. Therefore, CO_2 emissions at time t, measured in g CO_2/km, were computed through the following equation:

$$CO_2Emissions_t = FCS * FD * FC_t/100 \quad (13)$$

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

$$FC_t = FC_t * (1 - FE_t) \quad (14)$$

For PHEV, consistent with the fuel/electricity cost computation, the same driving pattern was considered for the computation of PHEVs emissions:

$$CO_2Emissions_t = (1 - \eta) * FCS * FD * FC_t \quad (15)$$

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:

$$Range_t = Range_{t-1} * (1 + FE_t) \quad (16)$$

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 was modelled exogenously, similarly to Fazeli et al. (2012) and Shepherd et al. (2012). BEVs range was defined considering a given battery size. Our 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 BEV more attractive. In 2012, lithium-ion batteries, with an average capacity of 25 kWh, provided a range of 150 km (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 of lithium-ion batteries until 2025 will provide a range of 240km (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, we considered $increment_t = 0.04$ during this period. Considering the above, the computation for BEVs range was made according to the following equation:

$$Range\ BEV_t = Range_{t-1} * (1 + increment_t) \tag{17}$$

The initial values for each attribute are summarized in table 4. These were based on characteristics of vehicles available in the Portuguese market.

	Purchase price (€)	Range (km)	Fuel/electricity costs 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 4- Attribute values in 2013.

4.2.2. Modelling attribute utilities

For the computation of attribute utilities the Stated Preference data was analyzed through Choice Based Conjoint Analysis/Hierarchical Bayes (CBC/HB) using Sawtooth® software. For the attribute "type of engine" the output was a part-worth utility for each engine. Figure 4 depicts the utilities for the type of engine for each scenario, showing that alternative engines have higher preferences in the future scenario. BEVs present the highest difference between scenarios.

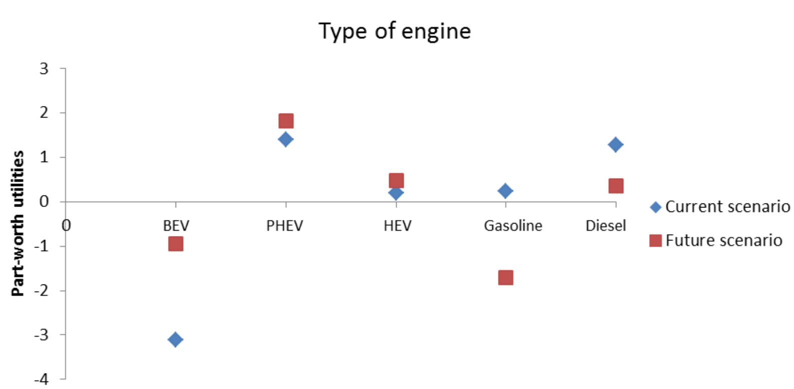

Figure 4 – Part-worth utilities of each type of engine for current and future scenarios.

For the other attributes, the output was a part-worth utility function for each attribute level, i.e. a structure of the consumer preferences in the surveyed population (Green and Srinivasan, 1978). This function estimates the utilities for each attribute level, for each consumer. 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 functions for all consumers for each scenario (figure 5).

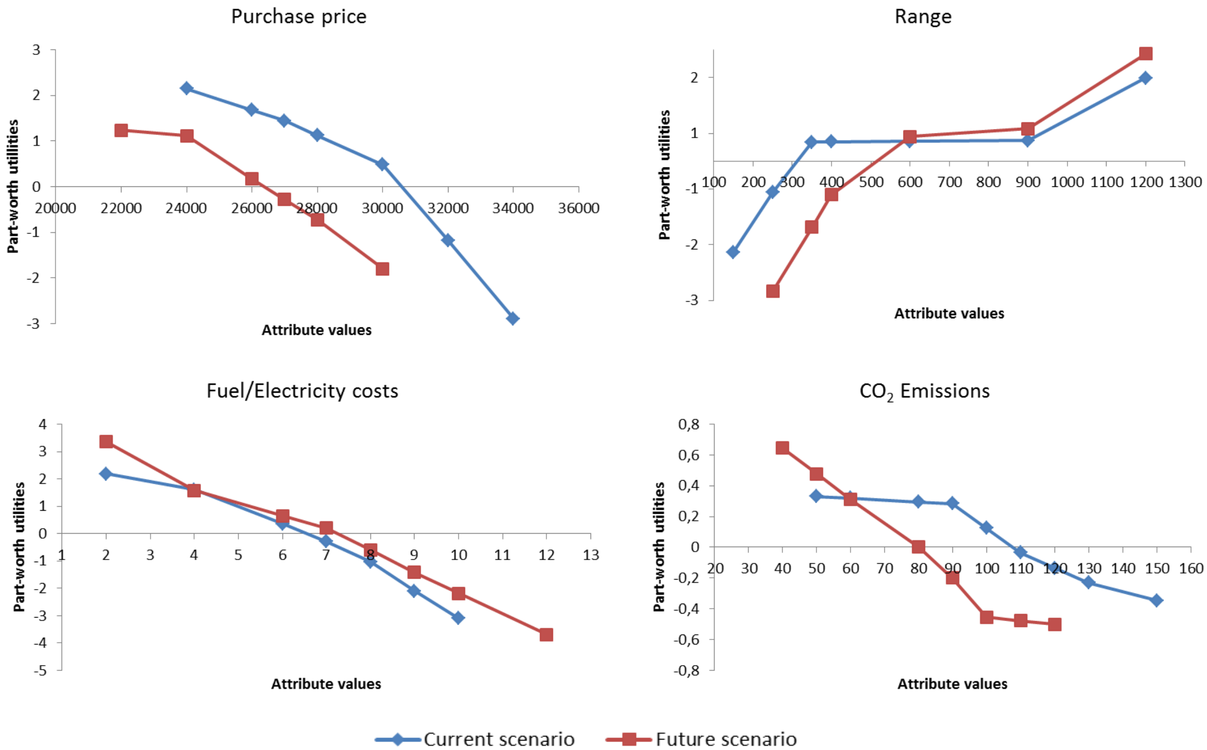

Figure 5 – Part-worth utility functions of each attribute for each scenario.

Since the attribute values vary over time, the range of the part-worth utility function of each attribute may not include all the values that they reach 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 the function was an almost perfect fit (where a R^2>0.99 for purchase price and fuel/electricity costs was found in both scenarios) the obtained function was used as utility function for that attributes (see an example in figure B.1, supplementary material Appendix B). For the attributes in which the computed function was a less satisfactory fit (where a R^2<0.99 for range and CO_2 emissions was found in both scenarios) the part-worth utility function was used within the attribute levels range through linear interpolation (Green and Srinivasan, 1978) and the values of the computed function were used only outside that range (see an example in figure B.2, supplementary material Appendix B).

4.3. Model validation

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 our model simulations started in the year of 2013, real data (ICCT, 2018) was already available for comparison with simulated results until 2017. The comparison allowed verifying that the simulated market penetration of AFVs was similar to real adoption of these vehicles (figure 6).

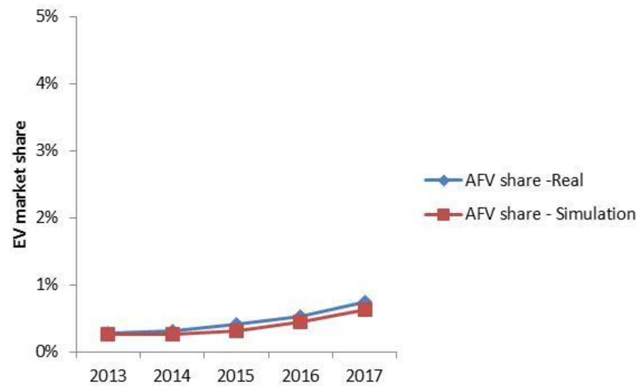

Figure 6 - Real vs simulated AFVs market share.

However, although the behaviour of the model was satisfactory during the analyzed period, the time range is too short to have robust conclusions about how our 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 our model differ (Fazeli's model comprised HEVs, PHEVs and ethanol E85). Thus, the predicted value that we compared between the two models was the total share of AFVs in the LDV fleet instead of a share of a specific type of AFV;
- The mid-point chosen to perform the comparison was 2030 as it was the last year of Fazeli et al.'s simulation;

After observing that our model predicted a higher AFV share for 2030 (12.5%) than the predicted AFVs share of Fazeli et al.'s model (approx. 7%), we tuned it in order to obtain a similar AFVs share by adjusting the constant values of "social exposure rate" parameter and the "type of engine utilities" (see calibrated values in Supplementary Material Appendix C).

As the core of our model was Struben and Sterman's model, a sensitivity analysis of the most sensitive parameters of their model was performed to analyse the robustness of our model regarding the defined values of those parameters. The sensitivity analysis was made by defining two scenarios with extreme values of each variable, scenario 1 and 3, and a scenario with "mid-values" of each variable range, scenario 2. The considered values are depicted on Table 5 and their impact on AFVs market share was analyzed (figure 7). The AFVs market share variations revealed that the model is more robust regarding the "growth rate" and "effective contact rate of drivers" parameters. The "effective contact rate of non-drivers" and "marketing" variables present higher variation regarding the scenario 1. However, the Vensim® sensitivity graphs (see Supplementary Material Appendix D), 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 variation of results.

Variables	Base-case scenario	Scenarios		
		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 – Values set for each scenario.

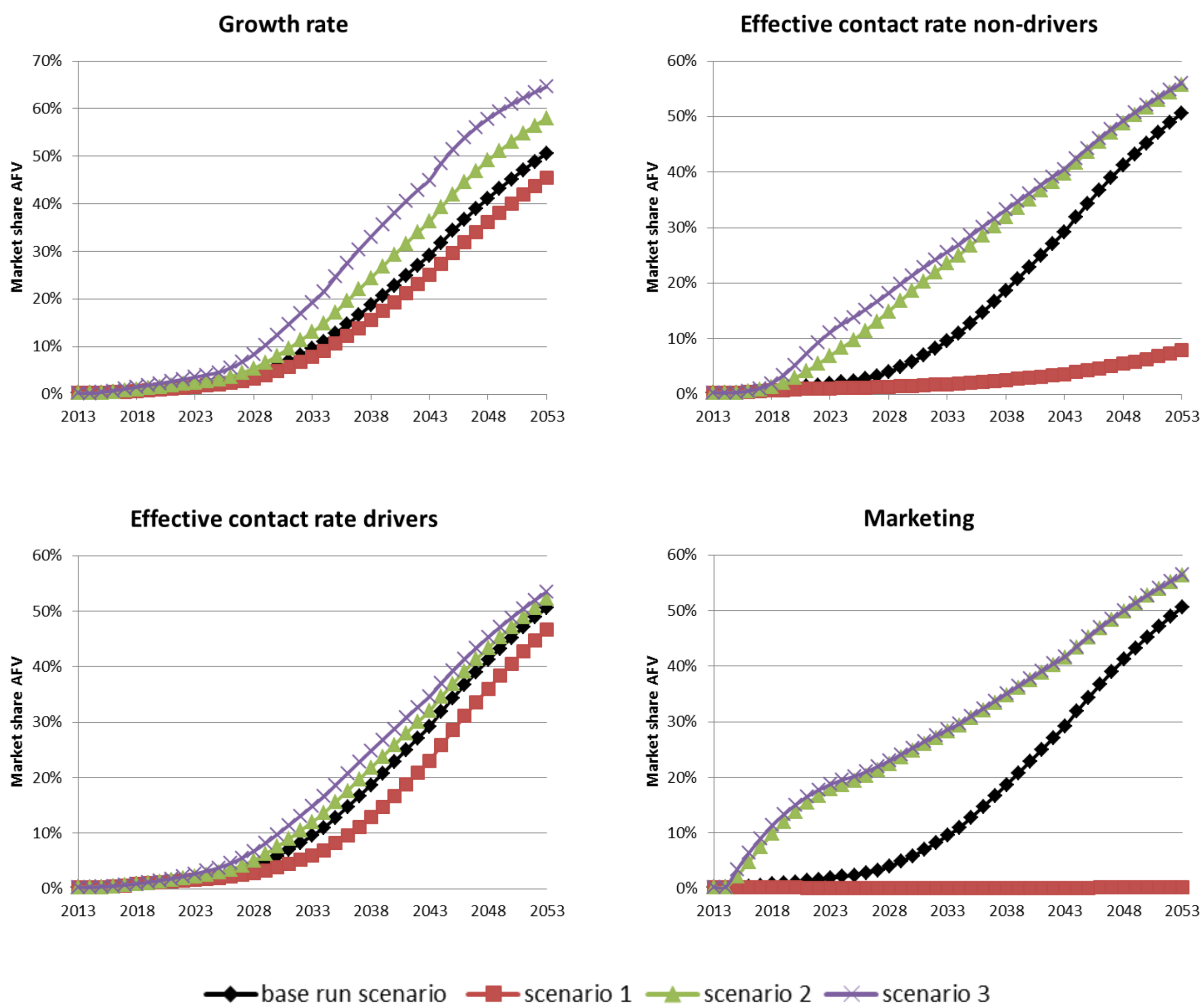

Figure 7 – Market share of AFVs considering the defined scenarios.

5. Results

5.1. Robustness analysis of the transition preferences models

As mentioned earlier two DP models were computed in order to verify if the models' outputs were robust. Observing the transition of preferences over time (1-λ_t) of each model allows verifying that the transition in Model DP1 occurs linearly through the simulation period, while the transition in Model DP2 ends in 2046, when the value defined as attractive range is reached (figure 8). Figure 9 and figure 10 depict the evolution of the LDV fleet and of the AFVs market share for each DP model. The results show the LDV fleet and the AFVs shares evolved in a similar way, allowing to conclude that the DP model is robust regarding the computation of the preferences transition. For this reason, we decided to use only the Model DP2 to compute the results henceforward, as it represents a more dynamic transition of preferences that is dependent on the BEVs range.

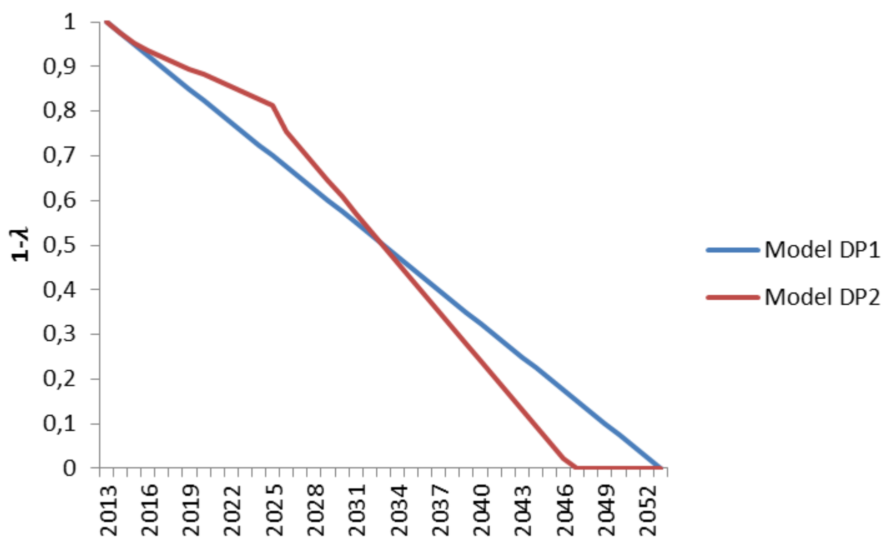

Figure 8 - Transition of preferences values over time for each DP model.

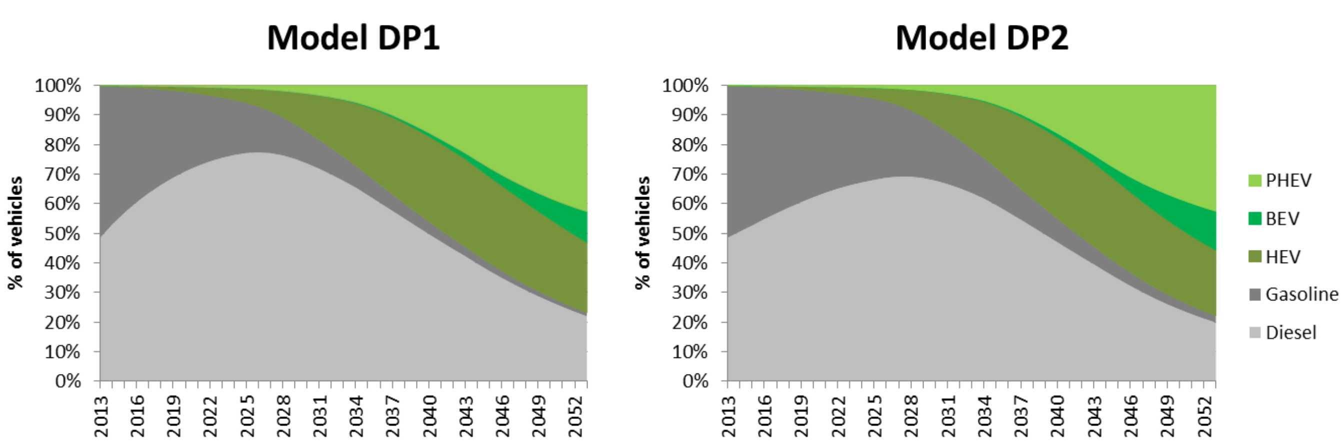

Figure 9 – Evolution of LDV fleet in Models DP1 and DP2.

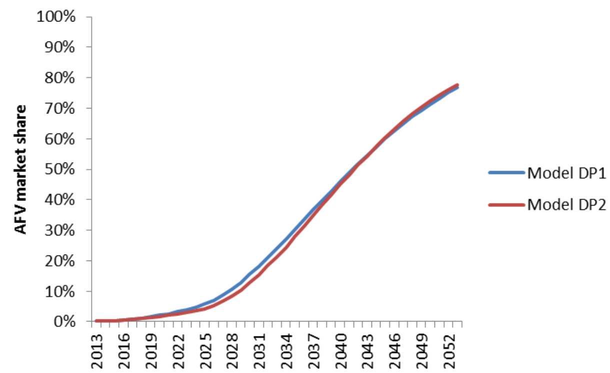

Figure 10 – Evolution of AFVs market share in models DP1 and DP2.

5.2. Impact of DP in AFVs diffusion

A comparison between the Model SP and Model DP2 was performed in order to verify if the impact of considering dynamic preferences was substantial. Figure 11 presents this comparison, showing 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;
- AFV market share: in Model DP2 the AFVs market share is almost the double of AFVs share in Model SP in the medium term (2033) and 26 pp higher in the long-term (2053);
- Vehicle utilities: the preferences structure regarding the ranking of vehicles in Model SP is more stable over time, where the main change is the PHEVs preferences that surpass Gasoline preferences in 2031 and HEVs and 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 time the final ranking of vehicles obtained with Model DP2 differs more from the initial one than the ranking obtained through Model SP.

In order to observe the individual impact of the dynamic transition of each attribute, several tests were implemented. In each test only one transition of attribute preferences was performed at a time, considering the preferences for the other attributes as static. The following tests were performed:

- Test 1: Model DP with dynamic preferences for type of engine
- Test 2: Model DP with dynamic preferences for price
- Test 3: Model DP with dynamic preferences for fuel/electricity costs
- Test 4: Model DP with dynamic preferences for CO_2 emissions
- Test 5: Model DP with dynamic preferences for range

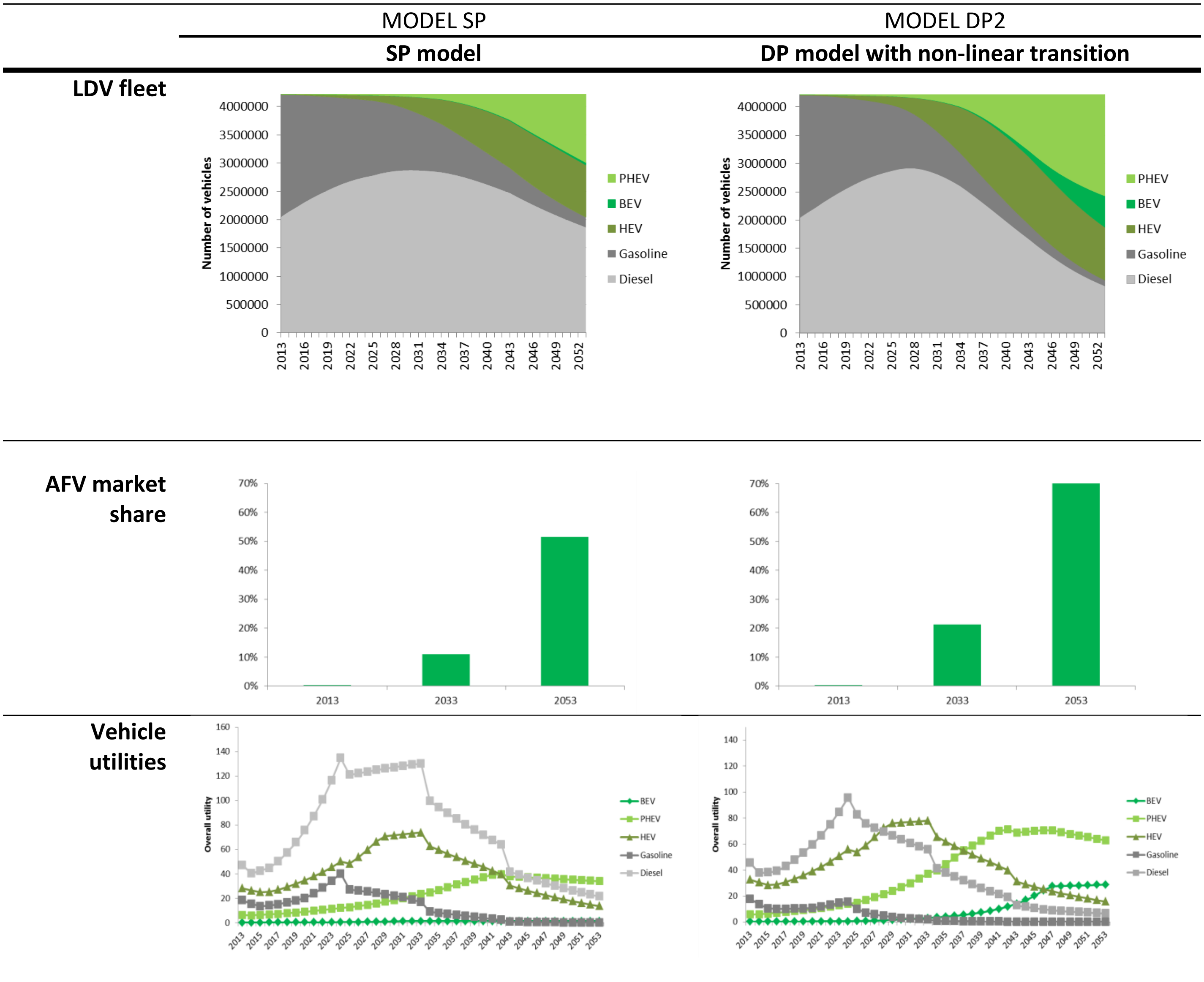

Figure 11 – Comparison between Model SP and DP1 regarding the LDV fleet, AFVs market share and vehicle utilities.

Figure 12 shows the impact of each test on the market share of AFVs compared to the outputs of model SP and DP2 (see evolution of LDV fleet for each test in the supplementary material Appendix E). The incorporation of dynamic preferences for each attribute did not always favour the market penetration of AFVs. The incorporation of dynamic preferences for the "type of engine" only (test Model SP + Dynamic preferences for type on engine) led to an increment of the market share of AFVs that was near the share achieved with the Model DP2 (where dynamic preferences were applied to all the attributes). This output was mainly due to the lower utility of ICEVs in the future scenario (see figure 4) that led consumers to switch these vehicles mainly for PHEVs and HEVs and, then, increasing the share of AFVs. The dynamic transition of preferences only for "CO_2 emissions" also markedly favoured the AFVs market penetration. The increment of AFVs share was due to the higher sensitivity of consumers to emissions increments in the future scenario (figure 5) that led consumers to switch Diesel vehicles for PHEVs. On the other hand, the incorporation of dynamic preferences for price and range did not favour the market penetration of AFVs, due to the higher sensitivity to these attributes in the future scenario (higher slopes for prices under 30 000€ and for ranges over 300 km in the future scenario than in the present). The transition of preferences for "fuel/electricity costs" led to the same results of Model SP.

Considering the results of the implemented tests above, we observed that the incorporation of dynamic preferences on vehicle attributes does not necessarily favour the diffusion of AFVs, but it is dependent on the evolution of the preferences of each attribute.

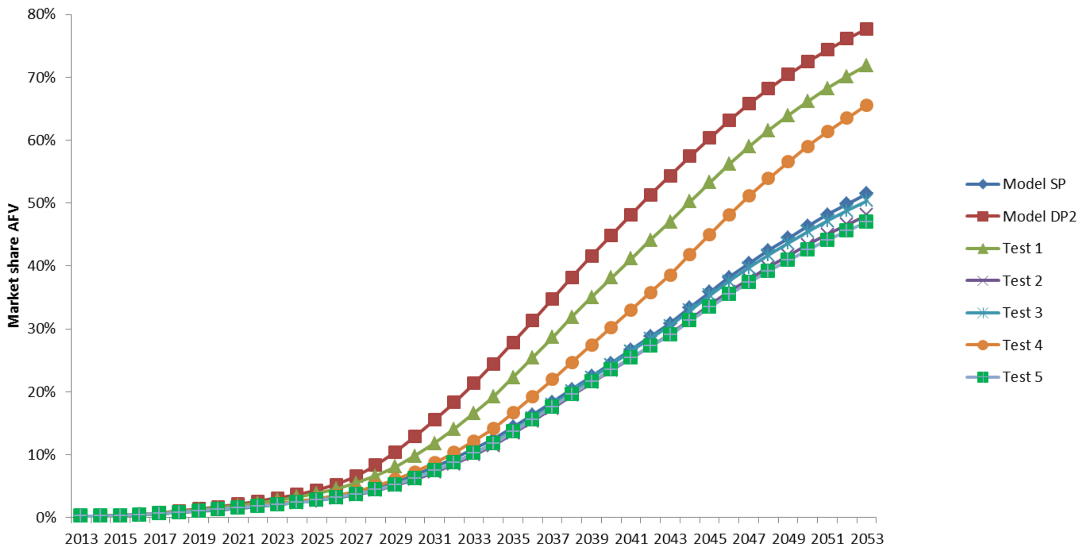

Figure 12 – Evolution of the AFVs market share for each preferences transition test and for the model SP and DP2.

5.3. Analysis of scenarios

5.3.1. Scenario 1: Subsidy scenario considering dynamic preferences

Acknowledging the importance of designing subsidy policies that are time and cost-effective we simulated policies that would be adapted to the dynamic preference of consumers, namely degressive subsidies, which decrease at a specific rate. Considering dynamic preferences, 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 increase over time due to the evolution of preferences (green line in figure 13). The scenario consisted in the implementation of BEVs subsidies considering a 5 million € budget, where several subsidies were implemented to increase BEVs share under the defined budget. Two policies with a constant subsidy (policy 1 and 2, see table 6) and three policies with degressive subsidies (policies 3 to 5) were applied, according to equation (18):

$$Final\ BEV\ price\ = BEV\ Price_t - subsidy_t \quad (18)$$

For instance, for policy 3, $subsidy_t$ was initially 30% of the purchase price and decreased at a rate of 2%/year.

Figure 13 presents the evolution of the BEVs subsidy according to each policy and budget restriction. Subsidies results are displayed in table 6, where the BEVs 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 BEV share increments are small, with the highest increment belonging to policy 2 (+2.5 pp) where a constant 10,000€ subsidy is applied. Regarding the long-term results, the most effective policies were two degressive subsidies, policies 3 and 5 where a 22.4% and 23.4% BEVs share were achieved, respectively (9.2 pp and 10.2 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.

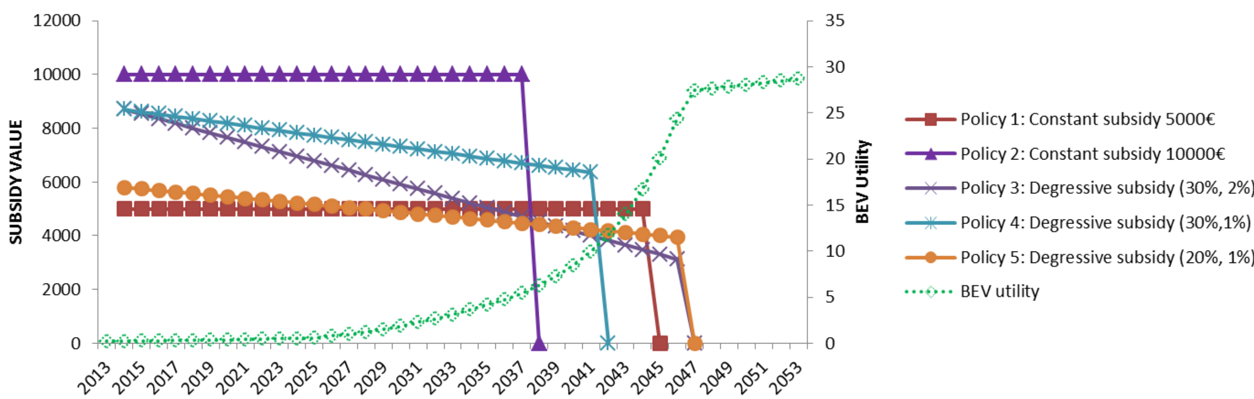

Figure 13 – BEV subsidy according to each policy and the evolution of BEV utility.

Scenario 1 – Target highest BEV share with 5M€ budget			
	BEV share in 2033	BEV share when subsidy ends[1]	BEV share in 2053
Base-case scenario	0.2%		13.2%
Policy 1: Constant subsidy 5000€	1.2%	16.6% (2044)	20.1%
Policy 2: Constant subsidy 10000€	2.7%	8.4% (2037)	15.8%
Policy 3: Degressive subsidy (30%, 2%)	1.4%	19.5% (2046)	22.4%
Policy 4: Degressive subsidy (30%, 1%)	1.7%	12% (2041)	17.7%
Policy 5: Degressive subsidy (20%, 1%)	1.1%	20.6% (2046)	23.4%

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

Table 6 – Market share results of the designed policies in the scenario 3.

5.3.2. Scenario 2: Learning effect scenario

The learning effect is an explanation about how the 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). As in the base case scenario the price of all vehicles was set constant, in this scenario this assumption is relaxed regarding BEVs price due to learning effects, where vehicle costs decrease with increments of cumulative production of vehicles (Sterman, 2000). Unit costs usually fall by a fixed amount every time the production 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).

At a global level, 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 can be modelled by making the product price endogenous through the incorporation of a learning curve (Sterman, 2000). However, the present study reports to a specific and very small market, and therefore modeling endogenously a learning curve, assuming the vehicles purchases of Portuguese consumers would boost the worldwide production of vehicles, would be unrealistic. Therefore, the learning effect was modeled exogenously in our model. The modeling of learning effect followed Sterman (2000), but the cumulative production was not affected endogenously by the adoption rate of the vehicle and, consequently, was treated as an exogenous variable. In this context, our Scenario 2 corresponds to modelling the impact that a costs reduction from a worldwide increment of BEVs production would have on their diffusion in Portugal.

Similarly to Weiss et al. (2012) the production costs of vehicles were considered approximately the retail price, as the production costs are usually confidential. 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. (2012), the price was divided into two components. One component concerns to the ancillary costs that comprise the non-engine related costs of the vehicle (vehicle chassis, the suspension, the interior, and the retailers’ markup), accounting for 82∓4% of the total vehicle price for ICE vehicles (Lipman and Delucchi, 2003). The second component comprehends the engine-related costs that, in the case of BEV, comprise 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∓4%), which in the case of BEV it was considered the highest value of this interval. Acknowledging that these engine-related costs are the target of the technological innovation, the effect of learning on price affected only this price component (Weiss et al., 2012) according to the following equation:

$$BEV\ Price = Ancillary\ costs + Engine\ costs * Effect\ of\ Learning\ on\ Price \tag{19}$$

The “Effect of Learning on Price” was computed by equation (13). The initial and 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.

$$Effect\ of\ Learning\ on\ Price = \left(\frac{Cumulative\ Production}{Initial\ Cumulative\ Production}\right)^{c}, \text{ where } c = Log_2(1 - f) \quad (20)$$

The variable c determines the strength of the learning curve and the variable f is the fractional cost reduction per doubling production. 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).

As a result of the assumption and definitions of the learning effect modeling, the BEVs price decreased to a minimum of 20,920 € and consequently to higher BEVs utilities (figure 14). The increment of BEVs utility led to a higher penetration of these vehicles in the market (55% in 2053) over PHEVs and HEVs, as can be observed on the LDV fleet composition under scenario 2 (figure 15). The ICEVs share between the base case and learning effect scenarios was similar, 22% and 17% respectively.

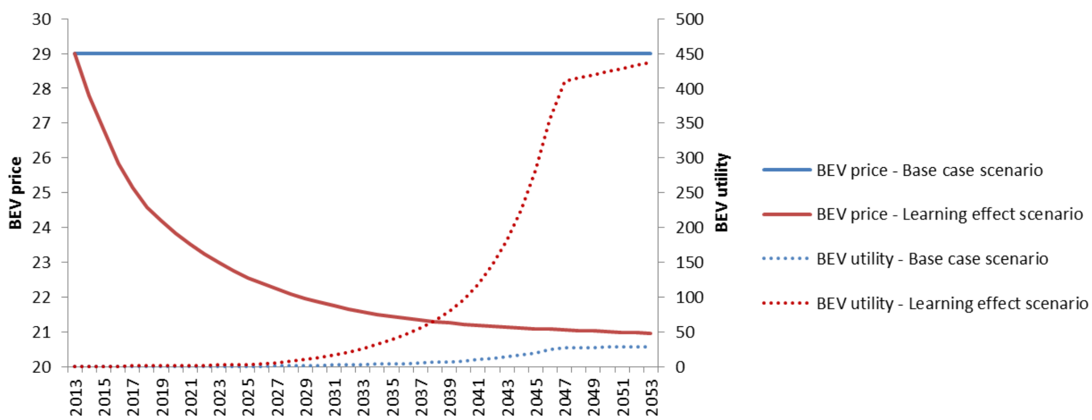

Figure 14 - Evolution of BEVs price and BEVs utility under the base case and leaning effect scenario.

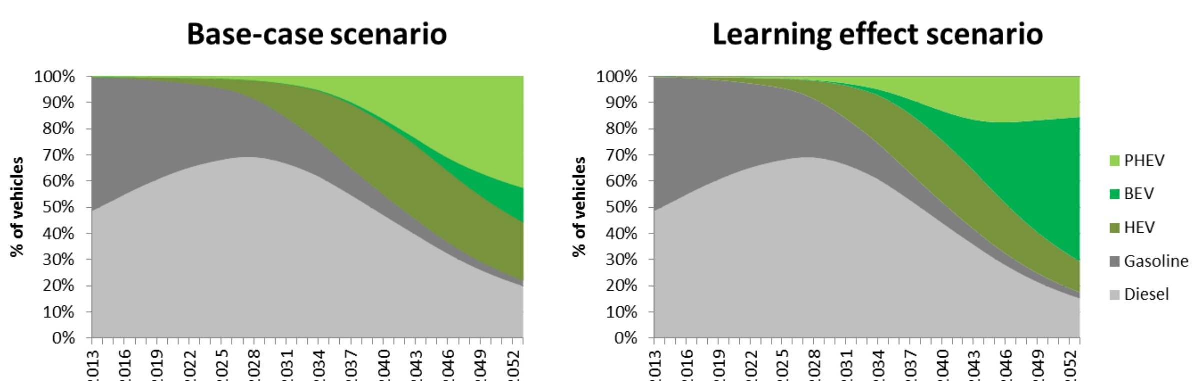

Figure 15 - LDV fleet composition under base-case and learning effect scenario.

6. Conclusions

This paper aimed at a) incorporating dynamic preferences on the AFVs diffusion model and b) analysing the effectiveness of subsidy policies adapted to dynamic preferences. As to the authors' best knowledge no other study incorporated dynamic preferences on diffusion models or simulated policies that were adapted accordingly, this study provides both methodological and empirical contributions to the literature. The methodological approach consisted in the incorporation of dynamic preferences in a reference AFVs diffusion model, developed by Struben and Sterman (2008).

For comparison purposes static as well as dynamic preferences were modelled, yielding markedly different AFVs market penetration results. This allowed concluding that, when dynamic consumer preferences are considered, the results of AFVs diffusion are significantly affected which is highly relevant for future studies aiming to predict market shares. Our results corroborate Meeran et al. (2017) findings by verifying that not including dynamic preferences when performing forecasts may lead to less accurate predictions of AFVs diffusion. Although our model performs a transition of preferences based on the evolution of BEVs range, future studies may test this transition based on other variables such as for instance, the evolution of vehicle sales or vehicle market shares.

The implementation of degressive subsidies, which grant a higher subsidy value in the time period when the preferences for AFVs are lower, stimulated AFVs adoption more effectively, i.e. higher market penetration was achieved with the same investment budget. These results give interesting insights for policy makers about the impact of considering dynamic preferences in the design of policies that aim to increase the AFVs adoption. Our results suggest that policy makers, in order to achieve more effective results of AFVs diffusion, should consider providing a higher purchase incentive for AFVs while consumers are less familiar with these vehicles and reluctant on purchasing them, and then progressively decrease the incentive as consumers become more familiar and more willing to purchase AFVs. The significant impact of the dynamic preferences of "type of engine" on accelerating the AFVs diffusion underline the potential of increasing AFVs visibility and familiarity to vehicle manufacturers, by for instance investing more in marketing and by promoting activities that allow consumers to have more contact with AFVs in order to deepen their knowledge about these new technologies. For future studies we suggest to analyze if adapting other policies to dynamic preferences, for instance tax incentives, would achieve similar of even better results.

Regarding the system boundaries some limitations can be pointed out to this model, such as the exclusion of the used vehicle market or the exclusion of the charging/fueling infrastructure. Future studies can further extend and complement the present model by including these variables. Another limitation of this study is the absence of a feedback loop that would represent the learning effect for battery range or costs resulting from increased production volumes, which can be also be included in future studies that address significantly larger markets.

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References

ACAP, 2013. Estatísticas do sector automóvel edição 2013.

Achtnicht, M., Buhler, G., Hermeling, C., 2008. Impact of service station networks on purchase decisions of alternative-fuel vehicles. Discussion Paper No. 08-088, ZEW Zentrum für Europäische Wirtschaftsforschung GmbH - Centre for European Economic Research.

Adams, W., Schmidt, W., 1998. Design for recycling and design for environment: Use of life cycle assessment at Ford motor company. Conference 23–25 September, Aalborg, Denmark., in: EURO Environment Proceedings.

Ahn, J., Jeong, G., Kim, Y., 2008. A forecast of household ownership and use of alternative fuel vehicles: A multiple discrete-continuous choice approach. Energ. Econ. 30(5), 2091-2104.

Argote, L., Epple, D., 1990. Learning curves in manufacturing. Science. 247(4945), 920-924.

Axsen, J., Mountain, D.C., Jaccard, M., 2009. Combining stated and revealed choice research to simulate the neighbor effect: The case of hybrid-electric vehicles. Resour. Energy Econ. 31(3), 221-238.

Axsen, J., Orlebar, C., Skippon, S., 2013. Social influence and consumer preference formation for pro-environmental technology: The case of a U.K. workplace electric-vehicle study. Ecol. Econ. 95, 96-107.

Bakker, S., Trip, J.J., 2013. Policy options to support the adoption of electric vehicles in the urban environment. Transp. Res. D Transp. Environ. 25, 18-23.

Beggs, S., Cardell, S., Hausman, J., 1981. Assessing the potential demand for electric cars. J. Econometrics 16(1), 1-19.

Bettman, J.R., Luce, M.F., Payne, J.W., 1998. Constructive consumer choice process. J. Consumer Res. 25(3), 187-217.

Bicer, Y., Dincer, I., 2016. Comparative life cycle assessment of hydrogen, methanol and electric vehicles from well to wheel. Int. J. Hydrogen Energ. 42(6) 3767-3777.

Borshchev, A., Filippov, A., 2004. From system dynamics and discrete event to practical agent based modeling: Reasons, techniques, tools. Proceedings of the 22nd international conference of the system dynamics society, July 25-29, Oxford, England.

Borthwick, S., 2012. Persuading Scottish drivers to buy low emission cars? The potential role of green taxation measures. Transport Research Institute, Edinburgh Napier University, in: Paper Presented at 8th Annual Scottish Transport Applications and Research Conference. Glasgow.

Caulfield, B., Farrell, S., McMahon, B., 2010. Examining individuals preferences for hybrid electric and alternatively fuelled vehicles. Transp. Policy 17(6), 381-387.

Chorus, C.G., Koetse, M.J., Hoen, A., 2013. Consumer preferences for alternative fuel vehicles: Comparing a utility maximization and a regret minimization model. Energ. Policy 61, 901-908.

Chéron, E., Zins, M., 1997. Electric vehicle purchasing intentions: The concern over battery charge duration. Transp. Res. A Policy Pract. 31(3), 235-243.

Cojocaru, M., Thille, H., Thommes, E., Nelson, D., Greenhalgh, S., 2013. Social influence and dynamic demand for new products. Environ. Model. Softw. 50, 169-185.

Cui, X., Liu, C., Kim, H.K., Kao, S.-C., Tuttle, M.A., Bhaduri, B.L., 2010. Multi agent-based framework for simulating household PHEV distribution and electric distribution network impact. TRB Comittee on Transportation Energy (ADC70), 1250: 21.

Decker, R., Trusov, M., 2010. Estimating Aggregate Consumer Preferences from Online Product Reviews. Int. J. Res. Mark. 27(4) 293-307.

Egbue, O., Long, S., 2012. Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. Energ. Policy 48, 717-729.

Eggers, F., Eggers, F., 2011. Where have all the flowers gone? Forecasting green trends in the automobile industry with a choice-based conjoint adoption model. Technol. Forecast. Soc. Change 78(1), 51-62.

Eppstein, M.J., Grover, D.K., Marshall, J.S., Rizzo, D.M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energ. Policy, 39, 3789-3802.

European Comission, 2000. Directiva 1999/94/CE do Parlamento Europeu e do Conselho Europeu.

European Commission, 2018. EU Transport in Figures. Statistical pocketbook 2018, Luxembourg: Publications Office of the European Union.

Ewing, G., Sarigöllü, E., 2000. Assessing consumer preferences for clean-fuel vehicles: A discrete choice experiment. J. Public Policy Mark. 19(1), 106-118.

Fazeli, R., Leal, V., Sousa, J.P.D., 2012. A new approach to design policies for the adoption of alternative fuel-technology powertrains. World Academy of Science, Engineering and Technology, International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering. 6(5), 891-898.

Gerssen-Gondelach, S.J., Faaij, A.P.C., 2012. Performance of batteries for electric vehicles on short and longer term. J. Power Sources. 212, 111-129.

Globisch, J., Schneider, U., Dütschke, E., 2013. Acceptance of electric vehicles by commercial users in the electric mobility pilot regions in Germany., in: ECEEE Summer Study Proceedings. Stockholm, pp. 973-983.

Graham-Rowe, E., Gardner, B., Abraham, C., Skippon, S., Dittmar, H., Hutchins, R., Stannard, J., 2012. Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: A qualitative analysis of responses and evaluations. Transp. Res. A Policy Pract. 46(1), 140-153.

Green, P., Srinivasan, V., 1978. Conjoint analysis in consumer research: issues and outlook. J. Consumer Res. 5(2), 103-123.

Green, P.E., Carmone, F.J., Wind, Y., 1972. Subjective evaluation models and conjoint measurement. Behav. Sci. 17(3), 288-299.

Greene, D.L., 2001. TAFV Alternative Fuels and Vehicles Choice Model Documentation.

Guðmundsdóttir, L.B., 2016. Exploring the diffusion of alternative fuel vehicles in Iceland using System Dynamics simulation. Master thesis. Science in Engineering Management. Reykjavik University.

Gyimesi, K., Viswanathan, R. (2011). The Shift to Electric Vehicles: Putting Consumers in the Driver's Seat. IBM Institute for Business Value, New York.

Hacker, F., Harthan, R., Matthes, F., Zimmer, W., 2009. Environmental impacts and impact on the electricity market of a large scale introduction of electric cars in Europe: Critical review of literature. Report of the European Topic Centre on Air and Climate Change.

Harrison, G., Shepherd, S., 2014. An interdisciplinary study to explore impacts from policies for the introduction of low carbon vehicles. Transp. Plan. Technol. 37(1), 98-117.

Hevelston, J., Liu, Y., Mcdonnell, E., Fuchs, E., Klampfl, E., Michalek, J.J., 2015. Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China. Transport. Res A Policy Pract. 73, 96-112.

Hidrue, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. Resour. Energy Econ. 33(3), 686-705.

Hoen, A., Koetse, M.J., 2014. A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. Transp. Res. A Policy Pract. 61, 199-215.

Huijts, N.M.A., Molin, E.J.E., Steg, L., 2012. Psychological factors influencing sustainable energy technology acceptance: A review-based comprehensive framework. Renew. Sustain. Energy Rev. 16(1), 525-531.

ICCT, 2013. European vehicle market statistics: Pocketbook 2013.

ICCT, 2018. European vehicle market statistics: Pocketbook 2018/19.

IEA. Hybrid and electric vehicles: The electric drive delivers. Implementing Agreement for Co-operation on Hybrid and Electric Vehicle Technologies and Programmes. International Energy Agency, 2015.

Janssen, A., Lienin, S.F., Gassmann, F., Wokaun, A., 2006. Model aided policy development for the market penetration of natural gas vehicles in Switzerland. Transp. Res A Policy Pract. 40(4), 316-333.

Janssen, M.A., Jager, W., 2001. Fashions, habits and changing preferences: Simulation of psychological factors affecting market dynamics. J. Econ. Psychol. 22(6), 745-772.

Jensen, A.F., Cherchi, E., Mabit, S.L., 2013. On the stability of preferences and attitudes before and after experiencing an electric vehicle. Transp. Res.D Transp. Environ. 25, 24-32.

Kabaday, E., Alan, A., Ozkan, B., 2013. Effects of Product Properties on Consumer Preferences and Behaviours: A Study of the Automobile Market. Int. J. Manag. 30(1), 349-361.

Karabasoglu, O., Michalek, J., 2013. Influence of driving patterns on life cycle cost and emissions of hybrid and plug-in electric vehicle powertrains. Energ. Policy. 60, 445-461.

Keith, D.R., 2012. Essays on the Dynamics of Alternative Fuel Vehicle Adoption: Insights from the Market for Hybrid- Electric Vehicles in the United States. Ph.D. Thesis - Massachusetts Institute of Technology, Engineering Systems Division.

Keles, D., Wietschel, M., Mo, D., Rentz, O., 2008. Market penetration of fuel cell vehicles – Analysis based on agent behaviour. Int. J. Hydrogen Energ. 33, 4444-4455.

Kieckhäfer, K., Wachter, K., Spengler, T.S., 2016. Analyzing manufacturers’ impact on green products' market diffusion e the case of electric vehicles. J. Clean Prod. 162, S11-S25.

Klier, T., Linn, J., 2008. The price of gasoline and the demand for fuel efficiency: Evidence from monthly vehicles sales data. Working paper. University of Illinois at Chicago.

Kwon, T.H., 2012. Strategic niche management of alternative fuel vehicles: A system dynamics model of the policy effect. Technol. Forecast. Soc. Change. 79(9), 1672-1680.

Köhler, J., Wietschel, M., Whitmarsh, L., Keles, D., Schade, W., 2010. Infrastructure investment for a transition to hydrogen automobiles. Technol. Forecast. Soc. Change. 77(8), 1237-1248.

Lachaab, M., Ansari, A., Jedidi, K., 2006. Modeling preference evolution in discrete choice models: A Bayesian state-space approach. Quant. Mark. Econ. 4(1), 57-81.

Leaver, J.D., Gillingham, K.T., Leaver, L.H.T., 2009. Assessment of primary impacts of a hydrogen economy in New Zealand using UniSyD. Int. J. Hydrogen Energ. 34(7), 2855-2865.

Lebeau, K., Mierlo, J.V., Lebeau, P., Mairesse, O., Macharis, C., 2012. The market potential for plug-in hybrid and battery electric vehicles in Flanders: A choice-based conjoint analysis. Transp. Res. D Transp. Environ. 7(8), 592-597.

Leiby, P., Rubin, J., 2004. Understanding the transition to new fuels and vehicles: Lessons learned from analysis and experience of alternative fuel and hybrid vehicles, in: Sperling, D., Cannon, J.S. (Eds.), The Hydrogen Energy Transition: Moving Toward the Post Petroleum Age in Transportation. Elsevier Academic Press, Burlington, MA.

Lipman, T.E., Delucchi, M.A., 2003. Hybrid-electric vehicle design retail and lifecycle cost analysis. Institute of Transportation Studies, University of California at Davis.

Liu, C., Rouse, W.B., Hanawalt, E.S., 2017. Adoption of powertrain technologies in automobiles: A System Dynamics model of technology diffusion in the American market. IEEE Transactions on Vehicular Technology.

Lüthi, S., Wüstenhagen, R., 2011. Renewable energy investment decisions under policy risk: An Adaptive Conjoint Analysis (ACA) approach, in: Marcus, A., Shrivastava, P., Sharma, S., Pogutz, S. (Eds.), Cross-sector Leadership for the Green Economy: Integrating Research and Practice on Sustainable Enterprise. Palgrave Macmillan US, pp. 37-52.

Macal, C.M., 2010. To agent-based simulation from system dynamics. Proceedings of the winter simulation conference. December 5-8, Baltimore, USA.

Malhotra, N., 2008. Marketing Research: An applied orientation. 5th edition. Pearson Education India.

Maness, M., Cirillo, C., 2012. Measuring future vehicle preferences: Stated preference survey approach with dynamic attributes and multiyear time frame. Transportation Research Record: Transp. Res. Rec. J. Transp. Res. Board. 2285, 100-109.

Mau, P., Eyzaguirre, J., Jaccard, M., Collinsdodd, C., Tiedemann, K., 2008. The “neighbor effect”: Simulating dynamics in consumer preferences for new vehicle technologies. Ecolog. Econ. 68(1-2), 504-516.

McManus, W., Senter, R., 2009. Market models for Predicting PHEV adoption and diffusion. University of Michigan Transportation Research Institute, Ann Arbor, MI.

Meeran, S., Jahanbin, S., Goodwin, P., Neto, J.Q., 2017. When do changes in consumer preferences make forecasts from choice-based conjoint models unreliable? Eur. J. Oper. Res. 258(2), 512-524.

Meyer, P.E., Winebrake, J.J., 2009. Modeling technology diffusion of complementary goods: The case of hydrogen vehicles and refueling infrastructure. Technovation. 29(1), 77-91.

Molin, E.J.E., Oppewal, H., Timmermans, H.J.P., 1997. Modeling group preferences using a decompositional preference approach. Group Decis. Negot. 6(4), 339-350.

Molina, E., 2013. Dynamics of the transition towards alternative fuel vehicles in advanced and emerging markets, in: System Dynamics Conference. pp. 1-32.

Musti, S., Kockelman, K.M., 2011. Evolution of the household vehicle fleet: Anticipating fleet composition, PHEV adoption and GHG emissions in Austin, Texas. Transport. Res A Policy Pract. 45(8), 707-720.

Nagelhout, D., Ros, J.P.M., 2009. Electric driving. Evaluation of transitions based on system options. No. PBL--500083010. Planbureau voor de Leefomgeving PBL.

Oliveira, G.D., Dias, L.C., 2015. Which criteria matter when selecting a conventional or electric vehicle?, in: Energy for Sustainability 2015 - Sustainable Cities: Designing for People and the Planet, 14-15th May, Coimbra. pp. 1-10.

Park, S.Y., Kim, J.W., Lee, D.H., 2011. Development of a market penetration forecasting model for Hydrogen Fuel Cell Vehicles considering infrastructure and cost reduction effects. Energ. Policy. 39 (6), 3307-3315.

Pasaoglu, G., Harrison, G., Jones, L., Hill, A., Beaudet, A., Thiel, C., 2016. A system dynamics based market agent model simulating future powertrain technology transition: Scenarios in the EU light duty vehicle road transport sector. Technol. Forecast. Soc. Change. 104, 133-146.

Pellon, M.B., Eppstein, M.J., Beasw, L.E., Grover, D.K., Rizzo, D.M., Marshall, J.S. (2010). An agent-based model for estimating consumer adoption of PHEV technology. Transportation Research Board (TRB), 10-3303.

Potoglou, D., Kanaroglou, P.S., 2007. Household demand and willingness to pay for clean vehicles. Transp. Res. D Transp. Envir. 12(4), 264-274.

Rogers, E.M., 1962. Diffusion of innovations, 1st ed. New York: The Free Press.

Samaras, C., Meisterling, K., 2008. Life cycle assessment of greenhouse gas emissions from plug-in bybrid vehicles: Implications for policy. Envir. sci. tech. 42, 3170-3176.

Scrosati, B., Garche, J., 2010. Lithium batteries: Status, prospects and future. J. Power Sources. 195(9), 2419-2430.

Shafiei, E., Davidsdottir, B., Fazeli, R., Leaver, J., Stefansson, H., Asgeirsson, E.I., 2018. Macroeconomic effects of fiscal incentives to promote electric vehicles in Iceland: Implications for government and consumer costs. Energ. Policy. 114, 431-443.

Shafiei, E., Davidsdottir, B., Leaver, J., Stefansson, H., Asgeirsson, E.I., 2014. Potential impact of transition to a low-carbon transport system in Iceland. Energ. Policy. 69, 127-142.

Shafiei, E., Davidsdottir, B., Leaver, J., Stefansson, H., Asgeirsson, E.I., 2015. Comparative analysis of hydrogen, biofuels and electricity transitional pathways to sustainable transport in a renewable-based energy system. Energy. 83, 614-627.

Shafiei, E., Davidsdottir, B., Leaver, J., Stefansson, H., Asgeirsson, E.I., 2017. Energy, economic, and mitigation cost implications of transition toward a carbon-neutral transport sector: A simulation-based comparison between hydrogen and electricity. J. Clean Prod. 141, 237-247.

Shafiei, E., Davidsdottir, B., Leaver, J., Stefansson, H., Ingi, E., Keith, D.R., 2016. Analysis of supply-push strategies governing the transition to biofuel vehicles in a market-oriented renewable energy system. Energy. 94, 409-421.

Shafiei, E., Leaver, J., Stefansson, H., Asgeirsson, E.I., 2015. Cost-effectiveness and potential of greenhouse gas mitigation through the support of renewable transport fuels in Iceland, in: Saygh, A. (Ed.), Renewable Energy in the Service of Mankind Vol I. Springer, Cham, pp. 145-157.

Shepherd, S., Bonsall, P., Harrison, G., 2012. Factors affecting future demand for electric vehicles: A model based study. Transp. Policy. 20, 62-74.

Soete, L., Arundel, A., 1995. European innovation policy for environmentally sustainable development: application of a systems model of technical change. J. Eur. Public Policy. 2(2), 285-315.

Sterman, J., 2000. Business dynamics: Systems thinking and modeling for a complex world. Irwin/McGraw-Hill.

Struben, J., Sterman, J.D., 2008. Transition challenges for alternative fuel vehicle and transportation systems. Environ Plan. B Plan. Des. 35(6), 1070-1097.

Tompkins, M., Bunch, D., 1998. Determinants of alternative fuel vehicle choice in the continental United States. Transp. Res. Rec. J. Transp. Res. B. 1641(1), 130-138.

Walther, G., Wansart, J., Kieckhäfer, K., 2010. Impact assessment in the automotive industry: Mandatory market introduction of alternative powertrain technologies. Syst. Dyn. Rev. 26(3), 239-261.

Weiss, M., Patel, M.K., Junginger, M., Perujo, A., Bonnel, P., Grootveld, G.V., 2012. On the electrification of road transport - Learning rates and price forecasts for hybrid-electric and battery-electric vehicles. Energ. Policy 48, 374-393.

Wu, W.Y., Liao, Y.K., Chatwuthikrai, A., 2014. Applying conjoint analysis to evaluate consumer preferences toward subcompact cars. Expert Syst. Appl. 41(6), 2782-2792.

Ziegler, A., 2012. Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for Germany. Transp. Res. A Policy Pract. 46(8), 1372-1385.

Şentürk, I., Erdem, C., Şimşek, T., Kılınç, N., 2011. Determinants of vehicle fuel-type preference in developing countries: A case of Turkey. Int. J. Global Warm. 3 (4), 329-338.

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Supplementary material

Appendix A – Portuguese data

A.1 - Government incentives for EVs adoption

Year	Program	Specific measures for EVs: Purchase Subsidy	Circulation tax (IUC)	Purchase tax (ISV)	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 A.1 - Summary of programs and government measures to support EVs adoption (authors' own).

A.2 – Evolution of number Alternative Fuel Vehicles models

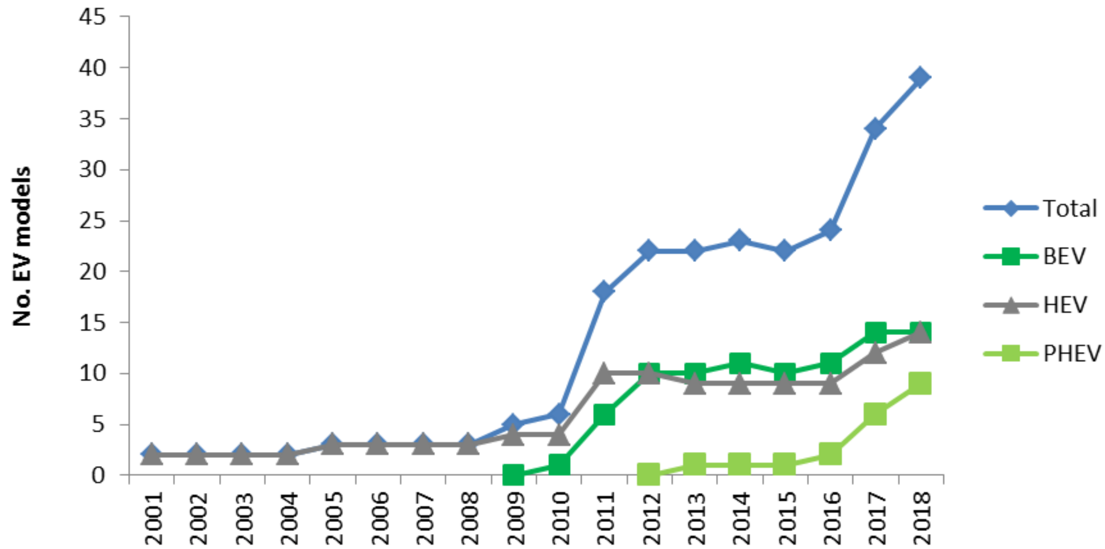


Figure A.2 - Number of AFVs models available in the market in each year (source: author' own).

A.3 – Sales of Alternative Fuel Vehicles

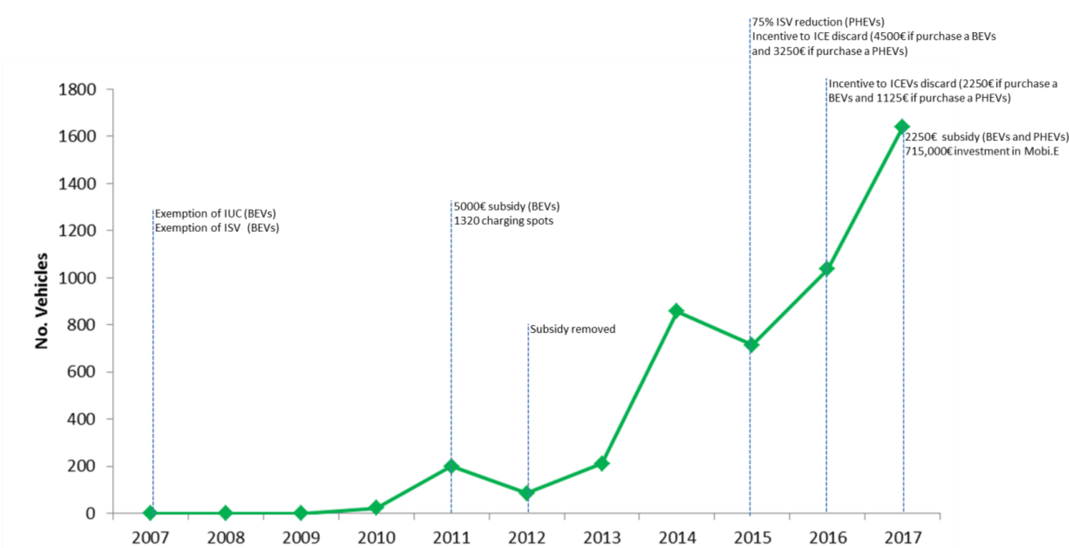


Figure A.3 - Sales of plug-in electric vehicles crossed with Portuguese government incentives for electric mobility (IUC=circulation tax; ISV= vehicle purchase tax) (authors´ own).

Appendix B – Examples of adjustment functions to utility functions

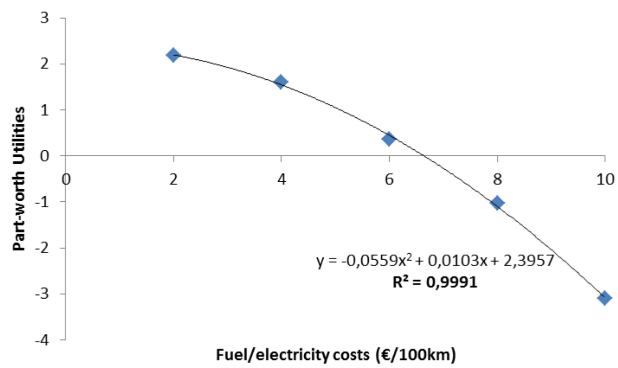


Figure B.1 – Part-worth utility function and adjustment function for the attribute Fuel/electricity costs (current scenario).

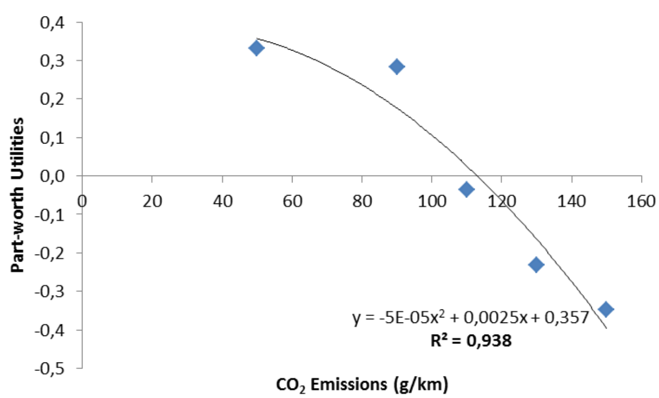


Figure B.2 - Part-worth utility function and adjustment function for the attribute CO_2 emissions (current scenario).

Appendix C - Calibrated values

	Value before calibration	Value after calibration
Social exposure rate	2.5%	1.9%
Type of engine utility: BEV	-3.10143	-2.799
Type of engine utility: PHEV	1.40169	1.4012
Type of engine utility: HEV	0.20332	0.0233
Type of engine utility: Diesel	1.26967	1.256
Type of engine utility: Gasoline	0.22676	3.661

Appendix D - Sensitivity analysis graphs

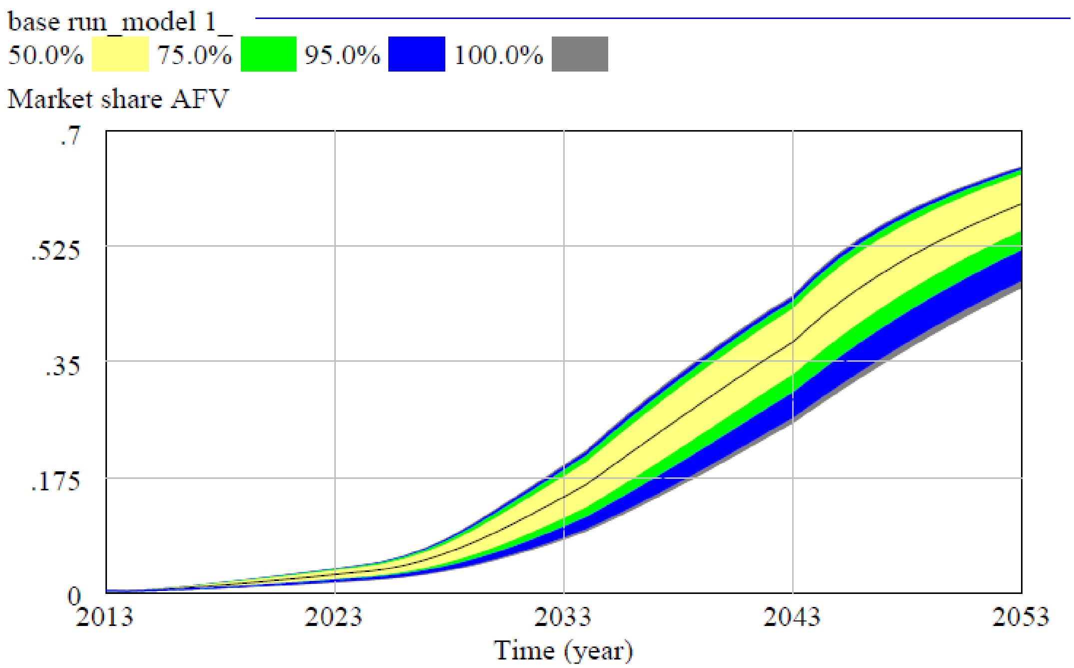


Figure D.1 – Sensitivity graph of AFV market share according to variations of “growth rate” variable.

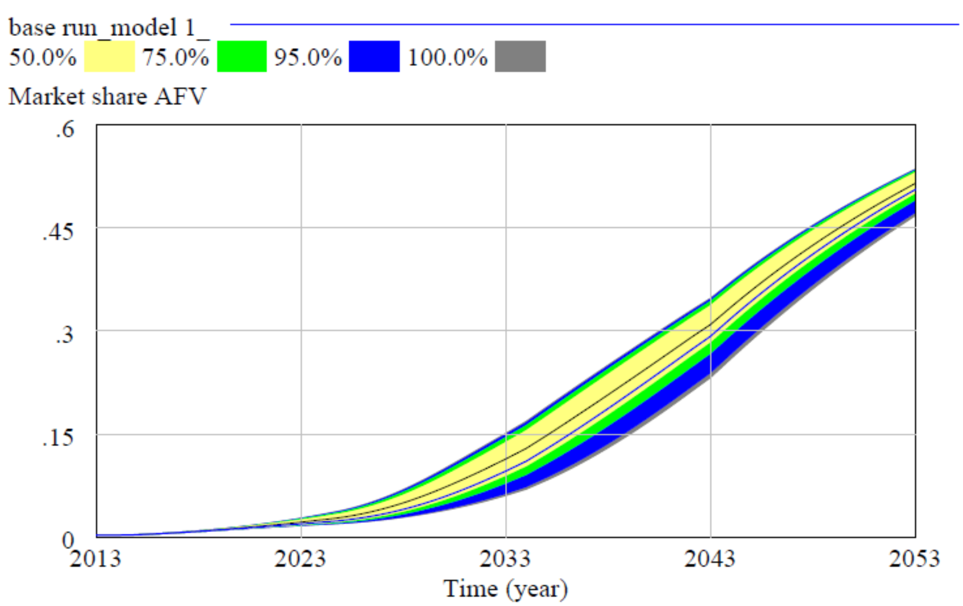


Figure D.2 – Sensitivity graph of AFV market share according to variations of “Effective contact rate drivers” variable.

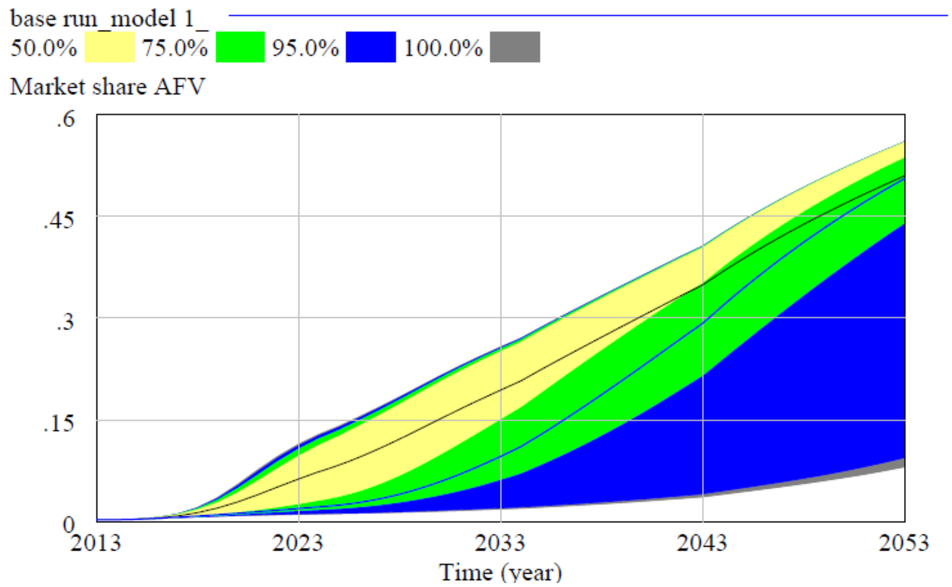


Figure D.3 – Sensitivity graph of AFV market share according to variations of "Effective contact rate non-drivers" variable.

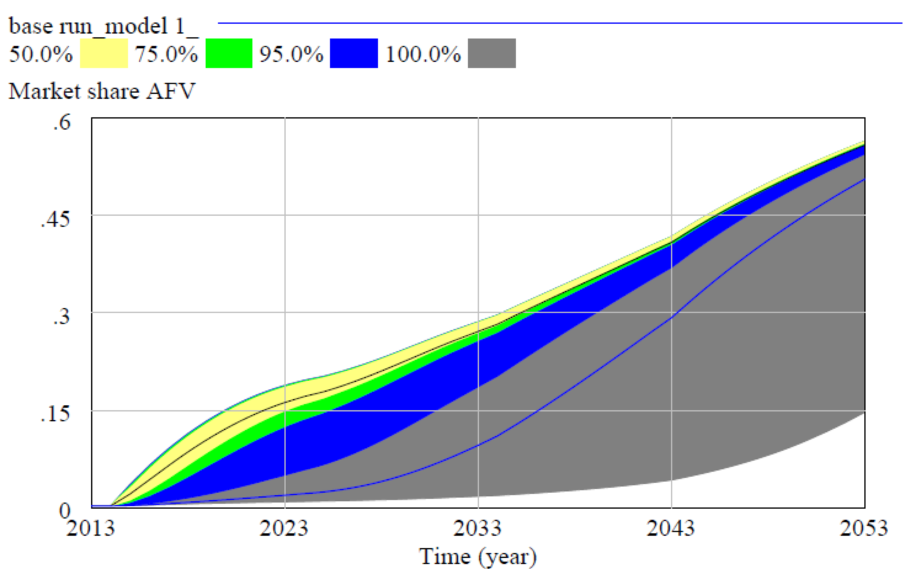
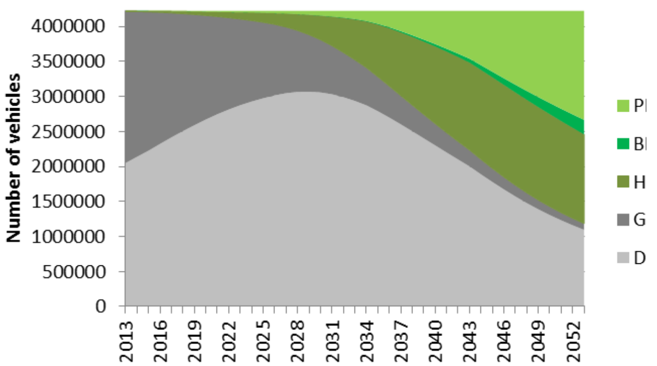


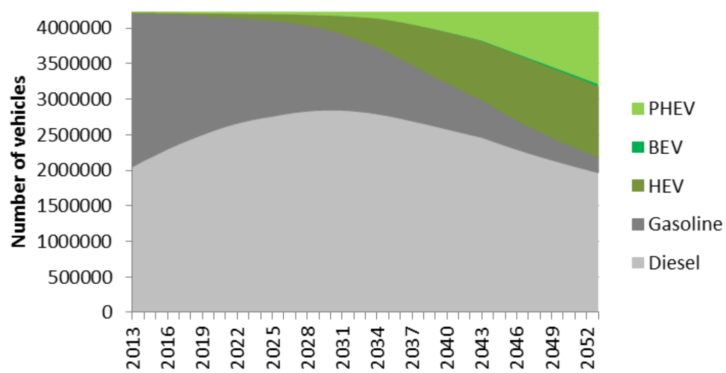
Figure D.4 – Sensitivity graph of AFV market share according to variations of "marketing" variable.

Appendix E – LDV fleet for attributes dynamic preferences tests

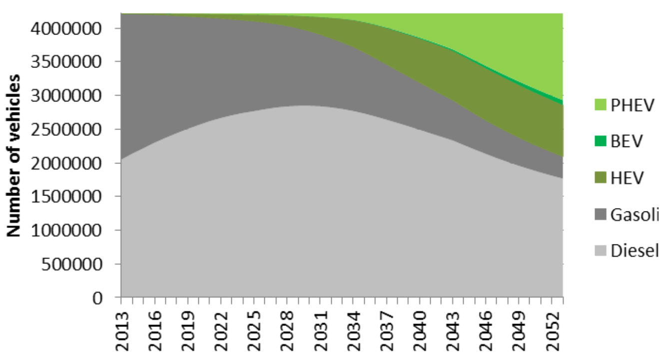
Test 1: Type of engine



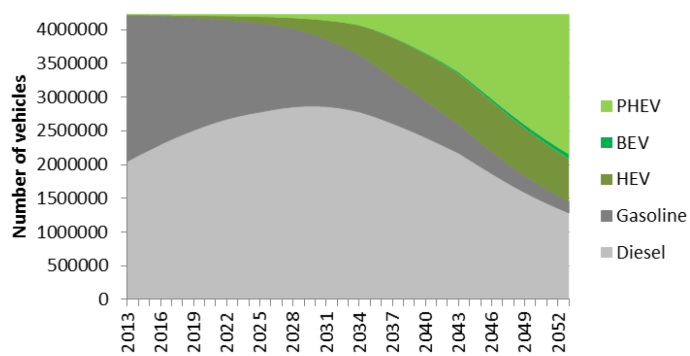
Test 2: Price



Test 3: Fuel/electricity costs



Test 4: CO_2 emissions



Test 5: Range