Implications of Changes in Consumer Attitudes and Preferences on Alternative Fuel Vehicle Adoption: A System Dynamics and Choice Modelling Approach

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I declare that this thesis is my own original work except where due reference is made. All substantive contribution by others to the work presented, including jointly authored publications, are clearly acknowledged.

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Abstract

With increasing awareness on environmental issues and fossil fuel dependency, a variety of alternative fuel powertrains have emerged into the vehicle market, providing vehicle consumers an unprecedented selection of transportation powertrain choices. In light of the global momentum of vehicle powertrain innovation and re-selection, it is of great importance to investigate the choices of today's vehicle consumers and the implications of consumer choices on the adoption of alternative fuel vehicles (AFVs). In consumer choice modelling and consumer decision-making theories, individual preferences and opinions on vehicle purchases are quantitatively investigated. Since the adoption of new transportation powertrains is also a societal behaviour that involves multiple stakeholders and intertwined dynamic feedback, the potential changes of consumer attitudes and preferences should be taken into account as well when understanding AFV adoption. Combining two modelling methods, system dynamics modelling and discrete choice modelling, this thesis investigates the implications of changes in consumer choices on AFV adoption, especially from the aspect of consumer attitudes and preferences. Based on the Australian vehicle market's diverse and purely market-driven environment, the research examines dynamic consumer attitudes and preferences and provides insights for vehicle markets that are more characterized by policy interventions.

The research depicts consumer choices in vehicle powertrain selection using a system dynamics model incorporating the results of a discrete choice model. The research is carried out in three main stages. First, preliminary dynamic hypotheses are proposed through exploring literature in individual decision-making, and analysing the observed historical trends in the market. Second, a market survey carrying out a stated choice experiment is conducted. A corresponding discrete choice model is performed with data collected through the stated choice experiment. The choice model captures quantitative information about consumer preferences and opinions within their decision-making process. It provides data input for consumer choice parameters in the research model and qualitative insights that contribute to final system dynamics structure. Finally, by incorporating the key dynamics identified in market observations with quantitative inputs from the discrete choice model, a final system dynamics model is formulated and implemented. This dynamic model expands the dimension of the discrete choice model and provides a holistic and dynamic view on vehicle consumer choices in AFV adoption.

The research model reveals that allowing timely feedback around consumer attitudes and preferences generates substantial behaviour changes in AFV adoption. The dynamic consumer attitudes and preferences affect powertrains' adoption paths significantly, especially for powertrains that are more recent and share less similarities with traditional powertrains. Furthermore, potential policy interventions are explored in the model through scenarios that address revealed characteristics of AFV adoption. This work shows that considering changes in consumer attitudes and preferences is important in understanding and forecasting adoption of AFVs, and wisely taking advantages of such dynamics can provide powerful momentum to improve adoption performance of alternative powertrains.

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Chapter 1 Introduction

1.1 The return of alternative fuel vehicles

When the automobile as a new form of road transportation had just emerged and started to replace the traditional horse carriages, there were multiple engine technologies and powertrains. Apart from petrol vehicles, the later dominator of the market, other forms of propulsions systems, such as steam and electric cars, were also available (Shields, 2007). Among this wide range of road transportation powertrain options, people eventually selected petrol vehicles as their go-to road transportation choice. However, the transition process of people switching from horses to petrol is lengthy and full of uncertainties (Sovacool, 2009). In most of the major vehicle market today, it took more than 30 years for petrol vehicles with combustion engine to successfully get adopted and to become the most significant vehicle powertrain in these markets (Sovacool, 2009, Shields, 2007).

After decades of petrol vehicle market dominance, the landscape of vehicle powertrain technologies started to change in the past years. Other forms of fossil fuel such as diesel, compressed natural gas, and liquefied petroleum gas (LPG) were introduced back into the automobile market. More recently, from 2000s, vehicles that do not solely rely on internal combustion engine and fossil fuel have been re-introduced. Hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), pure electric vehicles (EVs), and hydrogen fuel cell vehicles were introduced as more environmentally friendly alternatives to fossil fuel vehicles. The re-emergence of alternative fuel vehicles (AFVs) brought new possibilities to the vehicle market. These vehicle powertrains provide modern vehicle consumers an even wider range of road transportation choices than before. Another era of vehicle powertrain technology selection has come.

With the increasing awareness on environmental issues and fossil fuel dependency, the urge of finding a more energy efficient and environmentally friendly vehicle powertrain technology is getting stronger globally. However, the adoption of these new powertrain technologies has had mixed success globally. In Norway, where there is heavy policy reinforcement, the market share of electric vehicles (including plug-in hybrid and pure electric) has reached almost 30% in 2016 (International Energy Agency, 2017). While in major vehicle markets like the United States, the annual market share of electric vehicles still remained below 1% even with targeted policies to promote the adoption (HybridCARS, 2016). There lies immense uncertainty in the future of alternative vehicle powertrains. With global momentum of vehicle powertrain innovation and re-selection, better understanding of how today's consumers choose vehicle powertrains can aid an effective transition of transportation powertrains and help manufactures and policymakers comprehend the future landscape of a vehicle market.

1.2 AFV adoption as individual consumer choices

For individuals, the choice of whether to adopt an AFV depends on if the AFV is the most desirable option based on their requirements and preferences towards different vehicle attributes. As the core agent in AFV adoption process, consumers directly determine how AFVs are evaluated and selected. Therefore, the preferences and attitudes of vehicle consumers relate closely to the adoption of AFVs. By quantitatively investigating consumer preferences towards vehicle attributes, researchers are able to predict the possibility of consumers choosing vehicles with alternative fuel powertrains, and therefore forecast the adoption behaviour of AFVs.

Choice modelling is a prevalently used method that enables researchers to quantitatively investigate consumers' preferences and forecast the market shares of AFVs. In choice models, coefficients that quantitatively represent consumers' preferences are assigned to different vehicle attributes and the sum of these vehicle attribute values forms the overall utility of a vehicle. It is usually assumed that consumers will choose the vehicle that has the highest utility within their choice sets. By inviting potential consumers to choose amongst a range of vehicles that have different combinations of vehicle attribute values, researchers are able to use multinomial logit regression to reveal the associated coefficients that represent consumers' preferences. In the forecasting of AFV adoption, AFVs are represented as particular sets of vehicle attributes and are used as inputs for the choice model. A probability of consumers selecting the powertrain can therefore be calculated using the vehicle attribute values and consumer preference coefficients.

Choice modelling is especially useful to quantitatively study AFV adoption because it allows researchers to investigate consumer acceptance and potential market shares of vehicle powertrains with insufficient sales data for other quantitative analysis. It also supports relevant policy testing where researchers change the value of one or more vehicle attributes based on potential policy settings and observe the sensitivity of AFV market shares to the changes of different policy settings.

1.3 AFV adoption as a societal and dynamic change

Apart from individual choice behaviour, AFV adoption is also a societal change that involves more stakeholders than just vehicle consumers. Other stakeholders in the process, such as vehicle manufacturers, fuel providers, and policy makers, have great impacts on the performances of AFV powertrains and consequently affect consumers' choices and the adoption of AFVs. In response, changes in AFV adoption can also affect stakeholders' reactions and therefore lead to the additional changes of AFV performance. These kinds of interactions between different stakeholders and AFV adoption construct the interactive and holistic system of AFV adoption.

In the process of AFV adoption, time dimension is another important factor to consider. Successful adoption of AFVs will not happen overnight at one time point. The initial adoption of petrol vehicles took several decades, and the potential transition from petrol to alternative powertrains might take even longer time due to the increased uncertainty caused by multiple emerging powertrains.

During this lengthy process, not only vehicle performance will change, the consumers' preferences and attitudes towards AFV powertrains are not likely to remain the same either. Changes in consumer preferences and attitudes are due to a range of reasons, such as the life status change (Andreasen, 1984, Mathur et al., 2003), the overall evolution of economics in a country (Saunders and Saker, 1994), and the performances of vehicle attributes (Dimitropoulos et al., 2013, Heutel and Muehlegger, 2015). Consumer preferences and other variables that determine vehicle performance will change during the dynamic adoption process and these changes will have implications on the accuracy of adoption forecasting (Meeran et al., 2017) and consumer demand modelling (Liu and Cirillo, 2017, Gold and Pray, 1999).

1.4 Research motivation and objectives

Although choice modelling is useful for studying AFV adoption based solely on consumer preferences, it does not allow researchers to depict the timely feedback between different stakeholders in AFV adoptions. The static consumer attitudes and preferences that are derived from choice modelling and consequently used to forecast AFV adoption only represent how consumers make their choices based on the provided performances of AFVs at the time the choice model was implemented. The potential changes in consumer attitudes and preferences are not captured in the choice modelling process and subsequently excluded from consideration for AFV adoption forecasting (Liao et al., 2017).

Motivated by the possibility of changes in vehicle consumer attitudes and preferences and their implications to AFV adoption, this thesis aims to investigate the implications of changes in consumer choices on the adoption of AFVs with a focus on dynamics in consumer attitudes and preferences. The research objectives of this thesis are:

- To investigate the implications of potential changes in consumer attitudes and preferences on the AFV adoption,
- To quantitatively model consumer choices in AFV adoption from a holistic and dynamic viewpoint,
- To explore possible interventions for promoting AFV adoption based on the dynamics of consumer choices.

1.5 Research approach

In order to achieve the objectives of this research, a system dynamics modelling approach combined with a choice model is adopted. System dynamics modelling was introduced in the early 1960s by Forrester (1961) as a modelling and simulation tool that aimed at analysing how the dynamic behaviour patterns of system variables change in response to dynamic inputs. System dynamics was initially applied in business management. Over the past few decades, system dynamics has become a widely used computer-aided method for analysing and solving complex problems, which has been applied in many fields, including: policy design, health care, energy and environmental studies, and automotive industry and urban studies (Angerhofer and Angelides, 2000, Shepherd, 2014, Sterman, 2000). The choice of using the system dynamics approach is mainly due to the recognition that it allows researchers to bring in other modelling structures and to add dynamic and nonlinear relationships to the system while also allowing system and policies to interact across space and time (Shepherd, 2014).

In this combined model, the discrete choice model provides quantitative information about consumer choices and preferences while system dynamics model captures the interactions and feedback between different stakeholders in AFV adoption process and depicts the system changes over time. The model adds the evolution of vehicle performance and changes in consumer preferences and attitudes overtime. It also incorporates the reciprocal effects between AFV adoption and variables, such as various vehicle attributes that contribute to overall vehicle performance, consumer attitudes and biases, and consumer preferences. This combined modelling approach allows a data-rich and holistic viewpoint for understanding the impacts on consumer choice in AFV adoption.

In the process of building the model, a preliminary system dynamics model is first built based on theories in the literature and a historical market data observation. Theories on consumer decision-making process and innovation diffusion are explored to form the foundation of the system dynamics model. A historical market data observation is sequentially conducted to support and provide extra insights to the preliminary model.

After the preliminary model structure, a market survey carrying out a stated choice experiment and subsequent choice model is then conducted. The objective of this survey is to collect data for the discrete choice model as well as to qualitatively investigate consumer attitudes and their choices based on the current vehicle market. It provides data input for consumer choice parameters in the preliminary system dynamics model and qualitatively contributes extra insights to the finalization of system dynamics model structure.

1.6 Australian case study

In this thesis, the Australian vehicle market is selected as a case study to provide market context and validation of the developed model for the research. Data input for both of the market historical trends observation and the market survey are based in Australia. The main advantages for choosing Australia as the case study are given as follows:

- ❖ A matured and stable market

The vehicle market in Australia is highly matured and stable before the alternative fuel powertrains emergence. Although the annual vehicles sales volume fluctuates due to economics, there are no significant increases or decreases in overall vehicle fleet size. The vehicle ownership per capita is 740 vehicles per 1000 person (Australian Bureau of Statistics, 2014), which can be considered as stable within the research time projection. The matured vehicle market avoids possible changes of consumer attitudes and preferences due to exogenous factors, such as vehicle market growth and economic growth. Without the impacts of these exogenous factors, the Australian vehicle market provides a suitable context for studying consumer choices and preferences endogenously.

❖ A diverse market that includes various vehicle models and powertrains

Despite being a relatively small vehicle market, the Australian vehicle market is highly competitive. There are 67 vehicle brands offering more than 350 vehicle models originated from North America, Europe and Asia (Federal Chamber of Automotive Industries, 2014). The immense diversity in the market provides Australian vehicle consumers abundant vehicle choices and cultivates consumers' awareness to various vehicle models and technologies.

In addition, the Australian vehicle market consists multiple powertrains, ranging from relatively traditional diesel vehicles, LPG vehicles to the latest EVs and PHEVs. It provides a great market environment for researching the competition among different powertrains. In addition, due to their history and market development, Australian consumers also have different acceptance and attitudes towards these powertrains. There are relatively successful and failed adoptions of AFVs existing in the market. The diversity and vitality of the market presents a very suitable research context for consumer choice studies.

❖ Purely market-driven environment

The Australian vehicle market is heavily market-oriented in regards of AFV vehicle adoption. Unlike other equally matured and diverse vehicle markets, such as the United States, Japan, and Europe, the Australian market has little to no policy reinforcement specifically in promoting alternative fuel powertrains. Although consumers are provided with abundant vehicle models in a range of powertrains, there are no incentives for choosing a particular option. This means Australian consumers are not influenced by exogenous policy interventions and their preferences are purely established due to their background and beliefs instead of being biased towards any powertrains or features by heavy incentives or educational campaigns. The organically cultivated consumer preferences are well suited for examining consumer choices and conducting policy tests in the modelling process.

1.7 Thesis outline

The remainder of this thesis is organized as follows:

Chapter 2 presents a review of the literature of the field of innovation adoption and more specifically, the adoption of AFVs. This chapter first provides a generic review on the theory of innovation diffusion, defining the concept of innovation, the diffusion process, and the individual adoption process. Next, the chapter goes into detail to present a review based on studies about the adoption of AFVs. Literature around AFV adoption is reviewed from two viewpoints: individual vehicle powertrain choices, and dynamics around the aggregated effects of consumer choices. Based on the literature review, the research hypothesis that the dynamics around consumer attitudes and preferences can influence the adoption of AFVs is established. Research questions around the implications of such dynamics and the potential interventions for promoting AFV adoptions are proposed.

Chapter 3 introduces the design of the research. First, the requirements of the research design are recognised based on the research questions. Second, the research design of a combined modelling approach is established. This combined modelling approach utilizes both discrete choice modelling and system dynamics modelling to provide a quantitative model with a dynamic and holistic viewpoint. After introduction on the modelling steps of each modelling approach, the specific research steps of the thesis are established in the end.

Chapter 4 formulates the dynamic hypothesis of the system dynamics model through a theoretical foundation, which is based on previous theories around consumer choices, and the Australian vehicle market observation of historical trends within key dynamic variables. The theoretical foundation serves as a framework for the construction of key dynamic hypotheses and guidelines for the subsequent market historical trends observation. The market observation uses historical data to investigate the dynamics of the key variables that were identified through the theoretical foundation. Based on these two processes, key variables and hypotheses of their dynamics are proposed and the preliminary dynamic structure of Australian AFV adoption are established.

Chapter 5 further investigates the key variables and their dynamics in AFV adoption of Australia. By implementing a market survey and subsequent discrete choice model, this chapter provides crucial information for intangible key variables in AFV adoption both quantitatively and qualitatively. Especially, the discrete choice model provides the overall dynamics model with fathomable evaluation of key variables around consumer attitudes and preferences.

Chapter 6 describes the formulation of the final system dynamics model. Based on the previous two chapters, the dynamics of all key variables are established. This chapter introduces the dynamics of every key feedback loop and all assumptions and justifications of the model structure.

Chapter 7 presents the results of the system dynamics model. The model is first calibrated using historical sales data. After calibration, the model base scenario is established. Model tests, such as sensitivity analysis and model behaviour test, are performed next to gain confidence in the model. The base scenario is then analysed based on the performances of each key variable. To further understand the dynamics of the model and the influences of each key feedback loop, adoption behaviours based on extreme conditions of each key variables are investigated. Finally, possible policies and interventions for AFV adoption in Australia are discussed.

Chapter 8 provides an overview of the thesis and summarizes the key findings of the research. The research questions established in Chapter 2 are answered. Structural contributions and practical implications of the research are then presented. Finally, a discussion on directions for further work is provided at the end.

Appendices that present the market survey questionnaires and the coding for the final system dynamics model are attached at the end of the thesis.

Chapter 2 Literature Review

This chapter presents a literature review on studies that are related to the field of innovation diffusion, and more specifically, the field of AFV adoption. First, the research context of the thesis is laid out by a brief summary of the fundamental theory of innovation diffusion and a review of innovation characters and their implications to the diffusion process. These two sections provide the essential knowledge background for studying the adoption process of AFVs, i.e. the innovation in the transportation sector. Next, the subsequent sections of this chapter present a review of literature that is in the specific field of AFV adoption. Because AFV adoption is essentially the aggregated effects of millions of vehicle consumers choosing alternative powertrains as their vehicle powertrain selections (Liao et al., 2017), the review first goes through research that studied AFV adoption as consumer choices on vehicle powertrains. Factors in consumer choices found to be relevant to AFV adoptions are identified. The review then looks at the aggregated effects of consumer choices. Dynamics around the aggregated effects of consumer choices and endogenous feedback in AFV diffusion process over time are concluded. Finally, research objectives of this thesis are established at the end of the chapter.

2.1 Diffusion of innovation theory overview

Since the research theme is about the diffusion of AFVs, which are based on the innovative powertrain technologies, it is important to understand the fundamental theory on innovation diffusion. The most commonly applied theory on innovation diffusion is established by Everett Rogers in his book “Diffusion of Innovations” in 1962. The following sub-sections present a brief summary of innovation diffusion theory and provides the research context of the thesis.

2.1.1 Four elements in innovation diffusion

Diffusion of innovation theory is a theory that describes the process of a new idea/product/technology spreading within the society (Rogers, 2003). Rogers proposed four elements in the process of innovation diffusion: innovation, communication channel, time and social system (Rogers, 2003). An idea, practice or object will be recognized as an innovation if it is perceived as new by an individual or other unit of adoption. It matters little if the innovation has existed for years, as long as it is perceived as new, it can be seen as an innovation. In the context of this research, although alternative fuel technologies had already been introduced into the market for more than a decade, they are still considered an innovation compared to petrol vehicles.

Communication channels are the means by which messages get to be delivered from one individual to another, specifically from adopters to non-adopter. The most common communication channels are mass media and interpersonal channels. Mass media, namely radio, television, newspaper, and the internet, is the most rapid and efficient means for informing an audience of the existence of an innovation (Rogers, 2003). In contrast, the interpersonal communication channel that involves interpersonal interactions within two or more individuals who are very likely similar in socioeconomic status, education, and beliefs, are more effective in persuading an individual to accept an innovation (Greenhalgh et al., 2004, Goldenberg et al., 2001).

Time is the third element to the diffusion process of an innovation. The time dimension acts as a mediate variable in the diffusion process. By introducing the time dimension to innovation diffusion theory, researchers are able to investigate the topics such as adoption rate (Dooley et al., 2002), the characteristics of adopters (Dedehayir et al., 2017, Neyer et al., 2009), and the process of individual adoption decision-making (Rogers, 2003, Damanpour and Gopalakrishnan, 2001).

The social system is defined as “a set of interrelated units that are engaged in problem solving to accomplish a common goal” (Rogers, 2003). Since diffusion of innovations takes place in it, the social system can impact the result of innovation diffusion in multiple ways. In the work of Freeman (1995), the importance of the “national system of innovation” was investigated in historical perspective. The author argued that although external international connections are of growing importance, the impacts of the education system, industrial relations, government policies and many other national institutions are fundamental to innovation and national economic. In the study done by Valente (1996), the social network threshold model based on adopter categories was developed to analyse and predict the pattern of diffusion of innovations.

These four elements of the innovation process constitute the fundamentals of the innovation diffusion theory. In the next sections, the innovation diffusion process is reviewed in individual and societal perspectives respectively.

2.1.2 Innovation adoption decision process

From the individual perspective, the process of innovation diffusion consists of millions of individual adoption decisions over time and space. The adoption decision process that depicts steps of an individual evaluating and accepting an innovation is summarized in Figure 2-1.

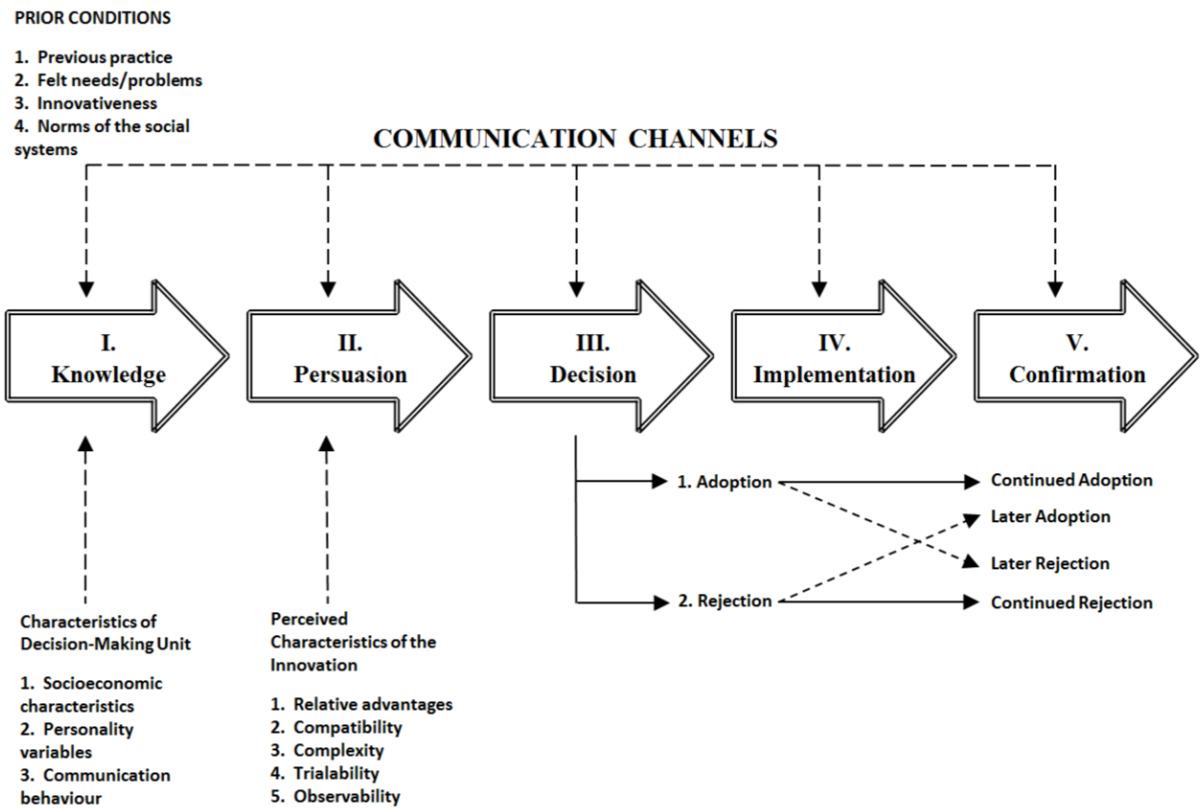


Figure 2-1 Rogers' adoption decision process (Source: from DIFFUSION OF INNOVATIONS, 5E by Everett M. Rogers. Copyright © 1995, 2003 by Everett M. Rogers. Copyright © 1962, 1971, 1983 by The Free Press. Reprinted with the permission of The Free Press, a Division of Simon & Schuster, Inc. All rights reserved.)

As Rogers (2003) stated it, the innovation adoption decision process consists of five stages: knowledge, persuasion, decisions, implementation, and confirmation. It first starts with knowledge stage, where an individual learns the existence of the innovation and gains understandings of how it functions. In the knowledge stage, it is not clear that if the awareness of the innovation creates the needs for the innovation or the other way around where consumers have specific needs so that they seek of knowledge of innovations.

Either way, the motivation for purchase is created at this stage. The second stage is the persuasion stage where the individual forms a negative or positive attitude towards the innovation. A knowledge-attitude-practice gap might exist and prevent the adoption from happening. For instance in the context of AFV adoption, favourable attitudes towards AFVs due to awareness of their environmental impact do not often translate into behavioural change (Lane and Potter, 2007). At the decision stage, the individual makes the decision of whether adoption or reject the innovation. Rogers had stated the adoption decision can be made quicker if the innovation has a partial trial basis (Rogers, 2003). The implementation stage occurs when an individual puts the innovation into use, while the confirmation stage describes the stage where an individual looks for support for the decision made about adoption. Unlike the previous three stages that happened strictly mentally, the last two stages involve the usage and repurchase of the innovation. During the confirmation stage, adoption discontinuance can happen in two situations: firstly, a better innovation replaced the current innovation, and secondly the performance of the innovation is not satisfying to the individual. In context of this research, the first situation describes an HEV adopter shifting to a EV in the next purchase, while the second situation depicts the HEV adopter moving back to a petrol vehicle for the next vehicle purchase.

The adoption decision process is embedded in the diffusion process. The four aforementioned diffusion elements are all influential to the decision-making process. Before the knowledge stage, prior conditions from the social system such as social norms and the innovativeness of its members determine if the innovation decision can happen (Nutley et al., 2002). Within the knowledge stage, the social system is also important. The characteristics of the decision-making unit (the potential adopters) are determined by the structure of the social system as well (Figure 2-1).

Moving on to the persuasion stage, the perceived characteristics of the innovation affect how individuals form their attitudes. There are five characteristics in total for describing the innovation: relative advantages, compatibility, complexity, trialability, and observability (Rogers, 2003). Relative advantages are defined as “the degree to which an innovation is perceived as being better than the idea it supersedes”. For instance, AFVs in general have the relative advantage of less emission and higher fuel efficiency than petrol vehicles. Compatibility describes if the innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters. AFVs’ compatibility lays in the similar driving experience and functions provided to the vehicle consumers. However, AFVs, especially EVs and PHEVs, might lack in compatibility in the aspect of refuelling habits. Adopters may find hard to reform their refuelling habits to suit the new technologies (Rogers, 2003). Complexity is defined as the degree of perceived difficulties in operating and using an innovation. Complexity along with the previous two characteristics, relative advantages and compatibility, were found to have the most consistent significant relationship to innovation adoption (Tornatzky and Klein, 1982). The last two characteristics are trialability and observability. These two characteristics are both relevant to individual's experience. Trialability is defined as the degree to which an innovation can be experienced, while observability is about whether the results of an innovation is visible to others. In the study of solar energy system adoption process done by Labay and Kinnear (1981), the observability for solar energy system become smaller as one becomes more familiar with the technology. This finding was echoed by the studies done by Bollinger and Gillingham (2012) and Kraft-Todd et al. (2018), where the increase of observability of the solar panel can promote the adoption of solar panel system in households in California.

This section introduced the individual innovation decision-making. Innovation diffusion is a process that happens both individually and socially. The following section will review innovation diffusion as an aggregated effect in society over time. Quantitative information about the diffusion process will be discussed on the basis of individual heterogeneity and individual learning.

2.1.3 Diffusion process based on individual heterogeneity

The diffusion of an innovation into the society is an aggregated view of the previously described innovation decision process. It concerns how innovations spread and are assimilated within a market. In the theory of (Rogers, 2003), the diffusion process is depicted based on the heterogeneity within social members, specifically, the heterogeneity within the innovativeness of individuals. Innovativeness of individuals is a direct determinant of perceived innovation characteristics (Yi et al., 2006).

Individuals accept the innovation through the course of the diffusion process. The degree to which an individual is relatively earlier in adopting new ideas than other members of a system defines this person's innovativeness. Based on their innovativeness, adopters are categorized into five groups: innovators, early adopters, early majority, late majority, and laggards. Innovators are defined as the first groups of social members who adopt the innovation. Individuals in this category are venturesome and willing to try new ideas despite the occasional setbacks (Hussain and Rashidi, 2014). They are extremely important to the diffusion process since the innovation is normally imported into the social system through innovators (Dedehayir et al., 2017). Compared to innovators, early adopters are more integrated within the social system. This adopter category includes the highest percentage of opinion leaders who have the most respect within the social system. Their positive opinions about the innovation decrease the uncertainty for other adopters (Venkatraman, 1989). Early majority includes individuals who are deliberate while later majority group is composed of individuals who are more sceptical. These two groups contain the highest number of the population within the social system. The last category is laggards. They tend to be suspicious of innovations and hold relatively traditional values.

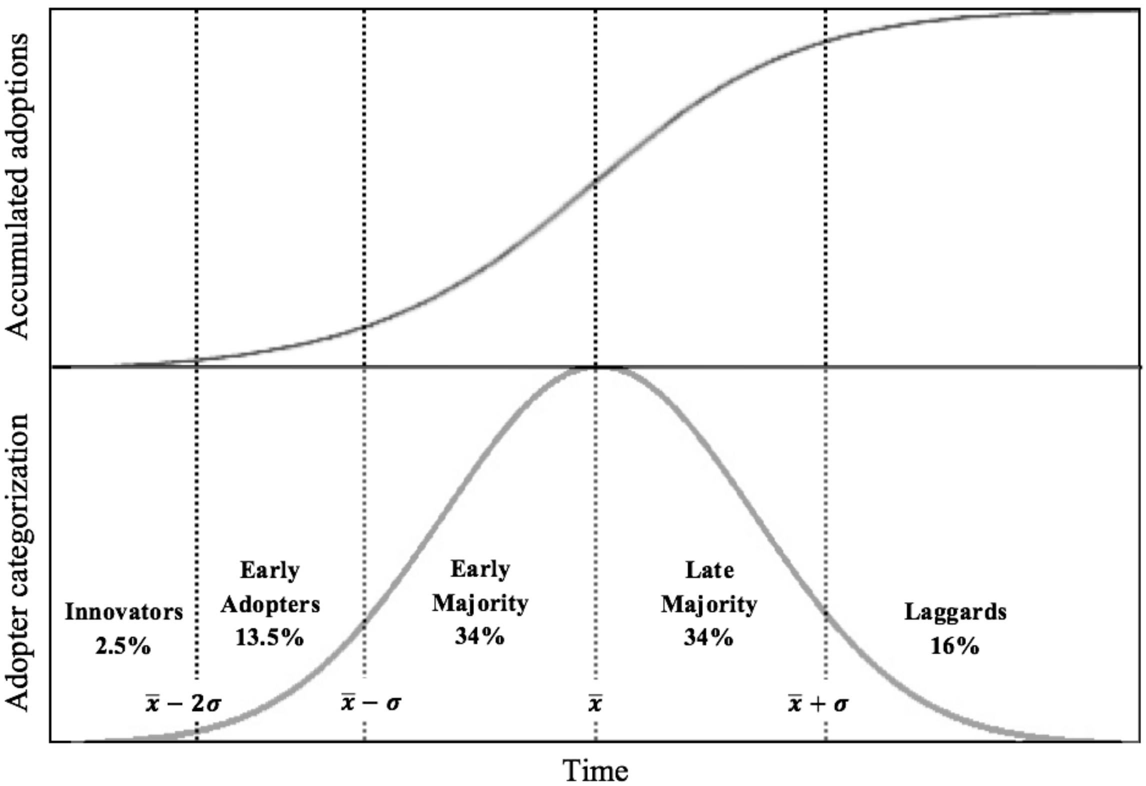


Figure 2-2 Rogers' Diffusion Process - Accumulated adoptions and Adopter categories (Source: Adapted from DIFFUSION OF INNOVATIONS, 5E by Everett M. Rogers. Copyright © 1995, 2003 by Everett M. Rogers. Copyright © 1962, 1971, 1983 by The Free Press. Reprinted with the permission of The Free Press, a Division of Simon & Schuster, Inc. All rights reserved.)

A bell-shaped normal distribution curve depicts the adopter categorization through the diffusion process (the lower half of Figure 2-2). The mean of the normal distribution ($\bar{x}$) represents the average time that a social member takes to adopt the innovation, while the standard deviation (σ) indicates the average amount of variance from the mean for a sample individuals (Rogers, 2003). The five categories of adopters can be partitions in the adoption rate figure with the mean and standard deviation. The area lying to the left of the mean adoption time $\bar{x}$ minus two σ represents the innovators who are the first 2.5% of the individuals in the social system to adopt the innovation. The subsequent adopter groups are parted by one σ interval in regards of timing of adoption.

In general, a successful innovation diffusion generates an S-shaped curve for the accumulated number of adoptions overtime (the upper half of Figure 2-2). At the beginning of the diffusion, the adoptions were made by innovators. After innovators, early adopters and early majority start to adopt the innovation. This is also the stage where the accumulated adoptions curve grows the fastest. After late majority have adopted the innovation, when the Laggards finally accept the innovation, the accumulated adoptions curve stagnates and reaches the adoption saturation level.

Since the diffusion process is composed of millions of individual decisions, the factors that are influential to individual decision-making process are also relevant in the diffusion process. Under the combined effects of the elements of the diffusion process, such as time, communication channel, and the social system, these factors become dynamic and changeable, and can generate momentums to push forwards the diffusion process. These dynamic relationships also form the foundation of the dynamic hypothesis of this research.

2.2 Characters of innovation and their implications to adoption

Innovation is the core element of the diffusion process. Its characters determine the implications to its adoption. The characters of innovations can be distinguished in three dimensions: public versus private consequences; the cost of the innovation; and static versus dynamic innovation (Karakaya, 2015, Wejnert, 2002).

2.2.1 Public versus private consequences

The diffusion of innovations can result in either private or public consequences, or in situations both (Karakaya, 2015). Innovations that result in private consequences mainly affect the individual adopters or small collective entities such as organizations, peer groups, and rural communities (Wejnert, 2002). These innovations are designed to improve the quality of individual lives or to reform social structure within organizations. Innovations that fit this character include new medical practices such as new fertility-control methods (Rosero-Bixby and Casterline, 1994), improving agricultural technologies (Sommers and Napier, 1993, Saltiel et al., 1994), or management styles within organizations (Straub, 1994, Palmer et al., 1993). For innovations with private consequences, their diffusion processes rely heavily on: i) spatial effects such as geographic proximity and interpersonal communications, and ii) the pressure of social networks. Rosero-Bixby and Casterline (1994) had found that social interactions within neighbourhoods had significant affected the adoption of new family planning practices across all socioeconomic strata in Costa Rica. In a study about adoption of on-officer videos (body cameras) in Southwestern United States, interactions with other patrol officers were found effective in providing a conduit for forming cognitive frames that increase body camera acceptability (Young and Ready, 2015). Similarly, in the study of Schultz et al. (2015), social marketing campaigns that focused on interpersonal communications and social network pressure were found to be effective in promoting the use of LED lighting in Vermont.

Innovations that lead to public consequences involve collective actors, such as countries, states within countries, and organizations and social movements, and are mostly concerned with issues of societal well-being (Wejnert, 2002). Innovations in this category include welfare and education policies (Borrego et al., 2010, Thomas and Lauderdale, 1987), state laws (Berry and Berry, 1990), and political models of democracy (Uhlin, 1995, Elkink, 2011). The diffusions of such innovations are mostly based on authority or collective innovation decisions and often leads to societal reforms that are historical breakthroughs. Innovations with public consequences are mainly adopted when information and imitative models are uniformly distributed (Wejnert, 2002). The spread of this kind of innovation is most effective when norms, values, or expectations about the innovation becomes deeply ingrained in the social system (Meyer and Rowan, 1977). In contrast to innovations with private consequences, diffusions of innovations with public consequences is less sensitive to media effect (Wejnert, 2002, De Vries et al., 2016, Dearing, 2009). In a study on the adoption of ideology in environmental movements, media covered information about the movement only became an influential channel once the goal of the movements had been well established within the society (Strodthoff et al., 1985). In the work of Loukis et al. (2017), the importance of social media effects was investigated by developing the social media monitoring method for promotion of innovations in public sector.

For many of the innovations, the consequences of the innovations cannot be distinctively distinguished (Wejnert, 2002). For most of the environmental innovations including AFVs, the consequences of such innovations are both private and public (Karakaya, 2015). The diffusion of such innovations not only can be beneficial to individuals who adopt the innovation, but can also provide public welfare as these innovations can reduce environmental harm for the whole society (Karakaya, 2015). For instance, the diffusion of AFVs can lead to potential savings on fuel spending in vehicle for consumers (Timmons and Perumal, 2016) (private consequence) and also reduce fossil fuel dependence for the society (Meyer and Winebrake, 2009, Chen et al., 2015) (public consequence). For innovations that result in both private and public consequences, their diffusion is a more complex and lengthier process in comparison with those that have only private consequences (Karakaya, 2015).

2.2.2 Cost factor of the innovation

The cost of an innovation can be monetary and nonmonetary, direct and indirect (Wejnert, 2002). Monetary and direct costs are typically easy to notice and comprehend, and are relative to the economic situation of the adopter (Wejnert, 2002). It can be the purchase price of an innovative product, the implementation costs of new facilities, or costs to reform social policies or institutions (Bunduchi et al., 2011, Wu et al., 2015, Carraro and Siniscalco, 1992). Indirect costs are not often clearly identified. Some examples of this kind of cost include costs of purchasing a new kind of fertilizer in order to use innovative seeds (Feder and Umali, 1993), and costs for research and development activities in the case of implementing innovative policies on reducing pollution level in industrial firms (Carraro and Siniscalco, 1992). Some of the indirect cost can also be nonmonetary, such as time and efforts spent on replanning the workflows to incorporate the innovation, radio frequency identification (RFID), into the management and routine of a healthcare organization (Bunduchi et al., 2011), and early cost of temporary loss of a firm's productivity in the case of e-commerce application adoption in small and medium-sized enterprises (Ghobakhloo et al., 2011).

For innovations with high costs, the economic aspects are usually the most important factors for comprehending the diffusion of such innovations (Rogers, 2003). When the innovation is perceived as associated with high costs, the potential adopter puts more efforts in understanding the outcomes, benefits, risks, the direct and indirect costs of the innovation, in both short- and long-term (Karakaya, 2015).

AFVs, as a type of commodity that is associated with relatively high price tag and reasonably long lifecycle, are regarded as high cost innovations in terms of direct costs. Furthermore, the diffusion of AFVs also requires indirect costs from both public and private sector, such as construction of refuelling facilities in public sector and adaption of new driving and refuelling habit by individuals in private sector. These characters all define AFVs as a high cost innovation, which can lead to more complex and time-consuming diffusion process in comparison with low-cost innovations.

2.2.3 Static versus dynamic innovation

The last character of innovation depicts whether the innovation changes or gets modified in the process of diffusion (Karakaya, 2015). For some innovations, they can get modified continuously in every adoption that takes place in space and time. A good example for innovations that have continuous modification is the solar panel. In the process of solar panel adoption by households, the innovation is modified constantly through time and space since the solar panel implementation has to be installed based on the specifics of the adopter's house. For such innovations, the role of the change agent in the diffusion process is especially important (Karakaya, 2015). Change agents are individuals who influence clients' innovation-decisions in a direction regarded as desirable by the agents (Rogers, 2003). Change agents can be entrepreneurs, local firms, and policy makers. They normally work with opinion leaders of the society to sway the direction of the diffusion process (Rogers, 2003). In the diffusion process of dynamic innovation, active involvement of change agents, for example, helping potential adopters discover and develop particular forms of innovation on a case by case basis, can significantly reduce the perceived complexity and therefore increase the possibility of adoption (Karakaya, 2015). For innovation adoption in firm-level, the dynamic perspective of the innovation is also regarded as important. In the study of Poot et al. (2013), the dynamics of open innovation as a new management style for firm research and development are investigate. The constant evolution of open innovation based on external and internal collaborations and information inputs has been addressed using a longitudinal analysis in the study.

AFVs, although are not as frequently modified during the diffusion process, are incrementally modified through the lengthy diffusion process (Karakaya, 2015). The dynamic perspective of AFV is of great importance for understanding its diffusion process.

In Section 2.2, the innovation characters were introduced and the implications of such characters to the adoption of the innovations were also addressed. AFV as an innovation can lead to both public and private consequences. The adoption of AFVs also involves high direct and indirect costs with relatively high level of dynamics. These characters predetermine that the diffusion process of AFVs is complex, lengthy, and dynamic. In the subsequent sections, literature in the specific field of AFV adoption will be reviewed and discussed.

2.3 Consumer choices in AFV adoption

Consumers as the most essential stakeholders in AFV adoption, determine whether a powertrain can be eventually accepted by the society. This section reviews research that study AFV adoption in the viewpoint of consumer choices. An overview of common research methods used in the field is presented first. Next, subjective and situational factors in consumer choices that are related to AFV adoption are summarized from these studies.

2.3.1 Overview of research in consumer choices and AFV adoption

To understand consumer choices on vehicle powertrain selection, different theories and methods are utilized. Two approaches to understand consumers' choices on powertrain are concluded from the literature. The first approach is to view AFV adoption as a behavioural response that comprises of the purchase and the use of AFVs (Li et al., 2017, Rezvani et al., 2015). This approach allows researchers to focus more on individual-specific psychological factors which influence consumer's intention for AFV adoption (Petschnig et al., 2014), while situational factors that are more objective are excluded from the research scope. Following this approach, common theories that are utilized to investigate AFV adoption are concluded by Rezvani et al. (2015): the theory of planned behaviour (TPB), normative theories, AFV symbolism, consumer innovativeness categorization, and consumer emotions. Studies often use a mix of several theories to investigate consumer psychological factors that can affect AFV purchase intention (Rezvani et al., 2015). Quantitative surveys (Krupa et al., 2014, Axsen et al., 2012) or qualitative interviews (Burgess et al., 2013, Caperello and Kurani, 2012) are usually used as approaches for acquiring data. These theories put emphasis on the psychological side of consumer intentions to adopt AFVs. However, situational factors that related to AFV adoption are not included. Especially, how consumer psychological factors interact with situational/objective factors in the system is not represented and cannot be simulated quantitatively.

The second approach is to view AFV adoption as consumers' evaluations of alternatives in their choice sets. In this approach, subjective factors, such as consumers' beliefs and demographics, and situational factors, like vehicle attributes and performances, are both incorporated. Consumer behaviours around AFV adoption are interpreted as evaluations of different powertrains based on their preferences and vehicle performance. Consumer preferences are explicitly quantified using logit models. In such way, consumer behaviour in powertrain choices is less obscure and links between consumer attitudes and objective factors are more explicit to model. Discrete choice modelling is the most representative method that is commonly used to solve problems around consumer preferences and AFV adoption (Al-Alawi and Bradley, 2013a). Discrete choice modelling uses stated choice experiments to collect consumer choices data by providing them with various hypothetical choosing scenarios that includes combinations of vehicle attributes and values (Hensher et al., 2005). Respondents evaluate the provided alternatives in the choosing scenario and make trade-offs between attributes based on their preferences to select their most preferred alternative. Collected choice data are then analysed using logit models to quantitatively reveal the consumer preferences associated with each vehicle attributes (Hauser and Rao, 2004). Because this method can incorporate both consumer subjective factors as well as situational factors from market, discrete choice modelling enables a more comprehensive conceptual framework for AFV adoption studies (Liao et al., 2017).

In the following sections, research findings from AFV adoption studies in both approaches are concluded. Factors that are influential to consumer choices in AFV adoption are grouped into two categories: subjective factors such as consumers' demographics, beliefs, and experiences with AFVs; and situational/objective factors such as vehicle performance, market conditions, and policy interventions.

2.3.2 Subjective factors in consumer choices

The most intuitive way to determine how consumers evaluate vehicle models in their choice sets is through consumer preferences. Consumer preferences, that are quantitatively revealed from stated choice experiments and discrete choice modelling, describe how situational factors in AFV adoption can affect the results of vehicle consumers decisions. In this section, factors that are related to consumer preferences towards alternative fuel powertrains and eventually affect the outcomes of consumer choices are concluded.

The influences of demographic factors on consumers' preferences and their intentions for AFV purchases are discussed in many studies. Age, income, education level, and occupation are often included in studies to observe whether differences in respondents' demographic background can lead to shifts in consumer preferences. Consumer age is often found to have negative effect on AFV adoption (Ziegler, 2012, Hackbarth and Madlener, 2013, Hidrue et al., 2011, Achtnicht et al., 2012). Income in general is intuitively regarded as influential on consumer decisions about AFV adoption (Li et al., 2017). In the work of Hackbarth and Madlener (2013), income levels of respondents that were indicated from the price of their last purchased vehicle, and respondents' preferences for alternative powertrains were positively related. However, in studies done by Hidrue et al. (2011), Zhang et al. (2011b), Bjerkan et al. (2016), income level was not found as a prominent indicator for consumers affinity towards AFVs. In regard to education level, Kim et al. (2014), Hackbarth and Madlener (2013), Hidrue et al. (2011) all concluded that higher education level in respondents are associated with higher consumer preferences with alternative fuel powertrains. Finally, for occupations, since some of the alternative fuel technologies such as pure electric vehicles are regarded as assemblages of advanced technology, the powertrain is more likely to be acceptable to technophiles (Hackbarth and Madlener, 2013, Egbue and Long, 2012). This finding was also mentioned in the work done by Plötz et al. (2014), where empirical data sets about German vehicle consumers were analysed to characterize early EV adopters.

In addition to demographic characteristics, beliefs and personal norms of consumers are important to consumer preferences on vehicle selection and their choice outcomes (Egbue and Long, 2012, Krupa et al., 2014, Schuitema et al., 2013). The purchase of AFVs, especially for the latest alternative powertrain technologies such as EVs and PHEVs, are regarded as a pro-environmental behaviour (Rezvani et al., 2015). Therefore, relationship with factors such as consumer pro-environmental attitudes, beliefs, and norms with their AFV choices and preferences are often investigated (Ziegler, 2012, Liao et al., 2017). In the study done by Beck et al. (2016), consumers' attitudes towards environmental issues such as energy crisis, air quality, climate change, and oil shortages were measured through a best worst scaling experiment. This attitude experiment was incorporated with a choice model to investigate the influences of consumer beliefs and attitudes to their preferences of different vehicle attributes. It was found that energy crisis, air quality and climate change concerns affect consumers' preferences on vehicle driving range. Plötz et al. (2014) also stated that awareness of environmental protection was an effective predictor of consumers' intention to purchase EVs. In the work done by Hahnel et al. (2014), activating environmental values within respondents lowered consumers' prices sensitivity towards EVs.

Apart from demographic characteristics and personal beliefs that are associated with consumers themselves, consumers' experience with AFV is also regarded as significant to consumer preferences in their decision-making process. In the context of AFV adoption, experience encompasses mostly knowledge of and practical experience with BEVs (Li et al., 2017). In the work of Burgess et al. (2013), it was found that practical experience is important in converting consumer attitudes towards EVs from sceptical to supportive. First-hand experience of EVs lead to more positive consumer perceptions and can also change consumers' stereotype of EVs. Similarly, positive relationships between EV adoption intention, and practical experience and EV-related knowledge were found in a Germany survey study done by Barth et al. (2016). In addition, Jensen et al. (2013) also showed that hands-on experience with EVs would shift the consumer preferences and attitudes to a positive direction. For instance, consumers would have fewer doubts after experiencing electric powertrains because first-hand experiences can help them to better understand their needs for EV driving range and therefore enhance their intention of EV adoption (Franke and Krems, 2013).

In this section, subjective factors that are influential to consumer preferences towards AFVs were concluded. In the next section, situational factors that are related to stakeholders other than consumers and are connected directly with consumer preferences will be reviewed.

2.3.3 Situational factors in consumer choices

In random utility theory that is applied in discrete choice models, consumers choice outcomes are determined by vehicle utility, which is based on consumer preferences and vehicle performance. Subjective factors that are influential to consumer preferences were discussed in the previous section, situational factors that determines the vehicle performance are concluded in this section.

Cost of ownership as an essential attribute of a merchandise is regarded as significant to consumer choices on vehicle powertrains. Cost of ownership is usually studied from two aspects: purchase price and operating cost. Purchase prices of alternative fuel powertrains are generally higher than their counterparts in the market (Al-Alawi and Bradley, 2013a). The incremental cost of alternative fuel powertrains was found to have a negative and highly significant influence on AFV utilities and the likelihood of AFV purchase (Brownstone et al., 2000, Potoglou and Kanaroglou, 2007, Mau et al., 2008, Helveston et al., 2015, Tanaka et al., 2014, Caulfield et al., 2010, Daziano and Achtnicht, 2014). Operating cost is also a vehicle attribute that appears in almost every study albeit slightly different format (Liao et al., 2017). Most of the studies measure operating cost as the cost of energy, either cost per distance or both fuel efficiency and fuel price (Musti and Kockelman, 2011). The effects of operating cost on vehicle utilities were found to be negative (Al-Alawi and Bradley, 2013a, Liao et al., 2017). The negative relationship between operating cost and vehicle utility provides some alternative fuel powertrains, such as EVs and PHEVs, with advantages over traditional powertrains since these powertrains generally have lower fuel cost (Mock and Yang, 2014). To combine these two aspects, some studies use the concept of payback period to investigate the cost of ownership of AFVs. The payback period describes the amount of time it takes to recover the incremental cost of the AFV purchase price by the savings on its operating cost. Shorter payback period leads to higher AFV utility and thus higher accepting possibilities of alternative powertrains (Tamor et al., 2013, Browne et al., 2012, Al-Alawi and Bradley, 2013b).

Another significant category of vehicle attributes that are influential to consumer choices is vehicle technical performance. For alternative fuel powertrains, one commonly investigated vehicle attribute is the vehicle driving range. Specifically, inadequate driving range of pure electric powertrain is regarded as a major limitation to EV adoption (Hidrue et al., 2011, Egbue and Long, 2012, Coffman et al., 2017). Limited driving range leads to range anxiety and can severely influence consumers' acceptance of EVs (Franke and Krems, 2013). It was found that due to the inadequate EV driving range, PHEVs might become more preferable to consumers when both EV and PHEV were presented in consumers' choice sets. Through an EV cost-payback model performed by Tamor et al. (2013), it was concluded that PHEVs will be more accepted than EVs under a particular consideration for trip planning and vehicle driving range. Another vehicle attribute that represents vehicle technical performances is greenhouse gas (GHG) emissions of the vehicle. Lower GHG emissions of EVs and PHEVs are regarded as a preferable attribute and often included in choice models (Jensen et al., 2013, Achtnicht et al., 2012, Tanaka et al., 2014). Influences of this attribute are more prominent when consumers' beliefs and attitudes are included in the analysis. (Hackbarth and Madlener, 2013) had found that environmental friendly consumers are more likely to penalize GHG emissions in their vehicle evaluations. In addition, in the work done by Beck et al. (2016), to respondents who are mentally more ready to change their driving habit to suit new powertrains, the negative impacts of vehicle emissions to overall vehicle utilities became more significant. Additional vehicle attributes that are related to vehicle's technical performances are fuel efficiency (Musti and Kockelman, 2011), maximum speed (Rasouli and Timmermans, 2016), acceleration time (Valeri and Danielis, 2015, Potoglou and Kanaroglou, 2007, Hidrue et al., 2011), and vehicle warranty (Mau et al., 2008).

The last group of vehicle attributes that determines vehicle performance and affects consumer choices is related to vehicle driving and using experience. The most discussed vehicle attribute in this category is the vehicle charging availability. To powertrains that need additional charging facilities such as EV, PHEV, and hydrogen vehicles, charging availability is essential to successful adoption of the powertrains (Speidel and Bräunl, 2014, Meyer and Winebrake, 2009). In most of studies, charging availability is measured as the percentage of the number of petroleum stations (Achtnicht et al., 2012, Horne et al., 2005, Potoglou and Kanaroglou, 2007, Hackbarth and Madlener, 2013). Other measurements, such as detour time for refuelling (Hoen and Koetse, 2014, Chorus et al., 2013), distance from home to charging stations (Rasouli and Timmermans, 2016), and stations' presence in different areas (Jensen et al., 2013), are also used to address the impact of charging availability to EV/PHEV adoption in studies. Other driving experience related vehicle attributes includes access to HOV (high occupancy vehicle)/express/bus lane, free parking, and reduced toll, etc. However, the results about significance of such vehicle attributes remained mixed within studies (Liao et al., 2017).

In addition to vehicle performance, vehicle model availability and diversity is also regarded as influential to consumer decisions (Liao et al., 2017). Compared to other factors, this factor is less discussed in AFV adoption studies, especially in the area of consumer choice modelling (Massiani, 2014). Only a few studies have included vehicle model availability and variety in the choice and addressed its significance to increase the possibility of consumers choosing AFVs (Hoen and Koetse, 2014, Chorus et al., 2013).

In Section 2.3, AFV adoption, from the aspect of consumer choices, was revisited through literature. Research approaches from two viewpoints, subjective and situational, were concluded. Subjective factors that influences consumer preferences and situational factors that determines vehicle performance and model availability were summarized. These two groups of factors jointly influence the final outcomes of consumer choices. Thus far, factors that are relevant to individual vehicle choices have been concluded. In the next section, research on dynamics around the aggregated effects of consumer choices will be reviewed.

2.4 Dynamics around aggregated effects of consumer choices in AFV adoption

In Section 2.3, factors in individual choices around vehicle powertrain selection were concluded. In addition to individual choices, diffusion of AFV in society is a lengthy process that aggregates the effect of millions of individual choices and involves multiple stakeholders within society. In this section, the dynamics in AFV adoption are reviewed. An overview of theories and modelling methods for investigating the dynamics in AFV adoption are presented first. Next dynamics from two aspects of consumer choices that are investigated in AFV adoption research are summarized respectively.

2.4.1 Overview of research incorporating dynamics in AFV adoption

As stated above, the AFV diffusion process has three main dynamic characteristics: long timeframe, aggregated effects, and involvement of other stakeholders. In order to understand dynamics in AFV adoption studies, modelling methods need to allow the incorporation of these dynamic characteristics. First, different from individual choices, the timeframe for AFV diffusion is much longer. The changes in model variables through time need to be depicted. Therefore, time dimension is quintessential to the modelling of dynamics of AFV diffusion. Second, the aggregated effects need to be observable in the model. AFV adoption is based on individual decision-making behaviour. However, the combined effect of these behaviours in the society generates dynamics within the AFV adoption system and provides more holistic view on AFV adoption. Therefore, effects of aggregated consumer choice decisions overtime need to be observed through the model. Finally, since the diffusion process also involves other stakeholders in the society such as vehicle manufacturers, policy makers, and fuel suppliers, allowance of interactions between stakeholders are preferred in simulation models. Keeping these dynamics characteristics in mind, three common modelling approaches that study the dynamics in AFV adoption: time series modelling, agent-based modelling, and system dynamics modelling are reviewed in the following paragraphs respectively.

Time series modelling is based on innovation diffusion theory where the diffusion rate of an innovation is determined by two information transition channels: mass media and interpersonal communications (Bass, 1969). The lifecycle of new products over time is captured through this modelling approach (Norton and Bass, 1987, Jeon, 2010). The commonly used model regressions in AFV adoption studies by time series modelling method are Bass (Bass, 1969), Gompertz (Gompertz, 1825) and Logistic model, with Bass model being the most prevalently used especially in marketing research (Al-Alawi and Bradley, 2013a, Hall, 2004). The original Bass model was introduced primarily as a tool for forecasting sales of new products. It suggests that consumers are influenced by a desire to innovate (coefficient of innovation $\boldsymbol{p}$) and a need to imitate others in the social system (coefficient of imitation $\boldsymbol{q}$) (Bass, 1969). With a fixed market share potential parameter N, Equation 2.1 allows historical data fitting and further sales forecasting, with $f(t)$ denoting the probability that someone in the target segment N will adopt the innovation by time t (Bass, 1969). The Bass model is parsimonious in parameters and easily fitted to empirical data, which explains its wide use in marketing (Mahajan et al., 2000).

$$f(t) = \left[p + \frac{q}{N} N(t)\right] [1 - f(t)] \tag{2.1}$$

Time series modelling has the advantage of ease of implementation, and utilization of historical data. However, certain model parameters, for example, the time of peak sales and the market potential of one powertrain, are required in advance, which makes time series model unreliable when the historical data are limited or there exists a competing product in the market (Al-Alawi and Bradley, 2013a). Although this modelling method can demonstrate the aggregated effects of individual consumer choices through the time dimension, it lacks the ability to incorporate the interactions between different stakeholders within the AFV adoption process. In addition, due to the simplicity of time series model regressions, the time series modelling approach cannot depict details about individual decision-making in the model (Meade and Islam, 2006). Other modelling methods are sometimes incorporated with time modelling to provide a more comprehensive view on AFV adoption. In the work of Higgins et al. (2012), a diffusion model to predict the penetration rate of EV, PHEV, and HEV across Victoria, Australia was constructed. Multi-criteria analysis and choice modelling were also incorporated to enhance the research model. Similarly, in the forecasting model of PHEV adoption constructed by McManus and Senter (2009), the diffusion model was extended with a consideration-purchase system dynamics model that was proposed by Struben and Sterman (2008) to enable the diffusion model to have a flexible market saturation level.

Compared with time series modelling, agent-based modelling comprises of a significantly higher level of complexity. Agent-based modelling is a computer based simulation methods that models the real system of interests as a set of interacting agents in a defined environment (Lättilä et al., 2010). In AFV adoption models that use an agent-based modelling approach, four agents that are related to AFV adoption are: consumers, vehicle manufacturers, policy makers, and fuel suppliers (Al-Alawi and Bradley, 2013a). Different from time series modelling, agent-based modelling is excellent at comprising different agents defined by their own characteristics and rules, and allowing collaboration, coordination and interaction between the agents (Al-Alawi and Bradley, 2013a, Lättilä et al., 2010). In the study done by Sullivan et al. (2009), all four agents were included in the simulation model to forecast the market share of PHEVs in the US market. Decision rules were added for each type of agents so that they could interact in every simulation cycle (one month) and jointly influence the PHEV penetration rate. Another feature of this modelling method is that agent-based models are mostly decentralized (Borshchev and Filippov, 2004). Agent-level data input allows the model to capture more complex structures and dynamics over the time dimension at granular level. For instance, Cui et al. (2011) developed a multi agent-based simulation framework to model PHEV ownership distribution at local residential level, where the heterogeneities in consumer behaviours were captured. Residential zones where PHEV market share increases rapidly were identified in the study (Cui et al., 2011). In another study done by (Shafiei et al., 2012), an agent-based model incorporating consumer choices was developed to investigate the market share penetration of future electric vehicles in Iceland. The agent-based model explores different scenarios where the vehicle attributes such as gasoline price, recharging facilities, EV purchase price and taxes were varied to determine the best possible market penetration of EVs in Iceland (Shafiei et al., 2012). However, due to the bottom-up modelling approach, the aggregated effect of consumer choice decisions can be hard to control in the model. Compared to the time series models and later introduced system dynamics models, the global model behaviour of an agent-based model cannot be defined directly. Instead, it can only be determined at individual level, and emerge as a result of all individuals that are included in the model and follow their own behaviour rules (Borshchev and Filippov, 2004). This also causes difficulties for model validation and verification. Agent-level data elasticities and model behaviour sensitivities to the changes of agent-level data are essential for simulation (Al-Alawi and Bradley, 2013a). Furthermore, the powerful ability of incorporating more dynamics in the model also requires much more computational resources, which can be a significant constrain for modelling (Rahmandad and Sterman, 2008, Macal and North, 2010).

System dynamics, as its founder Jay W. Forrester put it, is "the study of information-feedback characteristics of industrial activity to show how organizational structure, amplifications (in policies), and time delays (in decisions and actions) interact to influence the success of the enterprise" (Forrester, 1961, Forrester, 1958). It allows interactions among stakeholders within the system and has the ability to accommodate feedback and dynamics over the time dimension. System dynamics modelling is between agent-based modelling and time series modelling in terms of granularity of the model. It has the ability to incorporate individual behaviours in the model, normally with the constrains of uniformed distribution in consumer tastes and behaviours (Rahmandad and Sterman, 2008). Although system dynamics modelling does not depict specific heterogeneity in the model, model behaviour variation that caused by the underlying heterogeneity within the population can be observed from further sensitivity analyses. It also allows global definition of model behaviours, which enables straightforward modelling of aggregated effects of consumer choices in AFV adoption (Borshchev and Filippov, 2004). Another notable feature of system dynamics is that the modelling algorithm is based on continuous variables and a set of differential equations mathematically (Borshchev and Filippov, 2004, Popkov and Garifullin, 2007). Instead of discrete events and cycles modelled in agent-based models, system dynamics variables are continuous and mostly homogenous within one stock (Rahmandad and Sterman, 2008). In the context of AFV adoption, system dynamics modelling was often used to capture the accumulated effects of dynamics and feedback among different stakeholders (Shepherd, 2014). Struben and Sterman (2008) developed a system dynamics framework to model the uptake of AFVs. Extended on the Bass diffusion concept, the model framework included the influences of word of mouth, marketing and social exposure to AFV adoption. These impacts are hard to depict as an individual and discrete incident, however, can be captured within a system dynamics model. Depending on the aim of the modeller, different policy dimensions were added to system dynamics models of AFV adoption (Shepherd, 2014). In the work of Walther et al. (2010), manufacturer strategies and responses were investigated in a case study of California's low emission regulations. Recommendations for appropriate manufacturer strategies were provided. A system dynamics model that studied adoption of natural gas cars in Switzerland incorporated the co-evolution of natural gas cars and refuelling infrastructures (Janssen et al., 2006). Key indicators to assess the performance of the ongoing adoption process were provided.

Table 2-1 Summary of the three modelling methods

	Time Series	Agent Based	System Dynamics
Time dimension	Allow	Allow	Allow
Aggregated effect	Allow	Allow, more granular	Allow, more aggregated
Stakeholder interactions	No	Allow	Allow
	• Simple in format • Easy to implement • Need historical data and presumed market conditions	• Granular • Allows heterogeneity within the population • Bottom-up modelling	• High-level and more aggregated • Does not allow heterogeneity within the population • Global control of the model behaviour

In summary, the three modelling methods reviewed in this section are all able to capture the dynamics of AFV adoption quantitatively (Table 2-1). Time series modelling has the simplest format and is easy to implement. However, it lacks the ability to incorporate interactions between stakeholders and depict competitions between innovations. Both agent-based modelling and system dynamics modelling can capture all three aspects of the dynamics in AFV adoption. Agent-based modelling is more granular in modelling algorithm with the ability to model heterogeneity within the population. However, the bottom-up modelling approach does not allow direct global control over model behaviours. All calibration and model adjustments need to be done through manipulation of low-level parameters. It also requires more computational power compared to other modelling methods. System dynamics modelling has the ability to model the aggregated effects of consumer choices from global model formulation. It can incorporate individual consumer choices, however, does not allow specific heterogeneity within the population. Based on different aims and focuses of the model, these three modelling tools can be utilized to simulate the dynamic AFV adoption process.

These three modelling approaches can also be incorporated with each other depending on the aim of the model. For example, in the study done by Shafiei et al. (2013), system dynamics modelling and agent-based modelling are integrated to account for the different socio-demographic factors in the diffusion of AFVs. The model constructed by Struben and Sterman (2008) also incorporated the Bass diffusion model, which is a time series model, to factor in dynamics within the social environment of AFV diffusion.

This section reviewed three modelling methods that quantitatively depict the dynamics in AFV adoption caused by the aggregated effect of consumer choices. In the following sections, common dynamics within AFV adoption will be reviewed in the following two aspects: the social environment where consumer choices happen and situational factors within consumer choices.

2.4.2 Dynamics in social environment of AFV diffusion

This section summarizes the AFV adoption dynamics in the social environment of consumer choices. In Rogers' adoption theory, social system where the diffusion takes place is a crucial element in the innovation diffusion process (Rogers, 2003). Within the social system, both external and internal influences can affect the success of the diffusion (Rogers, 2003). In regard to the diffusion of AFVs, external influences largely come from the mass media marketing while internal influences are from individual's social network.

Correspondingly, in the Bass diffusion model, these influences are quantitatively captured as the innovator coefficient and imitator coefficient (Bass, 1969). The innovator coefficient p describes the effects of marketing, which are equivalent to the external influences. The imitator coefficient q describes the effects of word of mouth from personal social network, which are similar with the internal influences (Bass, 1969, Al-Alawi and Bradley, 2013a, Sterman, 2000). In the Bass diffusion and time series models, these two types of influences are the main driver of the diffusion process (Bass, 1969). In the model formulation, internal influences also depend on the population of adopters, which means the influences of word of mouth will become stronger if the number of adopters grows. This formulates a reinforced feedback about the word of mouth effect in the social environment of consumer choices. Similarly, in system dynamics models (Shepherd et al., 2012, Struben, 2006, Walther et al., 2010), the reinforcing effects were also captured using a feedback loop between AFV adoption rate and consumers' willingness to purchase. In the model framework proposed by (Struben and Sterman, 2008), the word of mouth effects were further divided into social exposure by AFV drivers and social exposure by non-AFV drivers. In an agent-based model, the word of mouth effects were also addressed as the number of AFV drivers the respondents talked to (Zhang et al., 2011a). The market pull from word of mouth effect was proven to have a significant impact to the adoption of AFVs in this study. In another agent-based model created by Eppstein et al. (2011), the reinforcing feedback between social network influences and PHEV adoption was incorporated in the model. Combined with marketing effects, the dynamics in social environment of consumer choices were depicted in this study.

The dynamic feedback in the social environment where consumers make powertrain choices can provide significant momentum for AFV diffusion take-off. In the next section, dynamics within consumer choice are discussed.

2.4.3 Dynamics in situational factors of consumer choices

Another group of significant dynamics that were often addressed in the literature are around the situational factors. In AFV adoption modelling studies, situational factors are often altered in scenario tests to observe the impacts of such factors on AFV adoption and test the intensity of relevant policies for AFV adoption promotion. Common manipulation of the situational factors in consumer choices are: purchase price reduction (by financial incentives or tax redemption (Diamond, 2009, Potoglou and Kanaroglou, 2007, Mau et al., 2008)); operating cost reduction (by exemption of road tax (Hackbarth and Madlener, 2013, Hoen and Koetse, 2014, Chorus et al., 2013)); and driving experience improvement (by increased number of refuelling stations (Sikes et al., 2010)). The varying values of situational factors were mostly exogenous with no feedback within model boundary.

In system dynamics models, because this modelling approach is particularly interested in the endogenous feedback within system boundary, the changes in situational factors are interrelated with the adoption behaviours. It was often assumed in the system dynamics models that the improvements in vehicle performance, such as vehicle purchase price drop, driving range extension, fuel efficiency improvement, and refuelling infrastructure increase, are because of the maturity of the technology and surrounding economics (Shepherd, 2014). In the system dynamics model constructed by Meyer and Winebrake (2009), the co-development of hydrogen fuel cell vehicles and hydrogen refuelling stations were investigated. The reinforced relationship between hydrogen vehicle market share and density of hydrogen stations was captured. Similarly, technological research and development of AFV powertrains was lined with the uptake of AFV market shares as well. Vehicle attributes that contribute to the overall attractiveness of the powertrain can be improved endogenously though learning by doing, R&D, and scale economies (Struben and Sterman, 2008, Shepherd et al., 2012, Struben, 2006, Keith, 2012a). Such dynamics captures the maturing process of the technology and presents a more comprehensive view on the development and adoption of AFVs.

2.5 Dynamics in consumer attitudes and preferences

In the Section 2.4, the dynamics identified in AFV adoption were reviewed. Consumer choice social context and situational factors are all dynamic with feedback with AFV adoption. In this section, possibilities of dynamic consumer attitudes and preferences are discussed.

In the review paper of Liao et al. (2017), dynamic consumer preference and attitudes were addressed. The authors provided two reasons for dynamic consumer preferences for EV. The first reason is that since EVs have just emerged in the vehicle market, consumers are expected to adopt the technology depending on their acceptance of innovation at different time points. The consumer preferences of early adopters and late adopters are expected to have different preference profiles (Rogers, 2003). Bockarjova et al. (2014) assigned people into five categories by their expected time of market entry and found that the preference profiles of different categories were different. Therefore, it is reasonable to assume that the preferences of consumers can vary over time. The second reason is that since EV is still relatively new to most consumers, their preferences and attitudes about the technology are expected to evolve along with technological progress and market penetration of the powertrain. If the consumer preferences shift significantly, the modelling results using static preference assumption may only be valid for a limited time (Liao et al., 2017).

Recall from Section 2.3.2, three subjective factors that are related to consumer attitudes and preferences were concluded: consumer demographics, consumer personal norm and beliefs, and consumers' experience with alternative powertrains. These three groups of factors determine consumer preferences towards AFV technology. It is intuitive to assume that changes in these factors over time can shift consumers' attitudes and preferences. For example, various studies reveal that consumers age has negative effects with their attitudes towards AFVs (Ziegler, 2012, Hackbarth and Madlener, 2013, Hidrue et al., 2011, Achtnicht et al., 2012), which suggests that younger generations are more likely to become adopters of AFVs. Over time, with increasing number of young people becoming mainstream vehicle consumers, the overall consumer preferences in the market may shift to be preferable to AFVs. In addition, Jensen et al. (2013) concluded that experience with EVs would shift consumer preferences and attitudes in a positive way toward adoption. Bühler et al. (2014) also revealed that experience can significantly change the perception of EVs in a field study conducted in Germany. This also provides evidence that the consumer preferences can shift during AFV diffusion process over time (Rezvani et al., 2015).

A few studies have addressed the importance of dynamic consumer preferences and attitudes. In the works by Maness and Cirillo (2012) and Liu and Cirillo (2017), a dynamic discrete choice model incorporates the repeated purchase behaviours to capture the changes in consumer preferences. However, endogenous dynamics in situational factors and social environment were not incorporated in the model. The implications of changes in consumer preferences and attitudes to AFV adoption have yet to be investigated, especially with incorporation of other endogenous dynamics in the AFV diffusion process.

2.6 Research hypothesis and research questions

Based on the literature reviewed in this chapter, further work is required to understand the possibility of changes in vehicle consumer preference and their potential implications to AFV adoption. Therefore, this research hypothesizes that the dynamics around consumer attitudes and preferences can affect the adoption of AFV and intends to answer the questions below:

- What are the dynamics of consumer attitudes and preferences in AFV adoption process?
- What are the implications of the changes in consumer attitudes and preferences to the adoption AFV?
- What are the potential interventions to promote AFV adoption based on a dynamic and holistic system viewpoint?

Chapter 3 Research Design

Chapter 3 introduces the design of the research. The chapter first explains the modelling method selection by presenting the requirements for the research design in order to answer the research questions and proposing a combined modelling approach of i) discrete choice modelling and ii) system dynamics modelling. Modelling steps of the two selected modelling techniques are subsequently introduced with elaboration of commonly used modelling tools for each technique. Based on the two modelling techniques, the modelling approach and steps for this research are established. Next, the chapter introduces the context and boundary of the research model, along with time horizon selected for the simulation. Finally, detailed research steps are introduced in three stages.

3.1 Research requirements and method selection

Based on the research questions proposed in the previous chapter, this section selects a suitable research approach for testing the research hypothesis. The section starts with discussion on the research requirements. Based on the specific requirements, the research design that incorporates two modelling methods is then introduced. The modelling steps of the two modelling methods that are adopted in the research design are also demonstrated. In the end, a summary and step by step research framework are given.

3.1.1 Requirements for the research design

To tackle the research question proposed in the end of Chapter 2, several requirements for the research design are proposed. First, the research needs to focus on consumer choices and decision-making. The research goal is to understand the dynamics around consumer choices and attitudes in regard to AFV purchases. Hence, this thesis takes consumers as the main stakeholder in the overall AFV adoption process. This research angle allows AFV adoption understandings to be based on individual and fundamental aspects and work its way up to the more aggregated and societal aspects.

Second, in order to understand consumer choices and preferences comprehensively, the research model needs to be quantitatively informed. Quantitative information not only provides more intuitive evidences for modelling and analyses, but also allows model behaviours and outputs to be observable and measurable. Especially for intangible factors in AFV adoption, such as consumer preferences and attitudes, quantitative information around these factors serves the purpose of the research much better than only qualitative information.

Third, the research should be systematic and holistic. Because the research goal is to investigate the implications of changes in consumer choices and preferences, the model should be able to allow changes in variables through time. Changes in variables can be due to external forces that are outside of the research scope. However, more importantly, changes in variables that are due to endogenous feedback need to be incorporated in the model. Feedback loops between model variables ensures that the dynamics behind model behaviours to be captured clearly and timely. This feature of the research design is critical to achieving the research goal and answering the proposed research questions.

3.1.2 Combined modelling approach

To satisfy the three requirements for the research design, a combined modelling approach of both discrete choice modelling and system dynamics modelling is adopted in this thesis. In order to focus on consumer choice process and provide quantitative information, a discrete choice model is incorporated in the research design. Recalling from Chapter 2 Section 2.3.1, within research approaches for studying the choices of consumers, discrete choice modelling is excellent at quantitatively depicting consumer decision-making and evaluation process in regard to product purchases. It is also based on data collected from real-world vehicle consumers, which endues the final model with more reliability. This modelling technique is very suitable for modelling consumer decision-making process and quantitatively fulfils the foundation of the research model.

To achieve a systematic and holistic view on AFV adoption, a modelling approach that depicts the dynamics around the aggregated effects of consumer choices in AFV adoption needs to be selected. In the literature review (Section 2.4.1), three modelling approaches were mentioned. Among them, system dynamics modelling allows timely feedback between model variables as well as gradual changes in all system variables through endogenous dynamics in the model. This feature of system dynamics modelling is unique among the three modelling methods and can satisfy the requirements of the research design precisely. In addition, the system dynamics model's ability to visualize dynamics and relationships between model variables provides extra clarity to model construction as well as model communication. Hence, system dynamics modelling is applied as the main modelling tool for the research. In the final research model, the aggregated adoption process that involves multiple stakeholders is achieved through system dynamics.

Therefore, a combined modelling approach of discrete choice modelling and system dynamics modelling is selected to fulfil the aim of this research. The steps of each modelling methods will be introduced in the following two sections.

3.1.3 Discrete choice modelling

Discrete choice modelling is a modelling tool that can measure consumer decision-making quantitatively. The general steps of completing a discrete choice model study is presented in Figure 3-1.

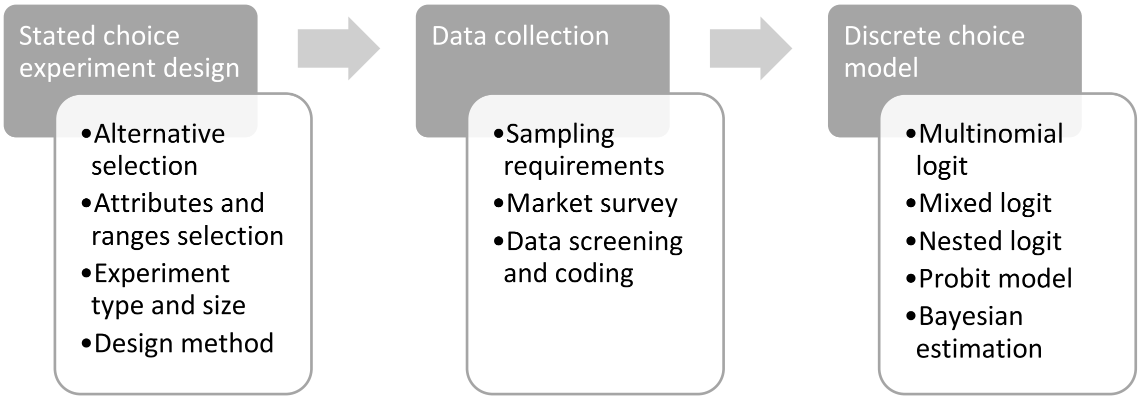


Figure 3-1 Discrete choice modelling steps

To perform a discrete choice model, consumer choice data need to be collected first. A stated choice experiment specifically designed for choice modelling is normally used to collect consumer choice data (Hauser and Rao, 2004). The design of stated choice experiment usually starts with determining the alternatives that are provided in the choice scenarios. Derived directly from the aim of the discrete choice model, all alternatives that are possible to be included in consumer consideration sets should be considered in this step (Hensher et al., 2005). Next the attributes and their value levels are determined. This step commonly requires a pilot study or a thorough review of the literature to help identification of the product attributes and their value levels (Reed Johnson et al., 2013). The design should avoid attribute ambiguity by providing relatable attributes with relatable descriptions (Hensher et al., 2005). The value selected for each attributes should include extreme conditions and be sensibly divided into multiple levels (Louviere et al., 2011). In experimental design, the experiment type and size can largely affect the efficiency of an experiment. A labelled stated choice experiment can differentiate different brands/types alternatives in the experiment and therefore acquire consumers' opinions associated with the brand/type of the alternative (De Bekker-Grob et al., 2010). The size of the experiment is determined by all the factors above. To achieve a manageable experiment size, design methods such as A-efficiency and D-efficiency design that depend on the efficiency of the experiment design are commonly used (Kuhfeld, 2010, Crabbe and Vandebroek, 2012).

Once the experiment is established, data collection is conducted via market survey. The survey format can be through mail (Brownstone et al., 2000), online panel (Hackbarth and Madlener, 2013), or asking respondents to fill out questionnaires at survey station (Helveston et al., 2015). Upon the beginning of data collection, sampling requirements should be first defined. The sample distribution and specific requirements directly affect if the collected data can accurately reflect consumer preferences within the targeted population (Hensher et al., 2005). With well-defined sampling quota, the collected data are more reliable. Once data collection is done, proper data screening and coding is required as well. Data screening is used to eliminate invalid responses (DeSimone et al., 2015), while data coding is to facilitate the following modelling step.

After data collection, model regression is performed for the final discrete choice model. There are different model fits for a discrete choice model (Train, 2003). A standard multinomial is the most basic and commonly used model fit as it reveals consumer preferences despite heterogeneity in the panel or correlations between provided alternatives (Train, 2003). Other model fits, such as mixed logit, nested logit and probit model cater to various goals and structures of the model. For example, mixed logit model is suitable for interests in heterogeneity within the panel (Hensher and Greene, 2003), while nested logit is excellent in acquiring consumer preferences regarding alternatives that are categorized into different classes (Bliemer et al., 2009).

3.1.4 System dynamics modelling

This section introduces the steps of system dynamics modelling process. Figure 3-2 presents the iterative modelling steps of system dynamics. System dynamics modelling, as a part of learning process, is iterative (Sterman, 2000), which is represented by the interlinked lines between each step located in the centre of Figure 3-2. System dynamics models usually go through constant iteration, continual questioning, testing, and refinement. In the following paragraph, details of each modelling step are introduced. Although the modelling steps are elaborated in an orderly fashion, the real modelling process involves iterations of modelling steps from one to any other (Sterman, 2000).

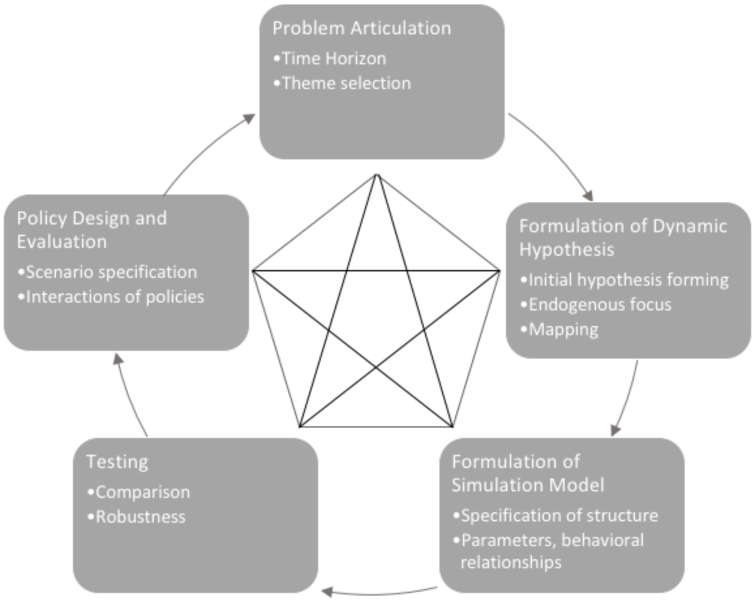


Figure 3-2 System dynamics iterative modelling process (adapted from(Sterman, 2000))

The initial step starts from problem articulation where the aim and focus of the model are defined with time horizon selected. In the next step, dynamic hypothesis is formulated. Endogenous relationships about key variables of the model are the focus of this step. The preliminary dynamics structure is proposed from such endogenous feedback. Modelling tools such as causal loop diagram, stock and flow maps are extremely useful to formulation of the dynamic hypothesis (Ford, 1999). In the next step, the simulation model is formulated. In this step, the model moves from conceptual realm of diagrams to fully specified formal model, with complete equations, parameters, and initial conditions (Sterman, 2000). Model testing is the next step. However, the testing of the model is especially iterative and normally conducted along each modelling step. Partial model tests are critical to construct a system dynamics model that are complex (Martinez-Moyano and Richardson, 2013). The final modelling step is policy design and evaluation. In this step, the modelling goal is often achieved by undertaking various scenario tests under different parameter settings.

Apart from the iterative modelling approach, system dynamics modelling also has two main diagramming tools for depiction of the feedback of the system: causal loop diagram, and stock and flow diagram. Causal loop diagram is a powerful tool to map the feedback structure of complex system (Sterman, 2000). The diagram usually consists of variables connected by arrows indicating the causal influences between these variables (Figure 3-3). The arrows denote the causal links among the variables and are assigned with polarities, either positive (+) or negative (-) to indicate how the dependent variables change when the independent variable change. Loops in the diagram are highlighted by loop identifier. "R" means that there is a reinforced (positive) relationship between the two variables (left of Figure 3-3), while "B" indicates the variables having a balancing (negative) feedback (right of Figure 3-3).

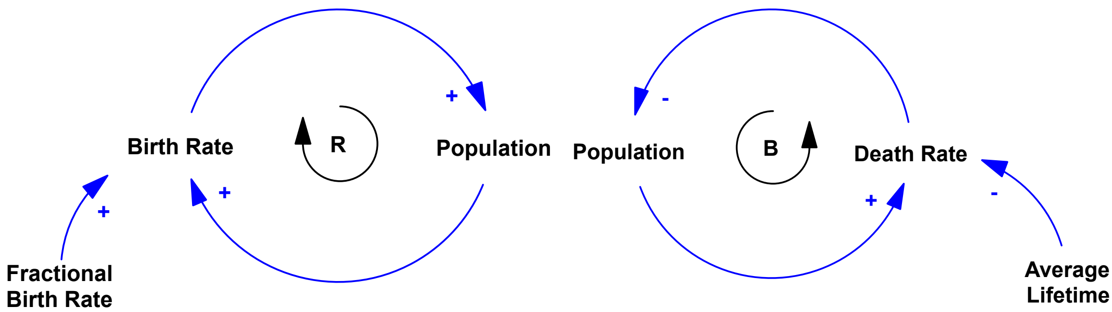


Figure 3-3 Causal loop diagram example

Stock and flow diagrams present one of the core concepts of dynamics system theory, which is the stock and flow structure. Stocks are accumulations and capture the state of the system. Flows represent the value/information that goes in and out of the stock with a period of time (shown in Figure 3-4) (Sterman, 2000).

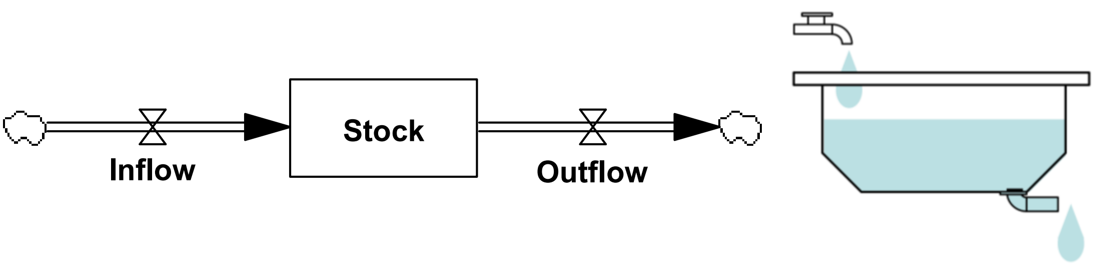


Figure 3-4 Stock and flow diagram example and the bathtub metaphor

A common metaphor for the stock and flow concept is the bathtub and faucet situation, where the stock can be seen as equivalent to the bathtub that represents the accumulation of the water flowing in through the incoming faucet less the water flowing out through the drainage faucet, with the two faucets symbolising the inflow and outflow of the stock (right in Figure 3-4). In mathematical expression, the net change of stock at time t can be expressed in Equation 3.1 (Sterman, 2000).

$$d(Stock)/dt = Net\ change\ in\ Stock = Inflow(t) - Outflow(t) \qquad (3.1)$$

3.1.5 Modelling approach summary

Based on the modelling steps of each modelling techniques introduced in previous two sections, a summary of the modelling approach of this research is presented in this section. The main modelling technique used is system dynamics modelling since it can accommodate larger research scope with more flexibility in terms of variables and dynamics included. Therefore, the main modelling process follows the steps of system dynamics modelling. For the choice model, the main purpose of this modelling method is to provide quantitative information to the main model and also inspire extra dynamics around consumer attitudes and preferences.

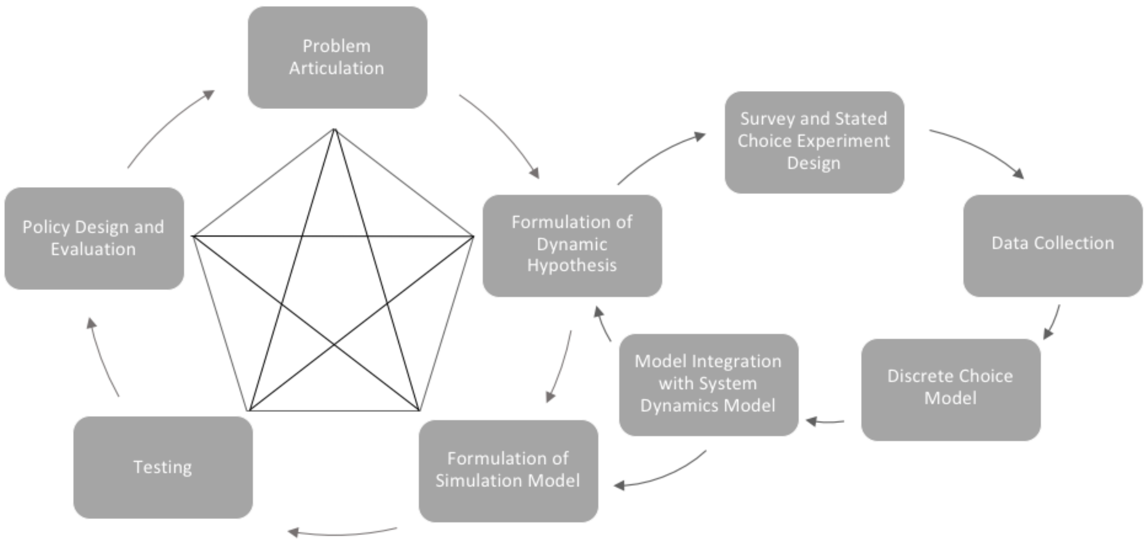


Figure 3-5 Modelling step framework

A modelling process framework is developed based on the modelling steps of each method. Figure 3-5 presents the modelling step framework. The iterative modelling process is adopted with incorporation of the discrete choice modelling process between the dynamic hypothesis formulation and model formulation steps. The results of the discrete choice modelling refine the model dynamic hypothesis as well as provide data for model formulation. With this framework established, detailed research steps will be discussed in Section 3.3. In the next section, as the problem articulation step for the research, model context, model boundary, and time horizon will be defined.

3.2 Research context and system dynamics model boundary

Based on the model framework identified in previous section, this section introduces the context and boundary of the combined model. The Australian vehicle market as the model context is introduced first. Next, the reasons behind the Australian vehicle market case study and implications of such case study are discussed. The section then defines the system dynamics model boundary. Reasons for excluding certain variables and dynamics in the system dynamics model are justified. Finally, time horizon of the research model is introduced.

3.2.1 Model context

As part of problem articulation in modelling steps, model context is introduced in this section. To model the consumer choices in regard to AFV purchases, a vehicle market is needed to provide the context for the model. For this research, the Australian vehicle market is selected as case study to provide context for the model. The following three reasons explain why the Australian vehicle market is selected.

First, the Australian vehicle market is established and stable before the emergence of alternative fuel powertrains. Australian has high vehicle ownership per capita (740 vehicles per 1000 person) (Australian Bureau of Statistics, 2014). Although the yearly vehicles sales volume fluctuates due to economics, there are no significant increases or decreases in overall vehicle fleet size. The mature vehicle market avoids possible consumer preferences changes due to exogenous factors such as vehicle market growth and economic growth, therefore provides a suitable model context for studying consumer choices and preferences endogenously.

Second, the Australian vehicle market has high diversity and competitiveness. There are 67 vehicle brands offering more than 350 vehicle models originated from North America, Europe, and Asian (Federal Chamber of Automotive Industries, 2014). The immense diversity in the market provides Australian vehicle consumers abundant vehicle choices and cultivates consumers' awareness to various vehicle models and technologies.

Finally, there is little to no policy interventions for AFV adoption promotion in the Australian vehicle market. Unlike other equally matured and diverse vehicle markets, such as the US, Japan, and Europe, the Australian market has little to no policy reinforcement specifically in promoting alternative fuel powertrains. Although consumers are provided abundant vehicle models in a range of powertrains, there are no incentives for choosing a particular one. This means Australian consumers are not influenced by exogenous policy interventions and their preferences are purely established due to their background and beliefs instead of biased towards any powertrains or features because heavy incentives or educational campaigns.

Dynamics around consumer choices and AFV adoption in the Australian vehicle market reflects common dynamics of AFV adoption in an established vehicle market with high competitiveness. Due to these characteristics, the Australian vehicle market is insightful and referential to other matured vehicle markets such as the American and Europe vehicle markets. Furthermore, due to its purely market driven adoption environment, the market can act as a plain canvas and is excellent for scenario tests with different policy interventions. These three characteristics of the Australian vehicle market make it very suitable for providing model context for this research.

3.2.2 System dynamics model boundary and time horizon

This section defines the boundary and time horizon of the system dynamics model. In the research model, AFV adoption in the Australian vehicle market alone is simulated. However, AFV technologies also emerge in other vehicle markets in the world, the global AFV adoption process can affect the AFV adoption in Australia as well. The model boundary defines the scope of the research model, and helps to draw the line where only dynamics and variables that are interesting to the research topic are included in the model (Sterman, 2000). Table 3-1 presents the model boundary chart. Endogenous, exogenous, and excluded variables of the research model are listed.

Table 3-1 Model boundary

Endogenous	Exogenous	Excluded
▪ Consumer attitudes and preferences ▪ Consumer awareness ▪ Partial vehicle performance ▪ Marketing funding ▪ Vehicle model availability	▪ Fuel price ▪ Fuel distribution ▪ Partial vehicle performance (technical development and purchase price)	▪ Macro Economy ▪ Second-hand vehicle market ▪ Heavy vehicle market ▪ Well-to-tank GHG emissions

In Table 3-1, endogenous variables to the research model includes variables that depict consumer attitudes and awareness, variables that capture vehicle manufacturers' reactions to the change in AFV adoption behaviours, and some of the vehicle performance that are relatively isolated in local market. Exogenous variables are critical to complete key feedback loops and included in the model. However, there is no endogenous feedback around these variables. Changes in such variables are due to external forces. In this model, exogenous variables include fuel related variables, partial vehicle performance such as technical development of AFV technologies and the vehicle purchase price. The reason for excluding fuel related variables from endogenous feedback is that fuel price-distribution system is largely dependent on other transportation and energy related areas. The endogenous feedback from Australian AFV sale volumes can be negligible to fuel price and distribution. For partial vehicle performance, since the Australian vehicle market is relatively small in sales volume, the revenues created by AFV sales growth are insignificant to boost up the development of technology development and purchase price drop due to powertrain maturing. These variables mostly depend on the global AFV adoption behaviours.

In the last category of Table 3-1, the excluded variables/factors are listed. Macro economy growth/recess can affect multiple model variables such as consumer demands, vehicle price, and fuel price. However, it is not included in the model scope. The economy system is a complicated system of its own, it is a deviation of the modelling goal to include such a complex system within the model. For second-hand vehicle market and heavy vehicle market, the consumer preferences for these markets are intuitively different from new vehicle market. AFV that flow into second-hand vehicle market and heavy vehicles in alternative fuel powertrains can affect the overall AFV adoption to some extent. However, it is not the aim of this research to understand the consumer preferences in those markets. Hence, these two vehicle markets are not within the scope of this research. The last factor listed in this category is the well-to-tank GHG emissions. The overall GHG emissions caused by a vehicle not only include the tank-to-wheel emissions, but also the well-to-tank emissions, which account for the emissions caused by deriving the energy from natural resource. In the context of Australia, since the Australian electricity is largely generated by noun-renewable fossil fuels (Department of the Environment and Energy, 2018), the relatively large well-to-tank emissions of Australian electrified vehicles can offsets the emission benefits brought by these vehicles during the tank-to-wheel phase. For the scope of this thesis, which are much focused on the consumer purchase and usage phase of the vehicle, the emissions from well-to-tank phase is outside the boundary of the model.

For time horizon of the research model, the model starts with year 2000, when the dynamics of the vehicle powertrain electrification trend started. In that year, hybrid electric vehicles are introduced into the market. It is around the same time when the landscape of the AFV market started to change with emerging technologies. The time projection of the model goes to 2075. Since AFV adoption process is a lengthy process, the time projection in the model contains 6-7 vehicle lifetimes to model the gradual diffusions of AFV technologies.

This section introduced the research model context, boundary and time horizon so that the research model scope is explicitly defined. In the next section, the rest of the research steps will be presented in three research stages.

3.3 Research stages

With research context and boundary determined, this section introduces the three research stages in this thesis. Based on the system dynamics iterative modelling steps (Sterman, 2000), the research was conducted following three stages: construction of preliminary model with dynamic hypotheses, model formulation via discrete choice model, and lastly final system dynamics model establishment and testing. These three stages followed the research step framework. In Figure 3-6, the three research stages are demonstrated within the research step framework. Dynamic structures of the final model were constructed first by theoretical foundations identified in literature, and then refined in the subsequent research of market observation, market survey, and discrete choice model. The research revisited the dynamic structure in every research stage until a satisfied structure was established at the end.

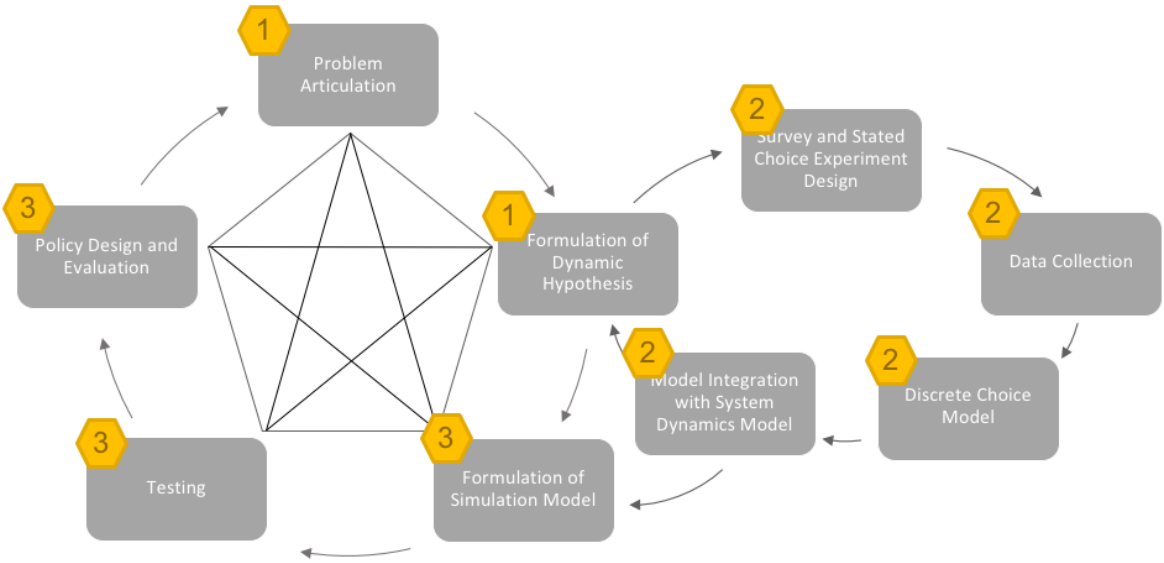


Figure 3-6 Research stages shown in modelling step framework

3.3.1 Preliminary dynamic hypotheses formulation

Preliminary dynamic hypotheses were formulated in the first research stage (conducted in Chapter 4). The theoretical foundation that provides the framework of the final model was first established via relevant theory searches in literature. Theories on individual consumer decision-making and societal innovation diffusion were investigated. Based on these theories, a step by step consumer decision-making process on AFV purchase was constructed according to established theories. This process followed the consumer-decision making process in general merchandise purchases as well as the process of individual adopting a new product. In addition, the process of innovation diffusion was also considered to ensure that the process incorporated the aggregated effects of individual's decision-making. This process acted as a guide for the subsequent key variable identification.

Key variables within each step were identified next. These key variables contained factors that were relevant directly to consumers decisions such as vehicle performance and consumer preferences, as well as factors that were related to the market environment that provided the context for consumer evaluation such as vehicle model availability and market awareness. Possible dynamics around key variables were hypothesized. Three endogenous feedback loops in AFV adoption were proposed based on the adoption steps and key variables.

Based on the identified key variables, an observation of historical trends in the Australian vehicle market was conducted next. In the market observation, historical data on tangible key variables were collected and analysed. The goal of this market observation was to provide empirical evidence for the dynamic hypotheses around key variable that were proposed earlier. Historical trends observed from the observation also acted as data input for later system dynamics model formulation. Furthermore, additional insights about dynamics around key variables were revealed. Based on the theoretical foundation and market observation, the preliminary dynamic hypotheses were established.

3.3.2 Model formulation via discrete choice model and market survey

In the second research stage, the intangible key variables were investigated through a market survey and a discrete choice model (conducted in Chapter 5). Insights revealed in the market survey and the discrete choice model helped refine the preliminary model quantitative and qualitatively.

The market survey was designed to investigate consumers' attitudes regarding to alternative fuel technologies, and more importantly to carry out a stated choice experiment that allowed data collection for the discrete choice model. This approach is commonly used in the field of choice modelling (Al-Alawi and Bradley, 2013a). A survey with stated choice experiment can efficiently gather information on consumer responses and choices for discrete choice modelling (Chorus, 2015).

The market survey contained attitudinal questions and a stated choice experiment which were designed for later discrete choice model. The attitudinal questions were designed to capture consumers' familiarity, knowledge level, and willingness to consider AFVs. For the stated choice experiment, D-efficiency design was adopted in experimental design because it is easier and faster for computational calculations (Sterman, 2000). In addition, this design method provides invariant comparison between two experimental designs that are under different coding schemes (Sterman, 1984).

The stated choice experiment chose vehicle attributes that were identified from the literature. The experiment varied the value of these vehicle attributes and provided different combinations of vehicle attribute values to respondents in multiple choice scenarios. The experiment contained 96 questions in total and were divided into 6 blocks of 16 choice scenarios. 537 responses were collected from Australian vehicle consumers who had purchased a vehicle within 24 months.

With the data collected from the stated choice experiment, a discrete choice model was performed. The choice model reveals quantitative data about consumer preferences in the Australian vehicle market. Standard multinomial logit and mixed logit model fits were performed. The standard multinomial logit model allowed consumer preferences against each vehicle attributes as well as the alternative-specific coefficients (ASCs) that depicts the unobserved consumer opinions around each powertrain. The mixed logit model provided additional information on the variation in consumer preferences due to respondents' demographic characteristics. Combined with the attitudinal questions in the market survey, the discrete choice model provided quantitative information for dynamic model formulation as well as qualitative insights that refined the dynamic structure of the final model.

3.3.3 Final system dynamics model construction and testing

The third stage of this research was final system dynamics model construction and testing (conducted in Chapter 6 and Chapter 7). After the discrete choice modelling in the previous research stage, an integration of discrete choice model and the system dynamics model was implemented. The model integration added the time dimension for and reduced complexity of the discrete choice model. It also inspired additional feedback loops to depict dynamics in consumer biases in the dynamic structure. A specific discrete choice model regression for system dynamics model provided quantitative input for the final model formulation.

Based on the repeatedly refined dynamic structure, the final model structure was established. A model calibration was sequentially performed to estimate key model constants as well as to match the model behaviour to real-world data. The model calibration determined the behaviour of the final simulation model. Based on the model constants derived in the model calibration, the model base scenario was established. Two model tests, sensitivity analysis and model behaviour test, were performed to gain more confidence in the model. The model base scenario was also further analysed in terms of the performances of each key feedback loop and the specific dynamics presented in the AFV adoption projection.

Using the base scenario as foundation, extreme condition scenarios of the model performances were performed next. Various scenarios where the values of key variables in the model were altered in order to achieve optimal AFV adoption performance were explored. Influences of key variables within the model were investigated. Finally, discussion and tests on possible policies and interventions for promoting AFV adoption based on real world context were presented.

3.4 Summary

This chapter introduced research design of the thesis. The research approach and methods were introduced and justified. Research context and boundaries were defined. Research steps were introduced through three stages: construction of preliminary model with dynamic hypotheses, model formulation via discrete choice model, and final system dynamics model establishment and testing. Aims and detailed research steps of each stage were demonstrated. In the following chapters, the research work and results in the three research stages will be presented.

Chapter 4 Dynamic Hypothesis Formulation

Following the methodology introduced in the previous chapter, the initial dynamic hypothesis for the system dynamics model is developed in this chapter. The dynamic hypothesis in this chapter is built on two parts: i) previous theories about consumer choices and innovation diffusion and ii) an Australian market observation of historical trends of key dynamic variables. In the first part, theoretical foundations around consumers making their purchase decisions and products being selected for purchase are explored. Based on the theoretical foundations, key variables in the system dynamics model and their dynamic structures are subsequently identified. These key variables guide a subsequent historical trends observation in the Australian market context. Evidence and trends from the past can depict the nature of change in vehicle adoption and provide us guidance on the possibilities and directions of future development and transformation (McDowall, 2016). Historical trends detected from the market observation help to develop better understandings of AFV adoption in Australia and subsequently provides additional insights for the construction of the preliminary dynamic hypothesis. In addition, time series data collected from this chapter will act as data input for later system dynamics model formulation and calibration.

The structure of this chapter is given as follows. Theories on consumer choices and decision-making are first introduced. Based on the theoretical foundation, key variables in AFV adoption model and their dynamic structures are identified. Next, a market observation on historical trends of these key variables is conducted. This observation covers the deployment of Australian AFV market and historical trends of key dynamic factors in the AFV adoption process. In the end, combining the theoretical and observational findings, key dynamics in Australian AFV adoption are identified and mapped using a causal loop diagram.

4.1 Theoretical foundation of dynamic hypothesis development

Since AFV adoption is fundamentally based on individual purchases of different vehicle powertrains, understanding how consumers make their vehicle purchase decisions is of great importance to the goal of the research and can serve as the foundation for developing the dynamic hypothesis of the research model. This section explores the theories of the consumer decision-making process and provides a theoretical foundation for later on research model construction.

Decision-making theories have long been a focus for many researchers. A great number of subsequent theories have been developed to demonstrate consumers' thought processes while purchasing a product. One of the models that was developed in the 1968 and continuously perfected over time is the consumer decision process theory by Engel, Blackwell, and Miniard (1968, 1995). The model (from now on will be called as the EBM model) has been widely used in various consumer behavior studies because it clearly presents the steps for need satisfying behavior while comprising of a broad range of factors that influence decisions. Figure 4-1 presents the six steps for describing the process of consumer decision-making: need recognition, information search, alternative evaluation, purchase, outcomes, and post-consumption behavior (Engel et al., 1995).

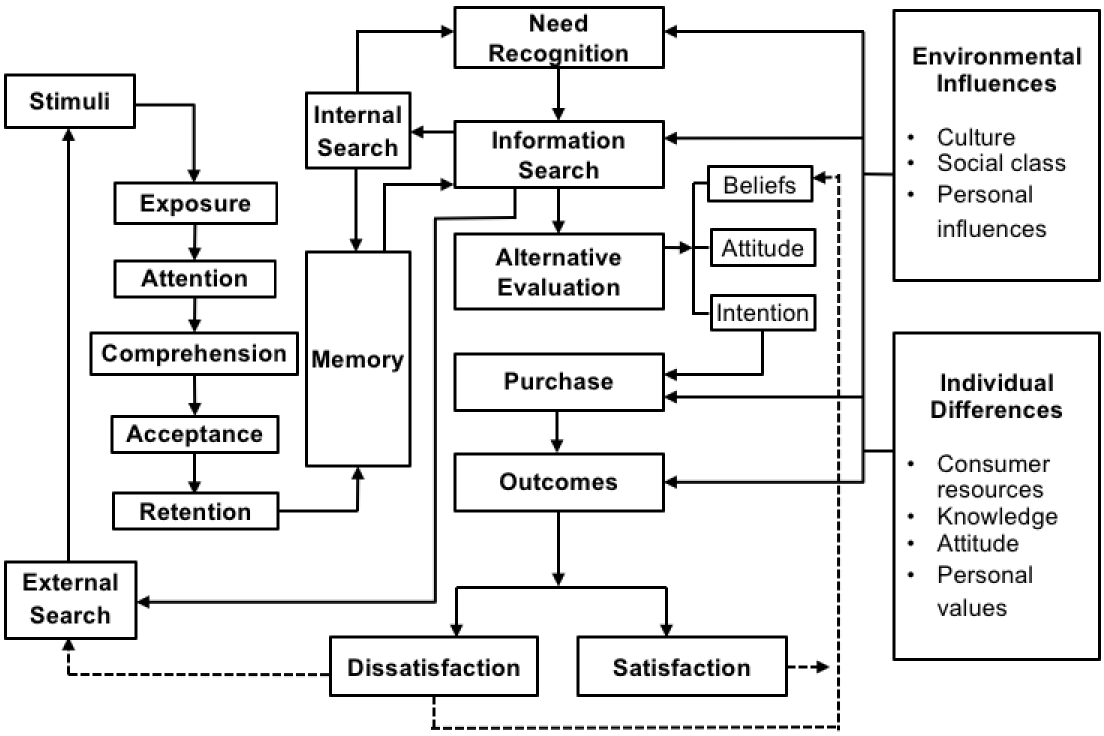


Figure 4-1 Consumer decision-making process (Source: from ENGEL. CONSUMER BEHAVIOR 6E, 6E. © 1990 South-Western, a part of Cengage, Inc. Reproduced by permission. www.cengage.com/permissions)

In the context of this research, the purchase process starts with need recognition when a consumer first recognises the need for a vehicle. The need recognition triggers the next step: information search. This step involves external and internal search. The left part of Figure 4-1 describes the internal search through consumers' memories and the external search from external stimulus. Any external information would go through information processing of exposure, attention, comprehension, acceptance, and retention, where consumers form their attitudes and opinions internally. For innovative products like AFVs, this process depends heavily on how information spreads within the society. Recall from Chapter 2 Section 2.1.1, in Rogers' innovation diffusion theory, the communication channels in innovation diffusion process describe the means by which information and messages of the AFV spread from the source to the receiver (Rogers, 2003). The mass media and interpersonal channels of the diffusion process determine the results of the information search in this step in consumer decision-making process.

After need recognition and information search, the next step in the EBM model is pre-purchase alternative evaluation. At this stage, a vehicle consumer has narrowed down the vehicle choices to a limited set of vehicle models. Within this set of vehicle models, the consumer selects the most preferred vehicle based on his/her evaluative criteria and preferences. In this step, the consumer is expected to have relatively rational decisions. Once the evaluative criteria are determined and decision rules are applied for evaluation, the final purchase decision will be made (Engel et al., 1995). This stage is where the consumer choice modelling takes place. The consumers preferences/evaluative criteria along with vehicle performance determine which car model will be selected. During this step, all vehicle models in consumers' consideration sets will be further narrowed down to one vehicle model for purchase

After the purchase step, the outcome step completes the rest of the consumer decision-making process. Although the outcome step does not directly address how consumer choose vehicles, satisfied or dissatisfied outcomes can influence consumer's next vehicle purchase by providing further experience and information, and consequently shaping consumers preferences and attitudes.

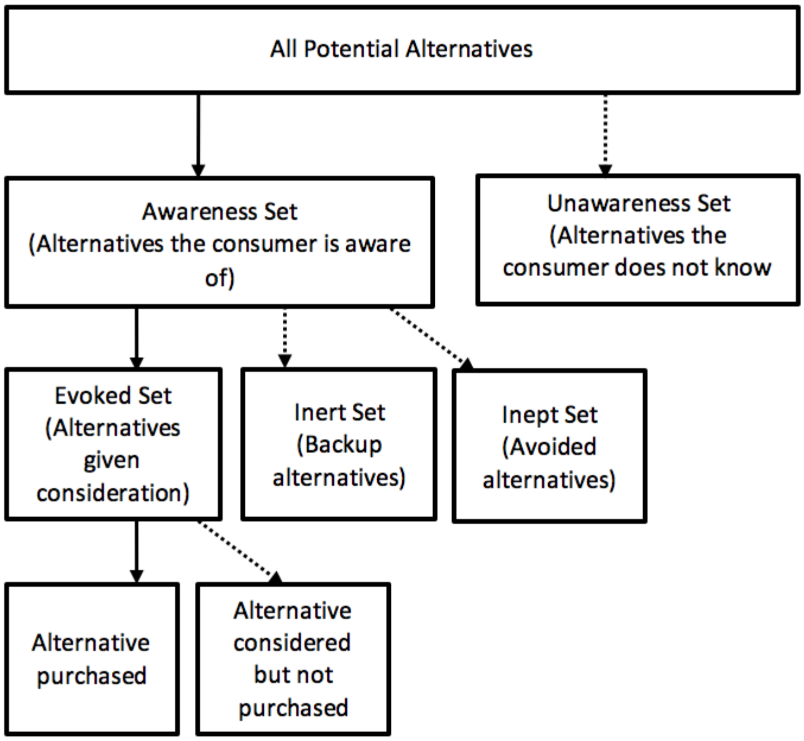


Figure 4-2 Alternative selection process (Source: from CONSUMER BEHAVIOR: BUILDING MARKETING STRATEGY, 8E by Hawkins et al. Copyright © 2001 by McGraw-Hill Education. Reprinted with permission of McGraw-Hill Education.)

Apart from the EBM model on consumer decision-making process, Hawkins et al. (2001) also described consumer choices from the view of product alternatives (Figure 4-2). In this process, for an AFV to be chosen by a consumer, it has to first enter consumer's the awareness set, and then the evoked set during the information search and pre-evaluation stage. Within the evoked set, consumer preferences and decision rules decide if the AFV can eventually get picked.

4.2 Identification of key variables and initial dynamic hypotheses

Based on the consumer decision-making process model and alternative selection process, key factors that may affect AFV adoption along the process of consumer choices and the dynamics around these key factors are discussed in this section. Since the research model is only interested in the consumers' decision-making process of vehicle powertrain selection, the last two stages in EBM model, the outcome step after purchasing is not of great importance to the construction of dynamic hypotheses of the research model. Therefore, only first four stages in consumer decision-making process up to the purchase step are selected as the theoretical foundation to the dynamic model.

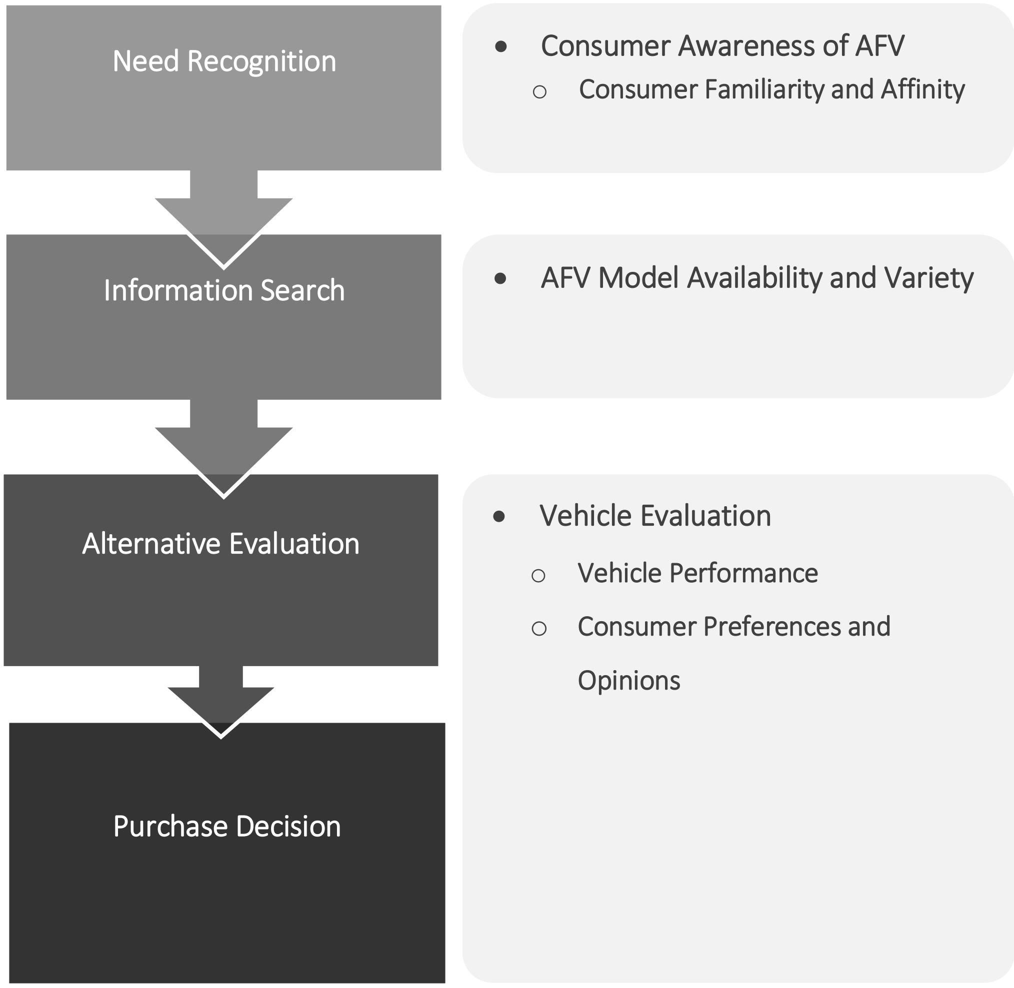


Figure 4-3 Key variables identified in the adoption process

The key variables in each step of consumer vehicle powertrain selection process are presented in Figure 4-3. In the consumer choice process, it starts with consumers feeling familiar with and being fond of the AFV technologies during the stages of "Need Recognition" and "Information Search", so that vehicle models with alternative fuel powertrains can go into the awareness set. Advertising effect and the word of mouth effect are the two main ways to increase consumer awareness. After entering the awareness set, the AFV model has to enter the evoked set, where consumers evaluate all vehicle models (Figure 4-2). In order to enter this set, vehicles in alternative powertrains have to be available and preferably in a variety of model ranges to meet the requirements of consumers in different market segmentations. Finally, the AFV has to be superior to all other alternative vehicle models in the evaluation phase of all models in the evoked set. In this phase, the performance of the AFV model and preferences and opinions of the individual are the most determining factors.

Recall from Chapter 2 Section 2.3, factors that are often regarded as influential to consumer AFV adoption decisions in the literature are divided into subjective and situational. Similarly, key variables identified through the theoretical foundation are in line with the findings from the literature. Key variables such as consumer awareness of AFVs and consumer preferences towards different vehicle attributes are subjective and intangible to measure. Key variables like AFV model availability and variety, and various vehicle attributes related to vehicle performance are situational and relatively tangible to measure. In the next sections, the dynamic structure of these key variables will be explained.

4.2.1 Consumer awareness

Consumer awareness, specifically consumers' familiarity and affinity of AFVs is the first necessary condition a successful AFV adoption requires in the individual adoption process. After adding the dimension of time and social system, consumer familiarity and affinity become dynamic and accumulative. There are two main ways to accumulate consumer familiarity: through advertisement and marketing, and through word of mouth effect. Advertising and marketing is the initiating force to start the diffusion process (Bass, 1969). After the minority innovators' acceptance of the innovation, word of mouth effect becomes the dominant force for consumer familiarity accumulation. The accumulation of consumer familiarity depends on how many people have known about the technology and how fast a new idea can spread within the network circles of consumers. This reinforced relationship between AFV adoption and consumer familiarity is the first key dynamic structure in this research (see Figure 4-4).

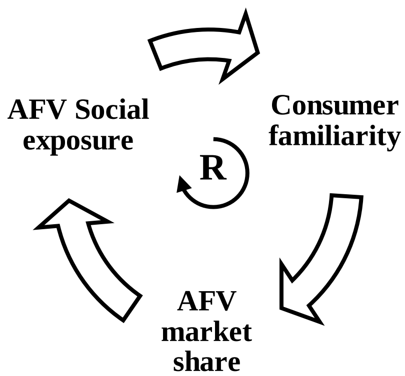


Figure 4-4 Consumer familiarity and AFV adoption

The familiarity of consumers is an intangible variable that is difficult to quantify its exact value and track its dynamic changes. In Chapter 5, consumer familiarity will be investigated using a nation-wide survey and the accumulation of consumer familiarity will be simulated within the system dynamics model.

4.2.2 AFV model availability and variety

A vehicle market comprises a variety of vehicle models and is divided into many market segments based on vehicle body styles, functionalities, and purchase price etc. In order to enter the evoked sets of consumers in all market segments, it is necessary for alternative fuel technologies to have a variety of vehicle models that caters for various consumer groups. To launch vehicle models in different powertrains requires manufacturers' time and capital investment, so the popularity of the powertrain in some extent determines how many vehicle models the manufacturers are willing to produce. This is another reinforced relationship between AFV market share and a key variable in the diffusion process (see Figure 4-5). In the subsequent data observation section, the historical trends of vehicle model variety will be investigated.

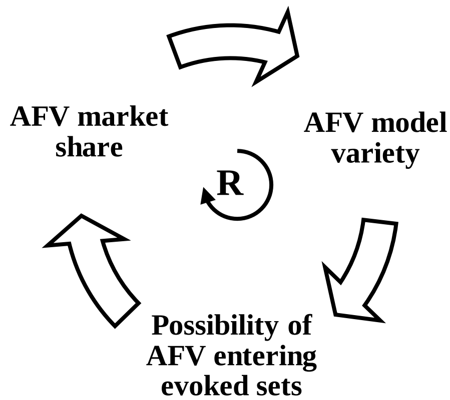


Figure 4-5 Vehicle model variety and AFV adoption

4.2.3 Vehicle model evaluation

Vehicle model evaluation is based on two categories of variables: vehicle performance and consumer preferences. Vehicle performance is defined by the value of various vehicle attributes that vehicle consumers consider when they make the purchase decision. In the context of AFV adoption, the vehicle attributes that can differentiate the performances of AFVs from petrol vehicles are the determining variables for whether AFVs are finally selected in the evaluation step. Some of the commonly considered vehicle attributes are: attributes that are related to the cost of vehicle ownership such as vehicle purchase price, vehicle operating cost, and registration tax; attributes that defines the technical performances of the car such as vehicle fuel efficiency, GHG emissions, and vehicle driving range; and attributes/factors that maximise the drivers' experience such as easy access to refuel facilities, shorter waiting time on vehicle acquisition , and access to bus lanes (International Energy Agency, 2017).

These vehicle attributes can change their values during the diffusion process. In general, with the increase in AFV popularity, performance will be improved because manufacturers become more willing to invest in AFV technologies research and development. The improvement of AFV performance will in response increase the competitiveness of the powertrains and help with boosting up the AFV market shares (see Figure 4-6). In the subsequent Section, the historical changes of AFV performance are presented.

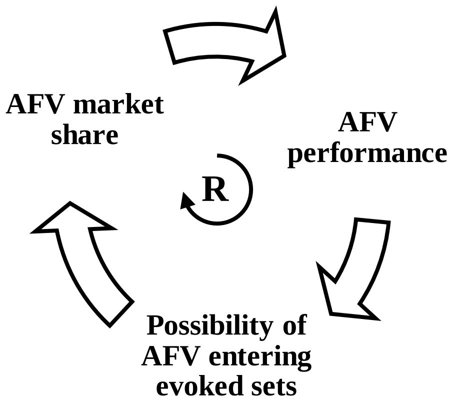


Figure 4-6 Vehicle performance and AFV adoption

Consumer preferences and opinions regarding these vehicle attributes determines how they evaluate alternative vehicle models in their evoked sets. However, such variables are intangible and not observable through available marketing data. Later in Chapter 5, the consumer preferences and opinions and their dynamics will be investigated.

Section 4.1 and 4.2 explored the theoretical foundation of consumer choices in vehicle powertrains and identified key variables within the AFV adoption process. The hypotheses dynamic structures of these variables were also presented (Figure 4-4 through

Figure 4-6). In the next section, historical trends of these key variables will be observed and discussed.

4.3 Australian alternative fuel vehicle market observation

This section presents an observation of historical trends in Australian AFV market. Historical trends of these key variables identified in the previous section are presented. Possible relationships between the market shares and these variables are explored.

4.3.1 The Australian vehicle market characteristics in regard to AFV adoption

The Australian vehicle market is a highly diverse and competitive market. There are 67 vehicle brands offering more than 350 vehicle models originating from North America, Europe and Asia (Federal Chamber of Automotive Industries, 2014). The immense diversity in the market provides Australian vehicle consumers abundant vehicle choices and also leads to a highly competitive market environment. Various vehicle brands compete with each other to occupy the rather small Australian vehicle market (only 0.81% of the global annual vehicle sales (The International Organization of Motor Vehicle Manufacturers (OICA), 2015)). Because the market has so many brands and vehicle models, an AFV technology needs to be adopted from multiple brands in order for it to achieve relatively significant market share. The highly competitive market environment inflicts additional difficulties on the adoption of new powertrains.

Apart from the high diversity and competitiveness, Australian AFV technologies also face a purely market-oriented environment. In contrast to major AFV markets such as countries in Europe, Asia, and North America, policy support that specifically aims at shifting the vehicle market towards alternative fuel powertrains are lacking in Australia. Policy support mechanisms for alternative powertrains are usually grouped into four major categories: financial incentives; support for research and development of AFV technologies; other instruments that increase the value proposition of AFVs; and targets, mandates and regulations (International Energy Agency, 2017). Without the aids of various forms of policy supports, Australian AFV adoption is driven purely by the market demands.

In Australia, the only financial incentives for alternative powertrains was the LPG vehicle scheme which was active during 2006 to 2014 and was only targeted at LPG fuelled vehicles. The majority of AFVs are not supported by financial incentives in Australia. Lack of specific financial incentives to reduce the cost of ownership gap between AFVs and traditional petrol vehicles leads to a purely market-oriented market condition for the adoption of the majority of AFV powertrains in Australia.

In terms of policy support for the research and development of AFV technologies, the only relevant policy in Australia is the Green Car Innovation Fund. This fund was provided by Australian government in 2008 aims at promoting vehicle technologies that reduce emissions and improve fuel efficiency. Toyota, as the only vehicle manufacturer that received funds for alternative powertrain development, received AUD 35million of this fund to produce the hybrid Camry in Australia in 2008 (Priestley, 2010).

Policy instruments for increasing the proposition value of AFVs usually provide advantages for AFVs in terms of reduced fees, privileged access, and time saving to AFV drivers. Some common policy implementations are: exemptions from access restrictions to urban areas, exemptions from usage fees for specific portions of the road network and privileged access to bus lanes and high-occupancy vehicle lanes. In this aspect, Australia currently does not have any form of policy to aid the adoption of AFVs.

The last category of policy support is targets, mandates and regulations. In this aspect, Australia also lags behind many countries. The current emission regulation for new light vehicles is ADR 79/04 in Australia. It was put into force in 2016 and is at comparable stringency as Euro 5 standard (Australian Government Department of Infrastructure and Region Development, 2017). This standard specifies the maximum levels of Hydrocarbon/Separate Non Methane Hydrocarbon, Carbon Monoxide, Oxides of nitrogen, and Particulates emissions permitted for light vehicles (Infrastructure and Regional Development, 2017). For comparison, the EU has adopted the subsequent Euro 6 standard since 2014 and equivalent standards are currently in force in most developed countries, including the US and Japan (Commonwealth of Australia, 2016). In terms of CO_2 emissions, there are no mandatory regulations specifically for its emissions reduction in the vehicle market in Australia. Compared to Europe and the United States that use mandatory emission reduction targets to regulate vehicle CO_2 emissions, Australia has yet to introduce a mandatory requirement for manufacturers to encourage powertrain technology shifting towards cleaner technologies. Since stringent emission standards or mandatory emission reduction targets can push the market towards cleaner powertrains

(Zhang et al., 2011a), lack of such policy means Australian AFV adoption is purely market-driven.

4.3.2 Australian AFV development

By the end of 2018, Australia has seen a total of six vehicle powertrains other than petrol vehicles: diesel vehicles, HEVs, pure liquid pure LPG vehicles, LPG dual fuel vehicles, EVs and PHEVs. As Figure 4-7 indicates, diesel vehicles appeared the earliest in the 1960s, mainly in the form of trucks and large SUVs. LPG dual fuel vehicles and pure LPG vehicles came later in 1980s. In 2000, influenced by global vehicle electrification trend, the first electric hybrid vehicle was introduced into the market, in the light passenger vehicle segment. Around the same time, diesel vehicles entered the same light passenger vehicle market segment and shortly became the direct competitor of HEVs. In 2010, EVs and PHEVs were introduced into Australia. These latest powertrains bring diversity into the market, offering consumers more choices on electricity-fuelled vehicles. Other powertrains like hydrogen fuel cell vehicles started to show up as conceptual vehicles in multiple cities around Australia (Blackburn, 2017). However, it is unclear whether this powertrain will be introduced into the market.

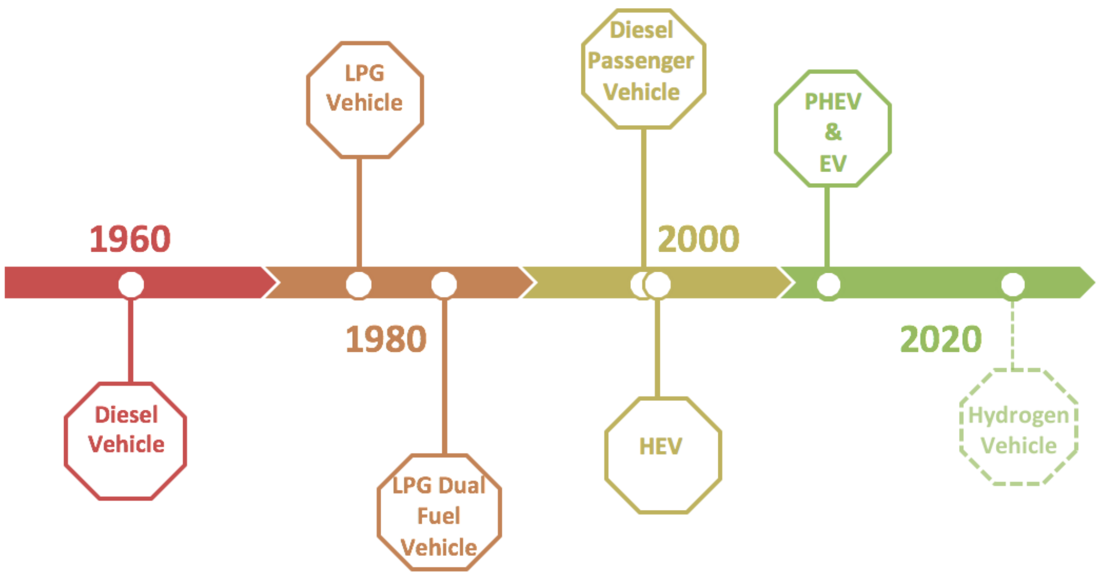


Figure 4-7 Australian alternative fuel technology timeline

This market historical observation focuses on the development of Australian AFVs from 2000 onward. In the year of 2000, the AFV market landscape became more diverse with the first attempt of vehicle electrification. With HEVs and passenger diesel vehicles entering into the market, the AFV market landscape started to show more dynamics and changes. This time point was selected to show the competition of different powertrains and the dynamics between AFV adoption and various relevant factors.

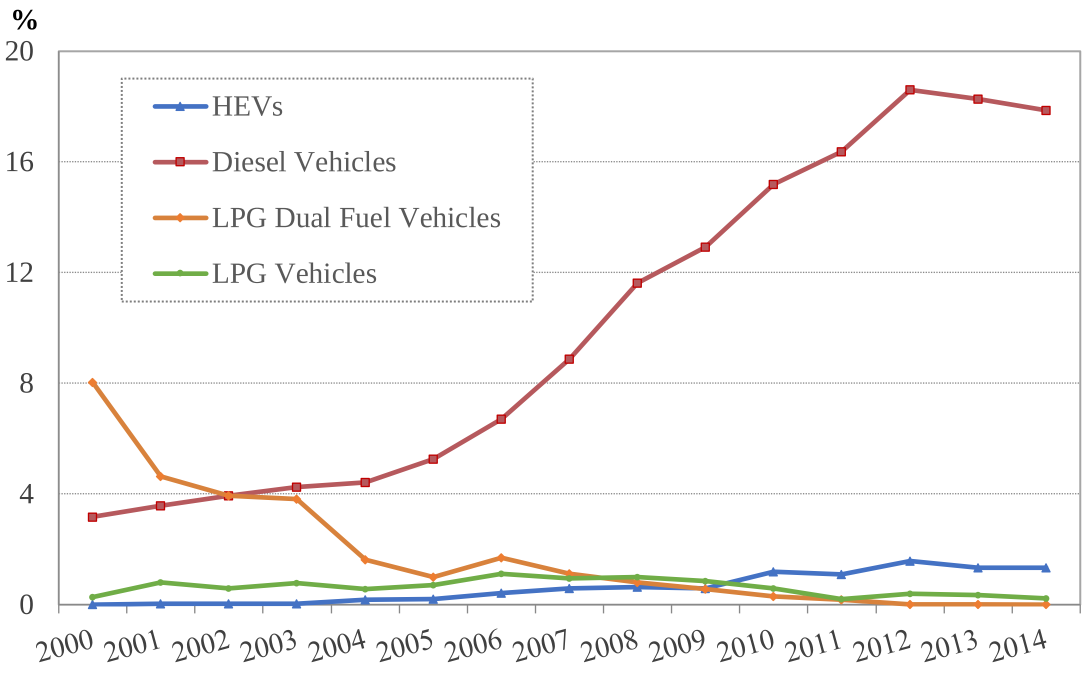


Figure 4-8 AFV market share in passenger vehicle and SUV segment (EV and PHEV excluded)

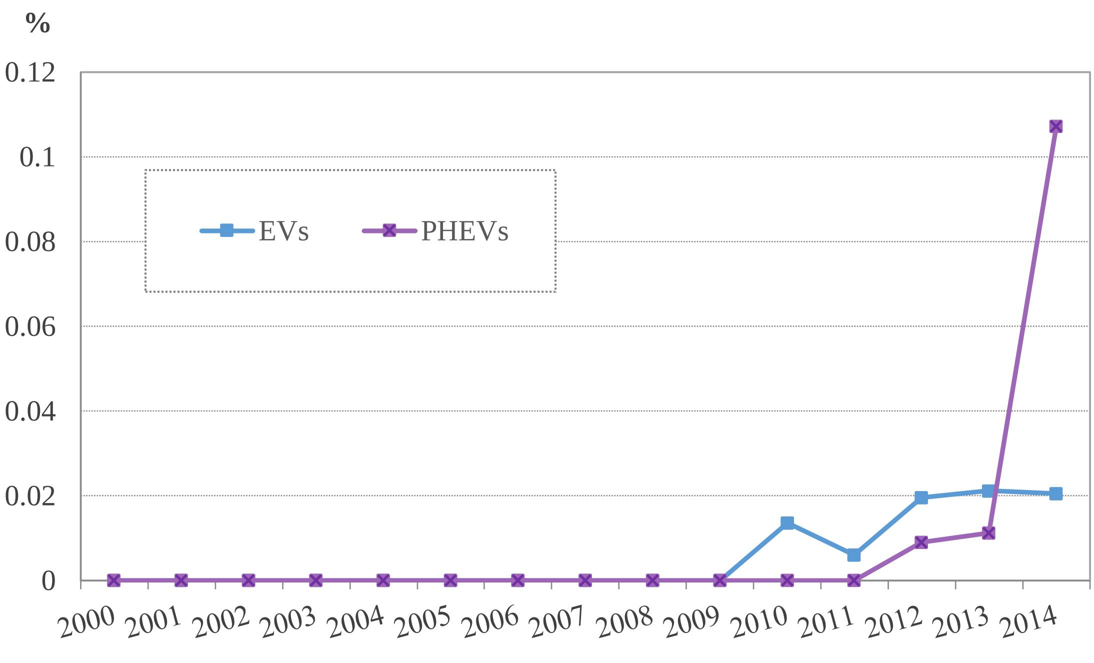


Figure 4-9 EV and PHEV market share in passenger and SUV segment

In Figure 4-8 and Figure 4-9, market shares of annual sales of each alternative powertrain are presented. LPG dual fuel vehicles had the highest market share at 8.03% in 2000.

Diesel vehicles were the second largest alternative fuel powertrain in the market. The relatively high diesel vehicle market shares were mainly composed of vehicles in the SUV market segmentation. After diesel passenger vehicles and HEVs entered the market in 2000, the landscape of Australian AFV market has changed rapidly. LPG fuelled vehicles lost their market share quickly and diesel powertrain became the dominant player in AFV market in 2003. The reasons why LPG fuelled vehicles was phased out might be the lack of vehicle models provided by the market, which will be discussed later in Sections 4.4.4. HEVs, on the other hand, have been slowly growing its market share and became the second largest AFV powertrain in the market in 2010. The late entrants, EVs and PHEVs, because of their late introduction to the market, occupy exceedingly low market share currently (0.034% and 0.015% respectively as shown in Figure 4-9).

The market environment for AFV adoption in Australia is introduced along with the development of various alternative fuel powertrains in Australia. In the following sections, an observation on the historical trends of key variables in Australian AFV adoption will be presented.

4.3.3 Summary of key variables included in the market observation

The key variables in Australian AFV adoption model were identified previously in Section 4.2. A market observation on the historical trends of these variables provides better understanding on the dynamic changes of these variables and their relationships with AFV adoption. Here in this section, a summary of key variables that are included in the market observation is provided.

Recall from Section 4.2, there are three categories of key variables: consumer familiarity and affinities in the need recognition stage, AFV model availability and variety in the information search stage, and AFV performance and consumer preferences in the evaluation stage. Among these key variables, consumer familiarity and affinities and consumer preferences are intangible variables where their value cannot be directly measured. Therefore, these variables are not included in the market observation (marked in light grey in Figure 4-10). Their value will be acquired in a national-wide survey on Australian vehicle consumers in the subsequent chapter.

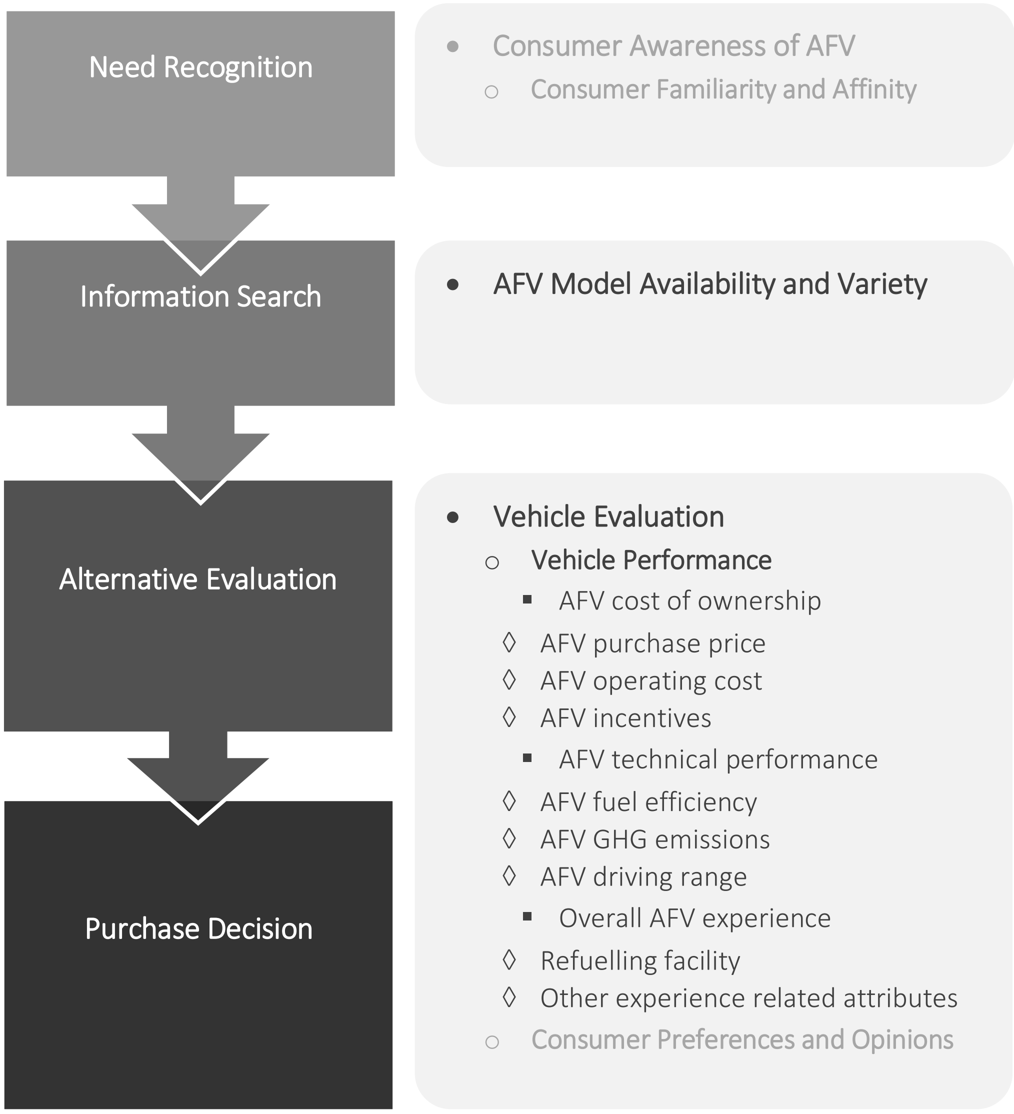


Figure 4-10 Key variables included in the market observation

As shown in Figure 4-10, key variables in black are chosen to be included in this observation. The first variable is AFV model availability and variety. It includes the number of AFV models and the variety of AFV body styles that are available in the market. A wide selection of AFV models that cater for various consumers who are interested in different vehicle body styles can increase the attractiveness of the technology and in turn encourage vehicle manufacturers to release more AFV models in certain body styles (Struben and Sterman, 2008, Sierzchula et al., 2014, van den Bergh et al., 2006).

The second group of variables is vehicle performance. Vehicle attributes are divided into three categories: cost of ownership, technical performance, and attributes to improve the overall experience of owning and driving an AFV. Cost of ownership includes AFV purchase price, operating cost, and financial incentives that target at AFV powertrains.

Technical performance includes fuel efficiency and GHG emissions of AFVs. Attributes related to the overall AFV experience contain AFV refuelling infrastructure and other experience related attributes such as privileged lane access, shorter acquisition time, and reduced usage fee.

Table 4-1 Data Sources

Data category	Source
Vehicle annual sales	Federal Chamber of Automotive Industry and IHS Automotive.
Number of vehicle models by fuel type	Federal Chamber of Automotive Industry and IHS Automotive.
Vehicle purchase price †	Redbook.com.au
Fuel price	Fuelwatch.wa.gov.au. (This website is a fuel price monitoring website created by the Western Australian government.)
LPG Scheme	Australian Government Department of Industry, Business Sector
CO2 emissions †	GreenVehicleGuide.gov.au.
Fuel efficiency †	GreenVehicleGuide.gov.au.
EV driving range	GreenVehicleGuide.gov.au.
Refuelling station †	Petrol: Australian Institute of Petroleum
	Diesel: Estimated based on the number of petrol stations and multiple websites/apps that provides fuel station locating services (e.g. Shell fuel finder, MotorMouth, BP site locator, Fuel map and Caltex)
	LPG: Estimated based on the number of petrol stations and statistics provided by Australian Institute of Petroleum.
	Electric: The total number of charging stations came from the statistics of the three main constructing companies/organizations for electricity stations (Chargepoint, Tesla Motors and RAC Electric Highway)

In the following sections, historical trends of these variables and their links with the adoption of AFVs in Australia will be investigated. Table 4-1 presents a summary of data sources in the subsequent market observation. Note that some of the data is not available annually. Those available in only discrete years are marked with "†".

4.3.4 Vehicle availability and variety

Historical data reveals that vehicle variety and powertrain market shares are closely linked. The number of AFV models and the variety of AFV body types has continued to increase since 2000, especially for more popular powertrains like diesel and HEVs (Figure 4-11). With the growth of vehicle variety, the market shares of these two powertrains have increased correspondingly. The same can be observed in the market share increase of PHEV. PHEV market share grows drastically in 2014 with the increase of model variety (Figure 4-13). For powertrains like pure LPG and LPG dual fuel, the vehicle variety drops correspondingly to the market shares of such powertrains (Figure 4-12). The decreasing number of vehicle models provided by LPG fuelled powertrains can be considered as one of the main reasons that the powertrains did not last long in the market.

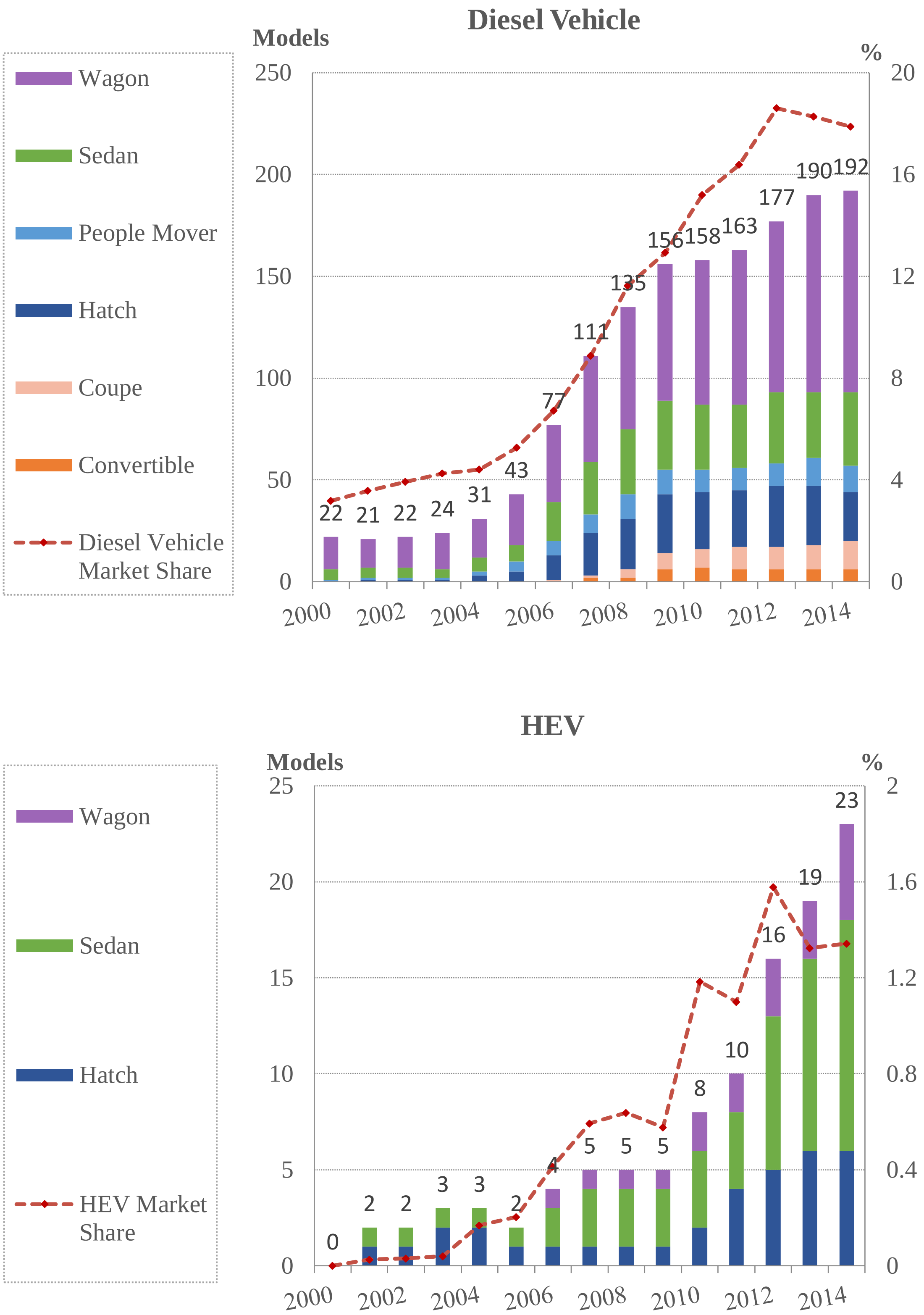


Figure 4-11 Diesel vehicle and HEV variety and market share

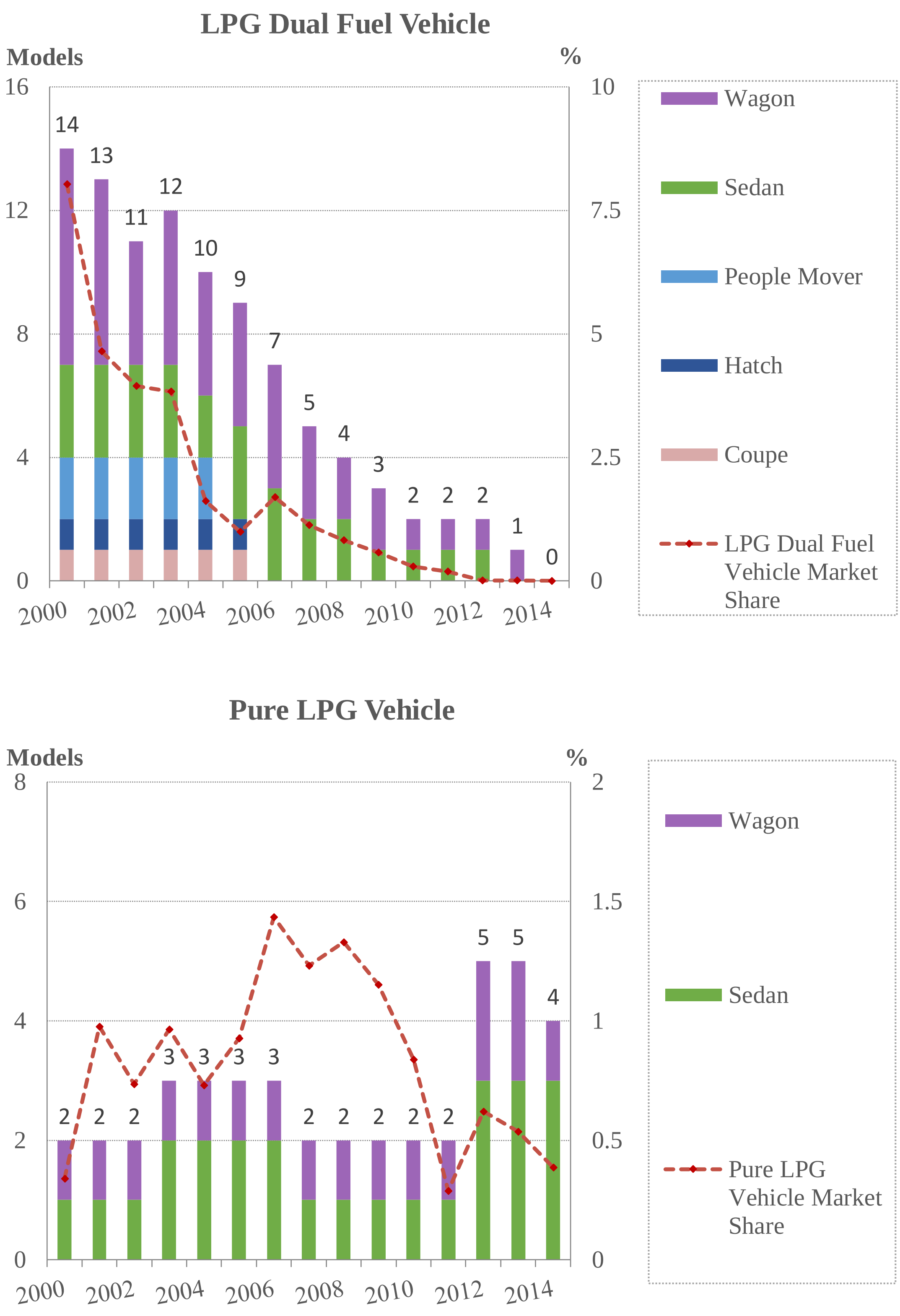


Figure 4-12 LPG dual fuel vehicle and pure LPG vehicle variety and market share

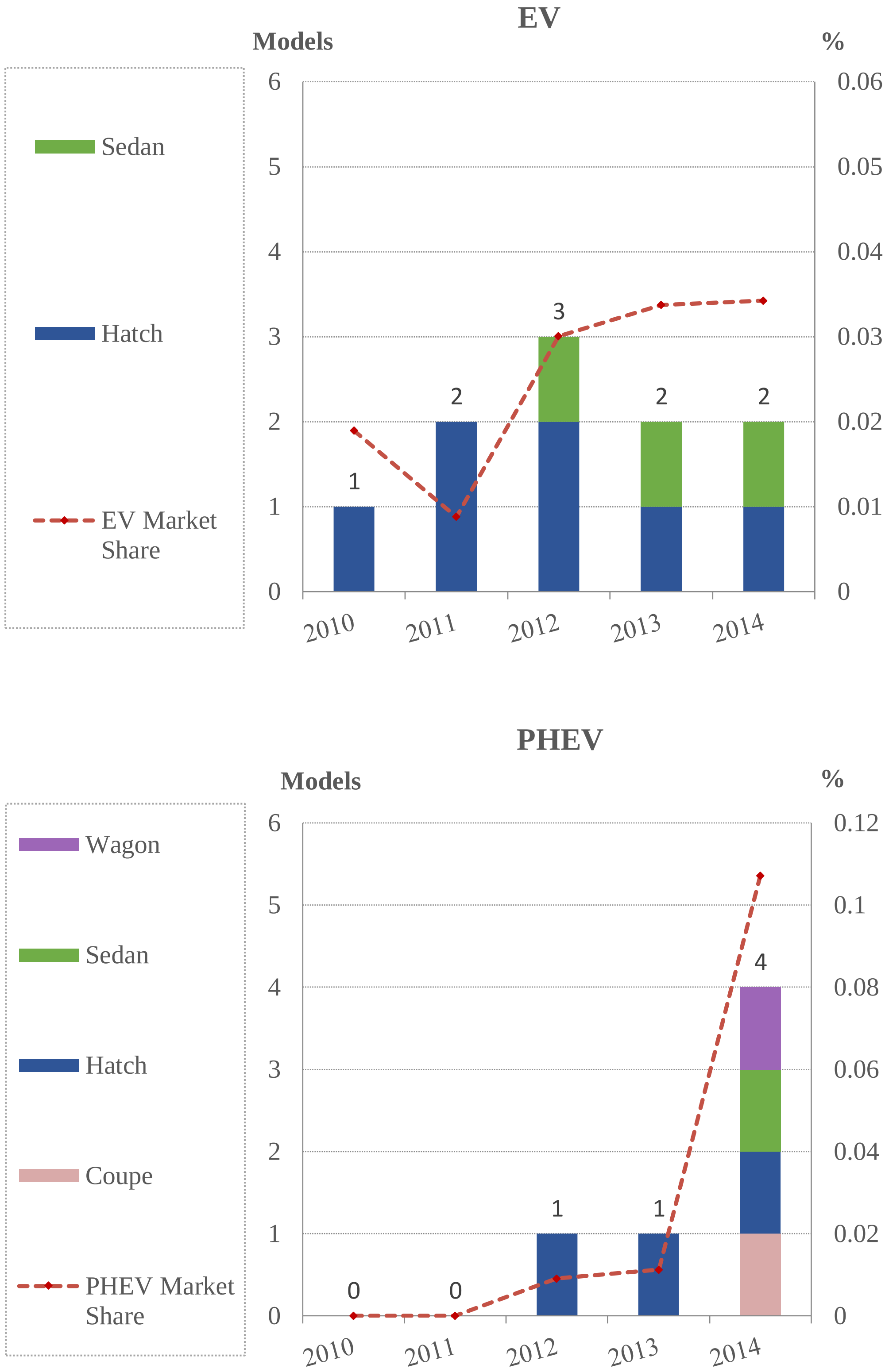


Figure 4-13 EV and PHEV variety and market share

The possible correlation between AFV market shares and AFV model availability and variety can be observed in the historical data. A wider range of vehicle models opens up to wider market segments and therefore spurs the adoption of AFVs. The positive impacts brought by adequate AFV variety on market shares can in turn broaden AFV variety.

With the increasing AFV market share, manufacturers will be inclined to release more AFV models to the market to take up additional market share. AFV vehicle variety will be therefore expanded. This reinforcing relationship between AFV market shares and vehicle variety can be one powerful force driving the AFV adoption in Australia.

The subsequent three sections will explore the historical trends of variables related to AFV performance. These variables are categorized into three groups: AFV cost of ownership, AFV technical performance, and attributes that related to overall AFV experience.

4.3.5 AFV cost of ownership

- AFV purchase price

The purchase price of an AFV normally is higher than a traditional petrol vehicle for its more advanced technology. This incremental cost for alternative powertrains is regarded as a significant drawback on AFV's attractiveness. Consumers who are sensitive to vehicle price will be more reluctant to choose an AFV despite their possible fondness of the technology.

Purchase price is regarded as one of the most influential variables in AFV adoption. In Australia, the purchase price gap between AFVs and traditional powertrains has been reduced gradually. Especially for diesel powertrain, the price gap has been nearly eliminated or even reversed for some vehicle models (for example, Volkswagen Passat and Audi Q5). The price drop of diesel vehicles in Australia leads to increase in overall diesel vehicle performance and therefore higher possibilities of diesel powertrain getting selected by consumers.

Accordingly, the incremental price of HEVs also decreased gradually making the powertrain more accessible to general consumers. Take the most popular HEV model in Australia Toyota Camry Hybrid for example, the incremental price of the hybrid version has been deducted from 7000AUD in 2009 to 2300AUD in 2018[1]. The relatively significant price drop of this HEV model also secures its predominant place in Australian

[1] The manufacture suggested retail prices of Toyota Camry models are derived from redbook.au.

HEV market. However, for most of the HEV models, the reduction in incremental price has been slow. The price gap between HEVs and petrol cars still exists and keeps impeding the adoption of the hybrid electric powertrain.

For the two more recent powertrains, the incremental price of EVs and PHEVs are still prominent. Combined with limited model variety and price range, the market shares of these two powertrains remained extremely low.

- AFV operating cost

Vehicle operating cost depends on multiple factors including the vehicles' fuel efficiency, the fuel price, and the distance travelled. Unlike the other two factors, the fuel price is the only variable over which vehicle consumers as individuals have no control. For vehicle consumers, they can mindfully include fuel efficiency as one of their evaluation criteria while making purchase choices or consciously adjust their travel distance and driving habits to minimize the vehicle operating cost. However, they are not able to actively control the energy price of different powertrains as individual consumers. The fuel price is an objective factor to operating cost for consumers. It is also more straightforward for consumers to access when it comes to the overall cost of different vehicle powertrains. Therefore, instead of the operating cost, fuel price is chosen for the historical trend observation.

The comparison of petrol, diesel and LPG retail prices from 2000 to 2014 is presented in Figure 4-14. Retail fuel prices including taxes in Perth was chosen as one example to show the price differences between petrol, diesel and LPG[2]. Dash lines are used to show the fuel price after converting to price per energy unit to standardize the energy density of petrol, diesel and LPG. When the energy density of petrol is set as 1 unit J/L, the energy

[2] Because Australian petrol and diesel prices are based on the Singapore fuel price AUSTRALIAN INSTITUTE OF PETROLEUM. *Australian Market Snapshot* [Online]. Australian Institute of Petroluem. Available: http://www.aip.com.au/pricing/snapshot.htm [Accessed 23/12 2015]. and LPG price is based on the Saudi Aramco price AUSTRALIAN COMPETITION & CONSUMER COMMISSION 2012. Fuel facts: Automotive LPG ACCC: Australian Competition & Consumer Commission., the fuel price fluctuations in all major cities are consistent across Australia. Although the national retail prices of these fuels are not the same as retail prices in Perth, Perth fuel price can still be representative for fuel price fluctuations and price differences between different fuels.

density of diesel is 1.155 units J/L, and the energy density of LPG is 0.758 unit J/L (U.S. Department of Energy).

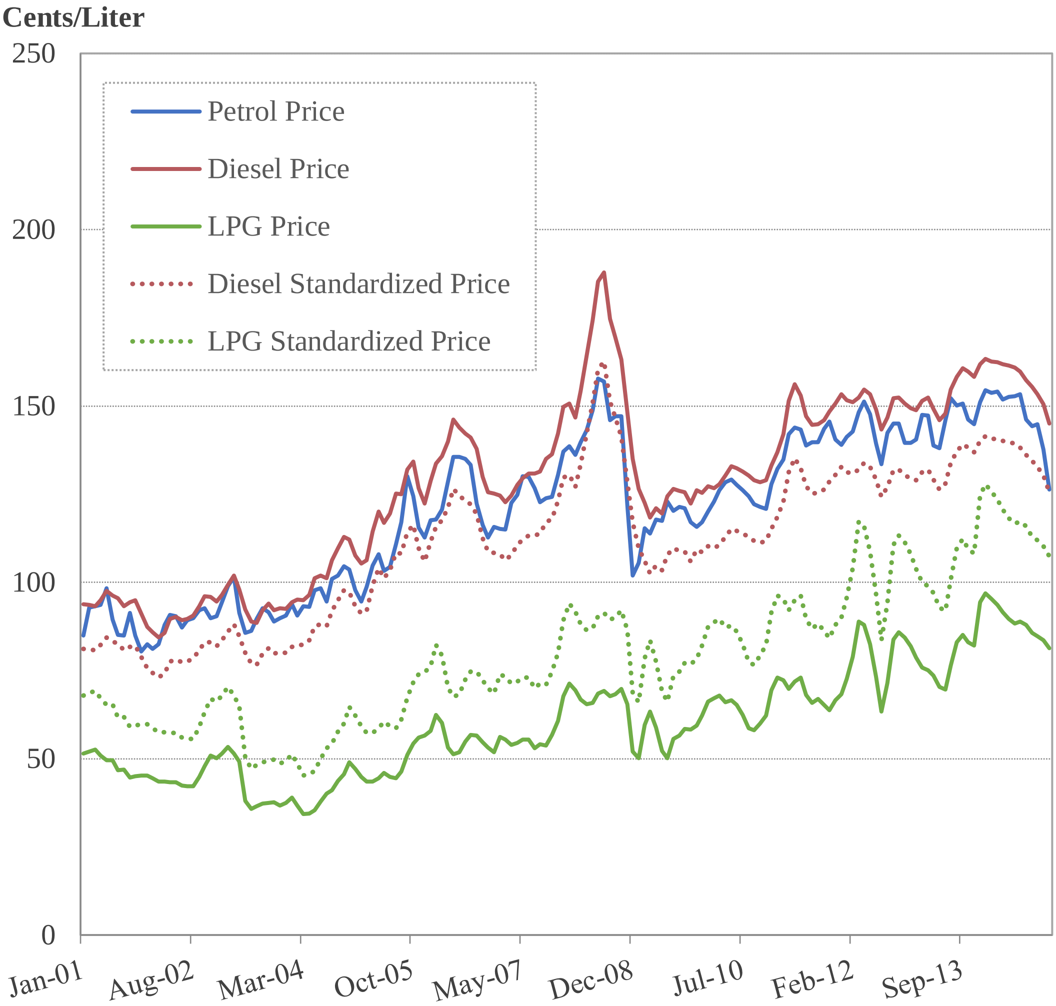


Figure 4-14 Historical fuel retail prices in Perth

In Figure 4-14, the prices of diesel and petrol fluctuated together. In general, diesel price is always slightly higher than petrol price. However, because diesel energy density is higher, the standardized diesel price turns out to be slightly cheaper when compared to petrol. The LPG price was about 50% cheaper of the petrol and diesel price. Even with energy density conversion, LPG price is still much cheaper than the other two. In recent years, LPG price has increased. The price gap between standardized LPG price and petrol price was shrinking, making the LPG fuel less attractive to consumers.

If adding AFV market shares to the figure, the link between fuel price and the AFV market shares can be observed. Figure 4-15, Figure 4-16, and Figure 4-17 present fuel price trends and the corresponding AFV market share changes. Petrol price is added as a dashed line as a reference for diesel and LPG prices.

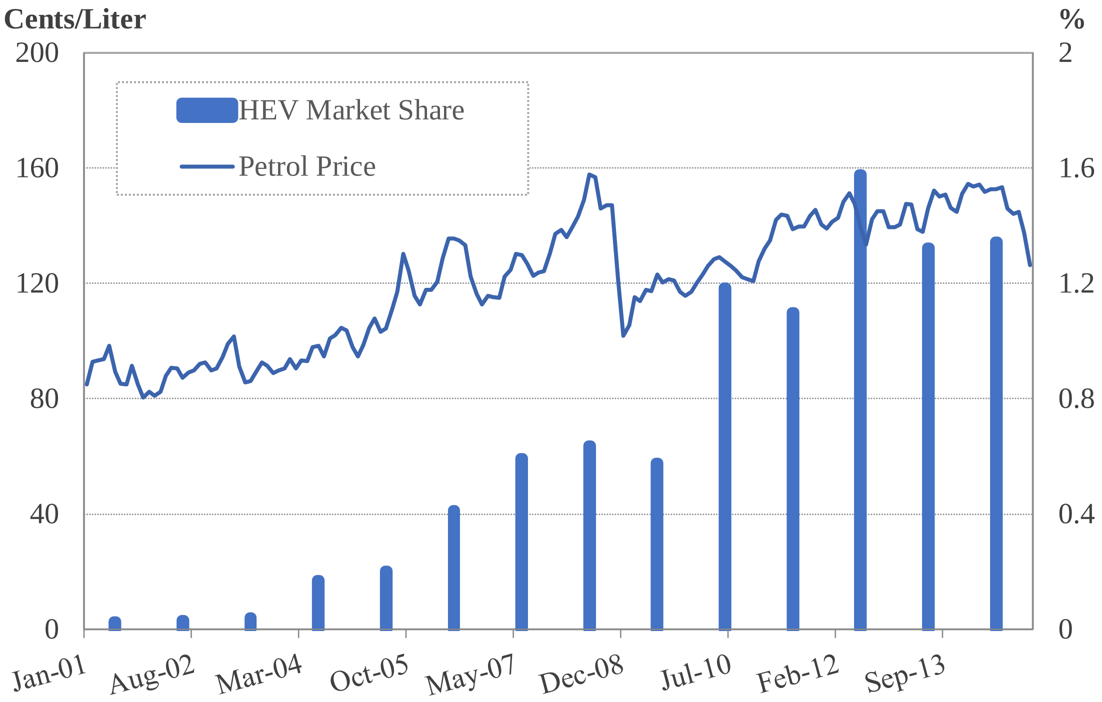


Figure 4-15 Petrol price trend and HEV market share

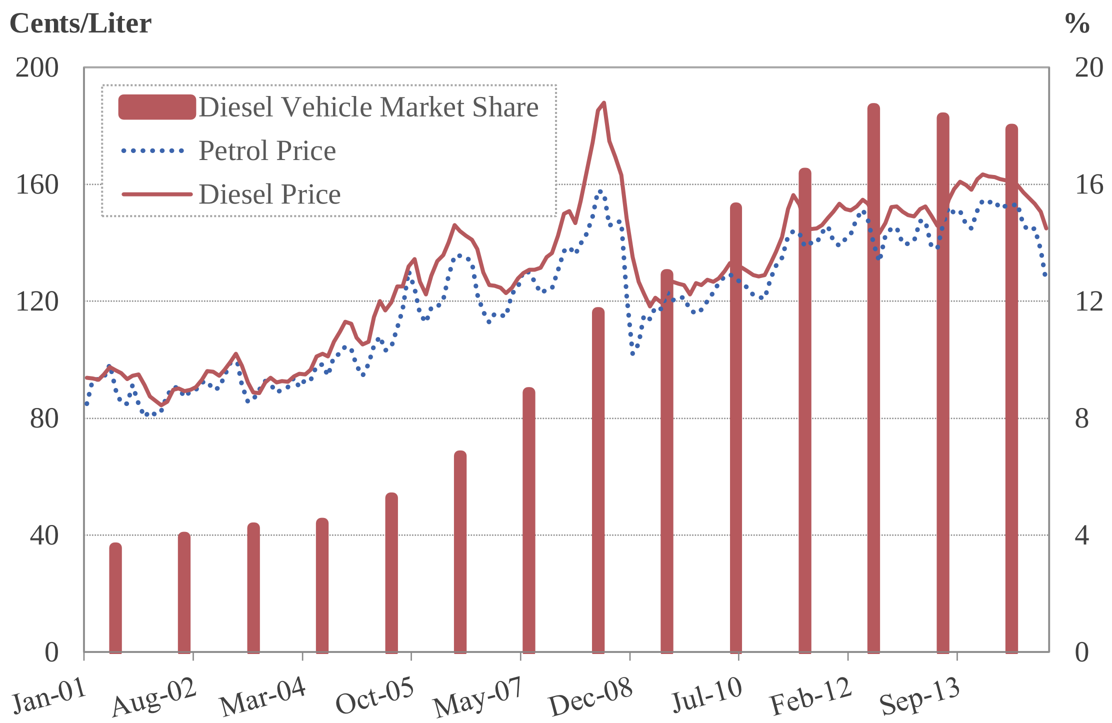


Figure 4-16 Diesel and petrol price trends and diesel vehicle market share

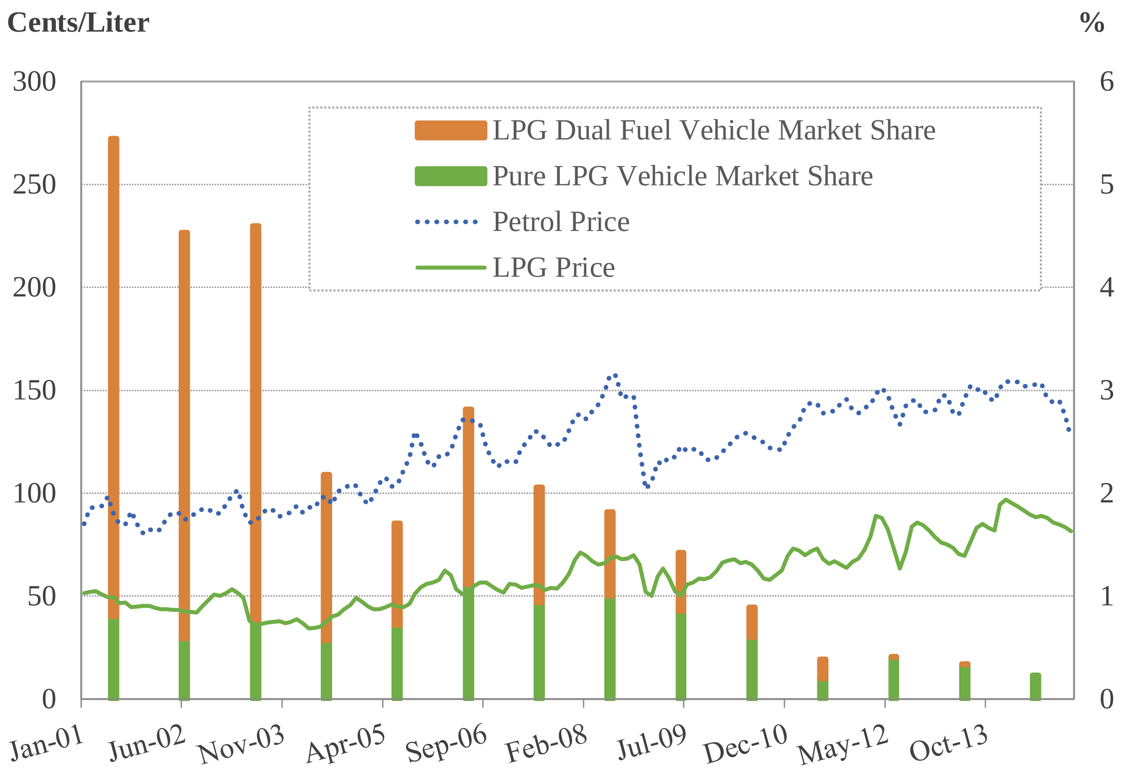


Figure 4-17 LPG and petrol price trends and LPG fuelled vehicle market share

The overall market shares for LPG fuelled vehicles, especially pure LPG vehicles dropped when the LPG price increased in Figure 4-17. In the early years of 2000s, the market shares of LPG fuelled vehicles increased slightly while the LPG prices dropped. Although LPG price decreased during that time, there was no significant changes in the relative differences between the prices of petrol and LPG fuel. After mid-2000s, the LPG price increases have reduced the relative advantages of LPG fuelled vehicles relative to petrol vehicles and thus the market shares of these powertrains decreased. However, for HEVs and diesel vehicles in Figure 4-15 and Figure 4-16, the links between their market shares and petrol or diesel fuel prices are insignificant to observe. Other factors such as the number of vehicle models, vehicle technology performance may be more influential than fuel prices.

In this section, electricity price and PHEV or EV are not included. The energy costs for one full charge of a pure EV are much less than refuelling a petrol vehicle tank from empty to full. The relative advantages of EV and PHEVs on operating costs are significant enough that it is reasonable to argue that fluctuations of electricity price will not notably change the advantages. However, for EVs and PHEVs, there are still serious challenges such as long charging time and lack of refuelling facility in the operating phase, which will be discussed in later sections.

- Financial incentives

As concluded in Section 4.3.1, specific incentives for AFVs are limited in Australia. The only targeted incentives for AFVs are the LPG vehicle scheme that applied to LPG fuelled vehicles exclusively[3]. This policy setting provides a good opportunity to isolate the influences of incentives and compare the adoption of AFV powertrains with and without incentives.

The LPG vehicle scheme, available from August 2006 to July 2014, was designed to encourage private vehicle owners to buy LPG powered vehicles or convert existing petrol or diesel vehicles into LPG dual fuel vehicles (Australian National Audit Office, 2009). The grant detail for LPG dual fuel vehicles and pure LPG vehicles are listed in Table 4-2. The first grant type can be only applied to consumers converting their already registered petrol or diesel vehicles to LPG operating system, which is not within the scope of this study. The second and third grant types are targeted to new LPG dual fuel or pure LPG vehicles.

[3] The Green Vehicles Stamp Duty Scheme in the state of Australian Capital Territory is another financial incentive that can be applied to AFVs. This differential duty scheme for new vehicles provides an incentive for the purchase of lower operating emission vehicles and disincentive against the purchase of vehicles with higher operating emissions (ACT GOVERNMENT Duty payable upon registration or transfer of a motor vehicle. *In:* ACT GOVERNMENT (ed.) *Transport Registration.* Access Canberra.). However, this scheme is not designed specifically based on vehicle powertrains. Furthermore, the annual vehicle sales volume in ACT represents only 0.15% of the total Australian new vehicle sales (AUSTRALIAN BUREAU OF STATISTICS 2014. 9309.0 - Motor Vehicle Census, Australia. Australian Bureau of Statistics.). The small market share of this state means the majority of new vehicles sold in Australia are not under any financial incentives that favours AFV powertrains.

Table 4-2 Grants for LPG fuelled vehicles

Grant Type	Grant Amount	Date of Purchase
LPG Conversion of registered vehicles	$2000	From 14 August 2006 till 30 June 2009
	$1750	From 1 July 2009 till 30 June 2010
	$1500	From 1 July 2010 till 30 June 2011
	$1250	From 1 July 2012 till 30 June 2012
	$1000	From 1 July 2012 till 30 June 2014
LPG Dual Fuel Vehicles	$2000	From 14 August 2006 till 30 June 2014
Pure LPG Vehicles	$1000	From 14 August 2006 till 9 November 2008
	$2000	From 10 November 2008 and 30 June 2014

From 1 July 2011, the LPG vehicle scheme was capped at 25,000 eligible claims in each year. Up to 30 June 2015, there were a total of 3696 claims paid for the second and third grant types, while the claimed payment for the first type was 315, 828 cases (Australian Government Department of Industry, 2015). The LPG technology has moved from new LPG fuelled vehicles towards self-converted LPG operating systems after vehicle purchase. This could be one possible explanation for the LPG fuelled vehicle market shares shrinkage.

Incentives for LPG fuelled vehicles and LPG fuelled vehicle market shares are presented in Figure 4-18. The market shares of LPG dual fuel vehicles and LPG vehicles increased at the inception of the LPG vehicle scheme. However, after the initial market shares boost, the market shares kept dropping regardless of the incentive growth in 2008.

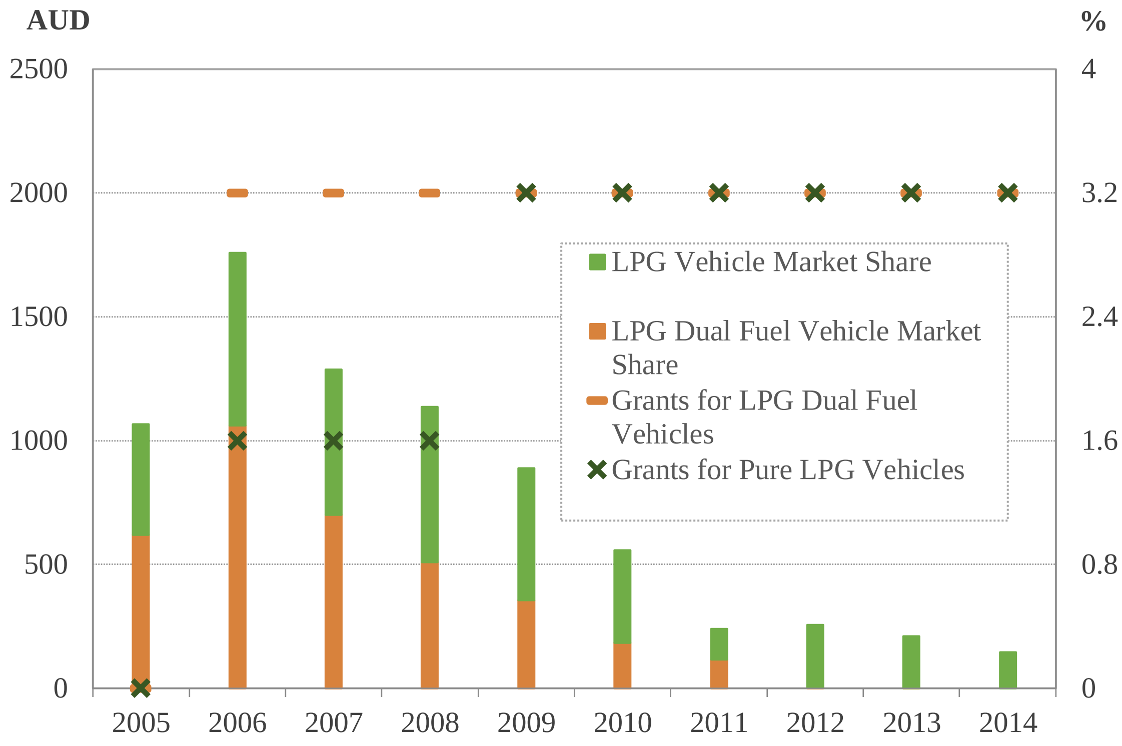


Figure 4-18 LPG vehicle scheme grants and LPG fuelled vehicles market share

Compared with other powertrains that are not entitled to any financial incentives, financial incentives for LPG fuelled vehicles did not significantly boost their market shares. Powertrains like diesel and hybrid electric vehicles surpassed LPG fuelled vehicles in market share when the financial incentives were effective. The incentives benefited their adoption for a short time but the influence was easily counteracted by other relevant factors, such as AFV model availability, AFV technological performance, and AFV driving experience.

4.3.6 AFV technological performance

Technological performance of AFVs includes the environmental performance of the vehicles and also the driving range

- <u>AFV CO2 emissions and fuel efficiency</u>

Compared with traditional petrol vehicles, most AFVs have the technological advantages of lower CO2 emissions during tank-to-wheel phase and better fuel efficiency. Advantages in these vehicle attributes make the vehicle appear to be more environmentally friendly and cost-effective. It directly increases the attractiveness of the powertrain, especially to consumers who have more awareness towards environmental issues.

Investigating the changes in CO2 emissions and fuel efficiency of different powertrains helps researchers to apprehend how well the technologies have been developed. Although vehicle technology advancement in Australia is largely dependent on global technology development and spillover, these vehicle attributes can still be representative of the maturity of a certain powertrain.

Three time points are selected to demonstrate and compare the historical trends of CO2 emissions and fuel efficiency in petrol, diesel, hybrid electric and LPG powertrains. In each of the time points, the average CO2 emissions and fuel efficiency of all new-released vehicle models are calculated based on data acquired from the official website "(GreenVehicleGuide)" that provides data on environmental aspects of all vehicle models sold in Australia since 2004. Because EVs and PHEVs have less than 5 years of history in the market and their CO2 emissions and fuel consumption are much lower than other powertrains, these two powertrains are not included in this comparison.

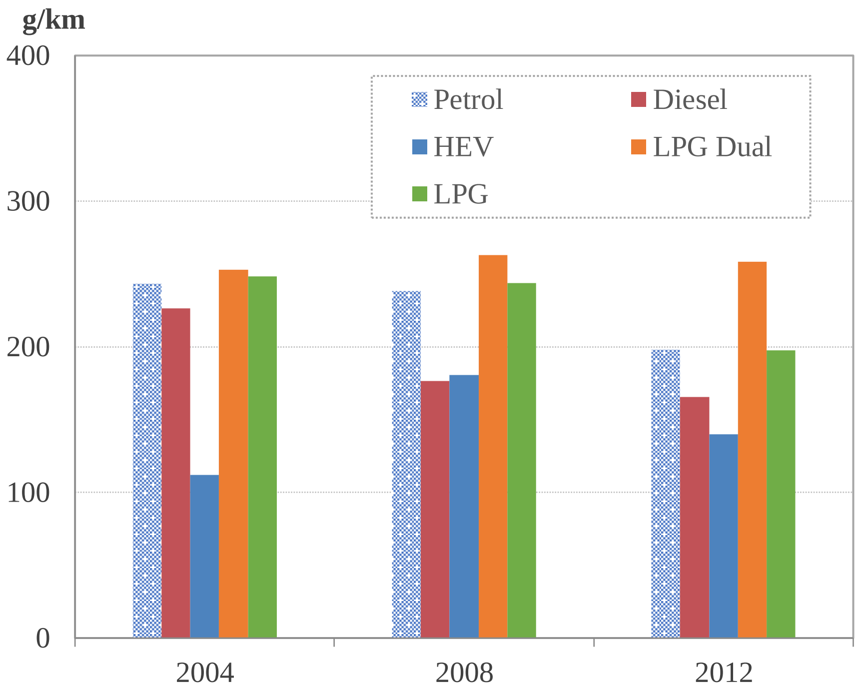


Figure 4-19 CO_2 emissions of petrol vehicle, diesel vehicle, HEV and LPG fuelled vehicle

In Figure 4-19, CO2 emissions trends of petrol, diesel, HEV and LPG fuelled vehicles are presented. Vehicle CO2 emissions have decreased for most of the powertrains, especially for diesel vehicles. Although the emission gaps between petrol and alternative powertrains like diesel and hybrid electric has been reduced, the relative advantages of AFV powertrains still remain. The average CO2 emissions of HEVs have increased in 2008 due to the release of bigger wagons in 2007 and 2008. However, HEV's overall emissions reduced in 2012 despite that more vehicle models were launched in the large SUV market segmentation. For LPG fuel vehicles, the CO2 emissions remained the highest over the years without notable decrease despite the fact that LPG fuelled vehicles are often promoted as green and environmental friendly.

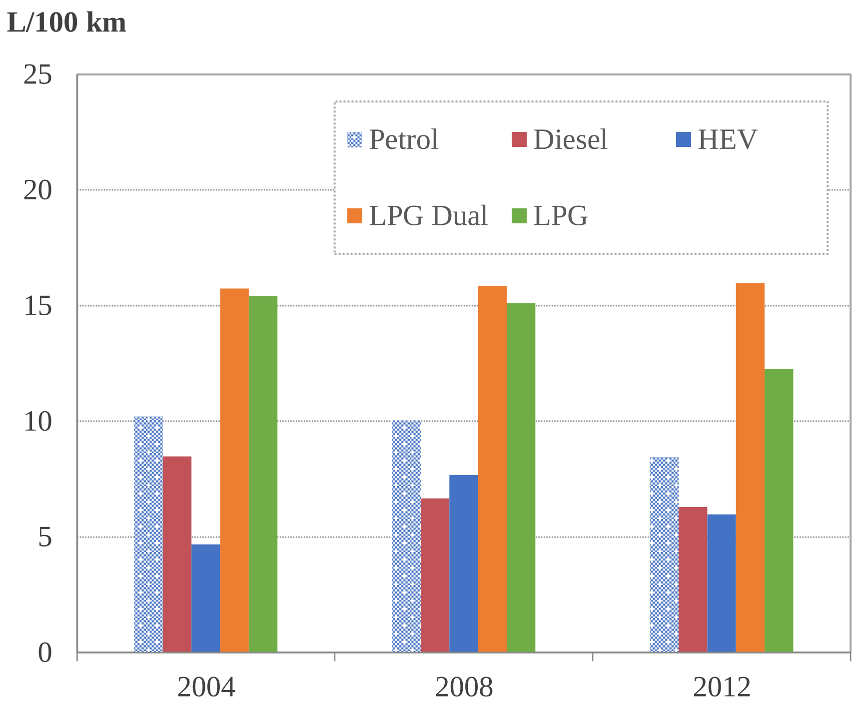


Figure 4-20 Fuel consumption of petrol vehicle, diesel vehicle, HEV and LPG fuelled vehicle

Fuel efficiency changes during adoption are presented in Figure 4-20. The average fuel consumption data is acquired using the same source as the CO_2 emissions. The trends of fuel consumption are considerably similar to CO2 emission trends. LPG fuelled vehicles have the highest fuel consumption due to the low energy density of the fuel. All powertrains except for LPG dual fuel vehicles reduced the fuel consumption over time. The fuel consumption gap between LPG fuelled vehicles and other powertrains expanded over the years, leading to the decrease in consumer affinity towards LPG fuelled vehicles.

Overall, CO2 emissions and fuel efficiency have been improved over the years for most of the powertrains. The general trends of producing vehicles with lower CO2 emissions and better fuel efficiency in Australian vehicle industry may have caused manufacturers' reluctance to release more LPG fuelled vehicles, especially LPG dual fuel vehicles, since

LPG fuelled vehicles generally have higher CO2 emissions and worse fuel efficiency comparing to other powertrains.

However, despite the improved average CO2 emissions and fuel efficiency in the fleet, the actual CO2 emissions and fuel usage for overall fleet still increased due to fleet and economy growth (Commonwealth of Australia, 2016). The lack of regulatory policies for reducing emissions and improving fuel usage efficiency of the fleet does not encouraged the vehicle brands to import the most advanced technologies into the Australian market.

- AFV driving range

Driving range is defined as the longest distance for a vehicle to travel with a full tank or fully charged battery/fuel cell. For vehicles with internal combustion engine, driving range is normally sufficient for drivers both in urban and rural area. However, for vehicles that have different propulsion systems, especially electric vehicles, driving range has become a major issue. Since electric vehicles are powered by batteries, the limited capacity of batteries has restricted the overall driving ranges of electric vehicles. Combined with confined refuelling facilities, driving range anxiety has become a significant concern of potential electric vehicle consumers.

EV driving range in Australia is dependent on global technology advancement. Since most of the EVs sold in Australia are imported, this important vehicle technical attribute is not an endogenous variable. Over the course of EV development, the driving range has been slowly improved (Figure 4-21). From 2009 when the first EV model was released in Australia to current year, the EV driving range has been extended. Even without the Tesla EV models, which are famous for their exceptionally long driving range, the average EV range has been slowly increasing.

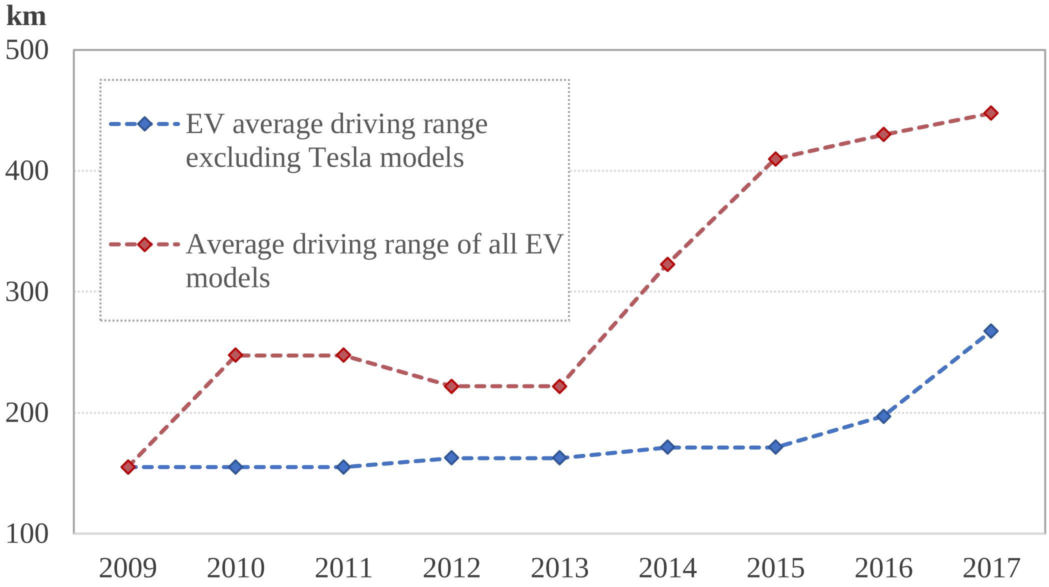


Figure 4-21 Australian EV driving range

4.3.7 AFV attributes related to the overall AFV experience

Apart from cost of ownership and technical performance, attributes that relate to the overall AFV experience can also affect consumer choices and AFV adoption. These vehicle attributes influence how the convenience and comfortability of owning an AFV. These section presents the development of such vehicle attributes in Australia.

- Refuelling infrastructure

Refuelling infrastructure availability has been identified as one of the most important factors to the adoption of AFVs that require alternative refuelling such as diesel, EV, PHEV, pure LPG vehicles, and LPG dual fuel vehicles (Chi et al., 2012, Wansart and Schnieder, 2010, Chen et al., 2015). A vast distribution of refuelling stations in both urban and rural areas allows frequent refuels and therefore reduces consumers' anxiety about AFVs' relatively short driving ranges. In order to construct an inclusive refuelling station network, there has to be enough adopters of AFVs so that the economic benefit of building a refuelling station is guaranteed. At the beginning stage of AFV adoption, the refuelling infrastructure construction is a key impediment to the adoption (Chi et al., 2012, Struben, 2006).

The overall number of petrol stations has reduced from over 20,000 sites in 1970 to 6300 sites now (Australian Institute of Petroleum, 2015). In the meantime, service stations that remained have moved to higher volume outlets in locations with greater traffic volume.

According to Australian Institute of Petroleum, the consolidation of petrol service stations has plateaued in recent years (Australian Institute of Petroleum, 2015).

Table 4-3 Number of refuelling stations and powertrain market share in 2014

Powertrain	Number of refuelling stations	Market share (%)
Petrol	6300	91.830
Diesel	6000	5.726
LPG	3200	0.388
Electricity	113	0.050

Table 4-3 shows the number of refuelling stations of different powertrains in Australia. Diesel fuel is the most prevalent alternative fuel in service stations in Australia. With nearly every service station providing diesel fuel, diesel vehicle driver can easily find a station for refuelling, even in relatively rural areas.

For LPG vehicles, Australia has a rather extensive LPG station network with over 3200 LPG stations scattered around the country (Shell, 2015). With more than 50% of fuel stations providing LPG (Australian Institute of Petroleum, 2015), fuel availability was not a major obstacle for LPG fuelled vehicle adopters. However, with the demise of the LPG powertrain, fuel stations are decommissioning their LPG bowsers, making the refuelling problem more prominent for LPG vehicle drivers (Huntsdale, 2017). In addition, refuelling stations that are equipped with LPG bowsers are largely situated in strategic locations for commercial users rather than across metropolitan areas, making refuelling their vehicles harder for private vehicle drivers (Energy Supply Association of Australia, 2014).

For EVs and PHEVs, there are very few electricity-recharging stations in Australia. Because EVs and PHEVs have only entered the market for less than 5 years, the electricity-recharging network has not yet been fully constructed, with only 133 public recharging stations in total in 2014. These stations are mainly located in urban areas near the coastline. Combined with private charging sockets from vehicle owners' houses, EVs can satisfy the daily commute demand in urban areas. However, large rural areas equipped with less EV recharging stations make longer trips between cities more difficult to realize. Currently, there is no well-established highway electric charging network in Australia except the first electric highway that consists a series of fast charging stations along the highway between Perth and South West (The Royal Automobile Club of WA 2015).

❖ Other attributes related to AFV experience

Other vehicle attributes that are related to the overall AFV experience include convenience of purchasing, maintaining, and driving the vehicle. Normally, these attributes are heavily influenced by policies. In other markets, supporting policies including exemptions from access restrictions to urban areas, exemptions from usage fees for specific portions of the road network, and privileged access to bus lanes and high-occupancy vehicle lanes are deployed to increase the AFV overall experiences and therefore promote the proposition value of the powertrain. In Australia, there is no relevant policies in this aspect. The lack of supporting policies in Australia magnifies the difficulties that AFV adoption face.

4.4 Key dynamics identified in Australian AFV adoption

Based on the observation of historical trends of the key relevant factors, the initial dynamic hypotheses that were identified in Section 4.2 are reflected by the data. This section summarises the historical trends from observation and discusses insights on key dynamics revealed in the market observation. At the end of this section, the key dynamic structure in Australian AFV adoption is mapped in causal loop diagrams.

4.4.1 Reinforcing relationship between vehicle variety and AFV adoption

The first key dynamic structure that is reflected in the data is the reinforcing relationship between vehicle variety and AFV adoption. In Section 4.3.4, historical data showed that the number AFV models and variety of AFV body style are closely linked with their adoption (Figure 4-11 through Figure 4-13). A variety of AFV models in the market can increase the relative advantages and social exposure of AFV powertrains and therefore boost up the adoption. The increasing market share of the powertrain will consequently encourage vehicle manufacturers to release more vehicle models in that powertrain targeting wider market segments. This reinforcing relationship acts as notable driven force for AFV adoption in Australia.

4.4.2 Competition between diesel and hybrid electric vehicles

The next interesting finding in the market observation is the competition between diesel passenger vehicles and HEVs. These two powertrains were introduced into the light passenger vehicle market around the same time. However, the two powertrains have quite disparate adoption paths (Figure 4-22). The market share of diesel passenger vehicles grew rapidly since its market introduction, while increase of HEV market share was significantly slower in comparison.

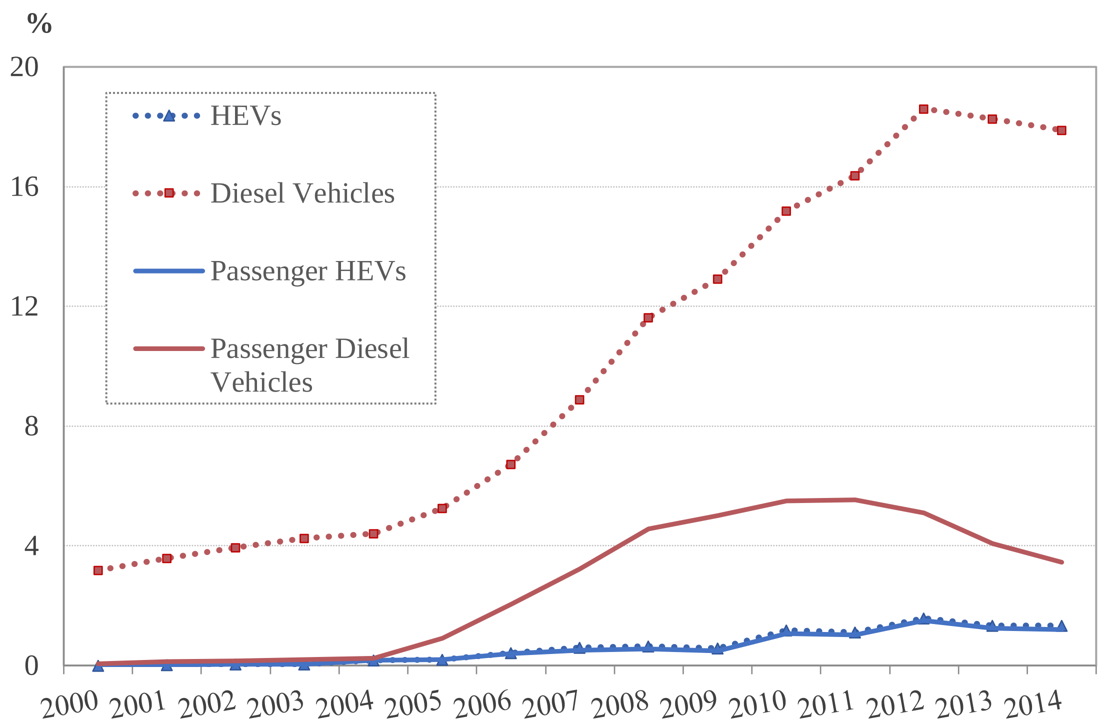


Figure 4-22 Market share of passenger HEVs and diesel vehicles in compared with market share in passenger and SUV segments

According to the key relevant factors that are investigated in this chapter, reasons for such development disparities between passenger HEVs and diesel vehicles are difficult to identify. Vehicle performance for passenger diesel vehicles and HEVs were comparable with each other. Both vehicle powertrains had relatively high incremental price at the beginning of the adoption. The fuel price combined with fuel efficiency of these two powertrains cannot be differentiated significantly either. The refuelling facilities and emission factors were even in favour of HEVs at the beginning of the adoption.

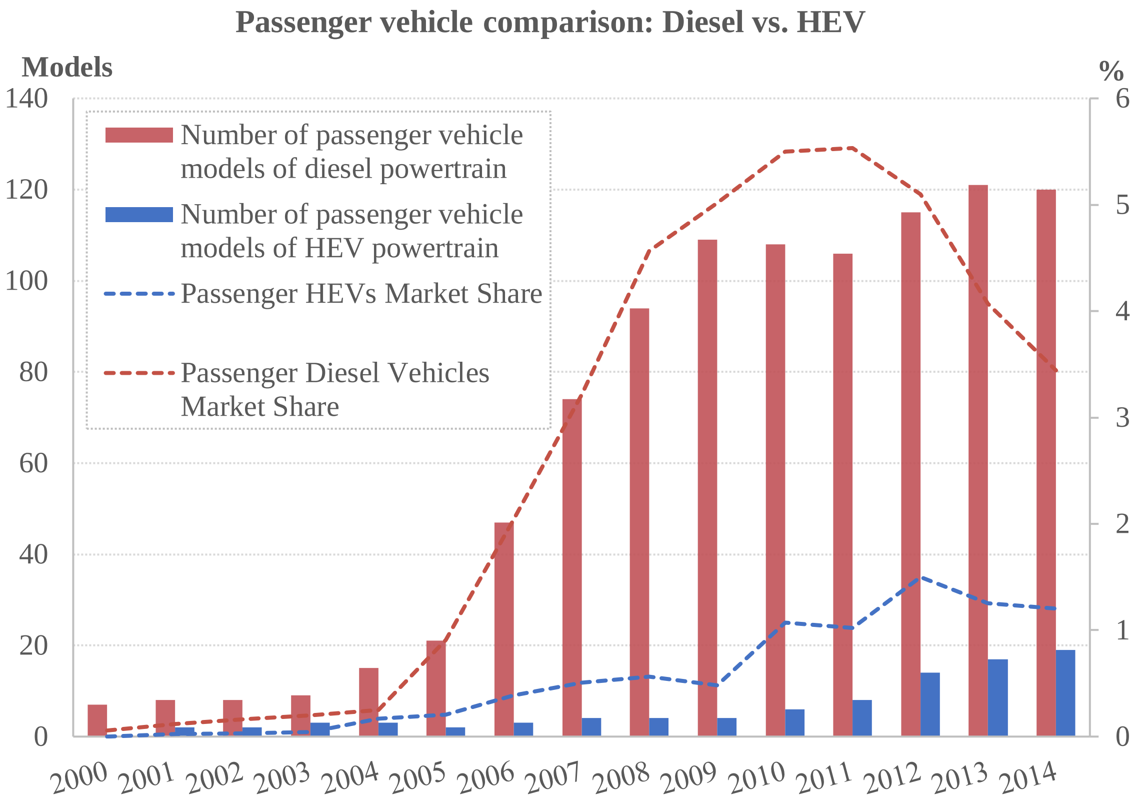


Figure 4-23 Passenger vehicle comparison

The only key variables that showed superiorities in diesel powertrain are vehicle variety (Figure 4-23). Passenger diesel vehicles always had higher number of vehicle models than passenger HEVs. However, the advantage of better vehicle model availability and variety had not given diesel powertrain huge boosts in terms of its market share at the beginning. Diesel had only gained popularity around 2004 where the vehicle model numbers had reached a more substantial level.

In addition to vehicle availability and variety, another possible explanation for the incongruent development of diesel and hybrid electric passenger vehicles is the disparate consumer familiarity and affinity of the two powertrains. It was addressed in many studies that consumers' familiarity with specific powertrain can significantly affect its adoption (Struben and Sterman, 2008, Shepherd et al., 2012, Cojocaru et al., 2013). It is reasonable to assumed that passenger diesel vehicles achieved better performance in adoption due to the higher familiarity caused by the powertrain's long history of heavy-duty diesel vehicles and relatively successful adoption of diesel powertrain in the SUV market segments. HEVs, on the other hand, without such advantages, are regarded as an unfamiliar and risky option when first entered the market. Lack of familiarity for HEVs might create an extra barrier for HEVs to get adopted.

Diesel powertrains are more likely to enter consumers' evoked sets for later vehicle performance evaluation because its greater consumer familiarity. In the first stage of the decision process, consumers narrow down their selections to a handful of vehicle models and form their evoked sets (Hawkins et al., 2001). Whether or not an AFV could get adopted depends on if AFV powertrains enter consumers' evoked sets. The lack of familiarity and observability for hybrid electric passenger vehicles may result in less chance of HEVs entering into consumers' evoked sets and therefore slower adoption than diesel passenger vehicles.

4.4.3 AFV vehicle performance in the evaluation stage

From market data observation, the historical trends of vehicle performance related variables are revealed. Some of the endogenous vehicle performance related variables such as AFV fuel efficiency, AFV GHG emissions, and refuelling facilities showed the reinforcing relationships that were hypothesized previously in Section 4.2. With the rising popularity of alternative powertrains, vehicle performance in these aspects are also increasing. Improved vehicle performance enhances the relative advantages of alternative fuel powertrains, and therefore increase AFV's possibility of adoption.

However, for some vehicle attributes, especially those are exogenous variables, their influences on AFV adoption were not prominent from historical data observation. Exogenous variables such as financial incentives and fuel price did not show the supposed influences with the AFV market shares. The most likely reason for such system behaviours is that all variables related to AFV performance work together with consumer preferences in the evaluation stage. Some of the isolated influences induced by a single variable can be counteracted by other vehicle performance related variables based on consumer preferences towards different vehicle attributes. For example, vehicle consumers who value more on savings for upfront purchase price will not choose the electric vehicle that has zero GHG emissions during the tank-to-wheel phase but comes with a higher purchase price tag. The environmental advantages of the EV are counteracted by the drawback brought by the high purchase price. In the next chapter, the combined effects of all variables related to vehicle performance will be revealed by quantitatively investigating the consumer preferences. The influences of these variables to AFV adoption will be quantified based on the discrete choice modelling.

The key dynamics revealed from the market observation verifies the initial dynamic hypotheses in Section 4.2. In the next section, these key dynamics will be mapped in causal loop diagram to form a preliminary dynamic hypothesis.

4.4.4 Key dynamics mapping in causal loop diagram

Based on the findings on relevant theories and data observation, key dynamics in Australian AFV adoption process are identified. There are mainly three reinforcing loops driving the AFV adoption: consumer awareness and familiarity loop, vehicle availability and variety loop, and consumer evaluation loop.

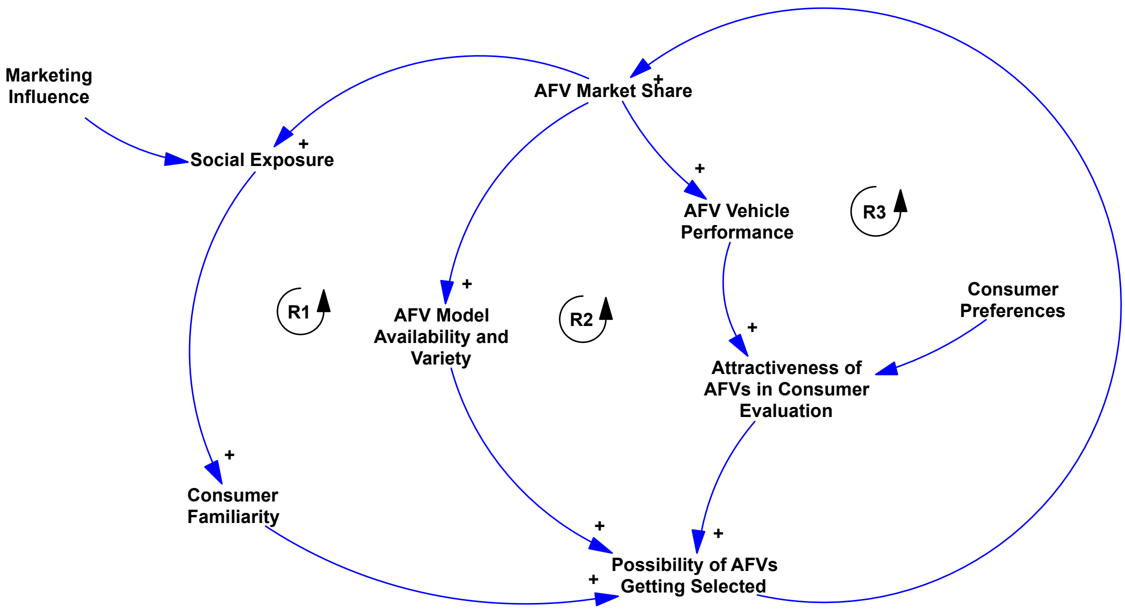


Figure 4-24 Causal loop diagram of key dynamic loops

Figure 4-24 presents the three key reinforcing loops with R1, R2 and R3 indicating the three loops respectively. Loop R1 depicts the consumer familiarity accumulation process. When consumer familiarity increases, the consumers become more likely to include AFVs in their evoked sets. The increased AFV market share will also boost the social exposure of the powertrain and therefore spur the consumer familiarity. Loop R2 is the vehicle variety loop where the AFV model variety and the AFV adoption form a reinforcing relationship. Larger AFV model variety leads to increased possibility of consumers choosing AFVs. The rising AFV market share also encourages vehicle manufacturers to release more AFV models. Loop R3 is the last reinforcing loop in the system. Although not all vehicle attributes that contribute to the overall AFV performance are endogenous and can be affected by the AFV adoption, there are several vehicle attributes that will evolve along with the increase of AFV market share and the maturation of the AFV platform. The improvement of AFV performance brought by the growth of the AFV powertrains will also make more AFVs stand out during the consumer evaluation stage. These three reinforcing loops are the main forces to drive the AFV adoption in Australia.

However, because the dynamics of the model mainly consist of reinforced relationship, once the equilibrium of the system was broken, the downward spiral effect caused by the reinforced relationship can be triggered and lead to drastic decrease in powertrain market shares. For instance, LPG fuelled vehicles experienced a great start in the alternative fuel market. However, over the years, the number of LPG fuelled vehicle models dropped significantly, which led to a drop in the market shares. In addition, because the price difference between LPG and petrol was getting smaller due to the excise on LPG fuel (Collett, 2013), the relative advantages of LPG fuelled vehicles became less prominent (observed in Section 4.3.5). Furthermore, the withdrawing of the LPG scheme grant in 2014 also made Australian consumers less interested in LPG fuelled vehicles (Huntsdale, 2017). The decrease in market shares of LPG fuelled vehicles have also led to less stations providing the fuel to driver (Cluff, 2017) and more difficult to maintain the vehicle as spare parts became harder to source and more expensive (Huntsdale, 2017), which further exacerbated the downward spiral for LPG vehicles. Because of the strong reinforced relationship in the system, once the number of LPG vehicle models was reduced and the cost of ownership slightly increased, the sales of LPG vehicles started to drop, which could lead to even less vehicle model in the market, and worse vehicle performance.

Another notable point about the causal loop diagram is that there lacks a balancing feedback loops to keep the system at equilibrium. In fact, the main balancing effect in the system that prevents exponential growth of the powertrain market shares is that finite consumer base cannot provide extra space for powertrains to exponentially grow. In order to gain more market shares in the market, an alternative powertrain had to seize market space that is occupied by other powertrains. The finite consumer base and the consequential competitions between different powertrains forms the balancing forces in the system. Because of such balancing feedback, the adoption for later and more innovative powertrains can be much more challenging.

4.5 Summary

This chapter investigated the basic dynamic structure of AFV adoption in Australia by exploring the literature for theoretical foundations and observing the historical trends of key variables in the system. The theoretical foundation serves as framework for the construction of key dynamic hypotheses and guidelines for a subsequent market historical trends observation. Observed historical trends of tangible key variables reflected the dynamic hypotheses and provided extra insights on Australian AFV adoption process. Finally, the identified key dynamics in Australian AFV adoption process were mapped in a causal loop diagram to complete the preliminary model structure. The driving and inhibiting forces of the system were introduced and discussed.

In the next chapter, the intangible key variables in AFV adoption, such as consumer preferences, consumer familiarity, and consumer attitudes and biases will be investigated. A stated choice experiment embedded in a market survey and a subsequent discrete choice model will be carried out. The market survey will provide further information on quantitatively understanding the AFV adoption process in Australia.

Chapter 5 Market Survey and Discrete Choice Model

In the previous chapter, key variables in AFV adoption were identified. Through the establishment of a theoretical foundation and an observation of historical trends in the market, possible dynamics around tangible key variables in AFV adoption were proposed and a preliminary model structure for the system dynamics model was developed. In this chapter, the two intangible key variables in AFV adoption, i.e. (i) consumer familiarity and affinity, and (ii) consumer preferences and opinions towards AFV, are investigated. These variables are studied by conducting a national market survey that includes a stated choice experiment to collect quantitative information about Australian vehicle consumers preferences and opinions. The survey also explores the familiarity and attitudes of Australian vehicle consumers towards alternative powertrain technologies to reveal further insights for the system dynamics model structure.

This chapter starts with the objectives of the market survey, which introduces the goal of the survey and how this survey can contribute to the system dynamics model. Then, the implementation of the market survey is introduced. The design of the attitudinal questions and the stated choice experiment are presented in this section followed with descriptions of survey implementation and collected sample distribution. The next three sections are dedicated to presenting survey results in regard to the two key variables: i) consumer familiarity and affinity and ii) consumer preferences towards AFVs. The attitudinal questions in the survey explores consumer familiarity and affinity, as well as the stated ranking of consumer preferences against a range of vehicle attributes. In order to provide precise quantitative information about consumer preferences, a discrete choice model is subsequently performed via the stated choice experiment embedded in the survey. This discrete choice model provides an accurate snapshot of quantitative information in consumer decision-making process. Finally, a summary of the market survey and the discrete choice model is presented at the end of this chapter.

5.1 Market survey objectives

Recall from Figure 4-3, key variables in AFV adoption steps are grouped into three categories (Consumer awareness of AFV, AFV model availability and variety, and variables within vehicle evaluation) based on the necessary conditions for adoption in each adoption step. In the need recognition step, awareness of AFVs is essential for an AFV to enter consumers' final evoked sets. The awareness can be explained by consumer familiarity as well as consumer affinity of the powertrain. In the information search step, AFV model availability and variety play a crucial part in the adoption course. The availability of AFV models in the market ensures that consumers from all market segments are covered and the possibility of AFV entering the evoked sets remains. The final category is around vehicle evaluation. In the evaluation process, relatively rational choices based on the overall performance of all of the vehicle attributes and consumers' personal preferences are made. In Chapter 4, key variables that depict AFV model availability and variety, and variables that describe vehicle performance in vehicle evaluation stage were observed and discussed. However, some key variables, namely consumer familiarity and consumer affinity towards AFVs, and consumer preferences in vehicle evaluation stage are intangible and hard to capture from historical data observation. Therefore, a market survey is developed in this chapter to investigate the value and dynamics behind these intangible key variables (see Figure 5-1).

For consumer familiarity and affinity, the market survey aims to gauge the level of consumer familiarity of different vehicle powertrains, understand how consumers view powertrain technologies, and discover their attitudes towards buying an AFV. Both qualitative and quantitative information about this key variable is acquired from the survey. Valuable insights on consumer opinions and attitudes towards alternative vehicle powertrains are captured.

As for consumer preferences and opinions, the survey carries out a stated choice experiment to quantitatively measure how different vehicle performance influences consumers' choice. By letting respondents choose their most preferred vehicle out of a range of vehicles with different combinations of vehicle attributes values, the stated choice experiment reveals respondents' preferences in their evaluation process using the discrete choice modelling technique. This stated choice experiment plays a vital role in the overall system dynamics model construction since it feeds quantitative data to consumer choice feedback loop in the system dynamics model as well as provides qualitative information about consumer decision-making process.

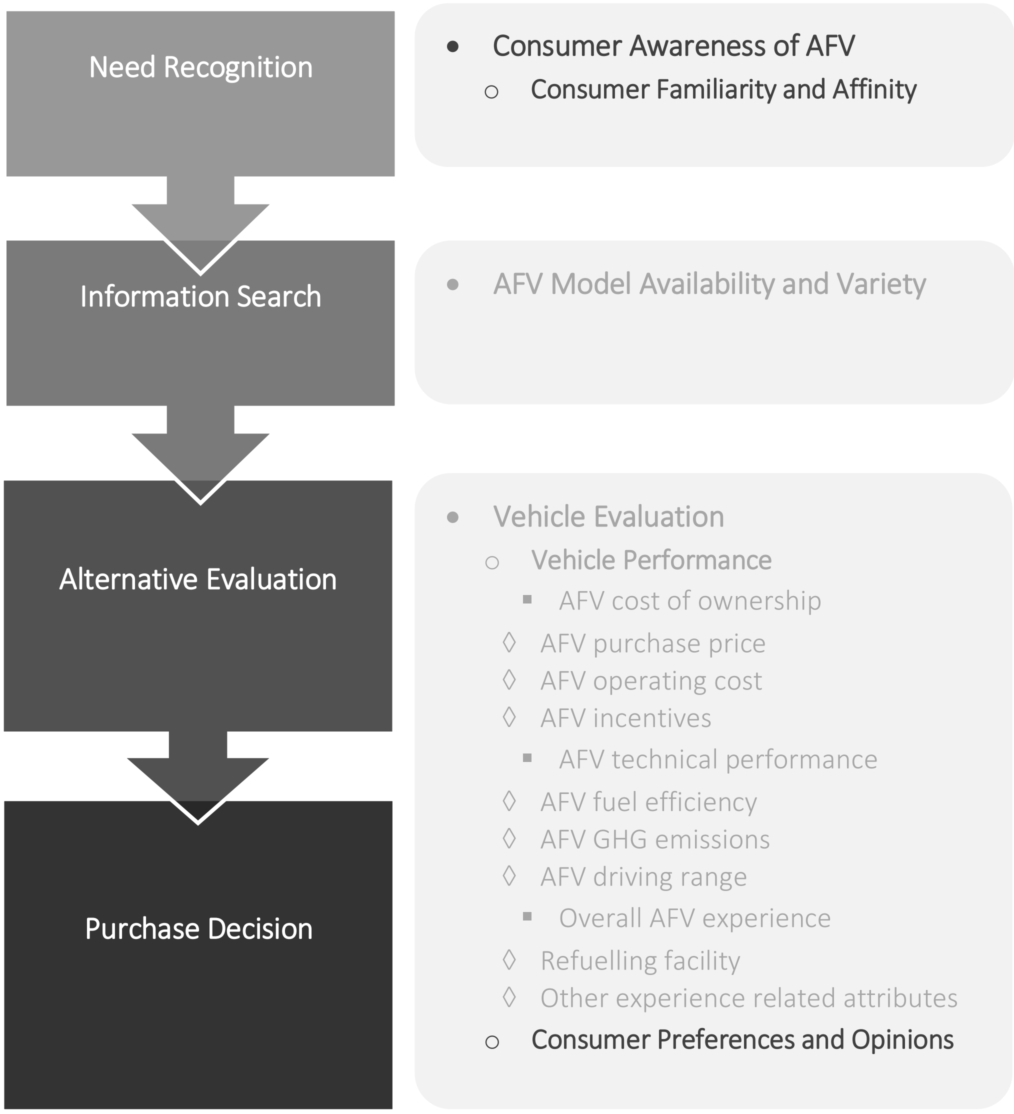


Figure 5-1 Key variables investigated in Chapter 5

In summary, the contributions of the market survey are two-fold. First, the market survey explores AFV familiarity and consumer opinions of Australian vehicle consumers. It presents a comprehensive picture of the vehicle consumers in the market and sequentially provides further insights on the dynamic hypotheses formation. Second and more importantly, the survey-embedded stated choice experiment and following discrete choice modelling provide vital quantitative data about consumer choices for the system dynamics model. In the following section, the details of market survey design and its implementation will be introduced.

5.2 Market survey design

A total of six powertrains were included in the market survey: petrol, diesel, hybrid electric, plug-in hybrid electric, pure electric and hydrogen. All powertrains included in the survey are currently available in the market except for hydrogen. Although hydrogen vehicles are not yet available to purchase in Australia, it has high possibility of entering the market in the future. The inclusion of such a powertrain in the stated choice experiment allows the author to explore consumer preferences around this yet-to-be-realized powertrain, which is one of the greatest advantage of stated choice experiment. By adding this powertrain in the survey, the benchmark of how consumers view a brand-new powertrain can be set. The comparison between consumers' preferences and opinions of this powertrain and other already-available powertrains can be made.

It is worth mentioning that not all powertrains that had existed in the market are incorporated in the survey. In particular, pure LPG and LPG dual fuel vehicles are not selected. Although these two powertrains entered the market relatively early, LPG fuelled vehicles now have very little share of the new passenger vehicle market. There are no LPG dual fuel vehicles selling in the market and only two pure LPG vehicle models provided by Ford. These powertrains have lost the majority of their popularity in the Australian vehicle market since its prime time in the 1990s. Asking consumers preferences towards powertrains that have already been phased out of the market is not necessary and cannot provide much useful information towards the development of future vehicle market landscape. Therefore, these two powertrains are not included in the market survey, nor will be included in the system dynamics model simulation in the following chapters.

In order to enhance the reliability of the market survey, demographic quotas were added to survey panel. A panel that represents the Australian vehicle consumers in terms of basic demographic characteristics such as age, gender, household income, and education attainment level is the data collection goal of this survey. Screening questions are added prior to survey questions to make sure the panel is representative of Australian vehicle consumers. In Section 5.3, the demographics of the survey panel will be compared with the national data for validation of the survey.

Market survey in this thesis is divided into three main parts: the first part is to gauge consumers' attitudes and knowledge towards AFVs; the second part is to carry out the stated choice experiment to reveal consumers' preferences in vehicle purchase decisions; the third part is to collect generic information about respondents' vehicle ownership and more demographic information for further analyses. In the following sections, design details of these three parts of the market survey will be presented.

5.2.1 Part One: Attitude questions for consumer familiarity and affinity

Australian consumers' attitudes towards AFVs are measured from four aspects: familiarity and experience level, knowledge and biases, vehicle attributes ranking, and willingness to consider purchasing AFVs.

In order to gauge Australian consumers' familiarity and knowledge level of AFVs, the survey asked respondents to indicate their experience level with different alternative powertrains out of five familiarity levels, from "never heard of it" to "I have owned/ am currently owning". Better familiarity and deeper understanding on AFV technologies increase the possibility of alternative powertrains getting selected to consumers' consideration sets. Survey responses of this question provide a general picture of how familiar Australian vehicle consumers are with different powertrains. This piece of information is also valuable to later dynamic model simulation and calibration.

Biases and knowledge about AFVs were measured by asking respondents to rate every powertrain they know in terms of fuel efficiency, CO_2 emissions, reliability and driving range. Fuel efficiency and CO_2 emissions were selected for the reason that these two vehicle attributes are often regarded as the most beneficial features of alternative fuel powertrains. By asking respondents to rate fuel efficiency and CO_2 emissions for alternative powertrains alongside traditional powertrains, information about whether respondents are fully aware of the benefits of AFVs were retrieved. Reliability was selected because it is regarded as the most important attribute for vehicles in the work of Caulfield et al. (2010). Although reliability is not a vehicle attribute that directly associates with vehicle powertrains, whether or not consumers perceive AFV reliability as the same as traditional powertrains is still an important piece of information to collect. Finally, driving range was selected as the last attribute for the bias and knowledge section. Limited driving range is a major concern for AFVs, especially for powertrains that rely solely on alternative fuel that are not prevalent in refuelling network. Information about whether consumers over or underestimate the challenge they will face if they switch to alternative fuel powertrains were gathered from this question.

In attitudinal questions, consumer preferences were also investigated. Respondents were asked to rate their preferences over twelve specifically chosen vehicle attributes. These vehicle attributes included attributes that were incorporated in the stated choice experiment questions as well as additional attributes that were not included in choice scenarios. The additional attributes are regarded as significant to consumers in vehicle choices through the literature but are not suitable to be included into the stated choice experiment since these attributes normally do not show substantial differences between traditional and alternative powertrains. These questions aimed at gathering information about what vehicle attributes were the most important in consumers' minds.

In the end, in attitudinal questions, consumers' willingness to consider AFVs were investigated. Respondents were required to first state if they had considered alternative fuel powertrains in their latest vehicle purchase. They were then asked if they would consider an alternative fuel equivalent to their latest vehicle purchase if the vehicle brand and model were kept the same. The second question was designed to measure consumers' willingness of AFV adoption without the interference of limited alternative fuel model variety.

5.2.2 Part Two: Stated choice experiment for consumer preferences

The second part of the market survey was dedicated to the stated choice experiment. The stated choice experiment can provide quantitative data for how consumers make their decisions within their evoked set. The coefficients associated with each vehicle attributes reveal how performances of different vehicle attributes influence consumer choices.

Before respondents proceeded to the stated choice questions, they were provided with a description page introducing each powertrain as well as all vehicle attributes that were included in the experiment. The provided description covered the basic information about the powertrains and vehicle attributes so that respondents clearly understood their tasks and the choice scenarios presented. Providing such information, although in an impartial way, might affect respondents' perceptions of the powertrains negatively or positively, especially in cases where the powertrain is completely unfamiliar to the respondents. However, since the description only provided the very basic information of the powertrains, the experiment could still capture consumers' attitudes and opinions towards alternative powertrains. The slight potential perception sways due to provided information were negligible compare to the overall consumer attitudes and opinions that the experiment captured.

The experimental design was created using statistical software SAS following the d-efficiency design method (Kuhfeld, 2010). Every respondent answered a total of 16 choice scenarios questions (an example of one choice scenario was shown in Figure 5-2), with each question providing 6 vehicles with different powertrains to choose from. The experiment was designed to be a branded choice experiment with each powertrain representing an alternative in the choice questions. The six powertrains that were included in the experiment are petrol, diesel, HEV, PHEV, EV and hydrogen vehicles. This wide range of powertrain types were selected to cover not only powertrains that are already exist in the market but also ones that are likely to be later introduced into Australia.

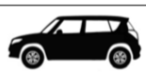
14	Powertrain type					
	Petrol Vehicle	Diesel Vehicle	HEV	PHEV	EV	Hydrogen Vehicle
Purchase price	$98,000	$33,000	$85,000	$111,000	$85,000	$59,000
Car size	 SUV/People mover	 Hatch/Wagon	 SUV/People mover	 Sedan	 Sports/Coupe	 Hatch/Wagon
Annual fuel cost	$2400	$1200	$1200	$1100	$500	$2400
Fuel availability	100%	100%	100%	100%	65%	15%
Driving range	>600 km	>600 km	>600 km	>600 km	600 km	300 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

Figure 5-2 Example of choice scenario question in the survey

There were five vehicle attributes used in the stated choice question design: vehicle purchase price, annual fuel cost, car style, fuel availability and driving range. The first four attributes were generic attributes that applied to all alternatives. While the last attribute, driving range, was an alternative-specific attribute that only applied to pure electric vehicles and hydrogen vehicles. The detail of the attributes and their levels can be seen in Table 5-1.

Table 5-1 Stated choice experiment attributes and levels

Attributes	Alternative	Number of levels	Levels
Purchase Price (AUD)	All six	8	20k, 33k, 46k, 59k, 72k, 85k, 98k, 111k
Annual Fuel Cost (AUD)	Petrol	4	800, 1600, 2400, 3200
	Diesel, HEV	4	600, 1200, 1800, 2400
	PHEV, EV	4	500, 700, 900, 1100
	Hydrogen	4	1200, 1600, 2000, 2400
Vehicle Body Style	All six	4	Sports/Coupe, Hatch/Wagon, Sedan, SUV/People mover
Fuel Availability (%)	EV, hydrogen	4	15%, 40%, 65% and 90% of current petrol service stations
	Petrol, Diesel, HEV and PHEV	-	100% fuel availability
Driving Range (km)	EV	4	150, 300, 450, 600
	Hydrogen	4	300, 400, 500, 600

There were two monetary attributes in the experiment, purchase price and annual fuel cost. A wide range of price levels was selected from 20k to 111k in order to cover the different prices for all body types and powertrains. No price increments were added to alternative powertrains to find out consumers' preferences towards powertrain despite any price differences. In this experiment, fuel efficiency was treated as a monetary attribute instead of a technical attribute. The reason of such arrangement was to reduce respondents' confusion about the different fuel efficiency units for alternative powertrains. Annual fuel cost is much easier to understand and relate to for respondents who are not tech-savvy (Massiani, 2014). It can also include the effect of fuel price so that the cognitive differences on powertrain prices between respondents are eliminated.

Vehicle body type describes the size and style of the vehicle. The size and style of the vehicle is particularly important to consumers however not often included in stated choice studies (Massiani, 2014). Here in this study, four vehicle body styles depicting both the style and size of the vehicle were included in the experiment so that aesthetics and functionality of the vehicle can be reflected in the choice question to some extent. In addition, visual aids (silhouettes of different vehicle body types) were provided in each choice scenarios to help respondents to distinguish different car sizes easily (Figure 5-2).

Attribute fuel availability was designed to investigate consumers' opinion about powertrains that require alternative refuelling, i.e. pure EV and hydrogen vehicles. Comparing alternative fuel availability to the established petrol service station network is the most intuitive way for respondents to gauge the fuel availability level of new alternative powertrains. Thus, percentage of the current petrol service station number were used in the survey to indicate fuel availability for our respondents. By doing this, respondents were automatically offered the information that the fuel availabilities of powertrains that can be refuelled at the petrol station (i.e. petrol, diesel, HEV and PHEV) are 100%. In the later model regression, fuel availability was used as a generic attribute simply because the respondents were provided with the information.

Driving range is an alternative-specific attribute for electric vehicles and hydrogen vehicles. Together with fuel availability, driving range has been identified to be a crucial vehicle attribute relating to consumers' fuel range anxiety (Needell et al., 2016, Franke and Krems, 2013). Four levels of driving ranges were selected for EV and Hydrogen vehicles. Different values were chosen to mimic the technology limitation these powertrains were facing.

5.2.3 Part Three: Demographic information from respondents

The final part of the market survey comprises questions that aims to get demographic information about respondents. More general questions about respondents' household size, the model and year of their latest purchased vehicle, their weekly commuting distance, and their vehicle ownership were asked. Respondents' age, gender, education and household income information were gathered to assist the analyses of survey results of part one and two. This demographic information adds additional dimension of the survey results analyses and allows the author to further understand consumer choices influenced by demographics.

5.3 Market survey implementation and survey sample

Survey data were collected using a paid online panel in July 2016. The sample was drawn from Australian consumers who have purchased a new vehicle within the last 24 months.

Adding such restriction on the panel made sure that respondents still have relatively fresh memory of their latest purchase and their knowledge about the current vehicle market is reasonably up-to-date. Respondents were also asked to choose based on their preferences during their latest purchase in the stated choice questions so that they could feel related to the choice scenarios and therefore provide more reliable data results. In order to ensure that the results of the survey can represent general Australian vehicle consumers, demographic quotas were set on gender, age, household income, and attained education level to be aligned with Australian population who are between 18 to 75 years old.

In total, 605 respondents completed the survey. Following data screening method guided by (DeSimone et al., 2015), responses that fell into the following criteria were eliminated: vehicle body type out of the study scope (i.e. respondents whose latest vehicle purchase was not a light passenger vehicle nor a SUV), patterned answers (respondents who select the same choices/levels/orders for all questions), semantic synonyms (respondents who have given contradicted answers), and unrealistic answers (respondents stated they have owned hydrogen vehicles before). After the data screening, we have a total of 537 valid responses.

A comparison of the sample and Australian population is listed in Table 5-2. The survey panel aligned with the national census data relatively well in terms of gender, with slight over representation of female consumers. In general, the panel under represented younger population and over represented elder population, especially consumers in age group 55-64. In terms of income level, the panel covered less low-incomed consumers and more mid-to-high-incomed consumers. As far as education attainment, the panel were composed of much more highly educated (with bachelor and master degrees) consumers. The limitation brought by the panel biases were put into consideration during data analysis.

Table 5-2 Demographic characteristics of the sample and the Australian population

Demographics group	Level	Sample %	National census (ABS) %
Gender	Male	46.74	49.77
	Female	53.26	50.23
Age	18-24	10.99	14
	25-34	16.95	19.8
	35-44	17.69	19.5
	45-54	16.39	18.9
	55-64	20.86	16.1
	65-74	17.13	11.5
Weekly Household Income	Less than AUD 299	2.61	3.36
	AUD 300 to 599	7.82	12.87
	AUD 600 to 999	11.92	17.04
	AUD 1,000 to 1,499	23.28	15.35
	AUD 1,500 to 2,399	24.77	21.90
	AUD 2,400 to 3,499	17.50	16.03
	AUD 3,500 to 4,999	5.96	8.02
	More than AUD 5,000	6.15	5.44
Education	Some secondary education	9.12	26.30
	Graduated high school	18.62	17.90
	Some university Education	10.99	18.40
	2-year university or trade school degree	15.64	9.30
	3 or 4-year university degree (bachelors)	29.24	16.80
	Master degree	13.59	3.00
	Doctoral degree	2.79	5.60

In this section, the survey design and implementation was introduced. In the following three Sections 5.4, 5.5, and 5.6, survey results in consumer attitudes and preferences will be presented respectively.

5.4 Consumer familiarity and affinity towards AFVs

This section presents survey results from consumer attitudinal questions. Consumer familiarity and experience level towards AFVs, their knowledge level with AFVs, and their willingness to consider and affinity of AFV models are discussed in this section.

5.4.1 Consumer familiarity and knowledge towards AFVs

In the study, respondents were asked to indicate their familiarity and experience level for a total of five alternative powertrains, including diesel, hybrid electric (HEV and PHEV), pure electric and hydrogen. Experience levels are assigned with scores from 1 to 5, 1 being the least familiarity level. The average scores of these five powertrains are shown at the top of each powertrain column in Figure 5-3.

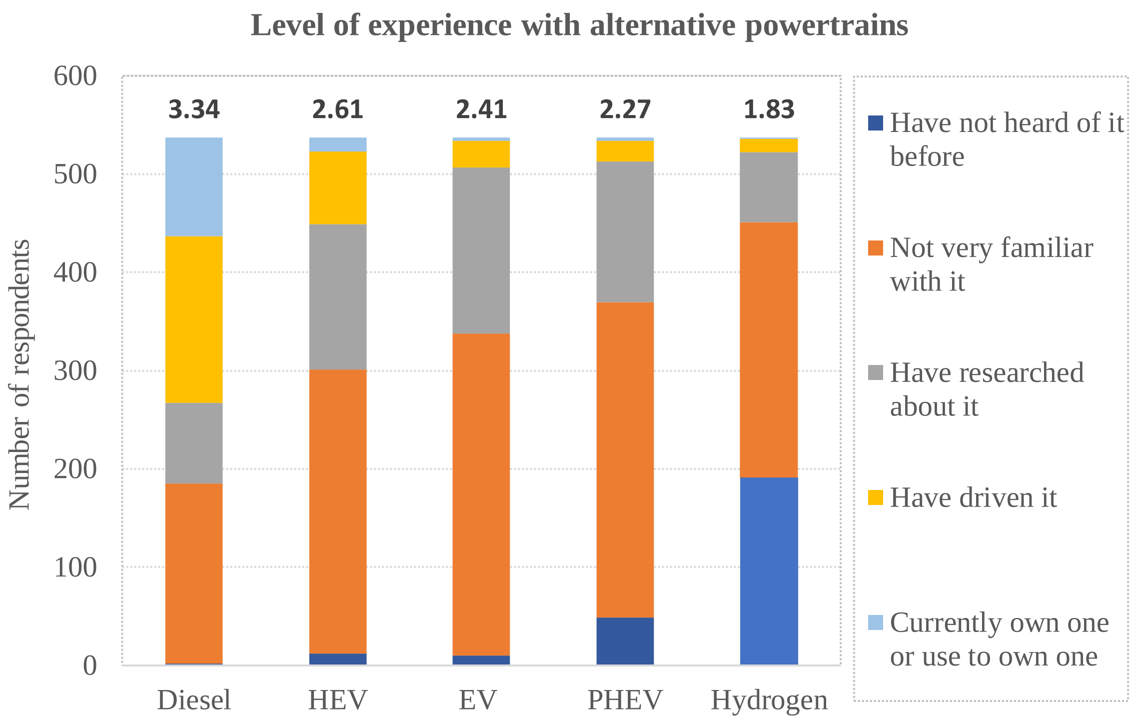


Figure 5-3 Level of experience with alternative powertrains

The familiarity scores are in line with how long these alternative powertrains have been introduced into the market. The results show that diesel vehicles enjoy the most familiarity among Australian vehicle consumers, with almost every respondent indicating he/she is at least aware of the technology. Hydrogen vehicles, being the only powertrain that has yet to enter the market, has the most respondents indicating they are either not heard of the technology or not familiar with it. Although EVs and PHEVs are known by most of the respondents, these two powertrains have less consumers having first-hand experience with the technology (i.e. have driven it or owned it).

Respondents who have at least heard of one alternative powertrain were asked to rate alternative powertrain(s) which they know of along with petrol powertrain in the following four vehicle attributes: fuel efficiency, CO_2 emissions, reliability and driving range. A score of 1 was given to very poor performance in vehicle attributes and 5 was given to great performance in vehicle attributes. The average scores of powertrain ratings in the four attributes are shown in Figure 5-4. Higher columns represented higher ratings in vehicle attribute for the powertrain.

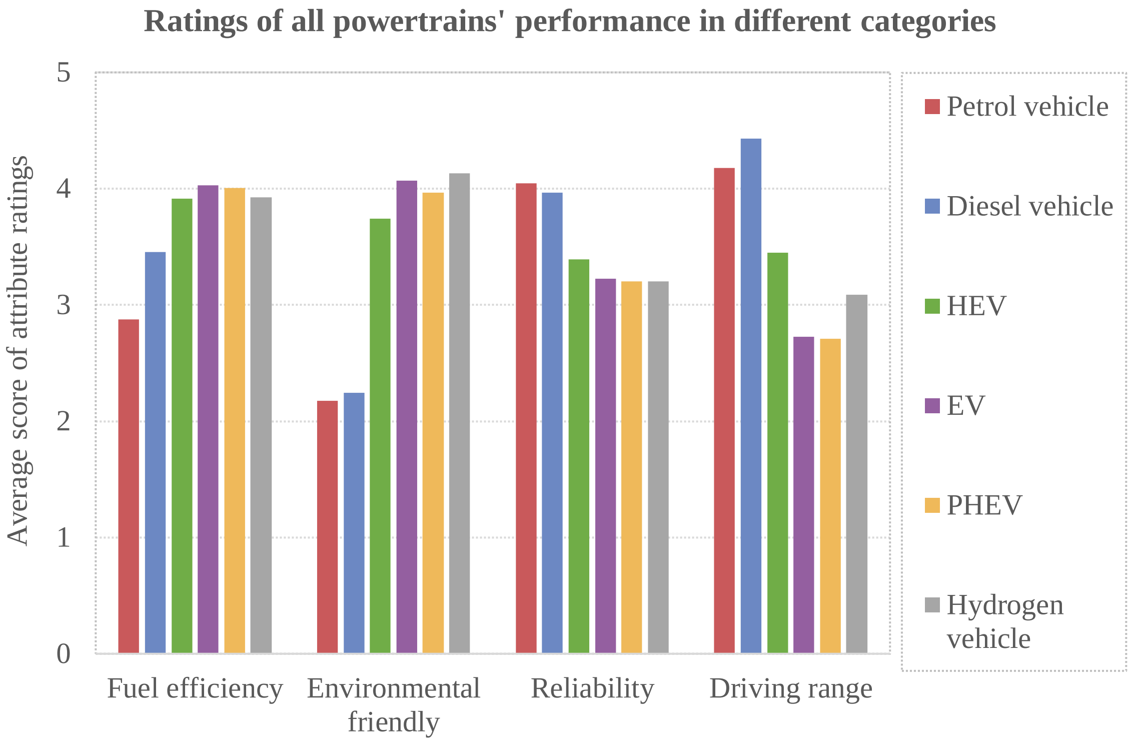


Figure 5-4 Ratings of all powertrains' performance in different categories

The benefits of alternative powertrains such as being more fuel efficient and environmentally friendly are recognized by most of the respondents. However, there are also significant biases around alternative fuel technologies. On average, respondents rated alternative powertrains lower in reliability, which is the most important factor Australian consumers consider in vehicle purchase (see Section 5.5). This bias towards HEV, EV, PHEV and hydrogen vehicles can significantly impede consumers from considering such powertrains. Many advantages of these powertrains might be neglected based on the reliability bias consumers hold against them. There are also biases around the driving range for hybrid powertrains among respondents. HEVs and PHEVs are considered having much shorter driving ranges than traditional powertrains despite the fact that these powertrains can be refuelled easily by petrol and does not have notable driving range issues.

5.4.2 Consumer willingness to consider

In consumer willingness to consider section, about 48 % of the 537 respondents have considered AFVs in their latest purchase (Figure 5-5 a). A further break down of consumers’ willingness to consider is presented in Figure 5-5 b. In the left columns, the number of respondents who have considered purchasing the powertrain are listed. Among different alternative powertrains, diesel vehicle is the most popular choice, followed by HEV. More recent powertrains like EV, PHEV and LPG vehicles have much less consumers who are willing to consider purchasing. In the right columns, the number of respondents who actually purchased the powertrain were also presented for comparison. The significant differences between the respondent percentages of considered and actual purchase indicated that even AFVs entered consumers' consideration sets, they were highly unlikely to get selected due to less advantage comparing to petrol powertrain during the evaluation stage.

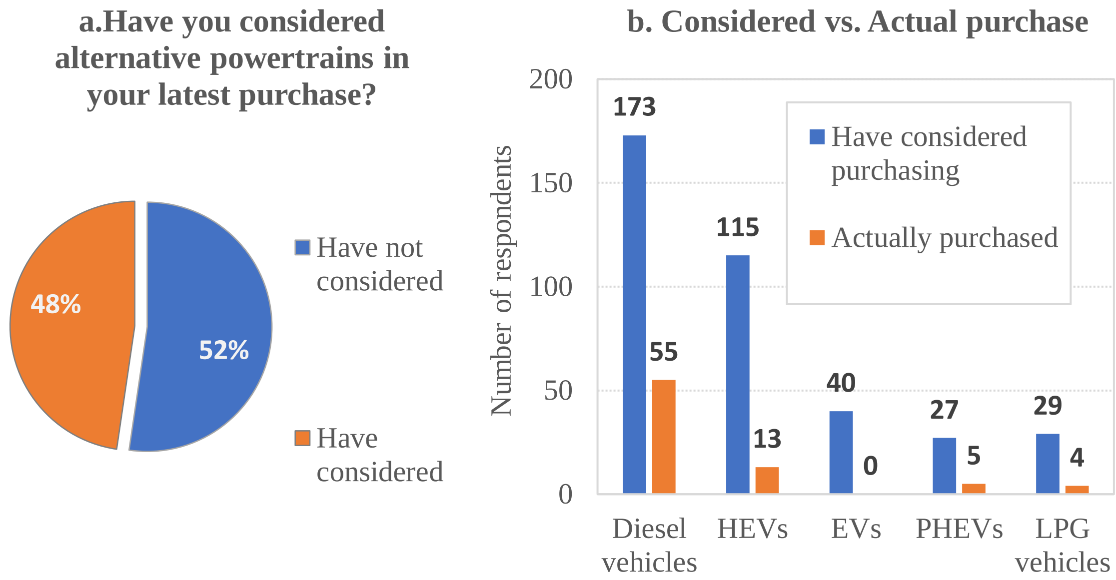


Figure 5-5 Willingness to purchase AFV in previous vehicle purchase

Consumers' willingness to purchase an AFV changes when they can choose the exact model as their latest purchase but in alternative powertrains (Figure 5-6). Comparing Figure 5-5 b and Figure 5-6, the number of respondents who showed significant interests in purchasing AFVs (respondents who are very likely to or willing to consider purchasing) have increased significantly for all powertrains. Taking HEV powertrain as example, there were 115 respondents stated that they had considered purchasing an HEV during their last vehicle purchase (Figure 5-5 b). This number increased to 322 (sum of top two sections of the HEV column, 113 plus 199) when the respondents were provided the exact vehicle model in hybrid electric powertrains (Figure 5-6). This result indicates that if the number and variety of AFV models are increased, consumers' likelihood of AFV purchase will rise as well. It also confirms the dynamic hypothesis of the reinforcing relationship between AFV model variety and AFV market share proposed in Chapter 4 Section 4.4.1.

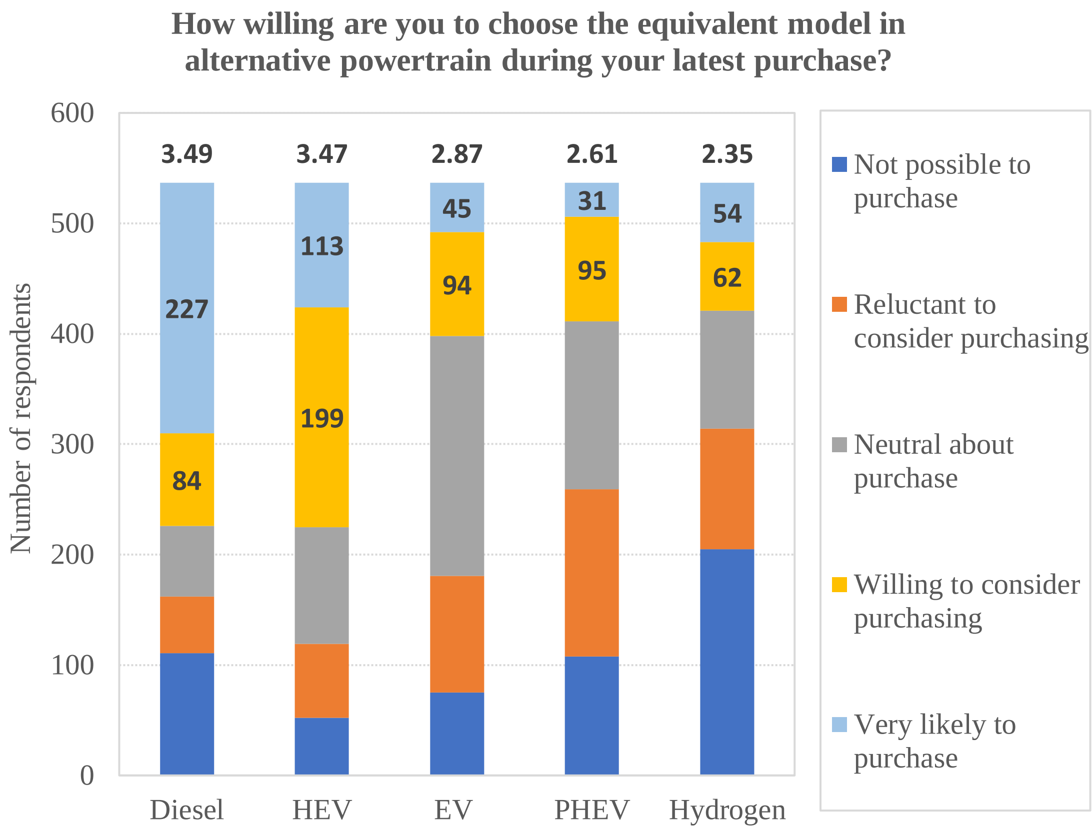


Figure 5-6 Willingness to AFV purchase in previous vehicle purchase if the model variant is kept the same

The average willingness score for each powertrain (displayed at the top of each powertrain column in Figure 5-6) was calculated by sequentially assigning 5 with "Very likely to purchase" to 1 with "Not possible to purchase". Among all alternative powertrains, diesel vehicles have the highest willingness to purchase score if model variety and number were not a constrain to consumer choices. However, there are a significant percentage of respondents selecting not to consider this powertrain at all. The score for HEVs is slightly lower than diesel vehicles with more respondents willing to consider switching to HEV when the vehicle model style is kept the same. For more recent powertrains, scores of willingness to consider are much lower. This result suggests that for HEVs, consumers may be more willing to adopt if more vehicle models are provided within a variety of vehicle body styles. However, the low scores for more recent powertrains indicate that limited number and variety of vehicle models is not the only reason to explain the low willingness to purchase. There are other constrains that impede AFV adoption in consumer choices.

In the next two sections, survey results on consumer preferences will be demonstrated. Consumer preferences ranking results and the regression results of the discrete choice modelling coming from the stated choice experiment will be presented and discussed.

5.5 Consumer preferences based on survey questions

Before the stated choice experiment, respondents were asked to rate a series of vehicle attributes from unimportant (assigned with 1) to very important (assigned with 5). Although many of these attributes are considered as extremely important factors by consumers, they cannot be differentiated by powertrains and thus are not included in the stated choice experiment. The score ranking for vehicle attributes shows that reliability (vehicle is less likely to break down) as the most important factor that consumers look for in their vehicle purchase. However, under the influence of consumer biases in AFV reliability (see Figure 5-4 in Section 5.4.1), consumers can easily give up the idea of switching to AFVs.

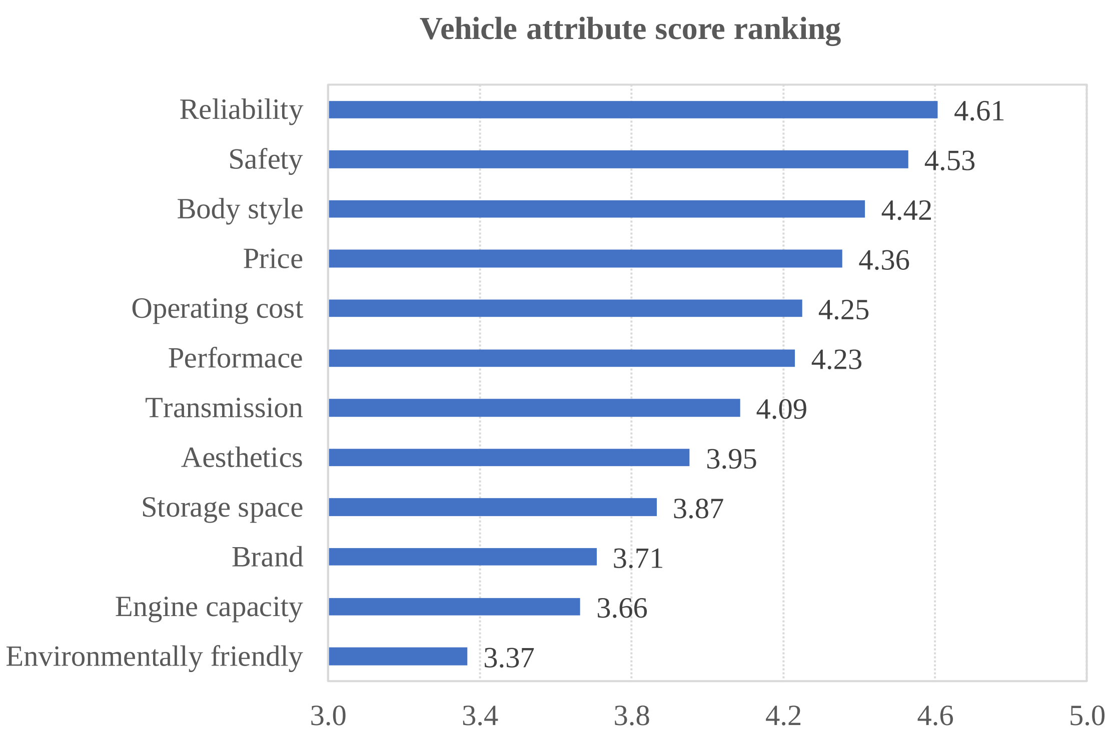


Figure 5-7 Vehicle attribute score ranking

Another attribute that is worth mentioning is vehicle body style, which ranks the third place before monetary attributes like price and operating cost. Body style of the car is heavily associated with the functionality of the vehicle. As suggested by the survey results, respondents tend to hold on to their body style preferences during vehicle purchases[4]. If alternative powertrain does not provide enough models in a particular body style, it is very likely that this powertrain will lose the consumers who are looking for that body style.

Lastly, the attribute “environmentally friendly” as the predominant benefit of alternative powertrains gets the lowest score in the ranking. Although most of the respondents recognised this vehicle attribute precisely and agree that alternative powertrains perform better than traditional powertrains in environmental impact (see results from Section 5.4.1), the low preference rating on this attribute suggests that AFVs are not attractive enough solely based on great environmental performance.

5.6 Consumer preferences and opinions from discrete choice modelling

Although consumer preferences rating in Section 5.5 can provide information about consumers’ opinions of different vehicle attributes, it failed to provide quantitative information about how consumers evaluate different vehicle attributes during their vehicle purchase. This section presents the results of the stated choice experiment where quantitative information that describes consumer preferences and how vehicle performance in different attributes can influence consumers’ choices are revealed. The section starts with the introduction of random utility theory and multinomial logit modelling techniques for choice models. Then, it describes the process of finding the right model specification that can provide most insightful choice model fit. Finally, the model regression results are presented and their implications are discussed.

5.6.1 Random utility theory and multinomial logit models

For stated choice experiments, standard and mixed multinomial logit models (Train, 2003, Train, 1998) are prevalent modelling techniques used to estimate the coefficients of various vehicle attributes contributing to the overall utility of a car.

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[4] In the stated choice experiment, respondents are more likely to choose vehicles that have the same body style of their latest purchased vehicle in the choice scenarios, supporting the findings in the above section where respondents regard body style as a substantial factor for vehicle purchase.

Random utility theory is used to describe the situation where a person n faces a choice among J alternatives. This theory assumes the utility of alternative j perceived from person n can be decomposed into the sum of utilities of all observable attributes ($\beta_n' x_{nj}$) and unobservable influences (ε_{in}), as the following equation presents:

$$U_{nj} = \beta_n' x_{nj} + \varepsilon_{nj} \ , \tag{5.1}$$

where x_{nj} is a vector of observed variables relating to alternative j and person n; β_n is a vector of coefficients which depicts person n's tastes associated with each of the observed variable; ε_{nj} is a random term that is independently and identically distributed (IID) extreme value.

In a branded stated choice experiment, the impacts the unobserved variables that associated with each alternative are also captured. In model specification for such experiment, dummy variables that represent each alternative j are also included in vector x_{nj}. The coefficients that associate with such dummy variables (β_{nj}) are called alternative-specific coefficients (ASCs). With the existence of ASCs, the random term ε_{nj} is set to having a zero mean in construction (Train, 2003). The ASCs are in relative terms with each other. In model specification, one alternative is set to have zero ASC and other alternatives in the choice scenario have ASCs relative to the one that are set as the benchmark zero. In this research, petrol powertrain is set as having zero ASC and all other alternatives will therefore have negative ASCs.

In standard multinomial logit models, it is assumed that respondents' tastes do not vary across the population, which means every respondent has the same taste for each attribute. Therefore, the possibility of alternative i being chosen by person n can be derived as:

$$Prob_{ni} = \frac{exp\,\beta' x_{ni}}{\sum_{j=1}^{J} exp\,\beta' x_{nj}} \ , \tag{5.2}$$

which is described as the standard multinomial logit model (Train, 2003).

If the taste varies across the population with density $f(\beta)$, the possibility of alternative i being chosen by person n can no longer be represented by the standard multinomial logit equation above. Instead, the probability equation that allows variations in consumer tastes is represented by the following equation:

$$Prob_{ni} = \int \left(\frac{exp\beta' x_{ni}}{\sum_{j=1}^{J} exp\beta' x_{nj}} \right) f(\beta) d\beta \, , \tag{5.3}$$

where density $f(\beta)$ is a function of parameters that depicts the distribution of β in the population (Train, 1998). A distribution is specified for the coefficients and then the parameters of that distribution are estimated. In common practice, density $f(\beta)$ has been specified to be normal or lognormal: $\beta \sim N(b, W)$ or $ln\beta \sim N(b, W)$ with parameter b and W being the mean and variance (Train, 2003). In this study, normal distribution is selected for car size, fuel availability and driving range while lognormal distribution is chosen for monetary variables purchase price and fuel cost for the reason that it is expected that all respondents to prefer to pay less when every other attribute being the same.

5.6.2 Discrete choice model regression results

Based on the random utility theory introduced in the previous section, three model regression specifications were used and the regression results are presented in Table 5-3. Model 1 is the most basic model fit with ASCs and all coefficients for vehicle attributes. Based on the basic fit, Model 2 incorporates demographic variables with each powertrain to show preferences of different consumer segments. Finally, Model 3 adopts mixed logit model specification and includes random parameters set for all vehicle attributes (i.e. purchase price, fuel cost, car size, fuel availability and driving range).

In terms of goodness of fit, Model 3 performs significantly better than the other two model fits. The log likelihood (LL) of Model 3 has been considerably improved from -11977 in Model 1 to -10636 in Model 3. A log likelihood ratio test between Model 2 and 3 performed as: 2(LL_{M3}-LL_{M2}) = 2606 > $\chi^2_{\alpha|\Delta df=4}$= 14.07. The log likelihood ratio value is much higher than the critical value (for degree of freedom at 4, p-value at 0.005) in the chi-square distribution, which also suggests that Model 3 is a significant better fit for the data. In another statistic test, the Akaike information criterion (AIC)[5], where the smallest value is the most preferred (Akaike, 1974), also suggests that Model 3 is a superior fit for data. The last statistical measurement is the McFadden R^2. This statistic is also called as a pseudo R^2 and often viewed as comparable to R^2 in ordinary least square (OSL).

[5] Akaike information criterion is calculated as: -2LL+2*k*, where *k* is the number of estimated parameters.

However, different from the R^2 in OSL, the ideal McFadden R^2 value for a model fit is in the range of 0.2 to 0.4 (McFadden, 1977). Among the three model fits, the best performed fit in terms of the McFadden R^2 is Model 3. Based on these three statistics, Model 3 best represents the data set. Therefore, the following discussion on choice modelling results will be mainly based on Model 3.

Table 5-3 Stated choice experiment parameter estimates[6]

	Model 1	Model 2	Model 3
Fixed parameter			
Diesel	-0.2365***	-0.2325***	-0.2426***
HEV	-0.4269***	-0.4220***	-0.5132***
PHEV	-0.4928***	-0.4910***	-0.6922***
EV	-1.8712***	-1.8801***	-2.2710***
Hydrogen	-1.9628***	-1.9580***	-2.4451***
Purchase price	-0.0280***	-0.0281***	-3.2228***
Car style (Hatch/Wagon)	0.6371***	0.6379***	0.8133***
Car style (SUV/People mover)	0.6231***	0.6247***	0.6948***
Car style (Sedan)	0.7046***	0.7073***	0.8909***
Fuel cost	-0.0395***	-0.0397***	-3.1181***
Fuel availability	0.0067***	0.0067***	0.0077***
Driving range for EV and Hydrogen vehicle	0.1402***	0.1397***	0.1878***
Diesel: Age	-	-0.0869***	-0.1294***
HEV: Age	-	-0.0681**	-0.1381***
PHEV: Age	-	-0.1102***	-0.1731***
EV: Age	-	-0.1132***	-0.2046***
Hydrogen: Age	-	-0.0266	-0.0840**
Diesel: Education	-	-0.0049	0.0188
HEV: Education	-	0.0722**	0.0909***
PHEV: Education	-	0.0673**	0.0839***
EV: Education	-	0.1305***	0.1196***
Hydrogen: Education	-	0.0595	0.1171***
Random parameters			
Purchase price	-	-	1.2375***
Car style (Hatch/Wagon)	-	-	1.3092***
Car style (SUV/People mover)	-	-	1.9895***
Car style (Sedan)	-	-	1.1136***
Fuel cost	-	-	3.6414***
Fuel availability	-	-	0.0967***
Driving range	-	-	0.1673***
Goodness of Fit			
Log likelihood	-11977	-11939	-10636
AIC	23978.9	23922.14	21330.14
McFadden R^2	0.17147	0.17412	0.26426

In Model 3, the ASCs for alternative powertrains are negative compared to petrol, which is set to 0 as reference. The values of ASCs are aligned with the familiarity levels identified previously with diesel vehicle being the most acceptable and pure alternative powertrains (i.e. pure EV and hydrogen vehicle) being least favourable. In addition, the

ASC differences between powertrains are worth noticing. ASC difference between petrol and diesel is the least, suggesting consumers do not penalize diesel powertrain too much in unobserved vehicle attributes. On the contrary, ASC differences between petrol and pure alternative powertrains (i.e. pure EV and hydrogen vehicle) are considerably large, indicating there are lots of negative opinions associated with these two powertrains in consumers' minds.

Coefficients for monetary attributes like purchase price and fuel costs are negative as expected. The preference for body style indicates the sports/coupe style is least preferred compared to other car styles. Among them, sedan is the most popular choice. Generic attribute fuel availability and EV and hydrogen powertrain specific attribute driving range have significant and positive coefficients, suggesting notable impacts of these two attributes.

When taking a deeper look at the coefficients values, one interesting pair of coefficients that worth observing is the coefficients for the only categorical vehicle attributes, vehicle body style, and the ASCs. The two groups of coefficients are both categorical, therefore can be compared by their value directly. For diesel vehicles and HEVs, the negative effects of ASCs brought by alternative powertrain technologies (-0.2426 and -0.5132) can be easily counteracted by providing consumers their preferred vehicle body style variety (all coefficients in body style categories are larger than 0.5132). However, for more recent powertrains such as EV and hydrogen vehicles, providing more variety and number of AFVs cannot largely counteract the negative effects brought by ASCs (ASCs for EV and hydrogen vehicles are all less than -2). This finding provides another quantitative evidence for conclusions drawn in Section 5.4.2, where consumers' willingness to purchase is still low for hydrogen vehicles and EV even with no constrains of vehicle model variety.

To further compare the coefficients of continuous vehicle attributes, willingness to pay (WTP) was calculated. The WTP is the maximum monetary amount that a consumer is willing to pay for a marginal improvement of another vehicle attribute. Based on the regression results presented in Table 5-3, the WTP can be calculated as the ratio of the

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[6] Statistical significance is displayed as * * * $p < 0.01$, * * $p < 0.05$, * $p < 0.1$, and no * $p > 0.1$ based on Maximum Likelihood estimation.

coefficients of a specific vehicle attribute and the coefficient of the purchase price (which has to be a fixed coefficient), with everything else kept constant (Louviere et al., 2000). Since the purchase price needed to be a fixed variable for WTP calculation, the WTP was calculated using the regression results of Model 2. Taking the scaling of variables into consideration, the final WTP for the continuous vehicle attribute variables are presented in Table 5-4. Among the three variables, fuel availability is the most important to vehicle consumers, while fuel cost is not as significant to them during evaluation.

Table 5-4 WTP value for continuous vehicle attributes

Variable improvement	WTP value
Annual fuel cost decrease by 1 AUD	14 AUD
Fuel availability increase by 1%	238 AUD
Driving range increase by 1 km	50 AUD

Furthermore, all random parameters' standard deviations are significant, indicating that unobserved heterogeneity across panel data is affecting the utility of these attributes. Comparing the value of random parameters with vehicle attribute coefficients, consumer preference for purchase price does not vary too much within the population. In other vehicle attributes, the variance in consumer preferences are considerable, suggesting large heterogeneity exists in consumer choices.

The added demographic characteristics of Model 2 and 3 shows that different demographic groups have disparate preferences towards AFVs. All four demographic characteristics (i.e. age, gender, household income and education level) were included in model regression trials. Among them, only age and education level showed a significant influence on the model fit. Household income does not have statistically significant influences towards the selection of powertrains. This may be due to a lack of purchase price increment to alternative powertrains or household income being not able to sufficiently represent the purchase power of consumers. Gender also did not show significance in influencing people's vehicle choice towards different powertrain. Women and men have no significant differences in preferences regarding vehicle powertrains. Because household income and gender did not show statistical significance in choice model, the final model results only include the two characteristics with statistical significance, i.e. age and education level attained.

Both age and education level attained are closely related to consumers' acceptance of AFVs. The regression results indicate that older consumers are less likely to choose alternative powertrains, especially pure EVs and PHEVs. Younger consumers generally are more open minded about AFVs than senior consumers. In addition, the results show that higher education level results in higher acceptance for more recent powertrains such as hybrid electric, electric, and hydrogen powertrains. Especially for pure electric and hydrogen powertrains, the quantitative increase in consumer preferences are considerable significant.

Lastly, the demographic biases in the panel should also be considered when analysing the choice modelling data. The over-represented elder consumer group may create less overall preferences to AFVs, while the over-represented highly education population may sway the overall consumer preferences to more preferences towards AFV. The two effects caused by panel distribution error are counteractant. However, when considering the both values of the demographic coefficients and the panel distribution errors, the impacts of panel distribution errors on revealed consumer preferences are not significant.

In this section, the results of the discrete choice modelling were presented. The best model fit (Model 3) quantitatively demonstrated how vehicle consumers evaluate vehicles within their choice sets based on their preferences and attitudes. The additional demographic factors added to the regression showed that consumers in different age groups and education attained levels have different tastes when choosing a vehicle. The following section will summarize the insights drawn from the market survey results and also how the survey can be integrated with the final system dynamics model.

5.7 Market survey insights for system dynamics model

In the previous section, the results of the discrete choice model were presented. In this section, insights from the choice model results are discussed and how it can contribute to system dynamics model is explained. Combined with the attitudinal question, the choice model provides both qualitative and quantitative insights to assist the completion of system dynamics hypothesis in AFV adoption. The following subsections discusses the findings from the discrete choice model along with previous attitudinal questions in four aspects: consumer familiarity and biases, AFV model availability and variety, adoption barriers related to vehicle performance, and variation and changes in consumer preferences and opinions.

5.7.1 Consumer familiarity and biases around AFVs

In the choice model, all ASCs for alternative powertrains are negative compared to petrol powertrain, whose ASC is set as zero. This suggests other factors that are not captured by the provided vehicle attributes can significantly affect how consumer make their selections in vehicle evaluation stage. In Model 3, these ASCs also vary with demographics, indicating these uncaptured factors also are affected by demographic backgrounds of the respondents.

These negative ASCs for alternative powertrains can be explained through the results of previous attitudinal questions and preference ranking questions. Recall from the first part of the market survey, Australian consumer familiarity and knowledge around AFVs were investigated. The results showed that there are significant biases around the reliability of alternative fuel powertrains, especially the more recent powertrains such as EVs and hydrogen vehicles. Since reliability is the most crucial factor in vehicle purchase decisions (see Section 5.5), biases on reliability can lead to distrust in the alternative technology and unwillingness to consider AFVs. This finding provides an explanation to the results of the discrete choice model. The ASCs that capture the average effect on utility of all factors that are not included in the model specification (Train, 2003) are notably lower for more recent powertrains such as EVs and hydrogen vehicles. In addition, the value of ASCs in alternative powertrains were in the same order as familiarity and experience level scores in the attitudinal questions, which further echoes the finding of consumer biases as one major hurdle for AFV adoption.

In addition, the attitudinal questions showed that for the majority of alternative powertrains, the awareness of the technology is relatively prevalent. For alternative powertrains that exist in the market, more than 90% of the respondents agreed that they are aware of the technology, even for the latest powertrain plug-in hybrids. However, the affinity of alternative powertrains was not as widespread. Only 48% of the respondents considered alternative powertrains in their latest vehicle purchase. Consumer affinity in alternative powertrains is not ideal despite the relatively prevalent awareness of alternative powertrains. Consumer willingness to adopt AFVs is heavily impeded by the distrust and biases identified in both attitudinal questions and the choice model.

Findings on consumer familiarity and affinity also showed substantial consistency with the dynamic hypothesis derived in Chapter 4 Section 4.2.1 and 4.4.4. Consumers' familiarity and experience level of different vehicle powertrains are in proportion with the length of powertrain histories. Earlier alternative powertrains such as diesel and hybrid electric vehicles enjoy greater familiarity and affinity from consumers because their longer existence in the market allowing consumers' familiarity and affinity to spread and accumulate.

In summary, the findings in the choice model and attitudinal questions have confirmed the consumer familiarity accumulation hypothesis identified in Section 4.2.1 and 4.4.4. More importantly, the discrete choice model results also indicated that there exist substantial biases around alternative powertrains technologies among Australian consumers. This new hurdle between powertrain awareness and willingness to adopt has created another feedback loop structure to the system dynamics model, which will be introduced in detail in the next chapter.

5.7.2 Importance of AFV model availability and variety

Another hurdle between powertrain awareness and willingness to adopt revealed in the choice model is AFV model availability and variety. As identified in Chapter 4 Section 4.3.4 and 4.4.1, influences of this key variable were further proved in the market survey. In the discrete choice model, the statistics have indicated persistence in respondents' choices of vehicle body style. The choice of vehicle body style in the answers of the choice scenarios were highly aligned with the vehicle style of respondents' latest purchase. Additionally, in the choice model, the statistical significant coefficients associated with vehicle body styles suggest particular vehicle body styles are an important consideration of consumers and their relatively high value indicates that the influences of vehicle body style to consumer choices are actually heavy. Furthermore, in the attitudinal questions, respondents expressed willingness to switch to alternative powertrains if the body style and model variant of their latest purchased vehicles could be kept the same.

These findings further support the dynamic hypothesis that limited model variants and body styles in AFV market may heavily encumber the market penetration of AFVs. Slow AFV adoption will lead to manufacturers reluctance to release more vehicle models in various body types and thus impede the adoption further. This viscous cycle is hard to overcome and is a critical hurdle to the adoption of alternative powertrains that have recently entered the market.

5.7.3 Adoption barriers related to vehicle performance

In Chapter 4 Section 4.2, three categories of vehicle attributes were identified as key variables to AFV adoption: AFV cost of ownership, AFV technical performance, and overall AFV experience. The market observation has explored the influences of these key variables on AFV market shares qualitatively. In the choice model, the exact influences of the selected key variables were quantitatively identified. The coefficients from the stated choice experiment and subsequent discrete choice modelling have confirmed that AFV performance can significantly influence the outcomes of consumer choices.

The survey results have quantitatively revealed how insufficient AFV performance in cost of ownership, technical performances, and refuelling facilities can affect the adoption of AFVs. In the stated choice experiment, vehicle attributes driving range and fuel availability were statistically significant especially for powertrains like EVs and hydrogen vehicles that rely exclusively on alternative refuelling. Short driving range and lack of refuelling infrastructure are two major technical/functional disadvantages for EVs and hydrogen vehicles (Potoglou and Kanaroglou, 2007, Ziegler, 2012, Hidrue et al., 2011). Moreover, high purchase price is another notable barrier for AFV adoption that was identified in this study and various previous research (Brownstone et al., 2000, Tanaka et al., 2014, Helveston et al., 2015). These vehicle performance barriers that cannot be mitigated immediately slow down the AFV adoption in Australia.

5.7.4 Variation and changes in consumer preferences and opinions

In the discrete choice model, statistically significant coefficients for the added demographic characteristics and the random parameter for various vehicle attribute coefficients confirmed variations in consumer preferences and opinions within the population. Choice modelling shows that consumers with higher education attainment level and younger age are more likely to choose alternative powertrains. These parameters indicate that consumers in such groups have less bias towards AFVs than others. This finding further proves that consumer preferences and opinions vary and additionally provides quantitative guidance for the possible changes of consumer biases in the system dynamics model.

5.8 Summary

This chapter investigated the intangible variables, namely consumer familiarity and affinity, and consumer preferences through a market survey and embedded stated choice experiment. Attitudinal questions in the market survey explored qualitatively and quantitatively the dynamics of consumers' familiarity and affinity towards AFVs and their perceptions and biases during vehicle evaluations. The choice model from embedded stated choice experiment in the survey provided quantitative information about the key variables in consumer preferences and opinions, and also offered valuable data input for the system dynamics model. The results of the market survey showed that there exist significant consumer biases against more recent powertrains in the market. These biases can be qualitatively identified in attitudinal questions and quantitatively measured through the discrete choice modelling of the stated choice experiment. The market survey also provided support for the dynamic hypotheses made in the previous chapter. The hypothesis about the impeding effect of limited AFV model availability and variety and variation of consumer preferences and opinions were confirmed by the market survey findings.

Details about the discrete choice model as the second modelling tool used in this thesis were presented in Section 5.6. This section covered information from the model specification formation to the implications of findings in the choice model. Finally, a discussion section on the insights of market survey was presented. The choice model along with previous attitudinal questions in the market survey have provided qualitative and quantitative input for the final system dynamics model.

In the following two chapters, final system dynamics model formulation and implementation will be presented. Integration of the discrete choice model and system dynamics model will be discussed. Key feedback loops and modules in the system dynamics model will be demonstrated. The model implantation and calibration are to be conducted. The simulation results along with scenario test on the effects of key dynamics to the AFV market shares will be presented and discussed.

Chapter 6 System Dynamics Model Formation

Chapter 6 introduces the final system dynamics model structure and formation. In Chapter 4 and Chapter 5, key variables in AFV adoption process were identified and the dynamic structure of these variables were investigated through market observations, survey, and corresponding choice modelling. This chapter concludes the findings from previous chapters and presents the final system dynamics model structure and formulation.

Chapter 6 starts with integration of the discrete choice model and the system dynamics model. Following the discussion about model integration with the market survey, a model overview with the introduction of the core structure of the system dynamics model and key feedback loops in the model is presented. Model subscriptions and how vehicle fleet aging chain is constructed are also introduced. Next, each of the key modules in the model are presented. The formulation of key variables, assumptions, and their justifications are then demonstrated in these sections. Finally, a summary of the model structure and formulation is presented at the end of the chapter.

6.1 Discrete choice model integration with system dynamics model

In this section, the integration of discrete choice model with the system dynamics model is explained. The market survey in Chapter 5 provides a snapshot of Australian vehicle consumers' attitudes and preferences in 2016. In the system dynamics model, these variables are set as continuous and dynamic, which means changes in the coefficients' value are allowed over time. The integration of a one-time snapshot choice model with a system dynamics model that has time dimension is of great importance to this research and is also challenging. This section goes through the steps of the integration of market survey and system dynamics model. Specifically, the incorporation of the choice model regression results and the system dynamics simulation will be discussed. Assumptions and procedures of this integration are also explained and justified. In the end, additional insights are drawn from the attitudinal questions for the system dynamics model construction.

6.1.1 Simplification of the choice model

The best fitting choice model regression (Model 3 in Section 5.6.2) is informative for providing valuable insights about consumers' preferences towards each vehicle attributes and their preferences variance based on their demographic background. However, the intricacy of the choice model could also bring immense complexity to the system dynamics model. The current model fit contains six powertrains with one categorical attribute of four types of vehicle body style, four continuous attributes (i.e. purchase price, fuel cost, facility availability, and driving range), and two demographic variables (i.e. age and education attainment level). For this choice model to be fully incorporated in the system dynamics simulation, the system dynamics model has to include the dimension of six vehicle powertrains, four corresponding fuel types and their refuelling facilities, and four vehicle body style in subscriptions. The added demographic variables also require the system dynamics model to include the dimension of vehicle consumers characteristics.

In order to achieve better efficiency and clearer depiction of the research problem, a simplification for the discrete choice model before model integration with system dynamics model is necessary. Two measurements were used to simplify the choice model: eliminate the body style vehicle attribute, and cut the demographic variables in the choice model.

The vehicle body style variable was included in the choice model to measure if consumers have different preferences towards vehicle body types and if this vehicle attribute is important to consumer vehicle choices. The statistically significant coefficients for vehicle body style from the choice model had proven that vehicle body style is critical to consumer vehicle choices and it is unlikely for vehicle consumers to switch body style based on the performances of other vehicle attributes (see Section 5.6.2). Based on this evidence, it can be concluded that a suitable vehicle body style acts like a precondition before the consumer evaluation stage and does not join the compromises made between other vehicle attributes during consumer evaluation. This finding also confirms the hypothesis made in the preliminary system dynamics model (Figure 4-24) where AFV availability and variety has a reinforcing relationship with AFV market share. Since this relationship has already been included in the preliminary system dynamic, the addition of vehicle body style in the choice model in consumer evaluation loop are repetitive and unnecessary. Furthermore, the inclusion of vehicle body style in the model can quadruple the model complexity because of the categorical property of this variable. Eliminating this vehicle attribute in the choice model fit for system dynamics model would bring much clarity to the simulation model. Therefore, vehicle body style variable is eliminated from the choice model during mode integration.

The other measure to reduce choice model complexity is to cut the demographic variables in model specification. The two demographic variables were added in the choice model to observe how respondents with different demographic background can have varied preferences towards vehicle powertrains. The results showed that these factors can affect how consumers form their opinions about vehicle powertrains and therefore influence their vehicle choices. However, these demographic variables are not necessary to be included in the consumer choice module of the system dynamics model since the model is interested in the aggregated effect of possible changes of consumer opinions and preferences in the overall population instead of consumer preferences based on different demographic groups. These variables are not essential to the goal of the system dynamics simulation model. Therefore, the demographic variables are excluded from the final model specification.

6.1.2 Discrete choice model fit for system dynamics model

The reduction of choice model complexity has brought clarity to the system dynamics model and settled the final choice model regression specification for the model. Table 6-1 presents the coefficients of the choice model regression results for the dynamic model simulation:

Table 6-1 Final choice model regression for system dynamics model[7]

Variable Name	Coefficients	Definition in simulation model
Diesel	-0.2443***	Consumer opinions and biases towards diesel vehicles
HEV	-0.4289***	Consumer opinions and biases towards HEVs
PHEV	-0.5268***	Consumer opinions and biases towards PHEVs
EV	-1.8395***	Consumer opinions and biases towards EVs
Hydrogen	-1.9573***	Consumer opinions and biases towards hydrogen vehicles
Purchase price	-0.0281***	Vehicle purchase price in Thousand AUD
Fuel cost	-0.0372***	Fuel cost in Hundred AUD
Fuel availability	0.0068***	Fuel availability in %
Driving range for EV and Hydrogen vehicle	0.1339***	Vehicle driving range in Hundred Kilometres
Goodness of Fit		
Log likelihood	-12179	-
McFadden R^2	0.15753	-
AIC	24375.92	-

In Table 6-1 , all of the coefficients are statistically significant (indicated by "***") based on maximum likelihood estimation. The definitions of all variable and their units in the simulation model are also listed. The coefficient values of this model fit are consistent with previous model regressions presented in Section 5.6.2. With no vehicle body styles, the ASCs representing the consumer biases are the only categorical variables in the model specification. Similar with previous model fits, vehicle powertrain is the most influential variable in the model due to the high absolute value of the ASCs. Within the continuous variables, fuel availability is the most valued variable based on consumers' willingness to pay, followed by driving range and annual fuel cost subsequently.

[7] Statistical significance is displayed as * * * $p < 0.01$, * * $p < 0.05$, * $p < 0.1$, and no * $p > 0.1$ based on Maximum Likelihood estimation.

6.1.3 Variation of coefficients over time

The final step in market survey and system dynamics model integration is to add the time dimension to the market survey results. The coefficients derived from the choice model represent consumers' preferences and biases in the system dynamics model. Because the goal of the system dynamics simulation is to investigate the implications of possible changes in variables involved in consumer choices to AFV adoption, the values of these coefficients are set to be adjustable in the dynamic simulation. Although the data input of vehicle consumer preferences and biases offered by the market survey is only captured in a snapshot at one time, it can still provide the simulation model sufficient information. These coefficients provide the quantitative information for the model and also allow the model calibration to year 2016, which improves the model accuracy significantly.

There are two groups of coefficients derived from the discrete choice model: consumer preferences that are associated with different vehicle attributes, and consumer biases that directly associated with different powertrains. For consumer preference coefficients, the shifts in their value are usually associated with economic development in society (Saunders and Saker, 1994), and life status changes in personal life (Andreasen, 1984, Mathur et al., 2003) with the passing of consumer generations. Because variables such as the economic development and corresponding life status change are outside of the system boundary of the model, shifts in consumer preferences coefficients due to the variables above are not represented in the model. Although no endogenous feedback was built around these coefficients, adjustments are allowed in later scenario tests. For consumer biases, since consumers biases and negative opinions are often linked with lack of knowledge (Burgess et al., 2013), the model assumes that marketing campaigns that are constantly advocating the potential benefits of a vehicle powertrains are effective for slow correction of consumer misconceptions over the course of its adoption. Using values derived from the 2016 market survey as a benchmark, the time dimension is added to model variable consumer biases. In Section 6.3.4, the details of how the model depicts the dynamics of consumer attitudes and biases will be presented.

6.1.4 Additional information provided by the market survey

Apart from the choice model regression of the stated choice experiment, the market survey also offers valuable insights in consumer familiarity and affinity around AFVs through a range of attitudinal questions. These questions contribute to the system dynamics model by improving the dynamic structures in the model and also providing guidance for later formulation and calibration of the system dynamics models.

Dynamics in consumer familiarity proposed in Section 4.4.4 has been supported by the findings in the market survey. The level of familiarity in one powertrain revealed in attitudinal questions reflects respondents' willingness to consider AFVs. In addition to confirmation of the proposed dynamic structure, market survey results in ranking and ratings of consumer familiarity towards different powertrains can also be utilized to provide benchmarks for later model calibrations.

In the attitudinal questions, the results also found that the limited availability and variety of AFV models can be a significant hurdle to AFV adoption. This finding is also echoed by the statistically significant coefficient for vehicle body style. Overall, it provides evidence to the dynamic hypothesis made in Section 4.4.4. In the system dynamics model, AFV availability module will be guided by these evidences. The dynamics structures and quantitative information around AFV availability will be derived from historical data observation and the survey findings. In the subsequent sections, the structure and formulation of the system dynamics model will be presented.

6.2 System dynamics model overview

Based on findings of the Chapter 4 and Chapter 5, the system dynamics model structure has been finalized. This section provides an overview of the system dynamics model structure and formulation. The final causal loop diagram is presented, along with the core model formulation. Next, model subscriptions in the system dynamics model are introduced. Finally, the fleet turnover in the model is explained and presented in a stock and flow diagram.

6.2.1 Causal loop diagram of core structure

The causal loop diagram of the final model structure is presented in Figure 6-1. There are four main feedback loops in the diagram, loops **R1** through **R4**, representing the four components in the core structure equation: consumer familiarity, vehicle model availability, vehicle utility, and platform bias (consumer biases against different powertrain platform).

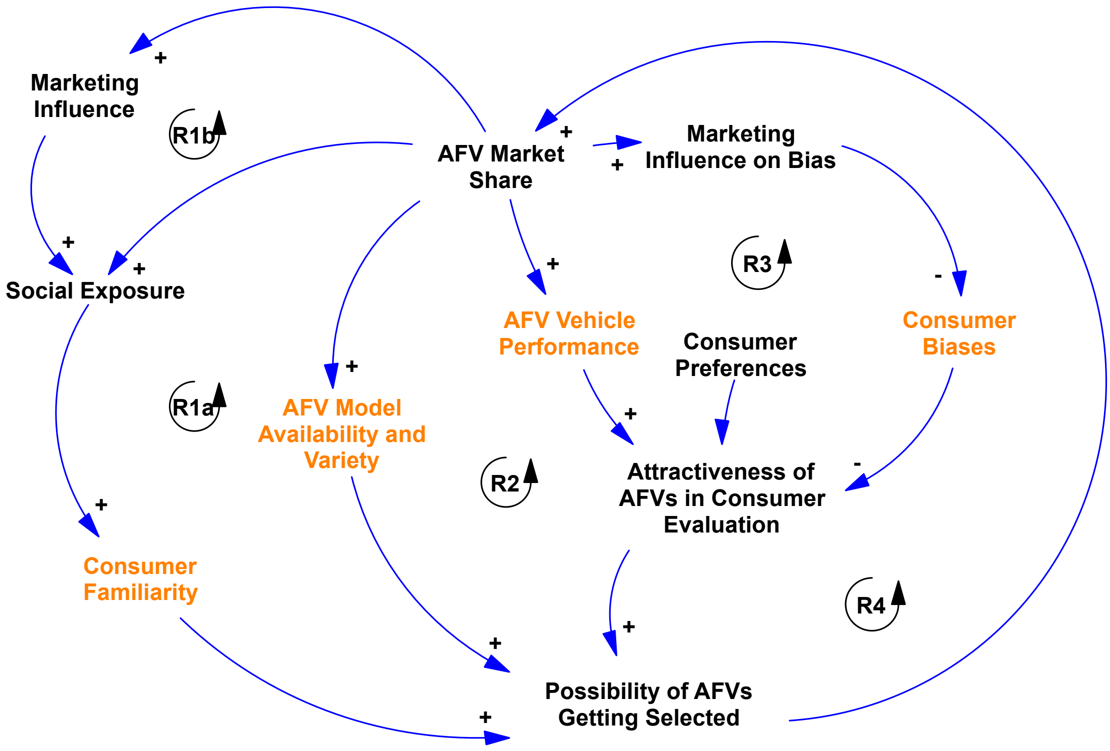

Figure 6-1 Core structure casual loop diagram

Compared with Figure 4-24 in Chapter 4, the final core structure here added the key variable revealed in the choice modelling, the platform bias (loop **R4**). These biases are derived from the ASCs in choice modelling and interpreted as the incorrect knowledge and perception towards alternative fuel platforms. Since platform biases still exist when consumers are fully familiar with the powertrain and willing to include the powertrain in their consideration sets, it is assumed that the spread of powertrain familiarity cannot reduce the platform bias. With familiarity accumulating through word of mouth, platform biases spread with it. These biases and wrong perceptions cannot be reduced by word of mouth effect. The only way to eliminate the bias is from marketing influences or educational campaign intervention. Feedback loop R4 depicts the reinforcing relationship of platform bias and vehicle market shares. The decrease of consumer bias will increase the chance of the powertrain getting selected and hence boost up market share. Higher market share of the powertrain will spur marketing and in result reduce the consumer biases.

Apart from the added loop **R4**, system dynamics model final structure also includes dynamics around marketing influences. In Figure 4-24, the market influence is listed as an exogenous variable. However, it is reasonable to assume that funding for marketing for promoting a powertrain increases as the market share of the powertrain rises and revenue of the powertrain grows. Therefore, the feedback loop **R1b** that depicts the dynamics of marketing influences is added to the final structure.

The rest of the feedback loops **R1a**, **R2**, and **R3** are kept the same as causal loop diagram for the preliminary model structure (Figure 4-24). Loop **R1a** represents the reinforcing relationship of powertrain market shares and consumer familiarity. Loop **R2** reflects the dynamics that providing more vehicle models by a powertrain increases the possibility of consumers including the powertrain in their consideration sets and therefore increases the powertrain's market share. This reinforcing relationship is observed in historical trends and presented in Section 4.3.4. Loop **R3** is the vehicle performance loop. The performance of vehicle determines the perceived vehicle utility in consumers' evaluation stage. The higher the vehicle utility, the more likely the powertrain gets selected. With the increase of market share in one powertrain, the vehicle utility of this powertrain can be improved correspondingly.

Each of the feedback loop has its own reinforced dynamics and own driven key variable. These key variables cannot directly influence each other unless via their mutual connecting variable "AFV's possibility of getting selected". The four key feedback loops are connected by this variable, which represents the AFV adoption rate. The four loops are inter-related by AFV adoption rate while also remain relative independence with each other.

In the causal loop diagram, there is no balancing loop displayed. However, the model does have balancing forces to keep the adoption behaviour in control. The main balancing force is the competition between powertrains caused by the finite market size. Similar to the Bass diffusion curve (Bass, 1969) or Rogers' S-shaped curve (Rogers, 2003), the growing capacity for one powertrain is always limited by the market size. In addition, the competition between powertrains can amplify the balancing effect further. Therefore, the model behaviour should generate similar curves as the previously mentioned two studies.

In summary, the causal loop diagram demonstrated four feedback loops, **R1** through **R4**. The formulation of the core structure of the final system dynamics model will be discussed in the next section.

6.2.2 Model core structure formulation

Recall from Equation 5.3, the choice modelling model derived in Chapter 5 Section 5.6.1, the possibility of vehicle consumer owning a vehicle of powertrain i choosing powertrain j is represented as:

$$Possibility_{ij} = \frac{exp\left(Vehicle\ Utility_j + Platform\ Bias_j\right)}{\sum_{j=1}^{J} exp\left(Vehicle\ Utility_j + Platform\ Bias_j\right)}. \tag{6.1}$$

In Equation 6.1, vehicle utility is a composite of various vehicle attributes and their associated weights. Values of these associated weights are derived from the discrete choice model in market survey in Section 5.6.2. Along with weights associated with vehicle attribute, platform biases are also deduced from the discrete choice model. The variable "platform biases j" means misconceptions that consumers usually have towards alternative powertrains. This variable is assigned with values of the ASCs in the discrete choice model. In Section 5.6.2, the ASCs are interpreted as consumers biases based on insights of the qualitative market survey as well as the definition of discrete choice specification.

Equation 6.1 derived from the discrete choice model can only represent the situation when a vehicle consumer has already put all powertrains into his/her consideration set. In choosing scenarios of the stated choice experiment, all powertrains are provided to respondents with detailed introduction of each powertrain. However, in reality, when a consumer has little familiarity towards an alternative powertrain, he/she will not place vehicles in this powertrain into the consideration set. The same kind of initial rejection before the evaluation stage can happen due to limited variety and number of vehicle models. Consumers cannot select a powertrain if there are no vehicle models provided by the powertrain in their desired body styles. To represent the elimination of powertrains entering consumer consideration sets caused by inadequate consumer familiarity and limited number of vehicle models before evaluation stage, the final equation for the core structure of the system dynamics model is presented as:

$$\begin{gathered} Numerator\ of\ Possibility_{ij} = Consumer\ Familiarity_{ij} * \\ Vehicle\ Model\ Availability_j * exp\left(Vehicle\ Utility_j + Platform\ Bias_j\right). \end{gathered} \tag{6.2}$$

$$Denominator\ of\ Possibility_{ij} = \sum_{j=1}^{J} Consumer\ Familiarity_{ij} * Vehicle\ Model\ Availability_j * \exp\left(Vehicle\ Utility_j + Platform\ Bias_j\right).$$

Compared with Equation 6.1, Equation 6.2 has two more components: consumer familiarity and vehicle model availability. The effects of these two added components have been observed in both of the market observations and the market survey. Together with vehicle utility and platform bias, the four components constitute the core structure of the system dynamics model. Each of the component establishes one core feedback loop in the system dynamics model, which was presented in the previous section in the form of causal loop diagram (Figure 6-1).

6.2.3 Model subscriptions in system dynamics model

In the system dynamics model, there are variables that depict the same variable for different powertrains or fuel types. In such cases, the dynamic modelling tool, model subscription, is used to integrate variables representing the same parameters but for different model subscripts. There are three types of model subscriptions in the model: powertrains, fuel types, and refuelling infrastructure types. For powertrains, same as the market survey, the system dynamics model contains six powertrains: petrol, diesel, hybrid electric, plug-in hybrid electric, pure electric, and hydrogen. Correspondingly, there are four types of fuel and refuelling infrastructures: petrol/petrol refuel, diesel/diesel refuel, electric/electricity refuel, and hydrogen/hydrogen refuel. Since plug-in hybrid can be refuelled by both petrol and electric refuelling infrastructure, a new powertrain subscription for fuel efficiency and refuelling is generated. Therefore, this powertrain subscription has one additional subscripts to differentiate plug-in hybrid vehicle refuelling that use petrol or electricity.

Within subscriptions, sub-ranges are established to provide ease for directing choice flows within different powertrains. Recall from the core Equation 6.2, key variable consumer familiarity has footmarks representing two powertrains: i and j. This indicates the familiarity of drivers of powertrain i towards powertrain j. In the fleet turnover aging chain presented subsequently, the model also faces the flow of consumer ascription from one powertrain i to another powertrain j. To efficiently demonstrate the direction of flows, powertrain subscriptions have multiple sub-ranges such as PowertrainFrom, PowertrainTo, and PowertrainSpillTo. PowertrainFrom represents the original powertrains. PowertrainTo represents the powertrains that the drivers shift to. PowertrainSpillTo represents the powertrains that are affected by the spillover effect to receive additional marketing benefit. Using these sub-ranges, it is much easier to construct the matrix that represents the familiarity accretion from one platform to another platform.

6.2.4 Vehicle fleet turnover in system dynamics model

In this section, the aging chain used to depict the vehicle fleet turnover is introduced. Vehicle fleet growth and turnover is one of the most important stock and flow structures in the simulation model. It acts as the foundation of vehicle flows within different powertrains due to vehicle consumer choices over the course of several decades. The mechanism of fleet turnover and powertrain flow is based on an aging chain. Figure 6-2 below shows the stock and flow diagram of the fleet turnover aging chain.

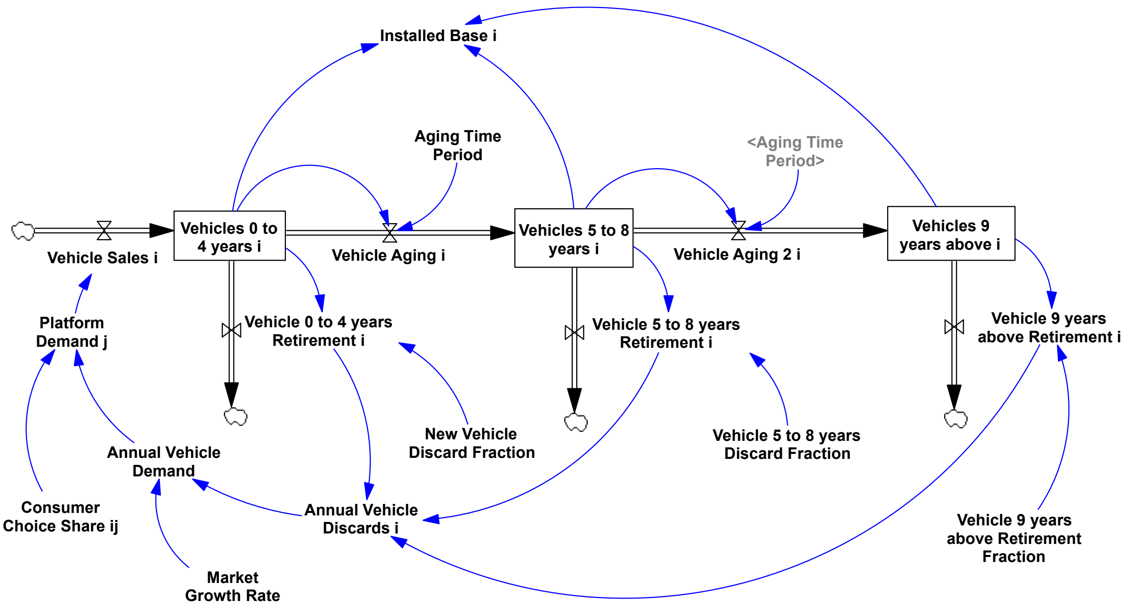

Figure 6-2 Fleet turnover aging chain in stock and flow diagram

In Figure 6-2, there are three stocks representing vehicles in three different age groups. Using a single stock for representation of the vehicle fleet fails to recognize that vehicles normally stay within the fleet for several years and can exit the fleet due to accidents and malfunctions based on their age. Therefore, a three-stock aging chain is selected to represent the vehicle fleet. According to Australian Bureau of Statistics (2014), the average vehicle age in Australian passenger and SUV fleet is 9.8 years, which is relatively young compare to other vehicle category or other vehicle market. The average scrapping age in Australian passenger vehicle and SUV fleet is estimated as around twelve years old. In order to distribute the fleet with three stocks, each stock represent vehicles that are four years apart in age. While vehicles flow from one to another stock, they are also differentiated by their powertrains. In the stocks and the flows variables, each “i” after the name of the variable means the powertrain subscription is added. By adding subscription to variables, the exact flows between powertrains over the simulation time are demonstrated.

As vehicles age, they go into the subsequent stock that representing the vehicle group with older age. In addition to naturally passing to the next vehicle stock, vehicles also have possibility to leave the fleet due to accidents, faulty, or early discard. These vehicles combined with retired vehicles that flow out from the last stock add up to the variable “Annual Vehicle Discards i”. If the fleet size is assumed to be constant, the annual vehicle demand would be equal to the annual vehicle discard. In this model, because the Australian vehicle market size is slightly growing over time, a constant market growth rate is added to the final annual vehicle demand variable. Therefore, the variable “Annual Vehicle Demand” is equal to the sum of the annual vehicle discards of all powertrains times the market growth rate (Equation 6.3).

$$\begin{aligned} &Annual\ vehicle\ demand \\ &= Makret\ growth\ rate * SUM(Annual\ vehicle\ discards\ i\ [Powetrain!]). \end{aligned} \tag{6.3}$$

Once the annual vehicle demand is determined, the annual sales that go into the first vehicle stock can be calculated. The variable “Vehicle Sales i” in the model is equal to platform demand j, which is a re-distribution of the annual vehicle demand based on “Consumer Choice Share ij” (Equation 6.4). The variable “Consumer Choice Share ij” represents the percentage of consumers owning powertrain i who choose powertrain j. Two subscription sub-ranges, PowertrainFrom and PowertrainTo, are used to direct the choice flow.

$$\begin{aligned} &Vehicle\ sales\ i[Powertrain] \\ &= Platform\ demand\ j[PowertrainTo] \\ &= SUM(Consumer\ choice\ share\ ij[PowertrainFrom!, PowertrainTo]) \\ &\quad * Annual\ vehicle\ demand. \end{aligned} \tag{6.4}$$

The vehicle fleet aging chain starts with powertrain annual sales going into the chain, then calculates the discarded vehicles to derived the annual demand, and finally redistributes the demand based on consumer choices results. This aging chain provides the foundation of the vehicle flows in the simulation model.

Section 6.2 provided an overview of the system dynamics model structure. Based on the findings in the previous two chapters, four key feedback loops in the system dynamics model are identified and presented in a causal loop diagram. In the next section, details and formulation of these key feedback loops will be presented.

6.3 Key feedback loops in the system dynamics model

This section presents the details of key feedback loops **R1** to **R4** in the system dynamics model. Each of the key feedback loops forms a module in the system dynamics model. Formulations of and assumptions made about these modules are introduced and explained.

6.3.1 Consumer familiarity accumulation

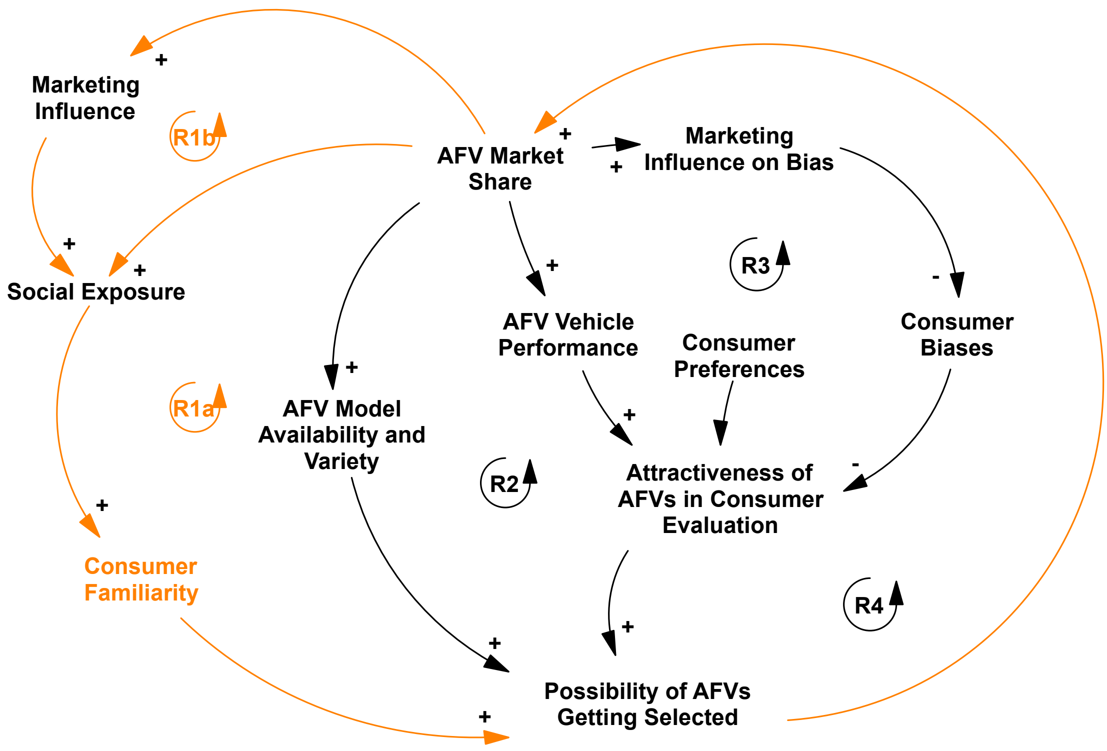

Figure 6-3 Consumer familiarity loop in core structure causal loop diagram

The dynamic structure of key feedback loop consumer familiarity **R1** is introduced in this section (highlighted in Figure 6-3). As one of the most important dynamics in new technology adoption, consumer familiarity accumulation was described as a major driving forces in innovation diffusion in the literature (Struben and Sterman, 2008, Rogers, 2003, Shepherd et al., 2012). From the market observation and survey in Chapter 4 and Chapter 5, consumer familiarity towards different powertrains in the Australian vehicle market are found to be in correspondence with the powertrains' market shares and with consumers' willingness to purchase (see Section 4.4.2 and Section 5.4). In the market observation in Chapter 4, the comparison of diesel and HEV passenger vehicles also suggested that the familiarity build-up in diesel passenger vehicles due to its longer history had potentially provided diesel passenger vehicles an edge on more successful adoption.

In this research, it is important to understand the differences between consumer familiarity and consumer biases (introduced in Section 6.3.4). Consumer familiarity plays an important role in the need recognition and information search steps in consumer decision-making process (see Section 4.1). It decides the possibility of a powertrain entering consumers' consideration sets. Consumer bias, on the other hand, exists later in the pre-purchase evaluation step. It affects the result of vehicle evaluation within consumer's consideration set.

The dynamics of these two variables are also different. Consumer familiarity accumulates because of word of mouth and the effect of marketing, while consumer biases originates when a powertrain is first introduced and reduced by marketing influences only. The familiarity of one individual can be spread through word of mouth, however, individuals' biases and negative opinions towards the powertrain will also pass on to his/her contacts within social network. Consumer familiarity can only be positively accumulated through time. It is the variable consumer biases that is able to capture the negative opinions towards the powertrain that disseminates within the society. Although these two variables play similar mathematical roles in the core structure equation (Equation 6.2), there are fundamental disparities between the functions of consumer familiarity and biases within the system dynamics model.

Familiarity is treated as a stock in this system dynamics module. It is described as the cumulate number of drivers of platform i who are familiar with the platform j. The inputs of the stock come from social exposure due to word of mouth and marketing influences, and familiarity gain through driver platform shifts due to new vehicle sales. The outputs of the stock include familiarity erosion due to consumer forgetfulness and familiarity loss due to vehicle discards.

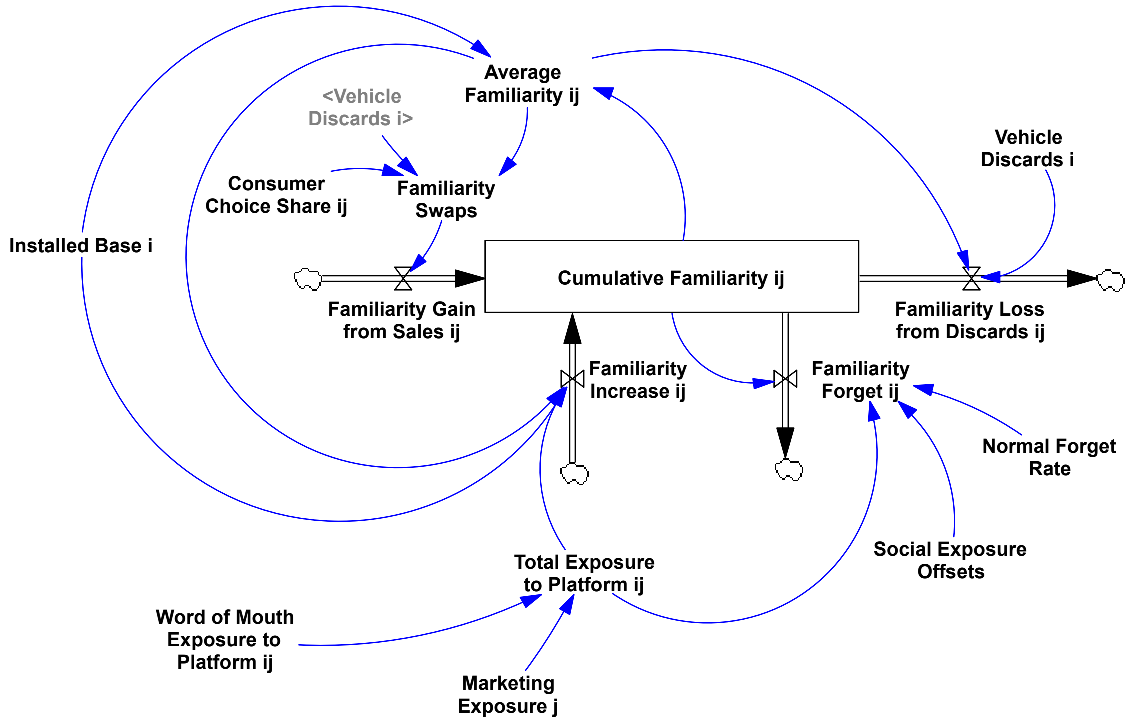

Figure 6-4 Familiarity dynamics in stock and flow diagram

In Figure 6-4, the rates “familiarity gain from sales ij” and “familiarity loss from discards ij” describes the gain and lose of drivers of platform i due to fleet turnover. The constant change in powertrain ownership due to new vehicle sales will cause drivers to shift platform. Once a driver shifts from platform i to j, his/her familiarity towards platform j becomes full. His/her familiarity toward another platform k would remain the same. However, because of the vehicle driver had switched platforms because of his/her new vehicle purchase, the familiarities he/she has now have a new denotation “jk” instead of the old “ik” to denote the platform shift of the driver. In Figure 6-4, the variable “Familiarity Swaps” depicts this familiarity platform swap with the help of changing between subscription sub-ranges “PowertrainFrom”, “Powertrain” and “PowertrainTo”. The rate “Familiarity Loss from Discards ij” is similar, because of the exit of drivers from powertrain i, familiarities of drivers from platform i towards other platforms were removed from platform i since the drivers stopped representing the platform i.

The other two input/output rates depict the familiarity gain and erosion due to social exposure and consumer forgetfulness. Social exposure consists of word of mouth and marketing effect. Recall from Figure 6-1, the two loops **R1a** and **R1b** around consumer familiarity are explained. These are the two reinforcing loops that drive the familiarity accumulation. Because it takes effort and attention to keep up to date with information of vehicle features and technologies (Struben and Sterman, 2008), consumer familiarity can also decay without constant marketing or social exposure. The output rate "Familiarity Forget ij" depicts consumer familiarity eroding if there is not enough exposure about the powertrain. The variable "Social Exposure Offset" acts as a benchmark to measure if the total social exposure can offset the erosion effect of consumer forgetfulness.

6.3.2 Vehicle model availability and variety

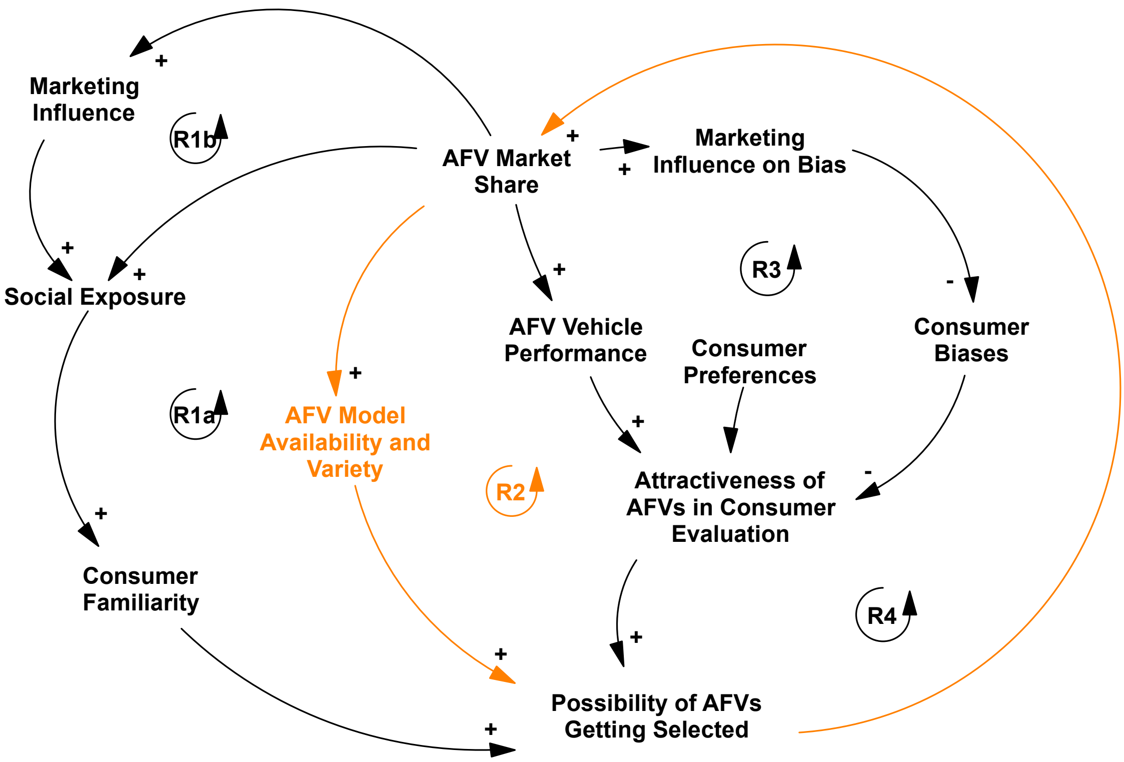

Figure 6-5 AFV model availability and variety loop in core structure causal loop diagram

This section presents the feedback loop **R2** around key variable AFV model availability and variety (highlighted in Figure 6-5). In historical trends observations in Chapter 4, the reinforcing relationship between the key variable the number and variety of vehicle models and powertrain market share was identified (see Section 4.3.4). In the simulation model, this variable is portrayed as the number of vehicle models provided by the powertrain. Based on market observations in Section 4.3.4, it is reasonable to assume the variety of vehicle styles is in proportion to the number of vehicle models provided. In addition, as previously addressed in Section 6.1.1, using the number of vehicle models provided to represent the vehicle variety can decrease the complexity of the model by reducing the subscription of different vehicle styles and provide the model conciseness and clarity. Hence, model variable “number of vehicle models” is used in this key feedback loop in the system dynamics model.

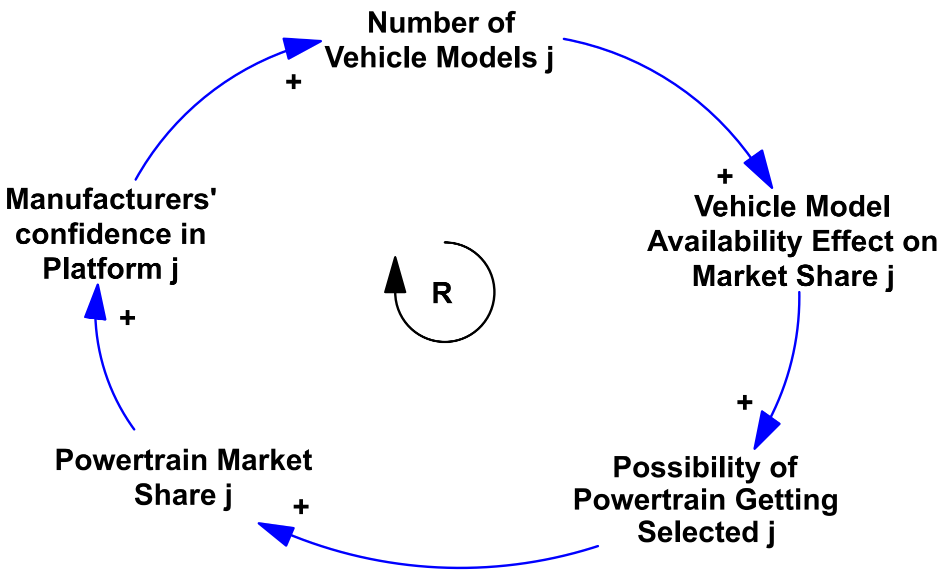

Figure 6-6 Dynamics of vehicle model number availability and variety

The reinforcing feedback is illustrated in Figure 6-6. The dynamic is easy to comprehend: powertrains with wider choices and bigger range of vehicle models can capture more segments of the market while powertrains with only a few vehicle models available in the market can lose large portion of market segments. The popularity of a powertrain usually determines if this powertrain is able to provide a wide range of choices to consumers. Hence, the powertrain with higher market shares and more matured technology are capable of launching more vehicle models and therefore has a greater chance to be included in consumer choice sets and get selected.

There are two challenges in model construction of this module: the dynamics of launching vehicle models by manufacturers and the effect of vehicle model number on the possibility of powertrain being included in consumers’ choice sets.

For the first challenge, since new vehicle model release is determined by manufacturer strategies that include multiple factors and confidential enterprise information, the simulation model is not able to depict the exact dynamic within automotive enterprises about launching vehicle models. To determine the dynamics of the vehicle model number, the most possible cause of change in vehicle model number, which is the change rates of market shares by powertrain, were first investigated. It is intuitive to assume manufacturers might adjust their strategies about launching new vehicle models by powertrains based on the changes of the powertrain market shares. However, investigation of powertrain market shares and powertrain number of vehicle models, including consideration of time delays, had not been able to identify any possible correlations between the two time-series data. The possible reasons for the lack of correlation between historical data are first lack of sufficient data, especially considering the time delay factors, or second but more importantly, the process of manufacturer strategy-making is intricate and difficult to determine by only one variable in the system.

Because increase in powertrain market share was observed as correlated with the growth of vehicle model number in market observation back in Chapter 4 (Figure 4-11 through Figure 4-13), the system dynamics model simplifies the dynamics of vehicle model number based on the powertrain market shares of past years. Based on historical data fit, it is assumed that the average market shares of the past three years have indicative influences on the current vehicle model number. Higher value in past year market shares will lead to more vehicle models to be launched into market. However, if market share or the number of vehicle models reaches to a sufficient level, there will be no more vehicle models to be released.

Figure 6-7 shows a quadratic curve that is used to represent this dynamic. The horizontal axis is the average market share of past three years while the vertical axis is the number of vehicle models in the current year. When the past year market share is low, the growth of number of vehicle models is rapid. If the curve reaches to the point A, where sufficient vehicle models are offered in the market, the curve becomes a straight line and the number of vehicle models no long increases. The exact x and y values of point A, i.e. sufficient average market share and sufficient number of vehicle model, are determined by calibration in the simulation model. The x and y values of point A presented in Figure 6-7 are estimated from model calibration in Section 7.2.

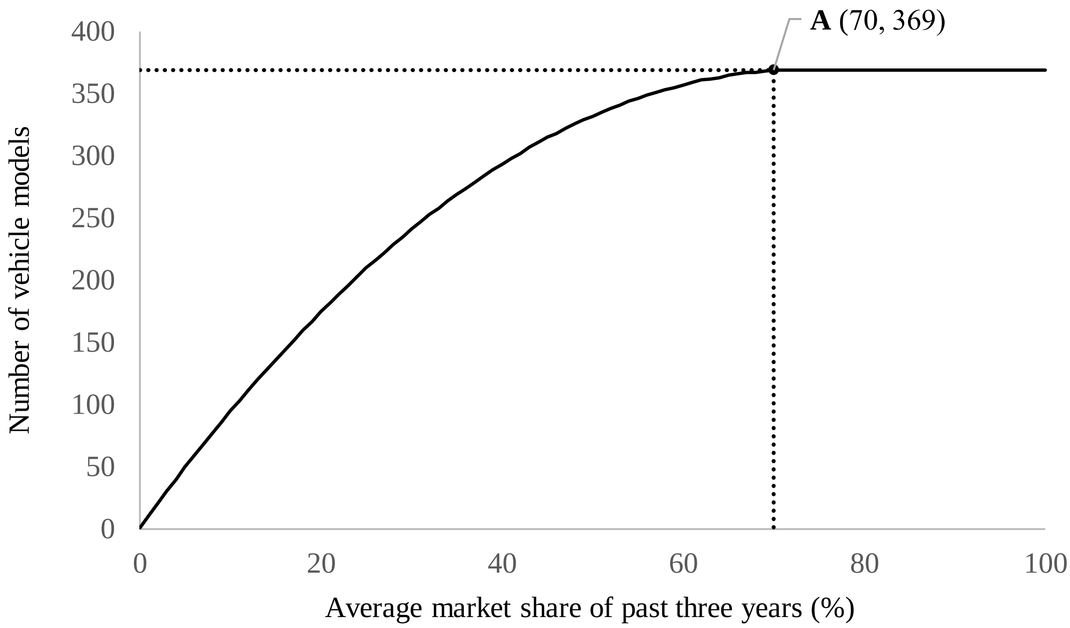

Figure 6-7 Number of vehicle model growth based on past year market share

Because the dynamics of vehicle model number is noticeably simplified in the system dynamics model, justifications and discussion of potential limitations of this arrangement are needed. The first concern is that the three-year market share average is insufficient to indicate the changes in vehicle model numbers since the development and launch of a specific vehicle model can take much longer time than three years. However, based on the historical data, the three-year average generated the best correlation with the powertrain vehicle model numbers. In addition, because the Australian vehicle market is heavily based on the global market trends, almost all current vehicle models are provided by manufacturers in other vehicle markets, such as North America, Japan, and Europe. Introduction of new vehicle models in particular powertrains into the Australian market depends on the research and development conducted in those major vehicle markets. In addition, since the Australian market sales volume is significantly smaller than major vehicle markets, the development of AFV technology and vehicle models is based on the AFV sales in Australia. This means that the time frame of introducing a new AFV model into the Australian market is significantly shortened from the standard vehicle model launch process. Therefore, the dynamics around three-year market share average and the AFV model number is more reasonable and valid.

The second concern is that the adapted quadratic relationship used in the system dynamics might not be efficient in depiction of changes in vehicle model number due to competition between powertrains. The simplified vehicle model number dynamics is based on the growth of the vehicle model number. Hence, the exit of vehicle models from the market is not clearly presented. However, luckily, the consequences of such model assumption are insignificant to the overall model behaviour. This is because that the effectiveness of vehicle model number is only sensitive when the vehicle model number remains low (see subsequent paragraphs in this section). Once the vehicle model number reaches certain level, the changes in vehicle model number effectiveness caused by vehicle model number reduction becomes relatively insignificant to the overall model behaviour. Based on the above discussions, the dynamics in number of vehicle models by powertrain is established.

The next relationship that needs quantification is the effect of vehicle model number on the possibility of powertrain being included in consumers' choice sets. The most critical character of this effect is that the relationship between the vehicle model and possibility of powertrain being included is not linear. When there are only a few vehicle models offered by one powertrain in the vehicle market, rise in number of available vehicle models can lead to significant market segment expansion of the powertrain. Once the number of vehicle models reaches to a sufficient level and the powertrain model variety had already covered the majority of the market, increase in the number of vehicle models can no longer drastically widen the market segments covered by powertrain. The effect grows quickly at the beginning and gradually slows down with increase of number of vehicle models. A logarithm growth fits these characteristics well, especially a natural logarithm growth that is often used in research since most natural phenomena follows an exponential law in their time evolution (Gelman and Hill, 2006). Therefore, a natural logarithm curve is selected to represent the relationship in the model. Since the natural logarithm growth does not have a limit, a growth cap at 100% is also added to the curve (Figure 6-8).

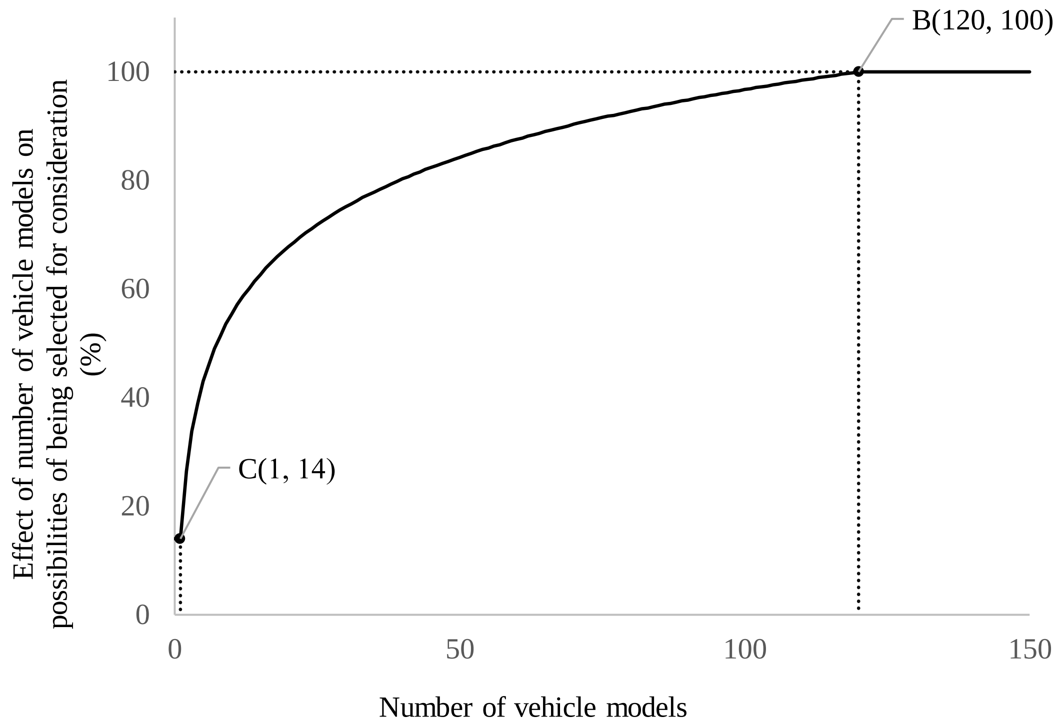

Figure 6-8 Effect of vehicle model number to a powertrain's possibility of being included in consumer consideration set

In Figure 6-8, there are two points that are critical to determine the trend of the curve: point C and B. Point C depicts the minimal market coverage (y value of point C) when there is only one available vehicle model offered by a powertrain. Point B captures the sufficient number of vehicle models (x value of point B) that can guarantee 100% market coverage by a powertrain. These two points determines the exact shape of the natural logarithmic curve. The values of minimal market coverage and sufficient number of vehicle models are derived from later model calibration in Section 7.2.

6.3.3 Vehicle performance and utility

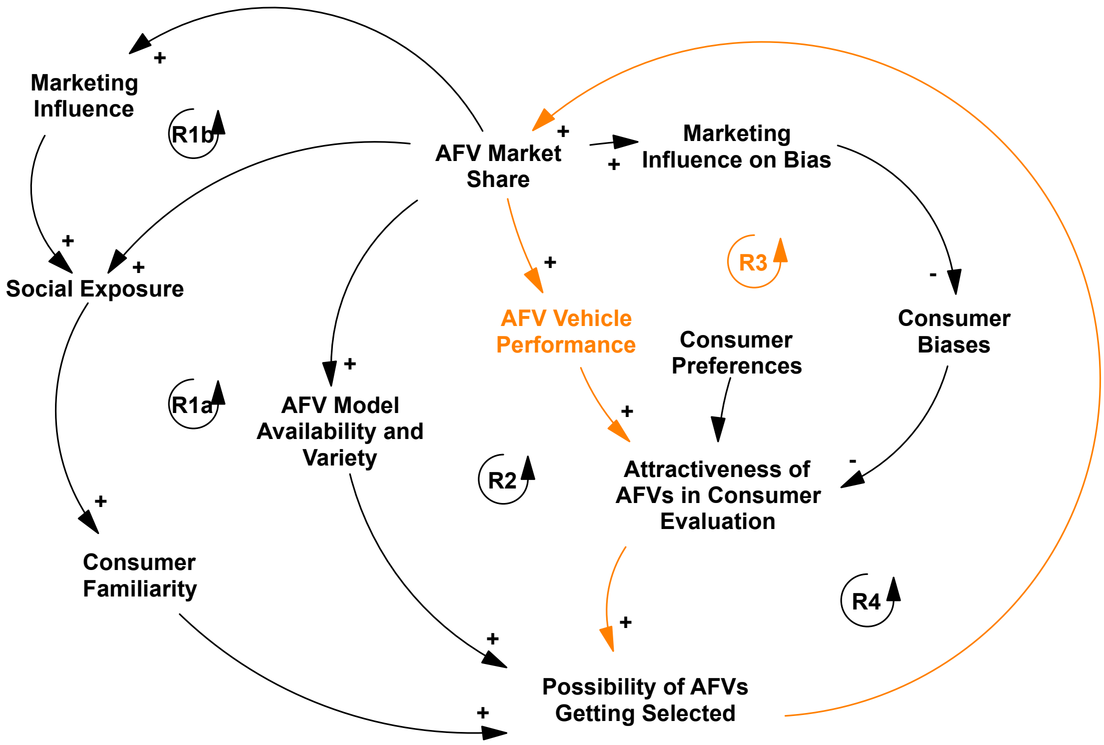

Figure 6-9 AFV vehicle performance loop in core structure causal loop diagram

This section introduces the formulation of the feedback loop **R3** around key variable AFV vehicle performance, which is highlighted in Figure 6-9. Vehicle performance and utility are closely linked with model specifications and regression results of the discrete choice model from market survey in Section 5.6.2. In Section 6.1.2, the discrete choice model specifications and final regression results for the system dynamics model is introduced. Based on the results of the choice model, vehicle attributes that constitute the vehicle utilities becomes the key variables in this module of the system dynamics model.

In Figure 6-10, the basic module dynamics is presented and four key vehicle attributes, purchase price, fuel cost, vehicle driving range, and fuel availability, are highlighted. Among them, the only vehicle attribute that is treated as an endogenous variable is fuel availability. As shown in Figure 6-10, fuel availability of a powertrain and its market share have a reinforcing relationship. Fuel availability represents the number and density of refuelling stations provided by a certain powertrain. When there are less refuelling facilities on the road, consumers may experience range anxiety and therefore not willing to select the powertrain in their vehicle evaluation process, which will affect the market share of the technology. The number of refuelling infrastructures depends on the popularities of the powertrain. When the market share of a powertrain remains low, the profit margin of refuelling infrastructures becomes undesirable due to limited potential users. Based on the work of Meyer and Winebrake (2009), this system dynamics model uses the number of registered vehicles as the determinant variable for the number of refuelling infrastructure. The formulation of the refuelling infrastructure dynamics will be introduced shortly.

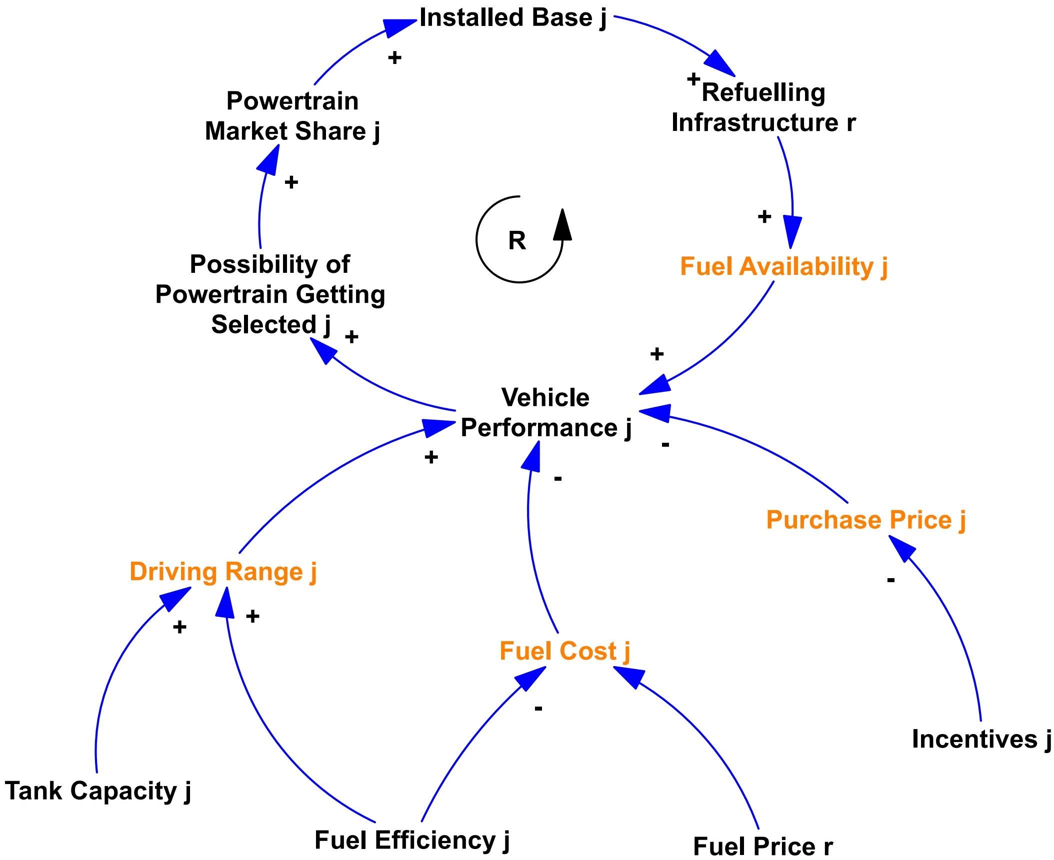

Figure 6-10 Overall dynamics of vehicle performance module

The system dynamics model treats other vehicle attributes, i.e. purchase price, fuel cost, and vehicle driving range, as exogenous variables. The change of these variables over time is not affected by any model variables and only relevant to external conditions. Although it is intuitive to assume all vehicle attributes will improve when powertrain becomes more popular, this model has excluded such reinforcing feedback due to the unique market background of Australia. The first reason is that based on the market observations in Chapter 4 Section 4.3, the historical vehicle performance of multiple powertrains do not support a strong reinforcing relationship with powertrain market shares. The second reason is that the sales volume of the Australian vehicle market is considerably limited compares to other countries. The global powertrain technology improvement driven by research and development, and the price reduction caused by technology maturing cannot be influenced by the sales and revenues generated in the Australian market. Thus, vehicle attributes involving technology improvements and purchase price reduction are treated as pure external variables in this model.

Although the other three vehicle attributes are exogenous in the system dynamics model, the vehicle performance in all powertrains are not set as constant through the years. Based on market observations in Chapter 4 Section 4.3, changes of vehicle performance are captured in this model. The formulation of all vehicle attribute variables is introduced next.

6.3.3.1 Model formulation of fuel availability reinforcing loop

To remain consistent with the discrete choice model, variable fuel availability in the system dynamics model is defined as the percentage of a sufficient number of refuelling stations. Same as the choice model, the system dynamics model sets the current number of petrol stations as the benchmark for a sufficient refuelling infrastructure network. Therefore, powertrains that refuel by petrol, i.e. petrol, hybrid electric, and plug-in hybrid vehicles, have 100% fuel availability from the simulation start time. Since diesel powertrain has a long history of large long-haul vehicles, it is also assumed that from diesel introduction date, diesel powertrain has 100% fuel availability. The only two powertrains that have fuel availability that is not 100% are pure electric and hydrogen. The number of refuelling infrastructure in these two powertrains will be compared with the current number of petrol stations to derive the fuel availability percentage.

The model uses number of registered vehicles in fleet to determine the dynamic changes to the number of refuelling infrastructures. Based on the work of Meyer and Winebrake (2009), the dynamic of refuelling infrastructure growth is illustrated in Figure 6-11. The increase rate of refuelling infrastructure is determined by a goal-seeking structure. The perceived fleet size is the average number of registered vehicles of last three years. Times with the ideal number of stations per vehicle, the ideal number of refuelling infrastructure are determined. The changing rate of infrastructure is the discrepancy between the ideal number of stations and the current number of stations.

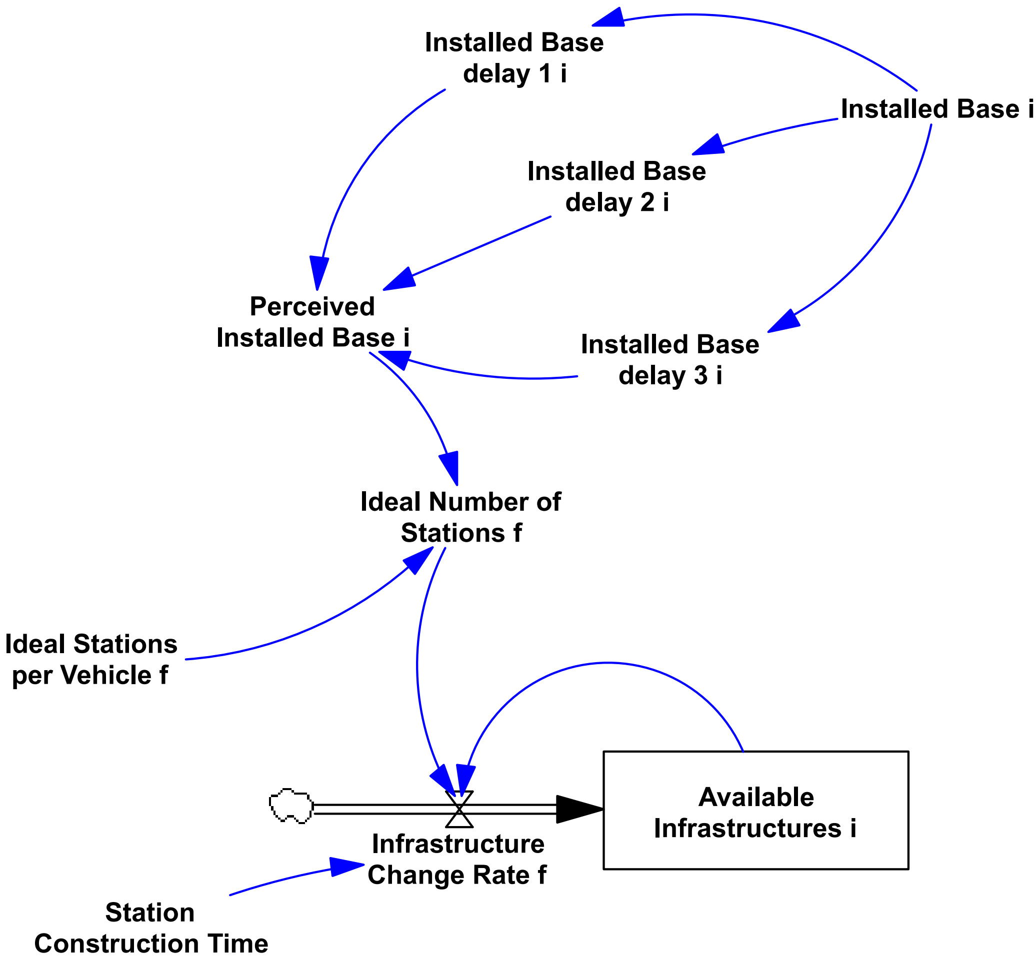

Figure 6-11 Dynamics of vehicle refuelling infrastructure

One arrangement about this module that is worth noticing is how to view PHEV in the refuelling situation. Because of PHEV powertrain can be refuelled at a petrol station, the refuelling availability for this powertrain is 100%. However, when it comes to the dynamics of refuelling infrastructure growth, PHEV is also relevant to the overall consumer demands for electricity stations. Therefore, the number of PHEVs in the fleet is part of the determinant of electricity stations. To distinguish the electricity and petrol refuelling demands of PHEV, percentage of PHEV driving distance by petrol fuel was established. The value of this percentage was set to 33% according to Karisson and Kullingsjö (2013).

Within the dynamics of this module, the most important variable is “Ideal stations per vehicle f”. It determines the goal of the stock “Available infrastructure i”. The ideal number of stations for hydrogen vehicles are based the work of Meyer and Winebrake (2009). The ideal number of stations for every pure electric vehicle is determined by the station/EV fleet size ratio of the most saturated EV market, Norway. It is assumed that in

Norway, where the market share of EV has reached to a significant 29% (International Energy Agency, 2017), there are enough electric vehicle recharging stations for EV and PHEV.

Table 6-2 Parameter value for ideal station number per vehicle

Fuel type	Number of stations	Fleet size	Ideal station number per vehicle
Petrol	6300[8]	14115057 [9]	0.00044
Electric	8521[10]	133260[11]	0.0639
Hydrogen	-	-	0.00092 [12]

In Table 6-2, the ideal numbers of stations per vehicle for each powertrain are presented. For comparison reason, the current number of stations per vehicle of petrol powertrain are also calculated. Unlike hydrogen vehicles and petrol vehicles, the charging pattern of electric vehicles is drastically different from traditional petrol cars, the ideal number of stations per vehicle of electric powertrain is much larger than petrol and hydrogen vehicles.

6.3.3.2 Changes of other vehicle attributes over time

This section explains the formulation of the rest of vehicle attribute variables: purchase price, fuel cost, and vehicle driving range. Although these variables are not depicted as

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[8] Data source: AUSTRALIAN INSTITUTE OF PETROLEUM. 2015. *Facts about the Australian retial fuels market and prices* [Online]. Australian Institute of Petroluem. Available: http://www.aip.com.au/pricing/facts/Facts_About_the_Australian_Retail_Fuels_Market_and_Prices.htm [Accessed December 2015].

[9] Data source: AUSTRALIAN BUREAU OF STATISTICS 2017. 9309.0 - Motor Vehicle Census, Australia. Australian Bureau of Statistics.

[10] Data source: NORSK ELBILFORENING. 2017. *Number of charging stations for electric cars in Norway from 2011 to 2017* [Online]. Statista. Available: https://www.statista.com/statistics/696548/number-of-electric-car-charging-stations-in-norway-by-type/ [Accessed Jan 15 2018].

[11] Data source: INTERNATIONAL ENERGY AGENCY 2017. Global EV Outlook 2017 - Two million and counting. International Energy Agency (iea).

[12] Based on value used in MEYER, P. E. & WINEBRAKE, J. J. 2009. Modeling technology diffusion of complementary goods: The case of hydrogen vehicles and refueling infrastructure. *Technovation,* 29**,** 77-91.

endogenous variables, the historical changes of these vehicle attributes are reflected in the system dynamics model. The trends of these variables are captured during the period of 2000 to 2014 since it is the period when historical AFV market shares are available for model calibration in this research. In order to acquire relatively accurate calibration results, the values of such external variables are simulated as closely as historical data performed.

- *Purchase price*

In the system dynamics model, it is assumed that the purchase price of an AFV is based on a base vehicle price plus the incremental cost for alternative fuel technology. Base vehicle price is the same for every powertrain and equal to the purchase price of traditional petrol vehicle. The incremental costs are different for each alternative powertrain. According to market observations in Section 4.3.5, earlier or more matured technologies such as diesel and hybrid electric, have less incremental costs than more recent or less matured technologies such as pure electric and hydrogen. Among all powertrains, petrol vehicles have the most advantages in purchase price while hydrogen vehicles suffer the worst from price disadvantage.

In reality, the price of new vehicles of one powertrain can vary widely due to brands and make, vehicle body styles, the accessories of the vehicles, and many other factors. The system dynamics model chooses not to represent the wide price range for one powertrain since the focus of the model is to investigate the insights of changes in consumer attitudes and preferences rather than focusing on only performances of vehicle attributes. Popular vehicle models of each powertrain at any time point are chosen as benchmarks for purchase price in the simulation model.

Based on the market observations data, purchase prices of various powertrains in the Australian market has slightly declined over time (see Section 4.3.5). Especially for diesel and hybrid electric vehicles, the incremental costs for these alternative fuel technologies have been drastically reduced. Combined with effects of inflation over time, the purchase prices of all vehicle powertrains (except for hydrogen since it has yet to be launched) have decreased. Among them, diesel incremental costs have the largest decrease and plug-in electric vehicle had barely changed any value since the powertrain is still relatively young in the Australian market.

In the simulation model, purchase price is allowed to change during the calibration period. Changes of powertrain purchase prices follow the aforementioned historical trends. After the calibration period, vehicle purchase prices are kept constant until scenario tests.

❖ *Fuel cost*

Fuel cost is defined as the annual cost for refuelling the vehicle. There are two variables that determine the value of fuel cost: fuel price and fuel efficiency. Both of them are external variables that change independently from other model variables. Fuel price is a relatively volatile variable that fluctuates from time to time. Historical fuel price trends from 2000 to 2014 were captured in Chapter 4 (see Section 4.3.5). From Figure 4-14, a general trend of petrol and diesel fuel price increases over time was observed. In the simulation model, similar growths in fuel price during calibration period are recreated.

Fuel efficiency is an indication of powertrain technological development. From market observations, fuel efficiency of petrol, diesel, and hybrid electric vehicle has each decreased over time (see Section 4.3.6). In the simulation model, fuel efficiencies of these powertrains are set to have similar changing rate as historical trends. Specifically, the improvements of fuel efficiencies are designed to gradually reach the fuel efficiency levels in 2014 from the market observation. However, for plug-in hybrid and pure electric powertrains, fuel efficiencies in the model are assumed to be the same level from the powertrain introduction dates because of their relatively short history.

Historical trends in both fuel cost and fuel efficiency variables are simulated in the system dynamics model during 2000 to 2014 in order to calibrate other intangible variables in the model. After the calibration period, the values of these two variables remained the same until later scenario tests for policy.

❖ *Driving range*

Driving range is the only alternative specific vehicle attribute in the system dynamics model. Only pure electric and hydrogen vehicles have this attribute included in their utility. In this model, driving range is calculated based on two vehicle technological variables: fuel efficiency and tank capacity. Dynamics of fuel efficiency variable is introduced in the preceding sub-section. For tank capacity, the model has converted all types of fuel to petrol based on their energy densities so that this technical variable for all powertrains can be calculated in the unit petrol litre equivalent per vehicle. Furthermore, this model has kept the variable as a constant for the calibration period. Same as fuel cost, variable tank capacity will remain the same during calibration until later scenario tests.

6.3.4 Consumer biases

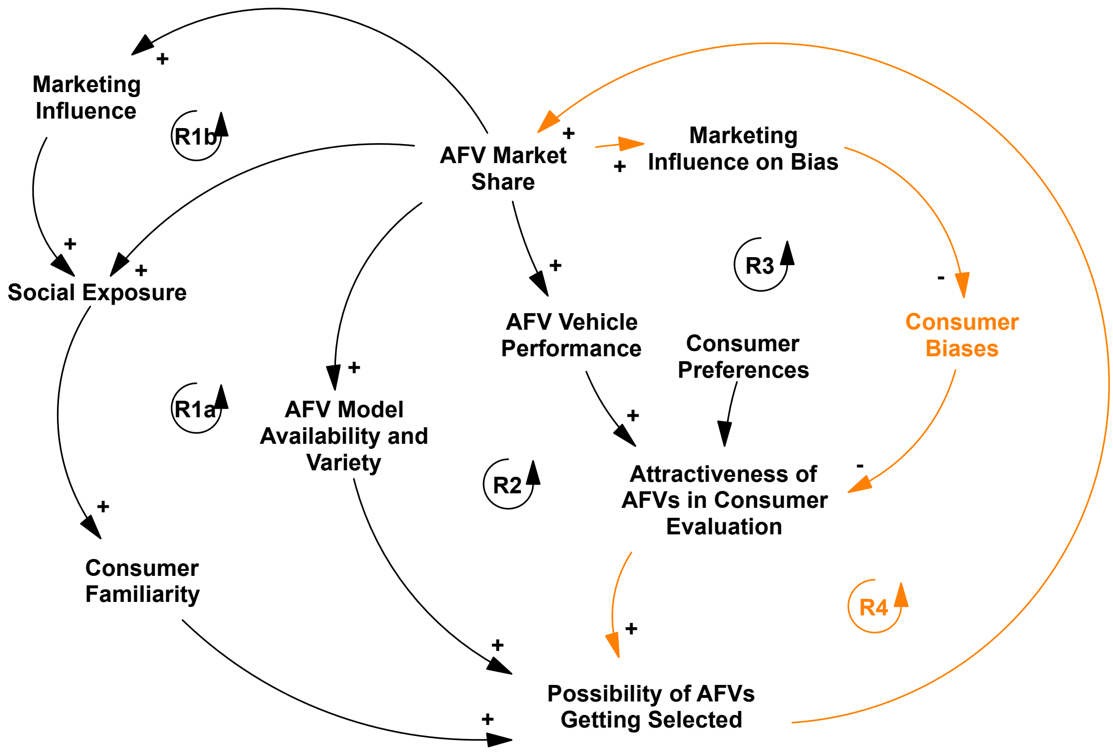

Figure 6-12 Consumer biases in core structure causal loop diagram

This section presents the feedback loop **R4** around consumer biases (highlighted in Figure 6-12). Consumer biases are revealed in the market survey as well as the choice modelling results from Chapter 5 Section 5.6.2. In the market survey questionaries, even consumers who had stated that they were familiar with alternative fuel technologies or had chosen to include AFVs into their consideration sets had exhibited strong biased perceptions. This indicates that even with enough familiarity, consumer biases still exist during the final evaluation stage in consumer decision processes. Therefore, it is reasonable to assume consumer biases and familiarities have different dynamics. Familiarity accumulation cannot reduce the consumer biases against a powertrain. In addition, consumer biases can spread with the familiarity accumulation through word of mouth effect.

In the system dynamics model, it is assumed that endogenous changes of consumer biases can only be affected by targeted marketing campaign. The effectiveness of marketing funds to bias reduction is estimated during model calibration in Section 7.2. Since it is assumed that the consumer biases can be reduced, the initial biases towards all alternative powertrains at model start time year 2000 are also estimated by model calibration. The ASCs revealed in the market survey are used as a benchmark for model calibration.

As Figure 6-13 shows, consumer biases are represented in the stock variable "Platform bias j". It is assumed that the bias value is at maximum level when the powertrain is introduced. The value of platform biases can only be reduced. Hence, there is only one rate variable "Bias Reduction Rate j" that acts as output of the bias stock. Assuming a constant marketing funding effectiveness on reducing bias, the rate of bias reduction depends on the amount of marketing funding. In the familiarity module, annual market funding is determined by the sales and revenue of different powertrain. Therefore, the powertrain with less bias has higher chance of being purchased after consumer evaluation and thus has higher market share and consequently more marketing funding to reduce consumer biases against the technology. In the current model setting, platform biases can be reduced to zero. Once the stock "Platform Bias j" reaches zero, the marketing influence on bias reduction will become ineffective and the reduction rate will change to zero.

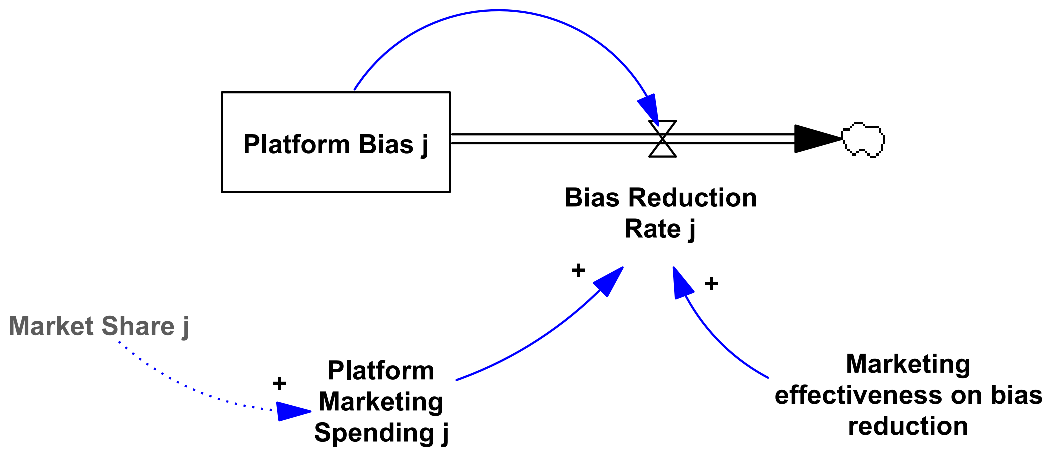

Figure 6-13 Dynamic of consumer bias

In model calibration (Section 7.2), the value of constant "Marketing effectiveness on bias reduction" is estimated. Values of platform biases of different powertrains in 2016 are used as benchmarks in the model calibration. These values are derived from the discrete choice model regression for the system dynamics model (see Table 5-3). After model calibration, the historical changes of biases of different powertrains were simulated. In later scenario tests, the powertrain biases can be intervened by provide more marketing funding targeted at reduce consumer biases.

6.4 Summary

This chapter presented the structure and formulation of the system dynamics model. The integration of discrete choice model from Chapter 5 and the system dynamics model were discussed in detail. Core structure of the system dynamics model was established. Next, four key feedback loops in the simulation model were revealed. Main assumptions and formulations of these feedback loops were explained and illustrated. In the next chapter, model simulation results will be demonstrated. Model calibration results and subsequent scenario tests on different policy approaches will be presented and analysed.

Chapter 7 System Dynamics Model Simulation and Testing

Chapter 7 presents the system dynamics model simulation and analysis results. Based on the model structure and formulation introduced in Chapter 6, this chapter presents the final system dynamics model implementation and simulation. Chapter 7 starts with the details about model implementation including model time projection, model simulation algorithm and parameter settings. Next, a calibration to estimate relevant parameter values is performed so that the model simulation results are best matched to the historical data. Once parameter values are acquired through calibration, the base run of the system dynamics model is simulated. Following the base scenario, the detailed dynamic performances of each key feedback loop in the simulation model are investigated. Using the base scenario as foundation, various scenarios where the values of key variables in the system dynamics model are altered to extreme idealized conditions in order to observe the changes of EV adoption performance are conducted. These extreme condition scenarios allow observations on the influences of key variables within consumer decision-making process. Next, discussions and tests on possible policies and interventions for promoting AFV adoption based on real world context are performed. Finally, a discussion on the findings of the system dynamics model followed with a brief summary of the chapter is given at the end.

7.1 Model implementation

This section introduces model implementation specifics such as the modelling environment, simulation algorithm, and simulation time projection for the system dynamics model. The model was built and simulated using modelling software Vensim DSS version 6.3. The simulation algorithm used for the model is Euler integration. This algorithm is known as the simplest and most obvious way to numerically integrate a set of different equations (Ventana Systems, 2018). Time projection of the model goes from the years 2000 to 2075, with the first 14 years as the calibrated period. Time unit is year, with a time step for simulation as 0.03125. The time step is normally set as a power of ½ for prevention of rounding errors (Ventana Systems, 2018). Since the finest time period for which a significant change may happen in this model is 1 month (with is approximately 0.08333 year), a time step that is smaller than 0.08333 is required for a refined integration of the model.

7.2 Model calibration

In the first step in dynamics model simulation, a model calibration is performed. In the model, precise values of some model constants are difficult to gauge, since most of these parameters are intangible. In order to estimate the values of these model constant, model calibration is performed. Model calibration minimizes the differences between real data and simulation results by varying specified model constants and deriving a combination of constant values that allow best match of simulation results to real data (Ventana Systems, 2018). By providing the model constants with reasonable varying ranges, model calibration can help the modeller derive accurate values for key model parameters (Ventana Systems, 2018).

In addition to parameter estimation, model calibration can be used as a tool for model validation testing. Although all models are wrong and there is no model can ever be truly validated (Sterman, 2000), to reproduce the real-world behaviour in the simulation model is a way to measure if a system dynamics model can achieve the goal of the model and provide insightful information to the modeller. In this research, although the initial model simulation before model calibration shows similar trends as historical data, due to uncertainty of model constants, simulated market shares cannot achieve a good match to the values of real-world data. After model calibration, not only can the historical trends of real-world market shares be captured, but also the values of these market shares be best matched. Once the model base scenario is calibrated to real-world data, later model scenario tests can provide more reliable and indicative conclusions about AFV adoption process.

This section presents the model calibration following the system dynamics reporting guidelines (Rahmandad and Sterman, 2012). It starts with introduction of the model calibration environment, followed by details of the payoff function that guides the calibration. Next, parameters that are set to be varied in the calibration and their value ranges are introduced and explained. Miscellanies in model calibration settings in the software are presented subsequently. Finally, the calibration results, estimated parameter values, and the statistics about the final calibration are shown.

7.2.1 Calibration environment and payoff list

In the same way model construction and scenario tests, model calibration uses Vensim DSS as software environment. Vensim calibration and optimization is achieved by providing the software a payoff list that defines the goal of the calibration result. Based on the list, a payoff number is calculated. This payoff number represents the differences between values for real data and simulation results. In the model calibration process, the software performs the model simulation repeatedly with different values for specified parameters. At the end of each simulation, a payoff number is calculated and compared with payoffs from other simulations. The goal of calibration process is to find the smallest differences (absolute value of payoff) between real data and simulated results within a finite number of simulations.

Weights in the payoff list are a piece of important information that determines the results of the calibration. In Vensim software, the calibration optimizer is based purely on the values of variables. Variables with larger value such as market shares for petrol and diesel vehicles are given more importance than those with smaller values such as market shares for PHEV and EV. To combat this problem, a dimensionless weight is assigned to each variable to balance the numerical differences between variables. Based on the Vensim manual (Ventana Systems, 2018), these weights are estimated to be approximately equal to the one over the standard deviation of the prediction error on variables. Based on reasonable guess (assuming 5% of data value variation for variables that vary considerably in their values first) and iterative trials and adjustments, the weights for each data variables were determined. With the weights defined, the payoff of each variable (data series) can be calculated as: $-\left((model - data) * weight\right)^2$. The total payoff is the sum of payoffs of all variables. The payoff list used for this model calibration is presented below in Table 7-1.

Table 7-1 Payoff list in model calibration

Model variable	Benchmark variable	Weight
Market share [Petrol]	ORIGINAL Market share [Petrol]	0.573
Market share [Diesel]	ORIGINAL Market share [Diesel]	0.614
Market share [HEV]	ORIGINAL Market share [Diesel]	3.92
Market share [PHEV]	ORIGINAL Market share [Diesel]	12.118
Market share [EV]	ORIGINAL Market share [EV]	29.4
Platform bias [Diesel]	Platform bias at 2016 [Diesel]	421
Platform bias [HEV]	Platform bias at 2016 [HEV]	3940
Platform bias [PHEV]	Platform bias at 2016 [PHEV]	345
Platform bias [EV]	Platform bias at 2016 [EV]	234

Two variables are used to create the payoff list shown in Table 7-1: market share and platform bias (consumer biases by powertrain). Monthly market share by powertrain is acquired directly through Federal Chamber of Automotive Industry. For the calibration period 2000 to 2014, monthly market share by powertrain provides abundant data points for the calibration. Another variable that acts as a calibration benchmark is the platform bias by powertrain. Values for platform bias in 2016 are derived from the market survey. Using the discrete choice modelling method, the exact values of the platform bias by powertrain were acquired. Strictly speaking, the platform bias level acquired though survey can only represent consumer bias at the time of the survey, which is July of 2016. However, since platform bias is not a variable that changes its value drastically, the bias values acquired from market survey act as calibration benchmark from 2016 March to 2016 August in order to provide more data points for the software during model calibration.

7.2.2 Constant parameters and their value ranges

In the simulation model, there are numerous model constants that help to build the model structure and define the model behaviours. Among them, only a few are chosen to be varied during model calibration. There are two main principles for a model constant to be estimated in model calibration: the value of model constant is intangible or uncertain and the model constant is significant to the dynamics or behaviours of the model. In order to be selected in model calibration, a model constant has to satisfy both of the requirements.

In addition to calibration parameter selection, it is also necessary to specify the value range within which each parameter is allowed to vary during calibration. These value ranges determine the parameter space over which search for the optimized payoff value is conducted. The value ranges for selected parameters are estimation based on the meaning of the model constants in real world with considerations for the extreme conditions of these model constants. The parameters selected for model calibration and their value ranges are listed in Table 7-2.

Table 7-2 Model constants selected to be calibrated

Model constant functionality	Model constant name	Model constant unit	Value lower bound	Value upper bound
Strength of dynamic effects	Effective contact rate between drivers	Dmnl/year	0.075	0.5
	Marketing effectiveness on bias reduction	Dmnl/million dollars	-0.001	-0.00001
	Marketing effectiveness on familiarity gain	Dmnl/million dollars	0.000001	0.0005
Formulation of dynamic feedback relationships	Minimal effect of number of vehicle models	Dmnl	0.1	0.45
	Sufficient vehicle number	Models	120	230
	Vehicle model 1	Dmnl	55	80
	Vehicle model 2	Dmnl	300	400
Initial conditions of key variables	Initial platform bias j [Diesel]	Dmnl	-2	-0.24
	Initial platform bias j [HEV]	Dmnl	-2	-0.42
	Initial platform bias j [PHEV]	Dmnl	-2	-0.52
	Initial platform bias j [EV]	Dmnl	-2	-1.83
	Marketing spending [HEV]	Million dollar/year	50	150
	Marketing spending [PHEV]	Million dollar/year	50	150
	Marketing spending [EV]	Million dollar/year	50	150

In Table 7-2, model constants selected in calibration are divided into three categories by their functionalities in the model. Model constants in the first category affect the strength of dynamic feedback in the model. For example, the model constant “Marketing effectiveness on bias reduction” determines the impact on consumer bias by one-million-dollar marketing campaign. Serving a similar function, the model constant “Effective contact rate between drivers” describes the possibility that one drivers’ familiarity can be passed on to another driver during one contact with people in their social network. These model constants affect the intensity of key dynamic feedback. In the second category, model constants determine the formulation of a relationship or a feedback. For example, model constant “Vehicle model 1” and “Vehicle model 2” decide how average market share of past three years can affect the number of vehicle models. These two values represent the x and y values of point A in Figure 6-7 respectively. Jointly, these two model constants determine the curve shape of the market share- vehicle model number relationship. Similarly, model constants “Minimal effect of number of vehicle models” and “Sufficient vehicle number” determine the curve shape of how model number can affect the possibility of a powertrain getting selected into consumer consideration set. Model constants in this category define the exact shape of relationship curves. In the last category, model constants are the initial conditions of key model variables. The values of initial platform biases of different powertrains and the initial marketing spends that started the familiarity accumulation are difficult to assess by estimation. In addition, these values are also critical to the model behaviours in regard to consumer biases reduction and familiarity accumulation. Therefore, calibration is used to derive the unknown information such as initial extra marketing funding and initial platform biases. Given reasonable value ranges, these model constants provide more flexibility to the model to allow more accurate calibration. The value range (lower and upper bounds of a calibration model constant) selection is based on judgemental estimation derived from the real-life meaning of the constants (Sterman, 2000).

7.2.3 Miscellaneous in model calibration specification

Apart from calibration payoff list and model constants selected for calibration, other specifications of model calibration defined in the software is presented in Figure 7-1.

```
:OPTIMIZER=Powell
:SENSITIVITY=Off
:MULTIPLE_START=RRandom
:RANDOM_NUMER=Default
:SEED=523
:OUTPUT_LEVEL=On
:TRACE=Off
:MAX_ITERATIONS=1000
:RESTART_MAX=0
:PASS_LIMIT=2
:FRACTIONAL_TOLERANCE=0.0003
:TOLERANCE_MULTIPLIER=21
:ABSOLUTE_TOLERANCE=1
:SCALE_ABSOLUTE=1
:VECTOR_POINTS=25
```

Figure 7-1 Miscellaneous information about the calibration

As Figure 7-1 shows, the optimizer used in Vensim software is Powell, which is a common method for model calibration. Multiple start is activated and set to option “RRandom”. This setting allows that the starting point of every new optimization are picked randomly over the range of each model constants.

7.2.4 Calibration results

In this section, calibration results are presented. The final calibration results are derived from 6552 simulations with a payoff number -516.268. The final estimated values of the model constants are listed in Table 7-3.

Table 7-3 Calibrated values of model constants

Model constant name	Calibrated value
Effective contact rate between drivers	0.111521
Marketing effectiveness on bias reduction	-0.000113619
Marketing effectiveness on familiarity gain	0.00003131
Minimal effect of number of vehicle models	0.140622
Sufficient vehicle number	120
Vehicle model 1	73
Vehicle model 2	369
Initial platform bias j [Diesel]	-0.30388
Initial platform bias j [HEV]	-0.50117
Initial platform bias j [PHEV]	-0.553295
Initial platform bias j [EV]	-1.87681
Marketing spending [HEV]	86
Marketing spending [PHEV]	50
Marketing spending [EV]	50

The calibrated market shares of the calibrated period (2000-end of 2014) are presented in Figure 7-2. Original data are also presented in the figure for comparison (dotted lines). Visually, the simulated market shares follow the same trend as the historical data. Note that the seasonal fluctuations are not captured because fluctuations in data inputs for variables that fluctuate constantly or vary across different types of vehicles, such as fuel price and seasonal consumer demand changes, are not included in the simulation model.

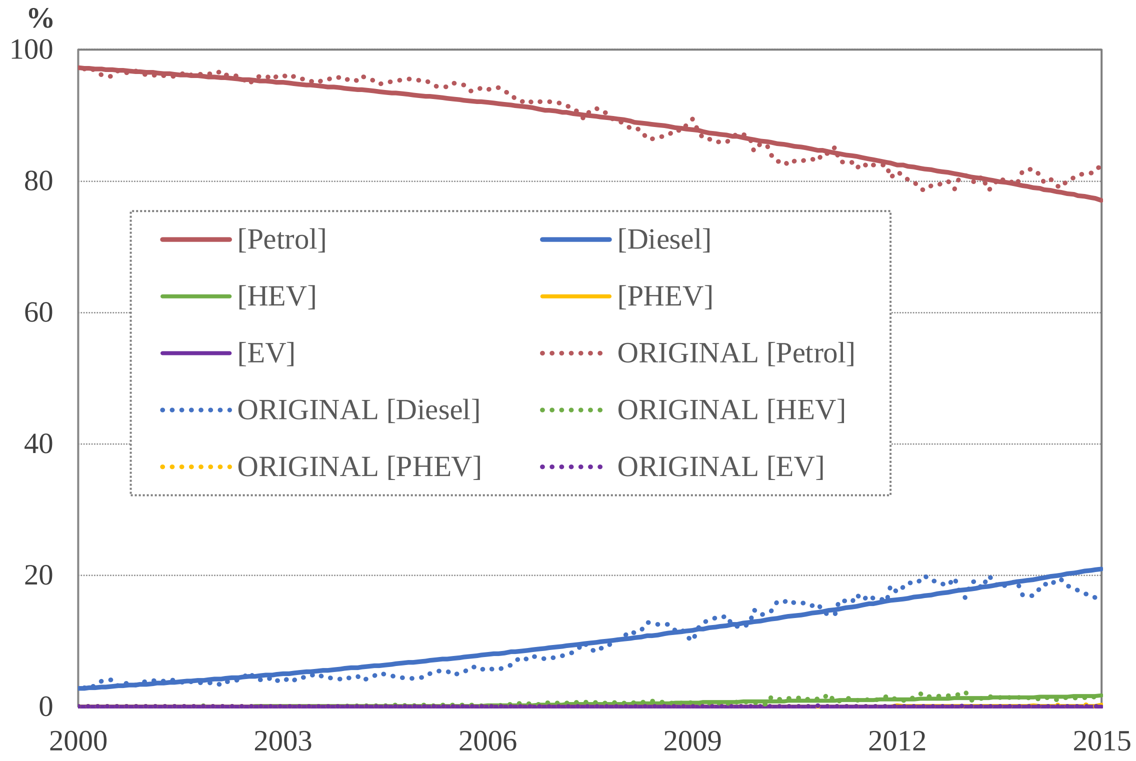

Figure 7-2 Calibrated market shares and historical market shares comparison

The statistics of model calibration is presented in Table 7-4. Descriptive statistics measurements used for point-by-point fit in this model are mean absolute error over mean (MAEoM), mean square error (MSE), and Theil statistics (with three components to represent the percentage of MSE due to bias, unequal variation, and unequal covariation respectively: U^m, U^s, and U^c). MAE is defined as the average absolute differences between model output X_m and real data X_d. It is a common statistic tool to measure the differences between simulated and real data. The MAEs for all benchmark variables are relatively small. However, for variables such as PHEV and EV market shares, because the data values are small, the MAEs for these variables cannot provide too much information to evaluate the quality of the calibration. The MAEoM is calculated as the percentage of MAE over the mean, which puts the MAE in perspective to the actual value of data. Among all benchmark variables, the MAEoMs for PHEV and EV have significantly higher value, suggesting relatively poor fit for these two variables. Because these two powertrains, especially PHEV powertrain, have the least data points for calibration, the accuracy of the calibration for these two powertrains was compromised. MSE is also frequently used measurement for average error between simulated and actual data. MSE, due to its calculation, penalizes large errors more than small ones (Sterman, 2000). Both of these measurements can only reflect the average error value and are unable to provide additional information about the model fit.

Table 7-4 Model calibration statistics

Variable	MAEoM(%) $\frac{\frac{1}{n}\sum\lvert x_m - x_d\rvert}{\overline{x_d}}$	MSE $\frac{1}{n}\sum(x_m - x_d)^2$	U^m $\frac{\overline{x_m}^2 - \overline{x_d}^2}{MSE}$	U^s $\frac{\overline{S_m}^2 - \overline{S_d}^2}{MSE}$	U^c $\frac{2(1-r)S_m S_d}{MSE}$
Market share [Petrol]	1.40889	2.38919	0.0273185	0.065089	0.907593
Market share [Diesel]	12.1164	2.25892	0.0447078	0.074338	0.880954
Market share [HEV]	24.8078	0.0589999	0.114331	0.019425	0.866245
Market share [PHEV]	158.594	0.0106719	0.303122	0.235264	0.461614
Market share [EV]	56.9335	0.00062316	0.115683	0.561363	0.322954
Platform bias [Diesel]	0.381931	1.17E-06	0.021488	0.978512	0
Platform bias [HEV]	0.0185543	8.44E-09	0.0036565	0.996344	0
Platform bias [PHEV]	0.148282	8.23E-07	0.031982	0.968018	2.29E-09
Platform bias [EV]	0.040984	7.59E-07	0.0001417	0.999858	0

In order to present a more comprehensive view on the statistics of the model calibration, statistics measurement that further decomposes the statistics error into systematic and unsystematic components is used. In Table 7-4, the last three columns present the Theil statistics that dividing the MSE into three components: MSE due to bias (U^m), MSE due to unequal variation (U^s), and MSE due to unequal covariation (U^c). Bias indicates that there are differences between the means of model simulation and real data. Unequal variation represents disparity in the variances of the two series. Unequal covariation means that the two data-series are imperfectly correlated. Based on these three error components, modellers can evaluate whether statistic errors are systematic or unsystematic (Sterman, 1984). Ideally, U^m should be as small as possible, with U^c containing the majority of the error and U^s shares the rest of the MSE.

For this model calibration, market share variables generally have good performance in the model fit. There is little to no bias in the variable means (U^m), with large covariation and relatively small unequal variation. Especially for the three powertrains that have longer history, i.e., petrol, diesel and HEV, the MSE error is relatively small. Their Theil statistics suggest that the statistic errors are mostly unsystematic (concentrated in U^c). It is worth noticing that for PHEV market share, the Theil statistics are less satisfying due to the powertrain's late introduction date and lack of data points for precise calibration. Considering the relatively short time since the powertrain had been introduced, statistic errors due to seasonal business cycles and other factors that are exogenous to the research scope become relatively prominent. The fact that market shares for other powertrains have satisfying model fit with MSE concentrated in U^c, suggests that the model does not have systematic errors and are sufficient to serve its purpose.

For platform bias variables, both MSE and MAE show little errors. The observation that the Theil statistics are primarily concentrated in the variant differences suggests the model and data have different trends. The variance errors for platform biases are anticipated and considered to be reasonable for the following reasons. Because values of platform biases acquired from the discrete choice model only represent consumer biases at one time point, the significance of calibration payoff for the biases are very likely to be overlooked due to lack of data points for calibration benchmarks. To solve this problem, additional data points for platform biases were implemented in the model as calibration benchmarks. Since the actual trends of the platform biases are unknown, the extra data points were kept at the same value as ASCs from discrete choice model. This arrangement prevents the platform biases variables from being neglected in model calibration. However, because of the additional constant data points, the trends of platform benchmarks are destined to be constants and are different from the simulated trends, which is shallow slopes. For the reasons above, such calibration errors are completely acceptable.

In this section, model calibration results are presented. Model behaviour after calibration matches the real-world data. Behavioural reproduction test via various statistics measurements provides confidence in the model. The model calibration section shows that the model is sufficient for demonstrating the proposed dynamic hypotheses and generating corresponding market behaviours depending on changes in different key variables. Recalling the purpose of the model, which is to better understand the dynamics of consumer attitudes and preferences in AFV adoption process and to investigate the implications of changes in different key variables, the model is regarded as capable to fulfil its purpose. In the following section, based on the results of model calibration, model base scenario will be presented. Further tests on model sensitivity and model behaviour will be conducted.

7.3 Model base scenario and testing

Based on model calibration, the model base scenario is established. This section starts with the presentation of market share projection of the model base scenario. Next, in order to gain more confidence in the model as well as further understand the model behaviour, two model tests are conducted. The first one is a numerical sensitivity test, where the model behaviour is investigated under plausible ranges of key model constants values. The second one is a model behaviour test for specific dynamic structure around platform bias reduction.

7.3.1 Market share projection in model base scenario

Based on the calibration results, the base scenario of the simulation model is established in this section. In Figure 7-3, the base run results are presented. It shows the trends of market shares of multiple powertrains through the simulation period without any external intervention. Within the time projection, diesel vehicles will become the most prominent player in the vehicle market, with market share of petrol vehicles following closely behind. HEVs are the third most popular powertrain in the market, with market share close to 30% and still increasing. The rest of powertrains perform less successful in terms of market penetration. Especially for the more recent two powertrains, pure electric and hydrogen, the market shares remain insignificant during the time projection.

Under the currently market condition, where no interventions or external forces to promote the adoption of particular powertrain, the overall adoption performance of alternative powertrains is not ideal. Except for HEVs, all AFV powertrains that involve refuelling with fuel sources other than petrol have low market penetration. For the two powertrains that only depend on pure alternative fuel, EVs and hydrogen vehicles, the market shares have remained below 1% during the whole simulation time projection.

Further discussions around the overall low adoption rates for AFVs will be presented in Section 7.4.

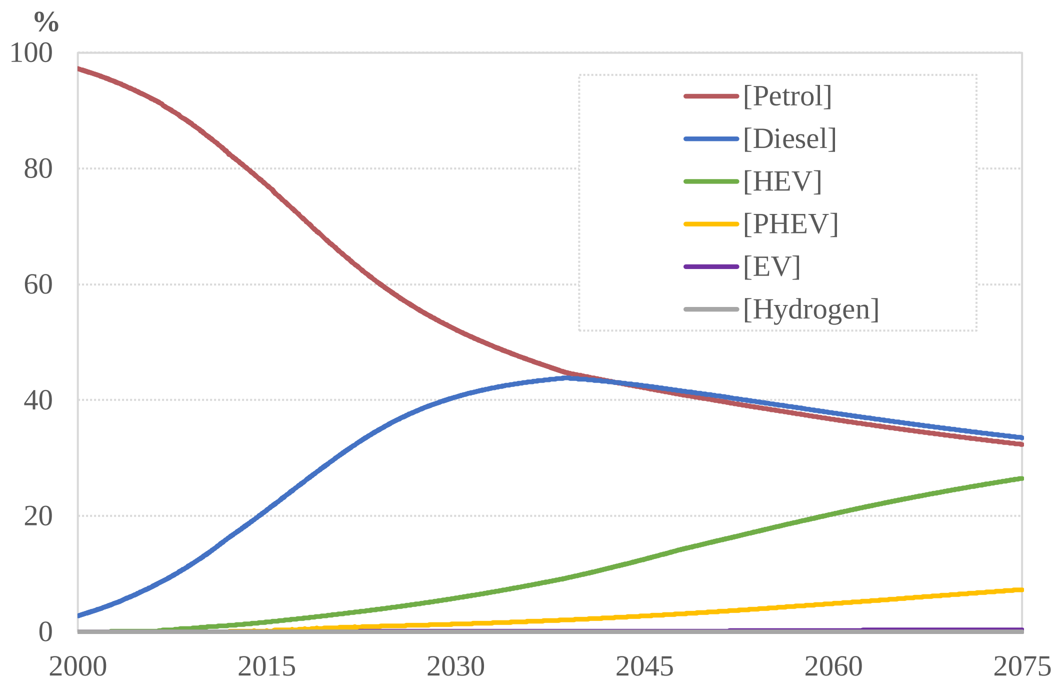

Figure 7-3 Base scenario– powertrain market shares projection

The powertrain market share projection of the base scenario of the model is presented in this section. Although the model calibration showed significant consistency between simulation and historical data, it is still unknown how sensitive the model behaviour is based on the value of the estimated constants. To explore the changes in assumptions about the numerical values of key model constants, a sensitivity analysis is performed in the next section.

7.3.2 Sensitivity analysis

Sensitivity analysis investigates whether the conclusions change significantly based on the purpose of the model when assumptions of the model are varied over a plausible range of uncertainty (Sterman, 2000). It reveals the potential model behaviours based on varying values of model constants and also puts the estimated model constant values in perspective while observing the influences of these model constants to the overall behaviour of the model.

According to Sterman (2000), when assessing sensitivity to parametric assumptions, the identification of the plausible range of uncertainty in the values of the model constants needs to proceed with caution. Overconfidence in the judgement about the parameter uncertainties is common, especially when the parameters are estimated statistically with confidence interval defined by the statistical tests. However, the confidence interval estimated in regression of model calibration can only account for one source of uncertainty, which is the sampling error. The effects of other errors in the model such as measurement errors, faulty specification of the model, or violations of the current hypothesis are not included in the confidence intervals derived from regression. It was suggested by Sterman (2000), the uncertainty range of numerical sensitivity analysis should be at least twice as wide as the statistically derived 95% confidence intervals.

Taking this research for example, the 95% confidence intervals for the estimated model constants are presented in Table 7-5 below. The confidence intervals are relatively narrow. However, the narrow confidence intervals are most likely due to the large sample size and cannot accurately reflect the uncertainty of the whole model structure. Therefore, the confidence intervals derived from the model calibration are not utilized for the sensitivity test.

Table 7-5 Confidence intervals from model calibration

Model constant name	95% Confidence interval	
Effective contact rate between drivers	0.110087	0.112487
Marketing effectiveness on bias reduction	-0.00011384	-0.00011339
Marketing effectiveness on familiarity gain	0.0000307	0.00003238
Minimal effect of number of vehicle models	0.13695	0.15168
Sufficient vehicle number	120	125
Vehicle model 1	68.8	74.6
Vehicle model 2	364.13	380.43
Initial platform bias j [Diesel]	-0.3047	-0.3026
Initial platform bias j [HEV]	-0.5013	-0.5010
Initial platform bias j [PHEV]	-0.5546	-0.5517
Initial platform bias j [EV]	-1.8989	-1.8747
Marketing spending [HEV]	86.58	86.83
Marketing spending [PHEV]	50	52.88
Marketing spending [EV]	50	52.47

To account for as many as errors from sources apart from the sampling errors presented in the statistically estimated confidence intervals, the numerical sensitivity test setting widens the uncertain range of model constants by using the 95% confidence bounds of normal distributions with the estimated value as mean and 25% of the estimated value as variance.

In regard to the selection of the model constants that are included in the numerical sensitivity test. Two conditions about model constants should be satisfied: highly uncertain and likely to be influential (Sterman, 2000). For the sensitivity analysis, the model constants that determine the intensity of the reinforcing feedback loops are selected. These constants define the impacts of the four key variables in the model and therefore determine the dynamics and behaviour of the model. In contrary, model constants that define the initial market conditions such as initial platform bias and marketing spending cannot determine the dynamics of the model and can only affect the model behaviour in terms of its beginning point. Therefore, such model constants are not included in the numerical sensitivity tests.

Table 7-6 Numerical Sensitivity test setting

Model constant name	Mean	Variance	95% Confidence interval	
Effective contact rate between drivers	0.111521	0.02788025	0.05687571	0.1661663
Marketing effectiveness on bias reduction	3.131E-05	7.8275E-06	1.5968E-05	4.6652E-05
Marketing effectiveness on familiarity gain	-0.0001136	-2.841E-05	-5.795E-05	-0.0001693
Minimal effect of number of vehicle models	0.140622	0.0351555	0.07171722	0.2095268
Sufficient vehicle number	120	30	61.2	178.8
Vehicle model 1	73.2692	18.3173	37.367292	109.17111
Vehicle model 2	369.386	92.3465	188.38686	550.38514
Sampling method				
Univariate	500 simulations for each constant, 3500 simulations in total.			
Multivariate	2500 simulations.			

Two sampling methods are selected for the sensitivity analysis: univariate and multivariate. The univariate method allows each parameter in the list change independently while others are held constant at their original value. The multivariate sampling method change all parameters together and allow observations of combined effects of the influential model constants. The setting of the sensitivity tests is presented in Table 7-6. The sensitivity analysis is conducted using the Vensim software. The number of simulations are 500 simulations for each selected model constant (3500 simulations in total) in univariate sampling setting and 2500 simulations in multivariate sampling setting.

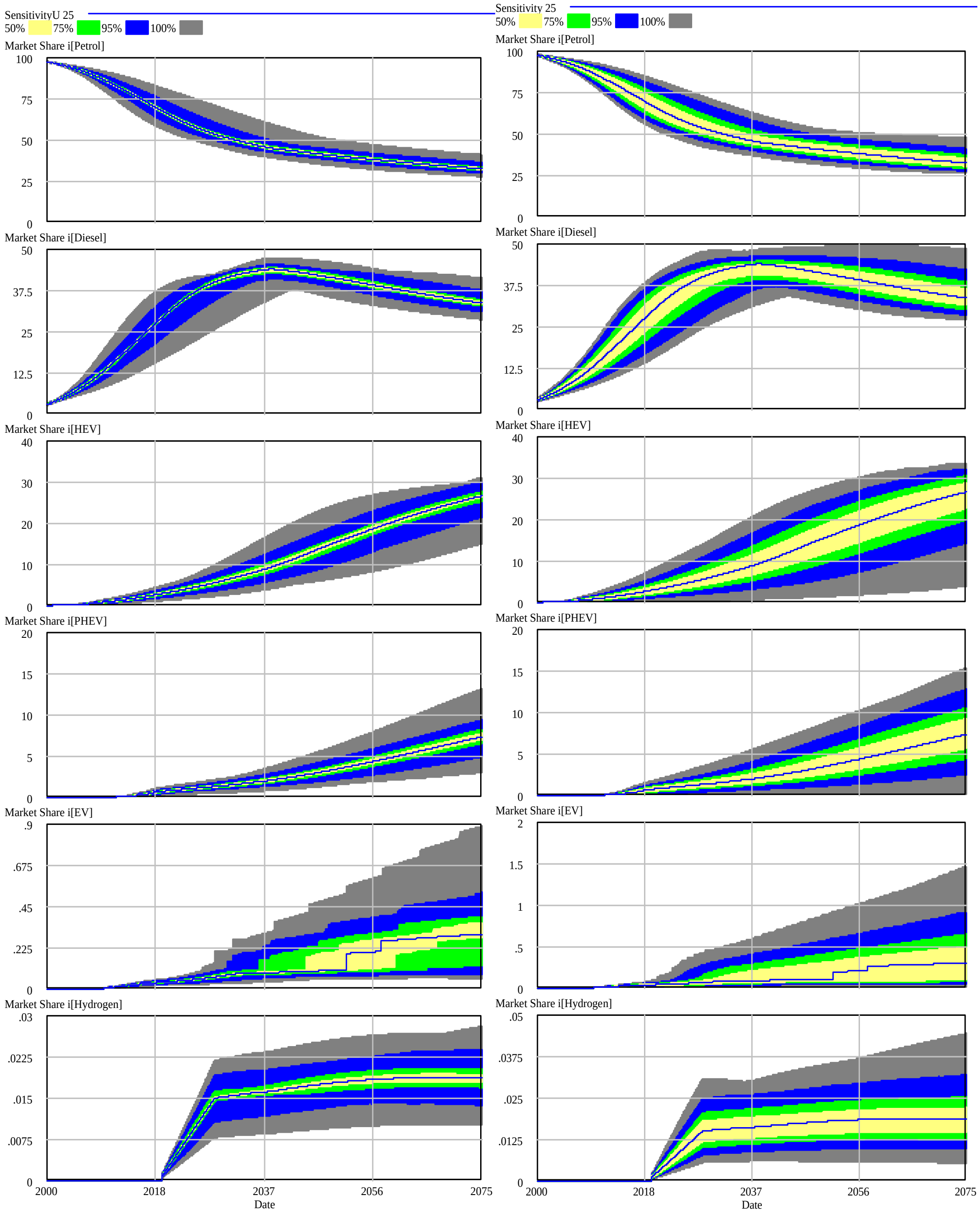

Figure 7-4 Sensitivity analysis –market shares (Left: univariate sensitivity test with ±25% variance; Right: multivariate sensitivity test with ±25% variance)

The results of the sensitivity test based on the two sampling methods are presented in Figure 7-4. There is no significant change in terms of model behaviour in the sensitivity test. Both univariate and multivariate sensitivity tests demonstrated the same trends in market shares as the base scenario, which suggests a robust model behaviour within the defined uncertainty range. In the multivariate setting (figure named "Sensitivity 25" at the right of Figure 7-4), the variation in market shares are greater than the univariate setting (figure named "SensitivityU 25" at the left of Figure 7-4). This is because the multivariate sampling method allows all values of the model constants to be varied at one time, and therefore allows the combined influences of the model constants variations to be presented. The relatively narrow range of model behaviour variation derived from the univariate sampling method also suggests that the uncertainty brought by single selected model constant is limited in this system dynamics model.

Focusing on the adoption paths of different powertrains, there is no inconsistency between the results of sensitivity analysis and the base scenario. Among all powertrains, the market share of EVs and hydrogen vehicles remain low despite the variation of model constants values (with EVs having less than 1% and hydrogen vehicles having less than 0.0375% in the multivariate scenario in Figure 7-4). This finding suggests that the low market share projections of EV and hydrogen powertrains are not caused by the strength of the reinforcing feedback loops in the system dynamics model. It is more likely that the inhibited adoption performances of more recent powertrains are due to the dynamic structure that relies heavily on reinforced relationships, the powertrains' poor vehicle performance, or large consumer biases against the powertrains.

From the sensitivity test, the variation of adoption paths of more matured vehicle powertrains and new powertrains have shown different patterns. For petrol, diesel, and HEV powertrains, the variations in adoption paths have already shown the saturation level of the powertrains. Especially for diesel and petrol vehicles, the variation on market shares of these two powertrains have evidently shown the plateau or peak levels, which suggests that the reinforcing driving forces of the system, such as familiarity accumulation due to word of mouth and marketing, platform bias reduction, and growth in number of vehicle models that ensures full coverage of different market segments, has already be fulfilled and the remaining adoption paths rely purely on the vehicle utility and consumers' presumably rational choices. While for more recent powertrain entrants, such as PHEVs, EVs and hydrogen vehicles, their adoption paths are still emerging. The different values within the plausible ranges of key model constants can only affect the speed and level of their market share growth instead of changing the adoption paths from long-term low market penetration to promising or successful adoption. The adoption of these powertrains relies heavily on the reinforcing feedback of the system and their market shares are more influenced by the dynamic structure of the model.

7.3.3 Model behaviour test around platform bias dynamics

In this section, model behaviour test around the dynamic structure of platform biases are conducted. One of the main findings from the discrete choice model in Chapter 5 is the potential influence of platform biases on AFV market shares. The discrete model result has quantitatively provided a snapshot of how consumers evaluate vehicles in their consideration sets. Because system dynamics models have the advantage of allowing system feedback through time, a dynamic structure that depicts feedback between consumer bias changes and powertrain market shares is established by incorporating the choice model with the system dynamics model. In the proceeding scenario, influences of such dynamic structure on AFV adoption behaviour are tested.

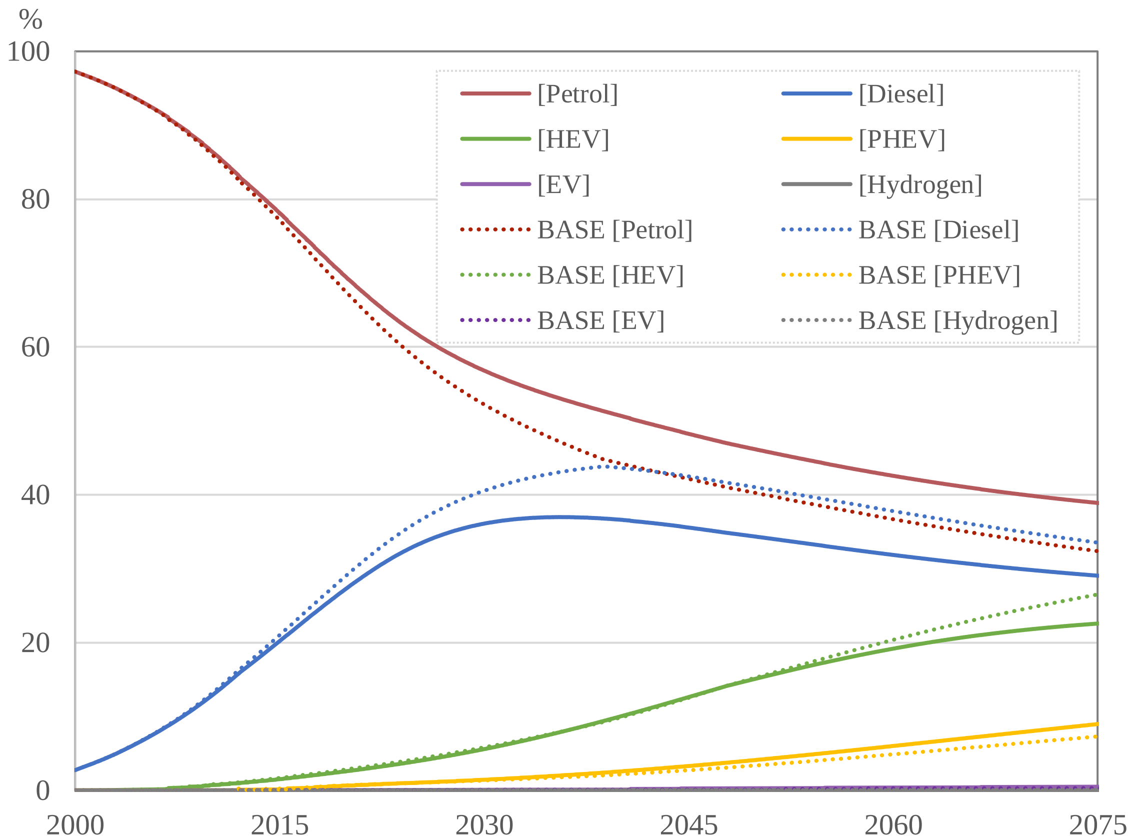

Figure 7-5 Simulated market share: no change in consumer bias versus base run

A comparison between simulation results of the base run (the dotted lines) and the scenario run with fixed consumer biases (the solid lines) is presented in Figure 7-5. The adoption behaviours of alternative powertrains have drastically altered due to the elimination of the dynamic structure in platform biases. With no endogenous feedback around platform bias, petrol powertrain's relative advantage on platform biases is maintained. Therefore, market share of traditional petrol vehicles is significantly higher compared with base run. In the base scenario, the reinforced feedback around platform bias reduction and market share growth provided crucial momentums for alternative powertrains adoption. Therefore, with no changes in platform biases, most alternative fuel powertrains have lower market share than the base run. The only exception is for PHEV powertrain. A possible explanation for its unique uprising in market share with no dynamic feedback in platform bias is that PHEVs have similar value of consumer biases with HEVs, so that the disadvantages caused by fixed platform bias of HEVs and diesel vehicles provide PHEVs extra market space to grow.

Overall, the scenario test has confirmed that dynamic feedback around consumer biases significantly affects the adoption behaviour of alternative powertrains. The dynamic feedback between platform biases and market shares provides extra momentum to the adoption of newer powertrain. Being a reinforced structure, this dynamic also presents additional challenges to powertrains that are more innovative and have less similarities with traditional powertrains. If powertrains have high consumer biases when they were first introduced into the market, the adoption process can be heavily affected by this dynamic. In the subsequent sections, the influences of the dynamic around consumer biases and possible corresponding measurements to enhance the adoption of AFVs will be further discussed.

This section presented market share projection in the model base scenario which was derived from the model calibration, and subsequently performed model tests around model's sensitivity to the numerical values of model constants and dynamics structure based on the model hypothesis. The two model tests provided extra validation for the system dynamics model and also revealed additional possible model behaviours based on different model constants values and model structural hypothesis. After the model tests and validation, next section will focus on analysing the underlying dynamics and mechanism of AFV adoption in the Australian market based on the base scenario of the system dynamics model.

7.4 Base run dynamics analysis

Based on the model calibration and two model tests for building confidence in the model, this section performs a detailed analysis on the simulation base scenario, including the dynamics of each key feedback loop in the model, and the alternative powertrains' adoption performances that were led by these dynamics.

7.4.1 Dynamics of key feedback loops in the base scenario

In this section, the detailed dynamics and performance of each key variable in the system dynamics model are introduced. Recall from Section 6.2, there are four key feedback loops that drive the adoption of alternative fuel powertrains in the Australian market: consumer familiarity towards the powertrain, number of vehicle models provided by the powertrain, vehicle utility of the powertrain, and consumer biases against the powertrain. In the base scenario, dynamics of the four feedback loops jointly determine the adoption performance of each powertrain. The dynamic performances of the key variables in the four feedback loops are presented in this section.

7.4.1.1 Consumer familiarity

Consumer familiarity level towards a powertrain determines the possibilities of consumers choosing the powertrain into their consideration sets. The accumulated consumer familiarity for different powertrains in the base scenario is presented in Figure 7-11.

In the simulation model, the accumulations of consumer familiarity towards different powertrains is driven by the word of mouth and marketing effect. In the base scenario, there are significant disparities in the increase of consumer familiarity of different powertrains. For the petrol powertrain, the initial consumer familiarity is 100% at the start of the simulation. Its familiarity level is barely changed during the simulation time. Diesel powertrain is the only powertrain except petrol that achieved full familiarity accumulation in the base scenario. For powertrains like HEV and PHEV, consumer familiarity levels grow more gradually through the simulation time than diesel vehicle. The consumer familiarity of HEV has reached a relatively high level (around 80%). The consumer familiarity of PHEV grows slower than HEV and has reached around 40%, which still poses noteworthy obstacle for the powertrain entering consumers' consideration sets. For the last two powertrains, EVs and PHEVs, consumer familiarity levels remain significantly lower. The low familiarity levels of these two powertrains have considerably narrowed the chances of adoption of EVs and hydrogen vehicles during consumer decision-making process.

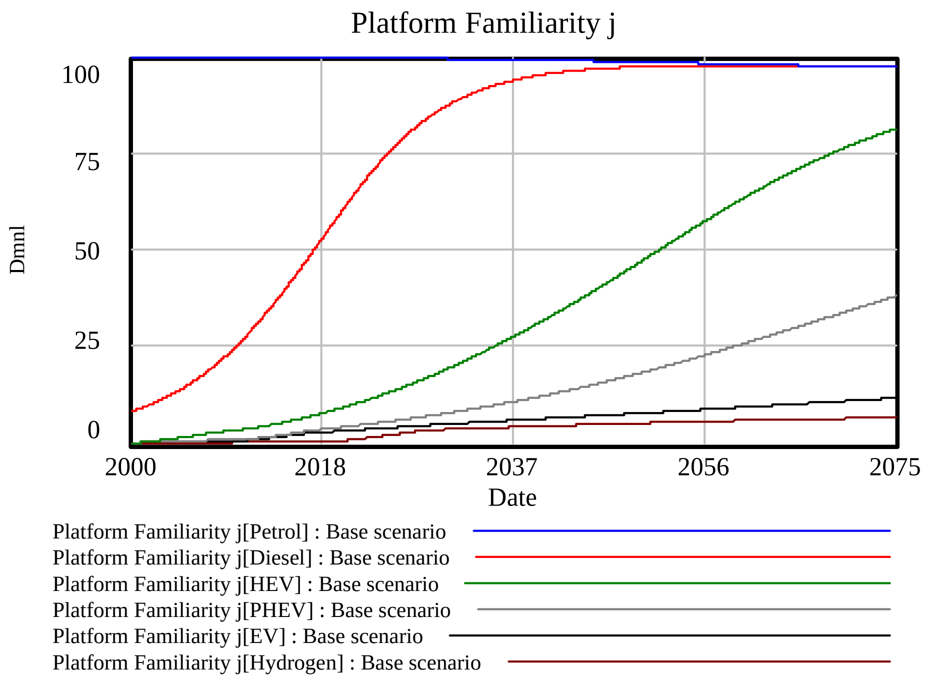

Figure 7-6 Base scenario – Platform familiarity (%)

7.4.1.2 Number of vehicle models

Apart from consumer familiarity, the number of vehicle models provided by powertrain also helps determine if the powertrain can be selected by consumers for the evaluation stage. The dynamics of number of vehicle models by powertrain and the simulated effects of vehicle model number on powertrain being selected for evaluation are presented in Figure 7-7 and Figure 7-8. Similar to consumer familiarity levels for different powertrains, petrol powertrain has the highest number of available vehicle models covers all market segments. The number of diesel vehicle models soon takes off and reaches the sufficient number that allow a 100% market segment coverage (shown as "1" in the figure). Although HEV powertrain has more gradual increases in the number of vehicle models, it also has reached sufficient level around year 50 (2050 in the simulation setting). The number of PHEV models grows more slowly and enables around 85% market segment coverage at the end of the simulation time projection. For EV and hydrogen vehicles, the growth in vehicle model number is so slow that the limited numbers of vehicle models provided by these powertrains significantly impede the adoption process.

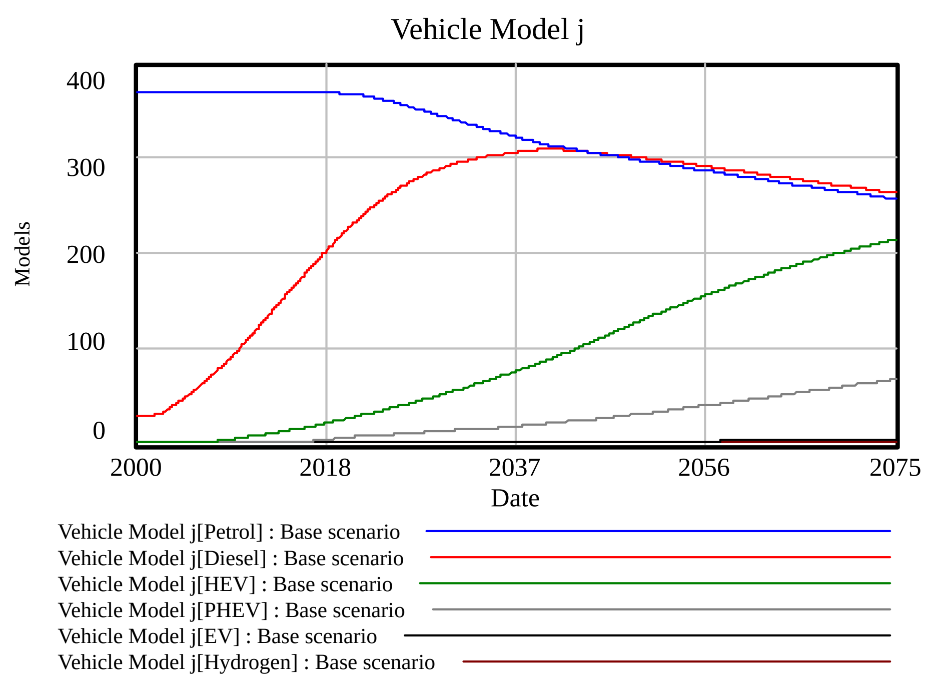

Figure 7-7 Base scenario – Number of vehicle models by powertrain

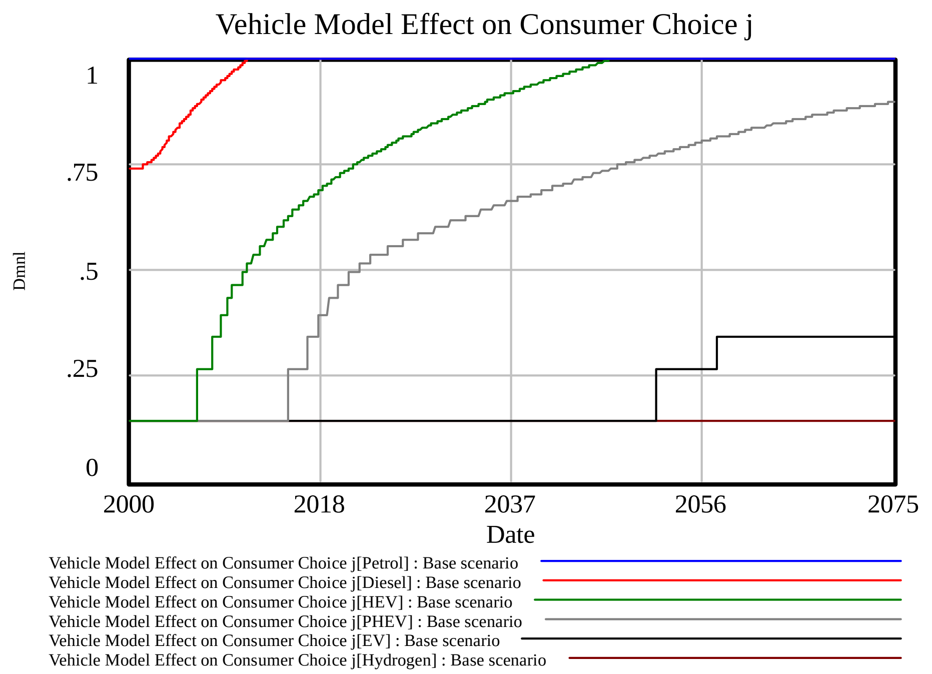

Figure 7-8 Base scenario – Effect of vehicle model number on the possibility of powertrain being selected into consideration sets (dimensionless)

7.4.1.3 Vehicle utility

When consumers enter the evaluation stage, vehicle performance in the aspects of different vehicle attributes and consumers' preferences regards to these attributes helps determine the evaluation results. The dynamics of vehicle utility in the base scenario are presented in Figure 7-9.

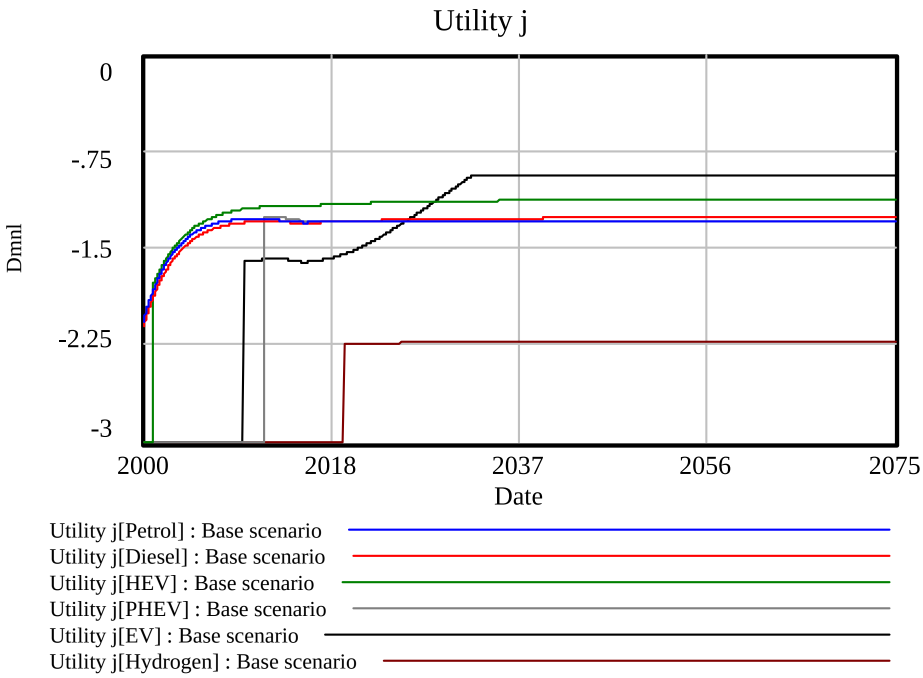

Figure 7-9 Base scenario – Vehicle utility

Vehicle utility is determined by consumer preferences and vehicle performance for different vehicle attributes. In the base scenario simulation, the model assumes constant consumer preferences and fixed vehicle performance after calibration period in all vehicle attributes except for the growth of refuelling infrastructures (see Section 6.3.3). The utilities of petrol, diesel, HEV and PHEV powertrains are relatively similar with HEV utility slightly better than the rest of the three powertrains. Hydrogen vehicles have the lowest vehicle utility in the base scenario simulation. For EVs, the utility starts slightly lower than petrol and increases gradually because of the growth of the EV refuelling infrastructures. Once the refuelling infrastructure reaches to ideal vehicle/station ratio, EV utility remains the same, better than all other powertrain.

7.4.1.4 Consumer biases

The last feedback loop that determines the powertrain adoption path is around consumer biases against powertrains. Consumer bias that is closer to zero (meaning no biases exist) generates a better chance of powertrain getting selected during evaluation stage and therefore leads to higher market shares of the powertrain. Since the biases can only be changed by marketing efforts, which are determined by the powertrain sales volume and revenues, higher market shares of the powertrain generate faster reduction of consumer biases (the value of the bias closer to zero).

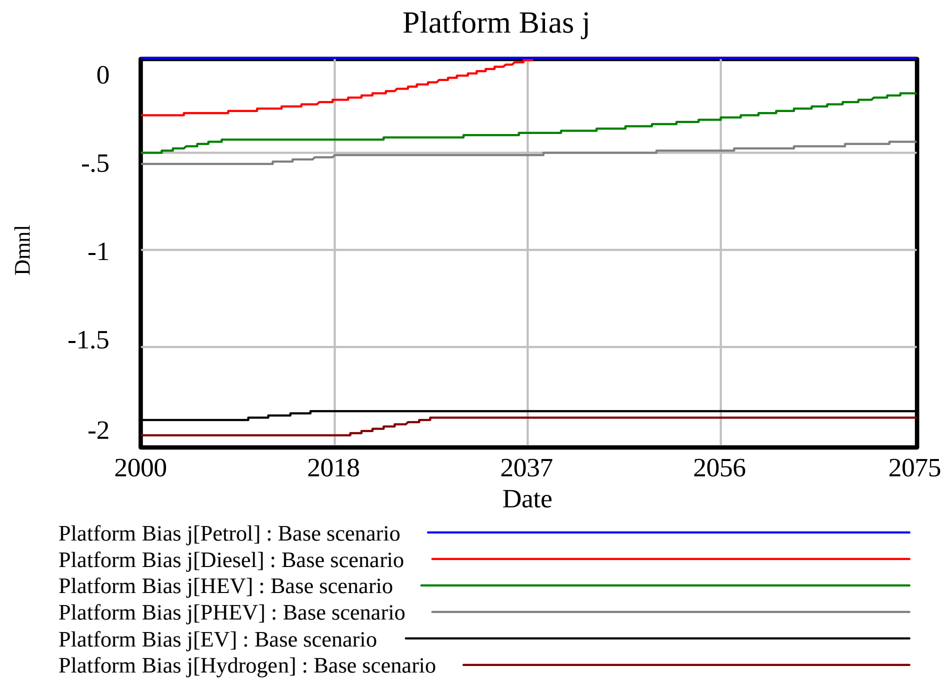

Figure 7-10 Base scenario – Platform bias

In the base scenario, consumers do not hold any bias against the petrol powertrain (Figure 7-10). For diesel vehicles, consumer biases are reduced to zero around year 2040 (year 40 in simulation), which indicates that consumers do not hold negative opinions specifically towards diesel powertrain after year 2040. HEVs and PHEVs have similar consumer biases at the start of the simulation time. However, consumer biases around HEVs reduces more rapidly while biases towards PHEVs barely changes through the simulation time. EV and hydrogen vehicles have the largest biases among Australian consumers. The consumer biases gap between EV and hydrogen platform biases and other powertrain biases has expanded during the simulation projection since the biases for EV and hydrogen vehicles have remained at the same level while the biases towards other powertrains were all reduced to different extents (Figure 7-10).

Section 7.4.1 presented the base scenario dynamics of the four key feedback loops in the system dynamics model. In the following section, the AFV adoption paths will be further analysed based on the dynamics of these four feedback loops.

7.4.2 AFV adoption led by the dynamics of key feedback loops

In the base scenario of the system dynamics model, the most noticeable adoption behaviour is the constantly low market share of EV and hydrogen vehicles. The projected market share for EVs and hydrogen vehicles remain at an extremely low level (Figure

7-11). Especially for hydrogen vehicles, its adoption progress has stagnated from the very beginning.

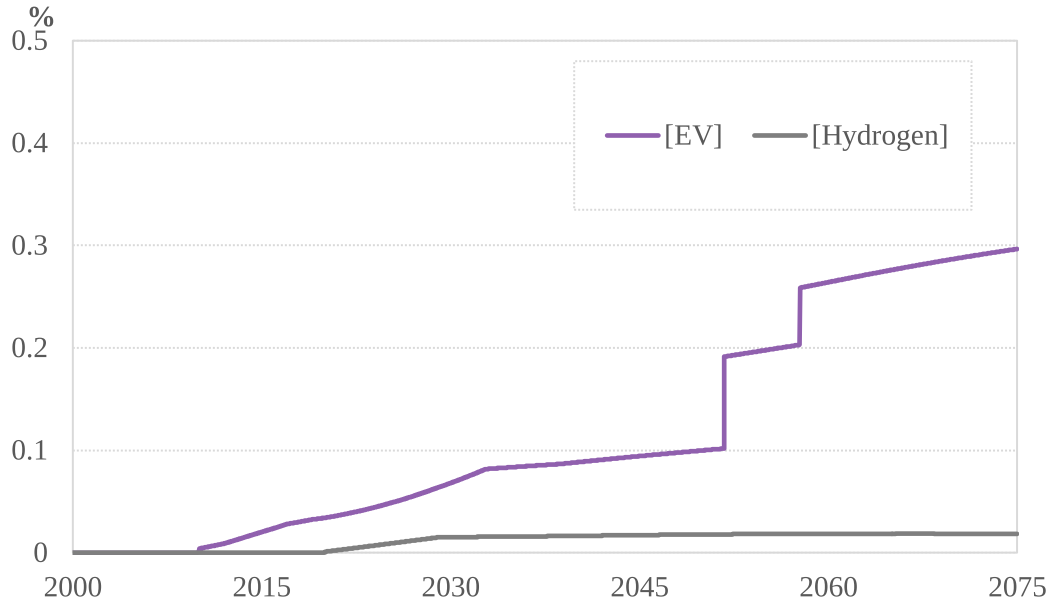

Figure 7-11 Base scenario – Market share projection of EV and hydrogen vehicle

To further investigate the adoption of EV and hydrogen vehicles, these two powertrains have different reasons for the low market shares. For hydrogen vehicles, the bottle neck for its adoption is the low utility in consumer evaluation stage (Figure 7-9). Based on the consumer preferences and estimated hydrogen vehicle performance, the overall utility of hydrogen vehicles has remained the lowest among all powertrains. In addition, since the powertrain has yet to be launched in the market, it suffers from the largest consumer biases among all powertrains. With high purchase price, high fuel costs, limited fuel availability, and heavy consumer biases, hydrogen vehicles have the least chance of being selected within consumers' consideration sets. Combining with the reinforced effects of consumer familiarity and low vehicle model availability, the adoption of hydrogen is far from successful in the base scenario.

The EV powertrain, on the other hand, suffers from low market share due to different reasons. Although at the time of market introduction, EV does not have the best vehicle utility, the powertrain soon achieves the best vehicle performance amongst all powertrains (Figure 7-9). However, even with the best vehicle utility score, EVs still cannot be successfully penetrated into the market. The two most likely explanations for this situation are the high consumer biases and relatively low consumer familiarity of the EV powertrain. Despite having the best vehicle performance, the large consumer biases have made EVs less attractive to consumers during their evaluation stage (Figure 7-10). Apart from the consumer biases, the slow familiarity build-up for EVs also heavily impedes the diffusion of this powertrain (Figure 7-6). The familiarity accumulation is relatively slow in the model base scenario, with the dynamic feedback for familiarity accumulation (word of mouth and marketing effects) largely based on the powertrain market share. This tight reinforced relationship has created an extra hurdle for EV adoption.

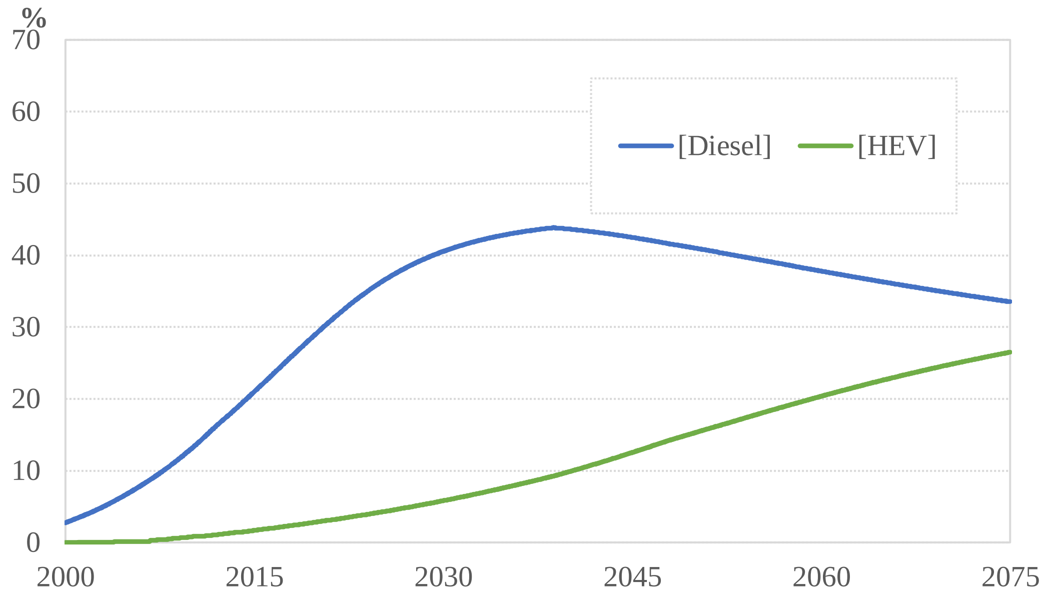

Figure 7-12 Base scenario – Market share projection of diesel vehicle and HEV

Another worth-noticing point in the base scenario is the adoption behaviour disparities between similar powertrains. The first pair of powertrains that have quite a bit of similarities however having distinct adoption paths are HEVs and diesel vehicles (Figure 7-12). With similar powertrain introduction time, diesel vehicles are adopted rapidly by vehicle consumers while HEVs gradually penetrate the market. Because the diesel powertrain already enjoys relatively high familiarity in the market due to its history in heavy vehicle sector, it was easily accepted by consumer (Figure 7-6). HEVs, on the other hand, takes off relatively slowly (Figure 7-6). However, with its more superior vehicle utility, the HEV powertrain slowly reaches a significant market share where market share self-sustains and keeps growing.

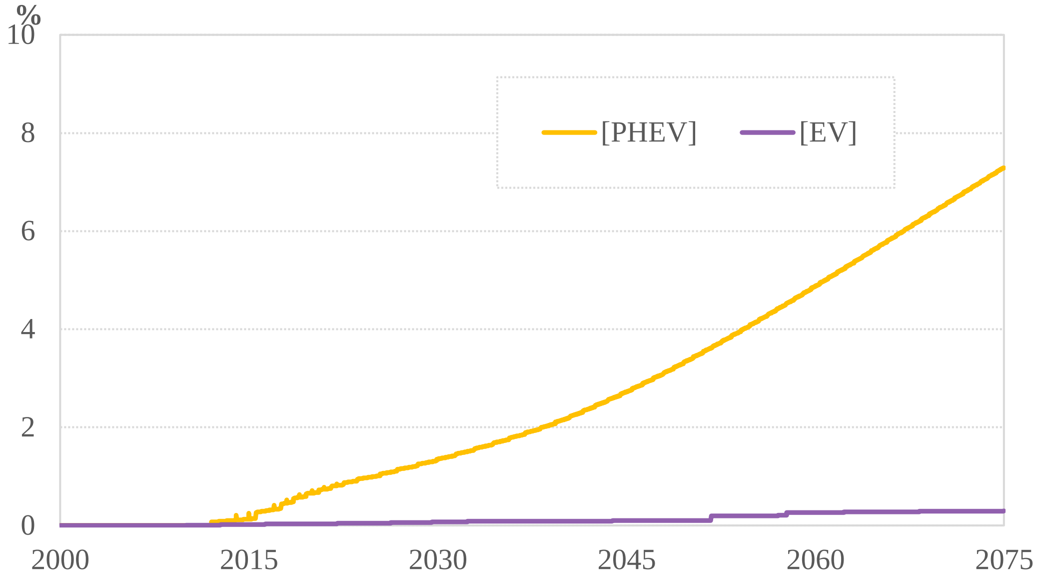

Figure 7-13 Base scenario – Market share projection of PHEV and EV

Another pair of powertrains that are worth comparing is PHEVs and EVs (Figure 7-13). These two powertrains are both relatively new. However, PHEV and HEV powertrains have disparate adoption paths. The only distinctive difference between them is that PHEVs has less consumer biases because the powertrain is more relatable to drivers who are used to traditional powertrains. EVs, although having potentially better vehicle utility, suffer from heavy consumer biases (Figure 7-10), and therefore are not accepted by the market. These two pairs of powertrains have demonstrated the significance of platform bias and consumer familiarity to overall market share.

Section 7.4 analysed the base scenario dynamics in detail and discussed the projected AFV adoption performance based on these dynamics. The low projected market shares for AFVs, especially EVs and hydrogen vehicles were explained. However, it is still unknown if the adoption performance of these more recent powertrains can be improved based on changes of key variables in these feedback loops. In the next section, based on the simulated market environment, AFV adoption behaviour in extreme conditions were explored by varying the key variables in the four feedback loops of the system dynamics model.

7.5 Key variables in AFV adoption performance in extreme conditions

In the previous section, the system dynamics model base scenario was investigated through the four feedback loops that drive the AFV adoption. The vehicle adoption performance led by these four feedback loops were analysed. In this section, the extreme condition scenarios of the adoption of AFVs are explored. The alternative powertrain chosen for extreme condition scenarios is the EV powertrain. EV is regarded as a promising alternative powertrain for reducing the tank-to-wheel GHG emissions and a main part of the global electrification trend in transportation sector (International Energy Agency, 2017). However, in the base scenario, the EV powertrain has a low projected market share despite its potentially high vehicle utility. The unexpected low market share projected in the base scenario is worth to be further investigated using the extreme condition scenarios.

In this section, the projected adoption performance of EV powertrain will be tested by changing the values of key variables of the four feedback loops to extreme conditions. Among the four key feedback loops, number of vehicle models and vehicle utility are situational and tangible while consumer biases and familiarities are relatively intangible since these two variables involve consumers' attitudes and opinions and are more difficult to directly intervene. In the following extreme condition scenarios, EV adoption performance change via variables like vehicle model number and utility are first investigated, followed by variables around consumer attitudes and opinions, i.e. consumer biases and familiarities towards powertrains. In the end, EV adoption performance via extreme conditions of combined variables are performed to observe the ultimate EV adoption behaviour change as well as the impact of EV adoption improvement on other alternative powertrains.

7.5.1 Variables that are subjected to direct changes

The number of vehicle models and the vehicle utility of the powertrains are situational variables that can be directly changed without endogenous feedback in the model. To test the EV adoption performance under the extreme condition of vehicle model number, the number of EV models and EV utility are changed to the best possible value to aid the EV adoption. The time of the value changes are set at year 2025. The values to be changed are listed in Table 7-7.

Table 7-7 Key variable changes in EV extreme conditions scenarios

Variable name	Unit of model variable	Change to value	Explanatory note
Number of EV models	Model	120	The number of EV models is changed to 120, which the sufficient number of vehicle models to full coverage in market segments.
Utility of EVs	Dmnl	0	The utility is changed to value 0, which is the highest possible value of the vehicle utility score. This means there is no penalty for vehicle purchase price and fuel costs in utility score.

❖ Extreme condition of EV model number

Within the model dynamics, if there is no constrain in regard to the availability and variety of EV models, the EVs would have a higher possibility of entering consumers' consideration sets due to full market coverage brought by the increase of EV models, and therefore yield a superior projected market share the powertrain. The projected market share after optimization of number of EV models is presented in Figure 7-14.

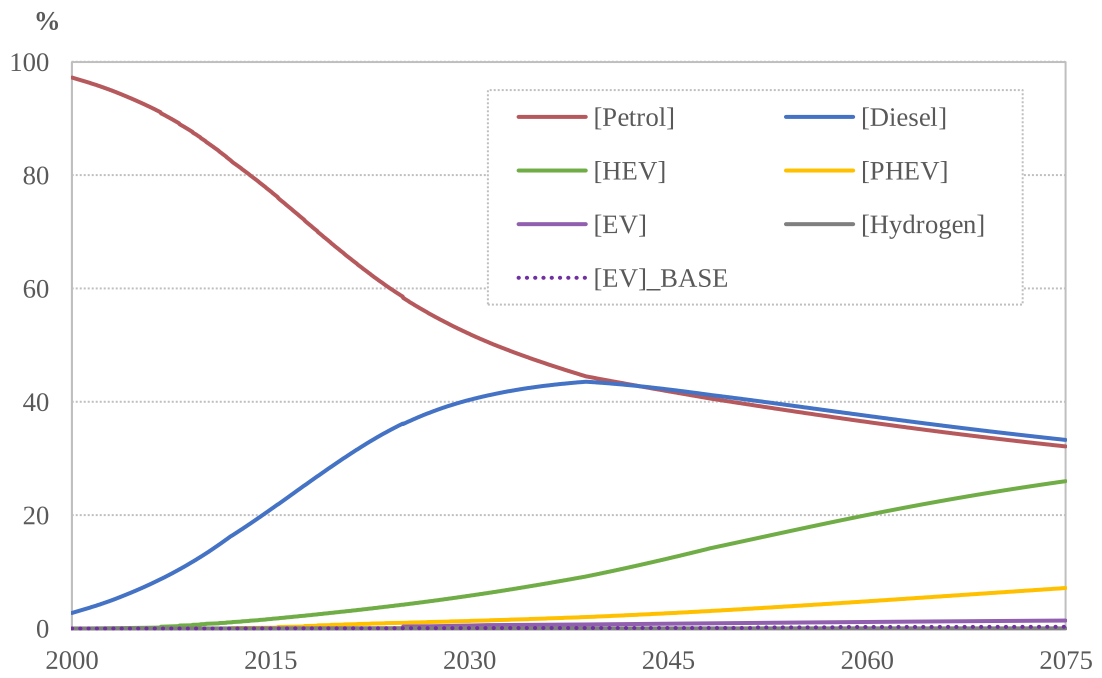

Figure 7-14 Extreme condition of EV model number – Market share by powertrains

Although the projected market share of EVs has increased slightly after introducing sufficient vehicle models, the increase in market share is not significant. The projected market share in year 2075 grows to 1.34% from the original 0.3%, which suggests that even with the vehicle model number increased to sufficient for full market overage, there are also other obstacles for EV adoption. To further investigate the EV adoption under sufficient number of EV models, the performance of other key variables in the simulation model are explored. Since EV utility is largely exogenous in the model, the changes in EV utility caused by increase in EV model number is minimal. Hence only dynamics of key variables consumer familiarity and biases are examined (Figure 7-15 and Figure 7-16).

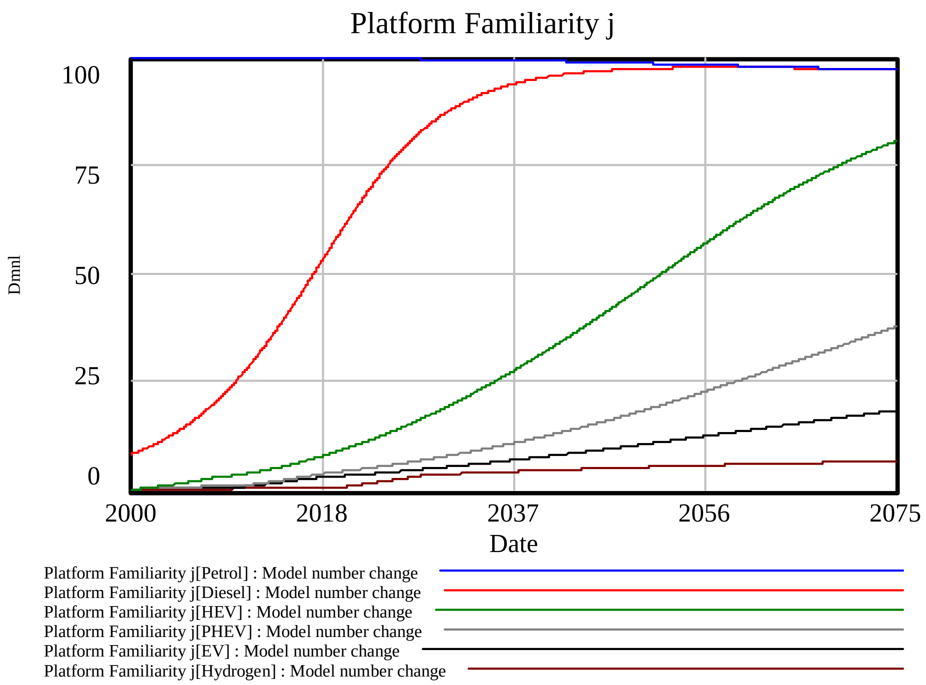

Figure 7-15 Extreme condition of EV model number – Consumer familiarity by powertrain

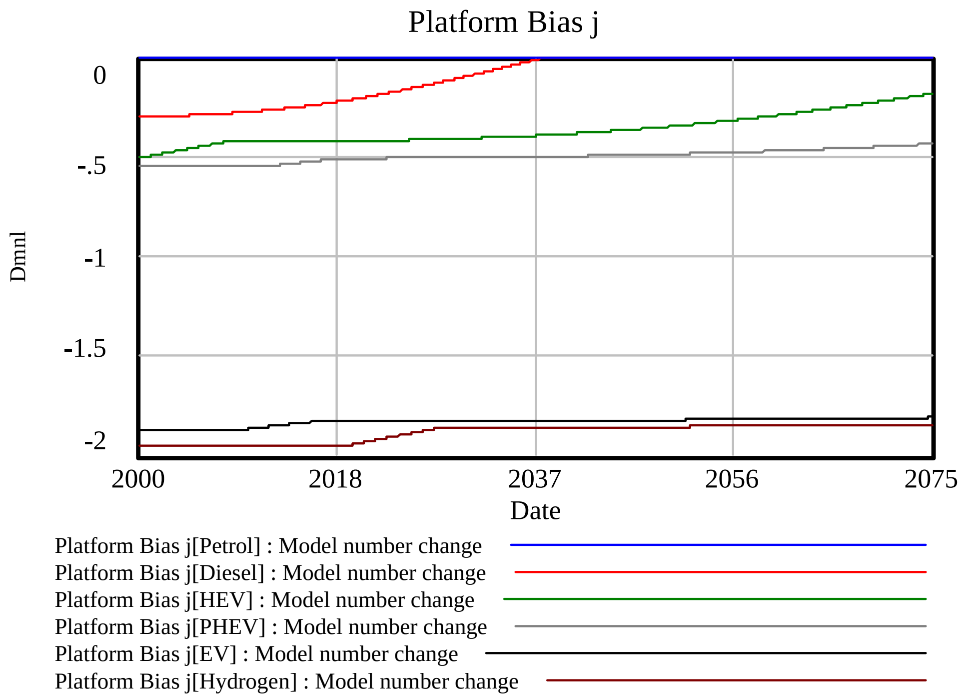

Figure 7-16 Extreme condition of EV model number – Consumer biases by powertrain

The escalation of EV model number has not brought significant changes in consumer familiarity and consumer biases against EV (Figure 7-15 and Figure 7-16). EV consumer familiarity is still at a low level and consumer biases against EV are heavy with little to no changes from the base scenario. The increased vehicle model availability and variety cannot influence the performance of other key variables, the reinforced effects of consumer attitudes and opinions are barely altered after the extreme idealization on the number of vehicle model provided.

❖ <u>Extreme condition of EV utility</u>

The projected market shares in the extreme condition scenario on EV utility are presented in Figure 7-17. Compared with the base scenario, the market share projection of EV has increased (from 0.3% to 3.6%), although not to a substantial extent. With the utility of EVs increased to the highest, the chances of EVs getting picked from consumer evaluation stage are improved. However, with the highest level of relative advantages compared to traditional powertrains, the market share projection of EVs still stagnates at a relatively low level. The adoption dynamics of EVs in this extreme condition scenario is further investigated based on the behaviours of other key variables in the model, especially key variables around consumer familiarity and biases.

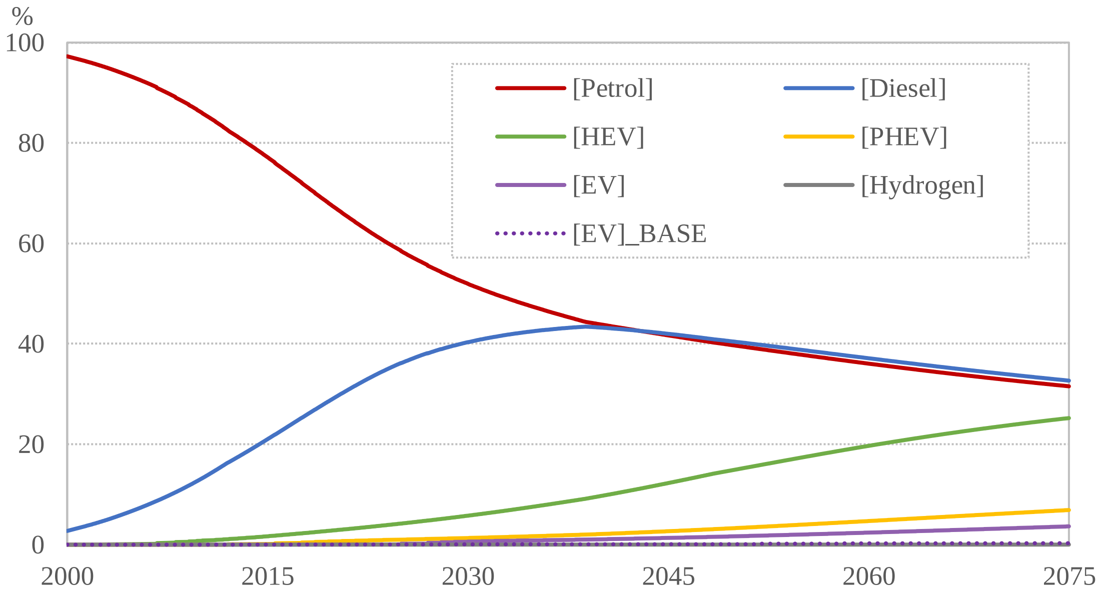

Figure 7-17 Extreme condition of EV utility – Market share by powertrains

The dynamics of the effects of vehicle model number to the possibility of vehicle getting selected in consumers' consideration sets is presented in Figure 7-18. Compared with the base scenario (Figure 7-8), the effect on consumer choice caused by number of EV models has noticeably increased. This indicates that the alteration in EV utility has caused the reinforcing feedback on the number of vehicle model to strengthen.

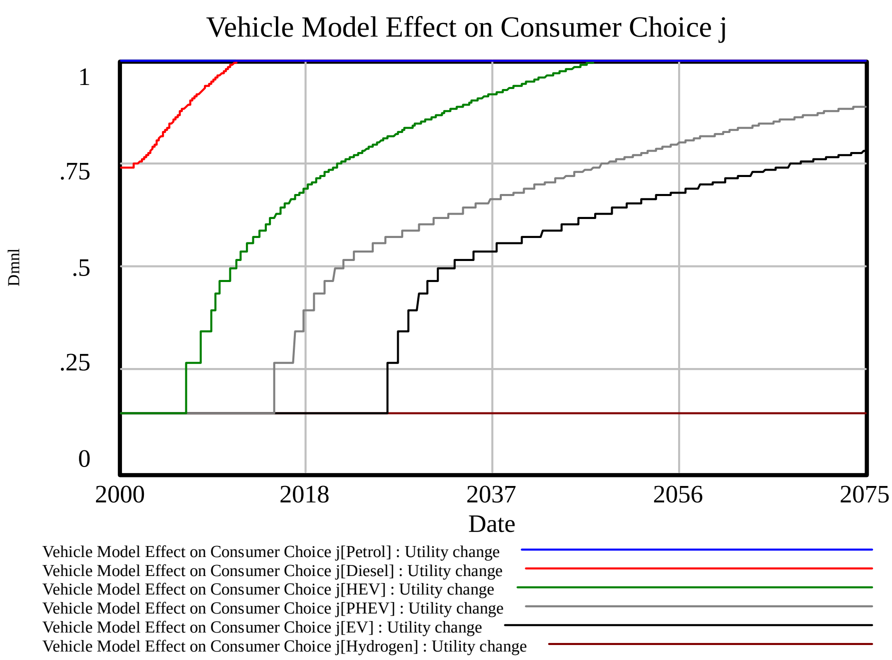

Figure 7-18 Extreme condition of EV utility – Vehicle model effect by powertrain

However, the dynamic performances of key variables that are around consumer attitudes and opinions, such as consumer familiarity and consumer biases against EV, are not altered extensively under the variable optimization based on EV utility (Figure 7-19 and Figure 7-20).

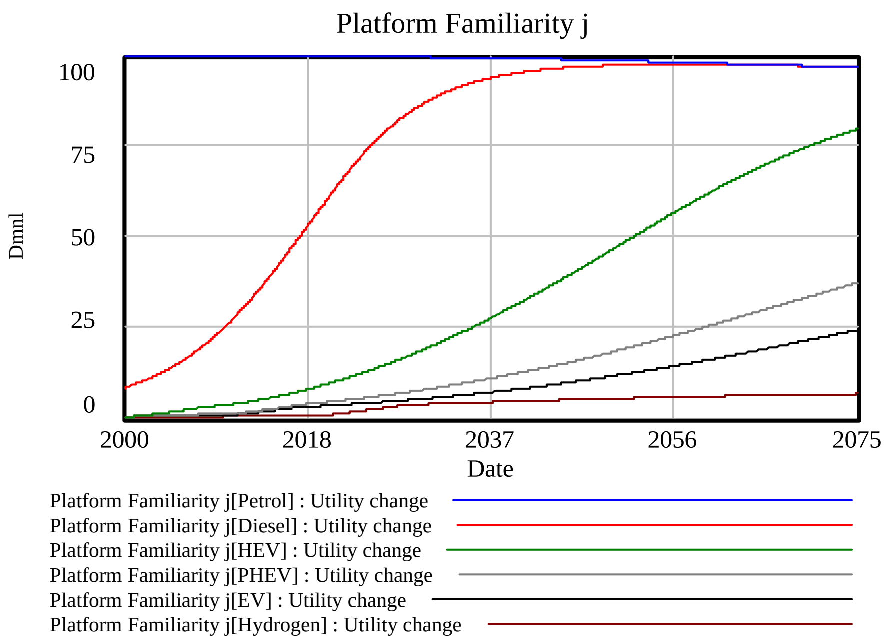

Figure 7-19 Extreme condition of EV utility – Consumer familiarity by powertrain

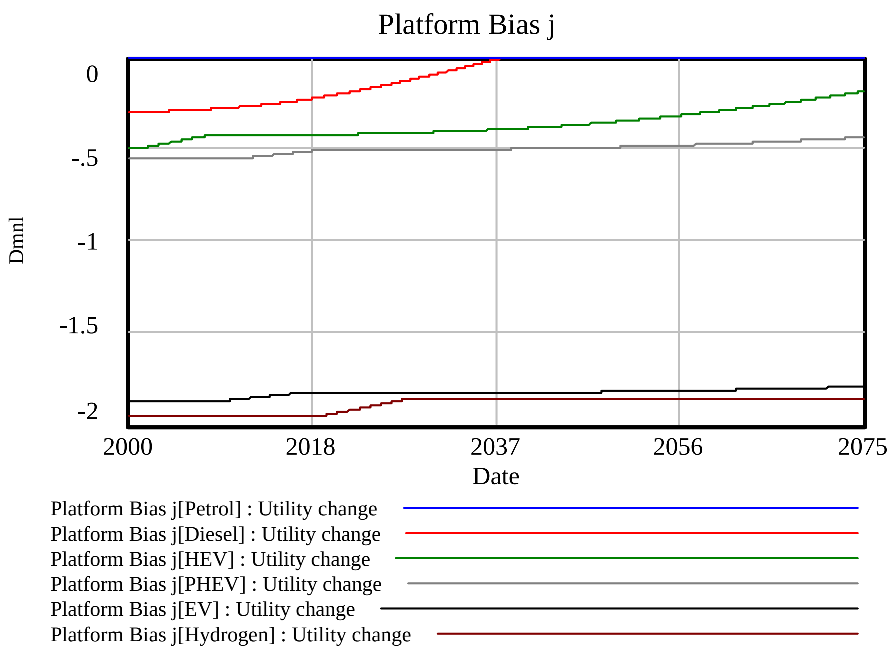

Figure 7-20 Extreme condition of EV utility – Consumer biases by powertrain

The idealized and unrealistic EV utility increase has changed the dynamics of EV adoption via higher vehicle utility in consumer evaluation stage and improved effect of EV model number on consumer choices. However, the drastic change of EV utility has failed to bring improvement to the dynamic performances of key variables around consumer attitudes and opinions. Therefore, the improvement on EV adoption brought by extreme condition of EV utility is still considerably limited.

In this section, key variables that are subjected to direct changes with no endogenous feedback needed were optimized to their best possible value to boost up the projected market share of EV powertrain. It was found that even under drastic and unrealistic key variable conditions, the adoption behaviour of EV powertrain has no significant improvement. The main obstacle in the poor EV adoption performance lies in the key variables that are around consumer attitudes and opinions and involve endogenous feedback and indirect changes, namely consumer familiarity and biases. Optimization of values in the key variables that are subjected to direct changes alone cannot spur the feedback effects of such variables. In the next section, the variables that around consumer attitudes and opinions will be put into extreme conditions to observe the changes in EV adoption behaviour.

7.5.2 Variables around consumer attitudes and opinions

This section investigates EV adoption behaviour under extreme conditions of consumer attitudes and opinions. The values of variables that describe the attitudes and opinions of vehicle consumers are difficult to change directly. Different from variables that are subjected to direct changes, any alteration in values of consumer attitudinal variables are normally due to changes in other model variables and related endogenous feedback. For consumer bias variable, its dynamics depends on the marketing funds spent on the powertrain, which depends on the powertrain's market share. This variable can be changed indirectly by external marketing or by individual incidents that affect consumers' perceptions of the powertrain. For consumer familiarity, the dynamics are composed of two feedback loops: one is marketing funding that determined by the powertrain market share; the other is the word of mouth effect. Amongst these two feedback loops, the latter contributes the majority gain in consumer familiarity. However, the word of mouth effect is driven purely by endogenous feedback and is not subjected to any external manipulation outside of the model, which makes the value of variable consumer familiarity inert to external manipulation. For the above reasons, EV adoption behaviour test under extreme conditions of variables around consumer attitudes and opinions only allows direct manipulation of variable consumer biases. Because the values of consumer familiarity level for different powertrains are heavily dependent on endogenous feedback and not able to be manipulated, the key variable consumer familiarity will not be included in this section.

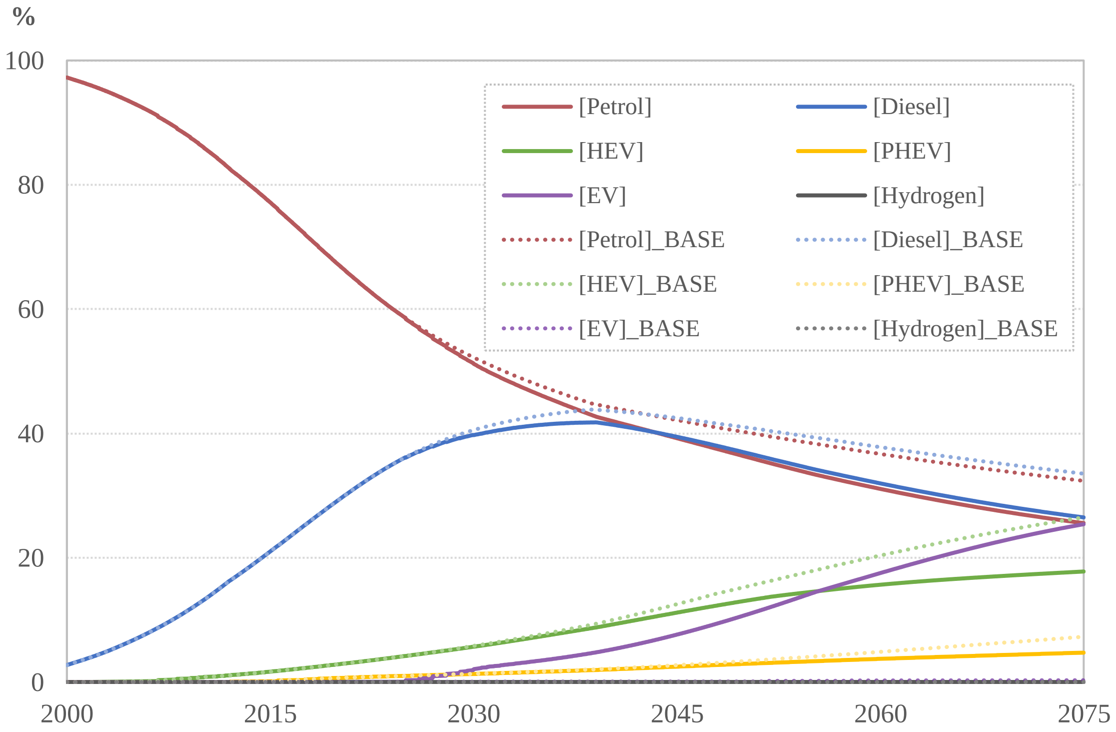

Figure 7-21 Extreme condition of EV consumer biases – Market share by projections

The consumer bias of EV is changed to zero in the extreme condition, which means that there is no bias towards EV powertrain within consumers. With no consumer biases like petrol powertrain, EV's projected market share has increased significantly (Figure 7-21). At the end of the projection timeframe, the market share of EV has surpassed the two hybrid electric powertrains and achieved the same level as petrol and diesel powertrains. Compared with the base scenario, which is presented using the dotted lines, the increases in EV market share have resulted in drops in projected market shares of all other powertrains, which is not observed from scenarios under extreme conditions of other variables in the previous section. This indicates that idealized condition of consumer biases can provide momentum to strengthen the reinforcing feedback of other key variables.

The dynamic changes in vehicle model effect and consumer familiarity are presented in Figure 7-22 and Figure 7-23. The performances of both loops are noticeably improved. Especially for consumer familiarity, the increase in EV familiarity had remarkably amplified the chances of EV getting selected into consumer consideration sets, which contributes to the overall increase in the projected market share of EVs (Figure 7-23).

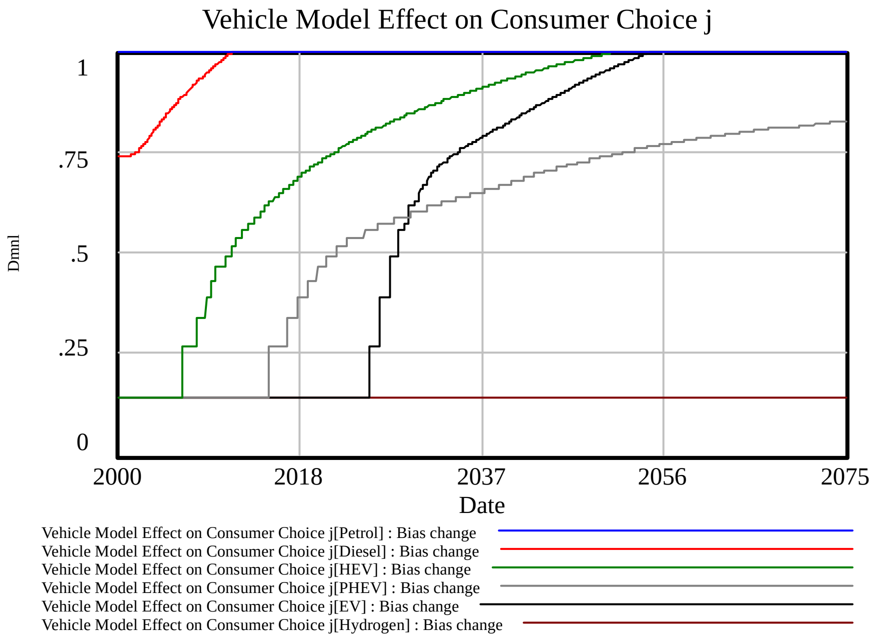

Figure 7-22 Extreme condition of EV consumer bias– Vehicle model effect by powertrain

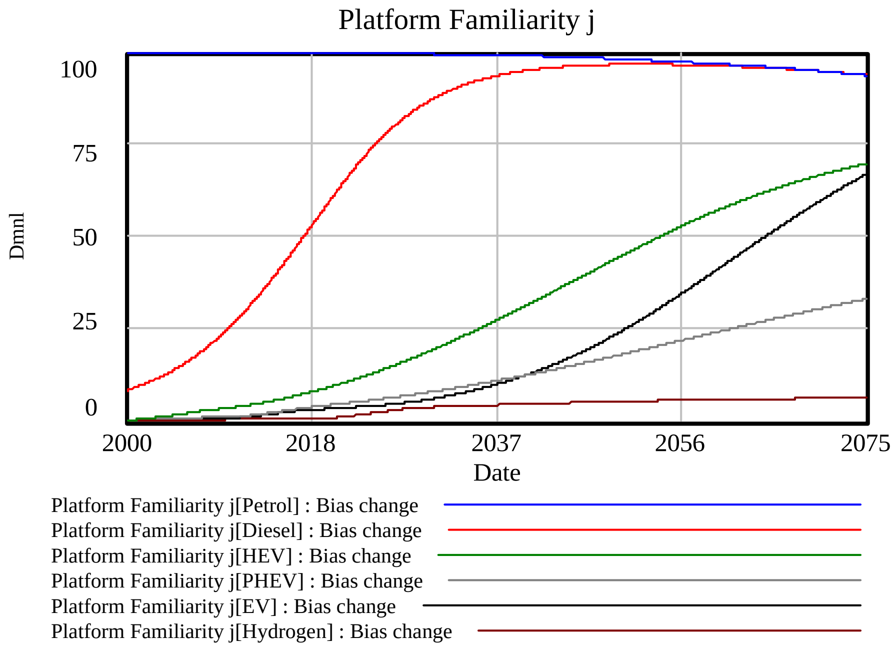

Figure 7-23 Extreme condition of EV consumer bias – Consumer familiarity by powertrain

It is striking that elimination of the consumer biases during evaluation stage can boost the adoption drastically. The momentum created by this idealized condition has also led amplified effects of other reinforcing loops such as vehicle model availability and consumer familiarity accumulation as well. To further investigate key variable consumer biases, one more extreme condition scenario is simulated and presented next.

The values of consumer biases against different powertrains are relevant only if compared with each other. In the evaluation stage, if the consumer bias of one powertrain is deepened, the relative consumer biases against other powertrains are reduced and the possibility that other powertrains getting chosen are increased. In real-world context, if petrol and diesel powertrains are penalized in their consumer biases, the relative attractiveness of other alternative powertrains are instantly increased. In Figure 7-24, the scenario where the petrol and diesel powertrains are penalized in consumer biases are explored to see the reaction of the adoption path of EV. In this case, consumer biases of petrol and diesel powertrain were changed to the same value of EV powertrain at year 2025.

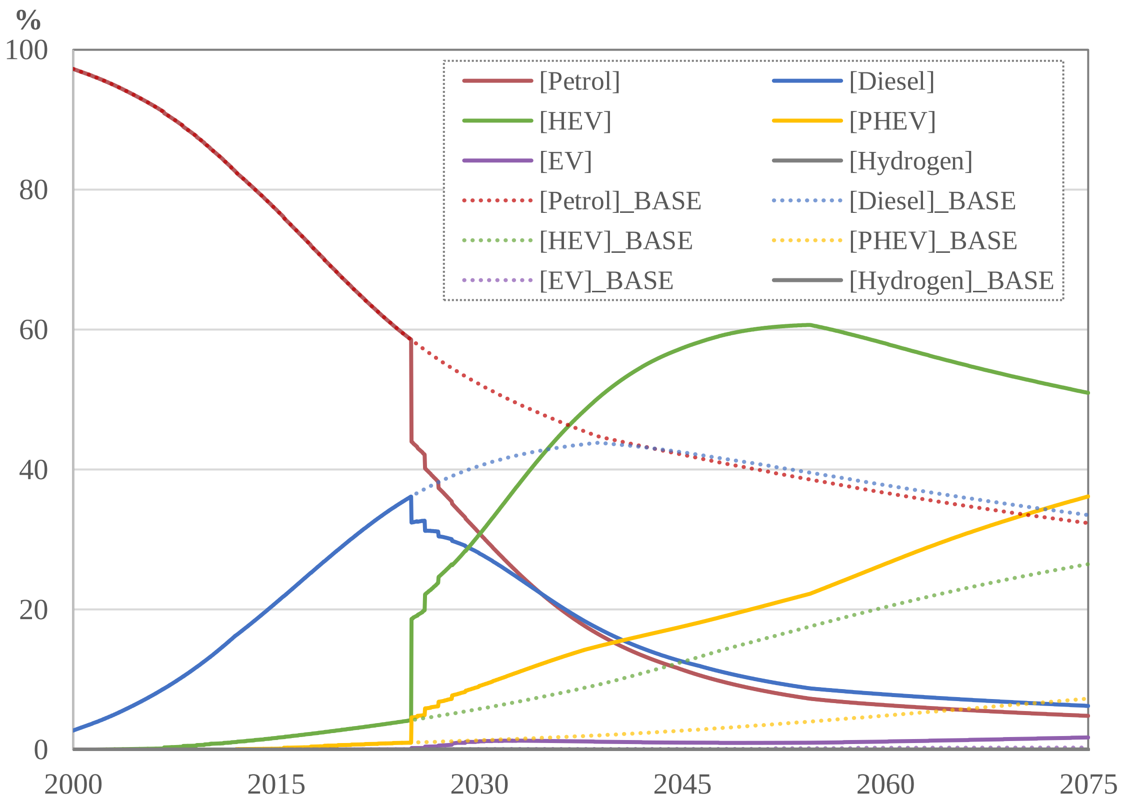

Figure 7-24 Extreme condition of petrol and diesel vehicle penalty – Market share by powertrain

In this scenario, the penalties on consumer biases of petrol and diesel powertrains have made substantial drops in projected market shares of the two traditional powertrains and also freed large market space for the rest of the powertrains. However, the penalties on petrol and diesel does not bring noticeable changes to the adoption of EVs. The void in the market are quickly filled by HEVs and PHEVs, rather than EVs and hydrogen vehicles. This result suggests that penalties on consumer biases of traditional powertrains cannot generate the same effect as consumer biases reduction of one powertrain. Although the relative advantages of petrol and diesel powertrains are scaled down, it hasn't made EV the most attractive powertrains in the market. Therefore, the projected market share of EV does not have a significant increase in this scenario.

In this section, EV adoption performance under extreme conditions of key variable consumer biases was investigated. The extreme condition of idealized EV biases was first conducted. The scenario when extreme penalties on petrol and diesel biases was then performed. Reducing consumer biases in EV powertrain resulted in significant increase in EV market share. The reinforced feedback of other key variables such as EV consumer familiarity and the number of EV models were also amplified. However, in the scenario of petrol and diesel biases penalization, the EV adoption was not improved due to the competition of other alternative powertrains such as HEV and PHEV. In the next section, EV adoption performance under extreme conditions of multiple key variables will be explored. These scenarios will investigate the influences of combined key variables and provide insights on the effects of such adoption performance improvement to the adoption of other powertrains.

7.5.3 Extreme condition scenarios based on combined key variables

This section investigates the effects of combined key variables, specifically the influences of variables that are subjected to direct changes under the condition where the consumer attitudes and opinions have reached an idealized level. This measurement provides an opportunity to observe the influences of situational variables, such vehicle utility and the number of vehicle models, on an alternative powertrain that has relatively high consumer familiarity and low consumer biases. To this end, the two situational variables for EV powertrain are altered to their extreme conditions 5 years later after the consumer biases idealized alteration.

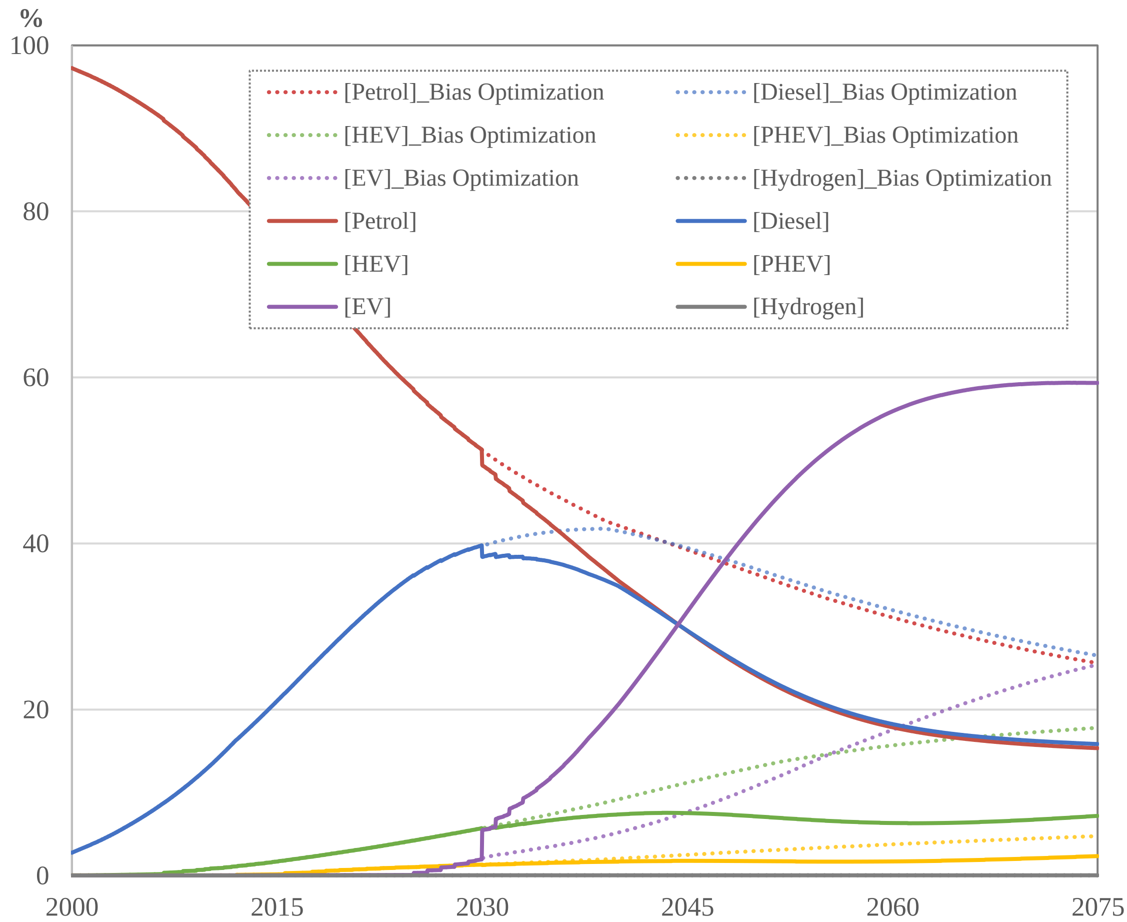

Figure 7-25 Extreme condition of EV consumer bias and subsequent EV utility change – Market share by powertrain

The projected market shares are shown in Figure 7-25 and Figure 7-26. To demonstrate the changes brought by the extreme conditions of vehicle utility or the number of vehicle models under positive consumer attitudes and opinions, the extreme condition scenario results based on consumer biases are also presented in dotted lines. It can be observed that the increase in EV projected market share brought by idealized condition of EV utility after EV consumer biases reduction is substantial (Figure 7-25). Comparing to the scenario where only vehicle utility was optimized (Figure 7-17), the increase in EV market share in this scenario is a drastic improvement. This simulation suggests that in general, for an alternative powertrain that have relative advantages in consumer attitudes and opinions, changes in it vehicle utility can be significantly influential to the adoption performance of the powertrain.

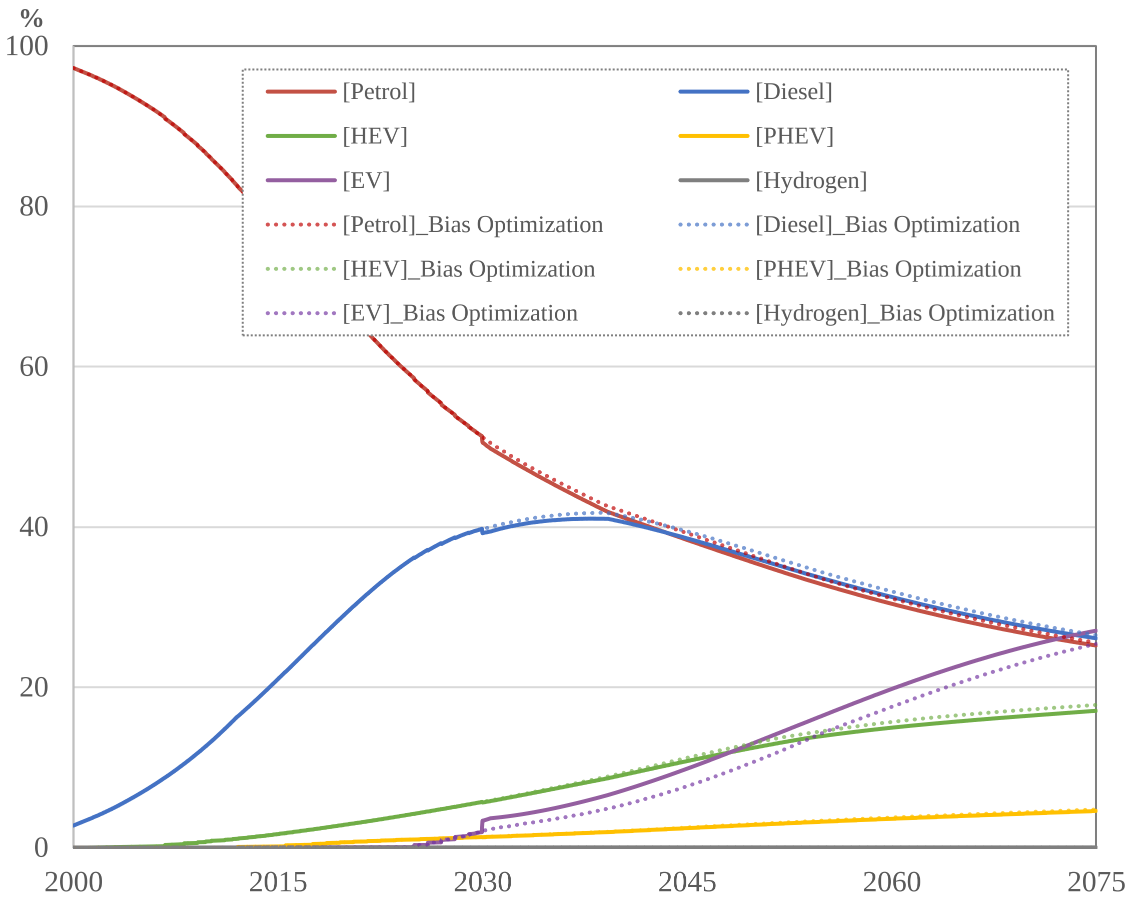

Figure 7-26 Extreme condition of EV consumer bias and subsequent EV model number change – Market share by powertrain

However, for key variable number of vehicle models, the increase in EV model number in 2030 cannot substantially boost up EV's projected market share (Figure 7-26). This suggests that an increase in the number of vehicle models provided by a powertrain cannot generate significant improvement to its adoption performance.

This section explored adoption performance variations based on idealized situational key variables under the extreme condition of positive consumer attitudes and opinions. The simulation results showed that for alternative powertrains that have positive consumer attitudes and opinions, optimization on vehicle utility can significantly improve the adoption performance while optimization on the number of vehicle models cannot influence the adoption noticeably. In the next section, EV adoption will be investigated under extreme alterations of all three key variables that were discussed previously. Although it is highly unlikely the extreme condition scenario setting will happen in real life, the scenario allows observation on the best possible market share EV powertrain can achieve and a better angle for investigation of competitions between various alternative powertrain adoption.

7.5.4 Extreme condition scenario based on all key variables

In this section, EV adoption performance under idealized situation of all three key variables is explored. The setting of this extreme condition scenario includes all previous variable value alterations in Section 7.5.1 and 7.5.2. Although this setting is not likely to happen in real life, the scenario can present how EV adoption performs under extreme conditions and what reactions other powertrains have under these conditions. The projected market shares of different powertrains in this extreme condition scenario (solid lines) and the base scenario (dotted lines) are presented in Figure 7-27.

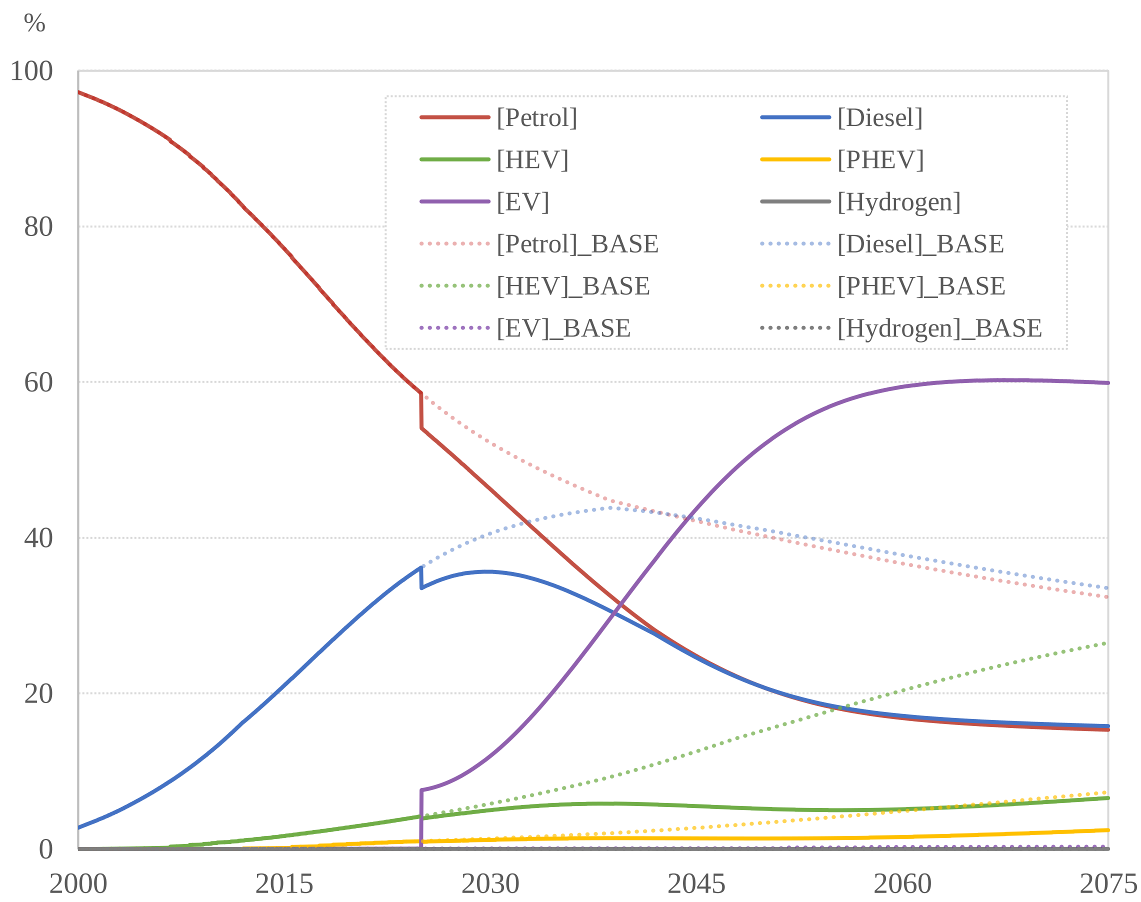

Figure 7-27 Extreme condition of consumer bias, number of models, and utility – market share by powertrain

The projected market share of EV has increased drastically in this scenario. At the end of the time projection, EV market share has reached to around 60% and become the absolute dominant powertrain in the market. The adoption of EV also reaches a plateau in the extreme condition scenario. This indicates that the reinforcing forces from the four key feedback loops has reached to their full strength and the projected market share of EVs at the plateau level are the best possible performance of EV adoption as long as no powertrain exit the market to free extra market space for EV and other powertrains.

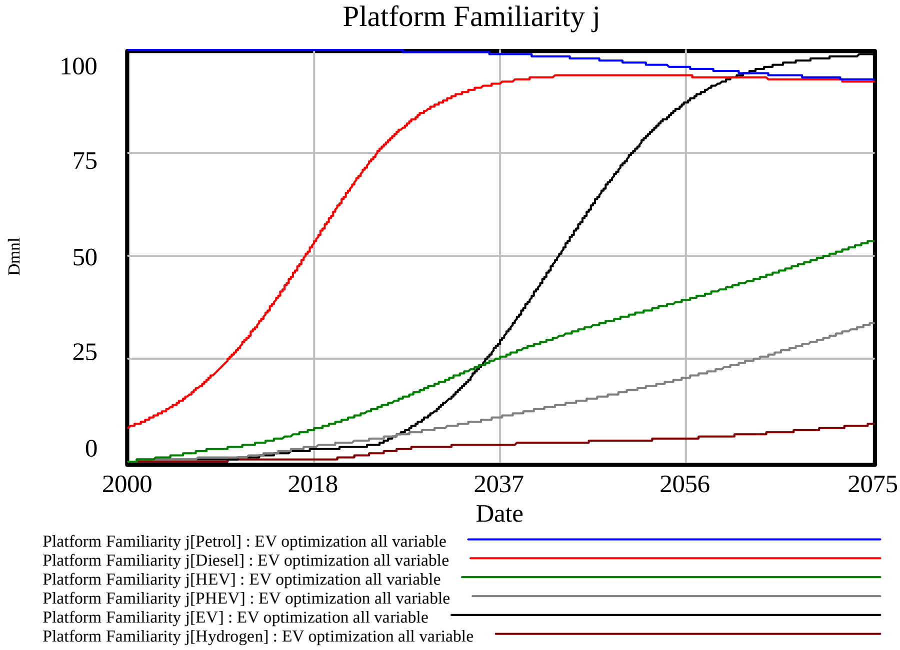

Figure 7-28 Extreme condition of EV consumer bias, number of models, and utility – consumer familiarity by powertrain

The dynamic performance of inert key variable consumer familiarity is shown in Figure 7-28. Consumer familiarity in EVs has reached to 100% in this scenario, which has not been achieved in the previous extreme condition scenarios. The fulfilment in EV consumer familiarity enables 100% chance of EV getting into consumers' consideration sets before evaluation stage. The plateau in EV market share reflects the possibility of EV getting chosen by a consumer with best utility and no consumer biases.

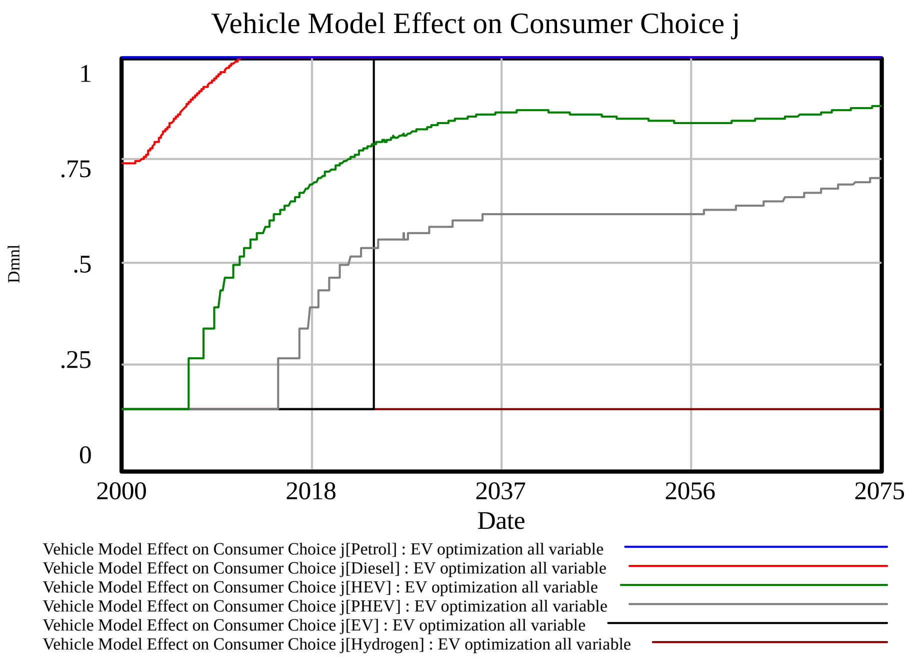

Figure 7-29 Extreme condition of EV consumer bias, number of models, and utility –Vehicle model effect by powertrain

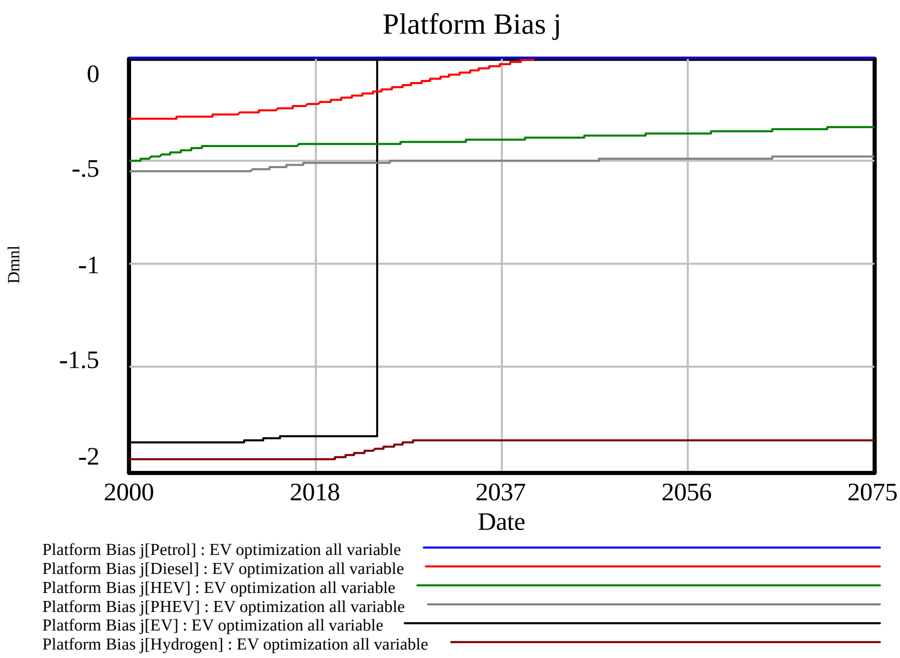

Figure 7-30 Extreme condition of EV consumer bias, number of models, and utility – consumer biases by powertrain

In this extreme condition scenario, the adoption paths of other powertrains are worth investigating as well. The surge in EV market share has brought drastic changes in market shares of other powertrains as well. The projected market shares of petrol and diesel vehicles have dropped in half, from around 30% to 15%. While for later alternative powertrains such as HEV and PHEV, the decreases in projected market shares are even more prominent. The improvement in EV adoption has brought severe damage to the adoption of alternative powertrains that are more dependent on the reinforcing feedback. Taking HEV for instance, in the base scenario, dynamic behaviours of variables such as consumer familiarity (Figure 7-6), effects of number of vehicle models (Figure 7-8), and consumer biases (Figure 7-10) of HEV powertrain all reflected the reinforced forces of these feedback loops. The values of these variables in HEV powertrain have shrunk significantly in the extreme idealized condition of EV adoption (Figure 7-28 through Figure 7-30). HEV consumer familiarity grows more gradually than the base scenario (Figure 7-28). The effect of number of HEV model on consumer choice stagnates and never reaches the full 100% (Figure 7-29). The reduction of consumer biases against HEV powertrain also slows down in this scenario, leading to slimmer chance of HEV powertrain getting selected in consumers' evaluations. For powertrains that rely relatively heavily on the reinforcing feedback, such as HEV, PHEV, and hydrogen vehicles, increase in EV adoption performance can create great hindrances to their adoption.

In Section 7.5, extreme condition of EV adoption was investigated via different key variables. Through the different extreme condition scenarios, the impacts of the key variables in the model were observed. In the extreme condition scenarios, key variables around consumer attitudes and opinions are more influential than variables that are subjected to direct changes. When the adoption path of one alternative powertrain is altered through idealized variable setting, the adoption of other alternative powertrains that more rely on the reinforcing forces of the model can be negatively affected. In the next section, based on the extreme condition scenarios conducted in this section, possible policy interventions for Australian AFV adoption will be discussed.

7.6 Possible policy interventions for promotion of AFV powertrains

Based on the extreme condition scenarios conducted in the previous section, this section discusses possible policy interventions for Australian AFV adoption. As mentioned previously, the variables that are subjected to direct changes are number of vehicle models and vehicle utility, the variable that can be changed indirectly is consumer biases against powertrain. For the last key variable, consumer familiarity of the powertrain, changes in this variable are mostly passive and based on endogenous feedback. Therefore, this section discusses possibly policy interventions in regard to number of vehicle models, vehicle utility, and consumer biases respectively.

7.6.1 Interventions on number of vehicle models

The number of vehicle models offered by powertrain determines the possibility that the powertrain enters consumers' consideration sets. In the extreme condition scenarios, the influences of increasing number of vehicle models provided by one powertrain were investigated under both circumstances of which consumer biases were reduced prior to vehicle number increase and consumer biases were remained. In the context of real-world implications, policy intervention on increasing the number of vehicle models in one powertrain do exist as well. Taking the Zero Emission Vehicle (ZEV) program for example, this policy affects 10 states in USA and regulates vehicle manufacturers to maintain at least 2.5 percent of its annual sales to be zero-emission vehicles (Califronia Air Resources Board, 2017). It is an effective way to urge manufacturers to provide at least one vehicle model that releases zero emission to the vehicle market.

In this simulation model, the sufficient level of vehicle model numbers in the model is 120 available models. If similar policies such as the ZEV program were to be implemented in the Australian market, considering that there are 67 vehicle makes in the Australian market (Federal Chamber of Automotive Industries, 2014), each vehicle make should release about 2 vehicle models in one AFV powertrain into the market in order to achieve the optimized effect. In the extreme condition scenario based on EV model number, the increase in projected market share caused by increase in vehicle model number to sufficient level is relatively minimal (Figure 7-14 and Figure 7-26). Therefore, it is reasonable to argue policy intervention around increasing number of AFV models might not be effective in terms of boosting up the adoption.

Another possible policy intervention around number of AFV models is the reduction in model number of traditional powertrains. In many vehicle markets, constrain on the number of petrol vehicle are likely to be implemented (Petroff, 2017). For instance, France announced that the country will not be selling petrol and diesel-powered vehicle by the year 2040 (Ewing, 2017). Similarly, Britain also plans to ban petrol and diesel cars starting in 2040 (Petroff, 2017). Such policies can effectively supress the market segmentation coverage by petrol and diesel powertrains and release market space for AFVs.

In reality, reduction in vehicle models in one powertrain can lead to decrease in the powertrain's market shares. Because of the diesel scandal happened in 2015 and introduction of the tougher real-world emission testing (Worldwide Harmonised Light Vehicle Test Procedure) promoted by the scandal in Europe, Volkswagen has been actively culling diesel models in their line-ups in the Australian market (Newton, 2018). In October 2018, diesel will disappear from the brand's passenger car line-up. Volkswagen's shift away from diesel powertrain has resulted the diesel passenger vehicle sales of the brand down 28% year-on-year (Newton, 2018). Although this is only one vehicle make in one market segment and cannot represent the whole vehicle market, the sales data of Volkswagen shows that vehicle manufacturers shifting away from one powertrain can result in direct drop of the powertrain's market share and freeing market space for other powertrains.

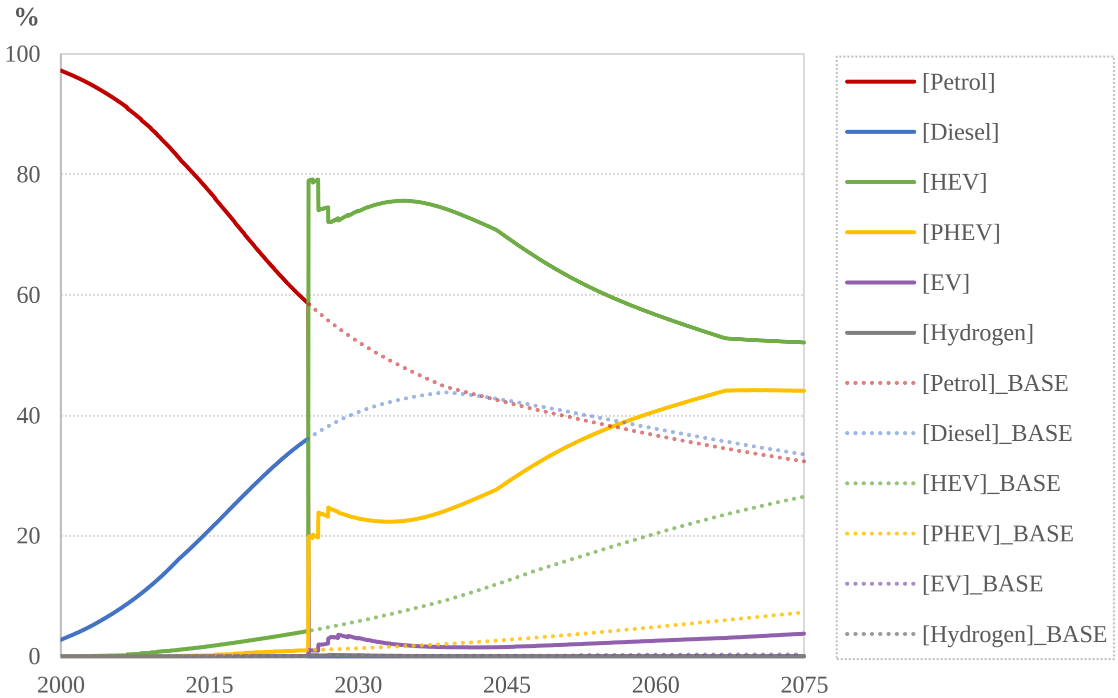

Figure 7-31 Policy intervention on petrol and diesel vehicle model number

An extreme scenario where the number of petrol and diesel vehicle models are reduced to zero in year 2025 is presented in Figure 7-31. The simulation shows that when the petrol and diesel powertrains are forced out of the market, the market space is filled primarily by HEVs and PHEVs. The disappearance of petrol and diesel powertrains also leads to amplified reinforcing feedback of consumer biases and familiarity (Figure 7-32 and Figure 7-33). Particularly, the key feedback loops HEV and PHEV consumer biases and familiarity are strengthened immediately after the elimination of the two dominant powertrains. This indicates that extreme reduction in vehicle model number of traditional powertrains can effectively improve the adoption of alternative powertrains that have higher market shares already.

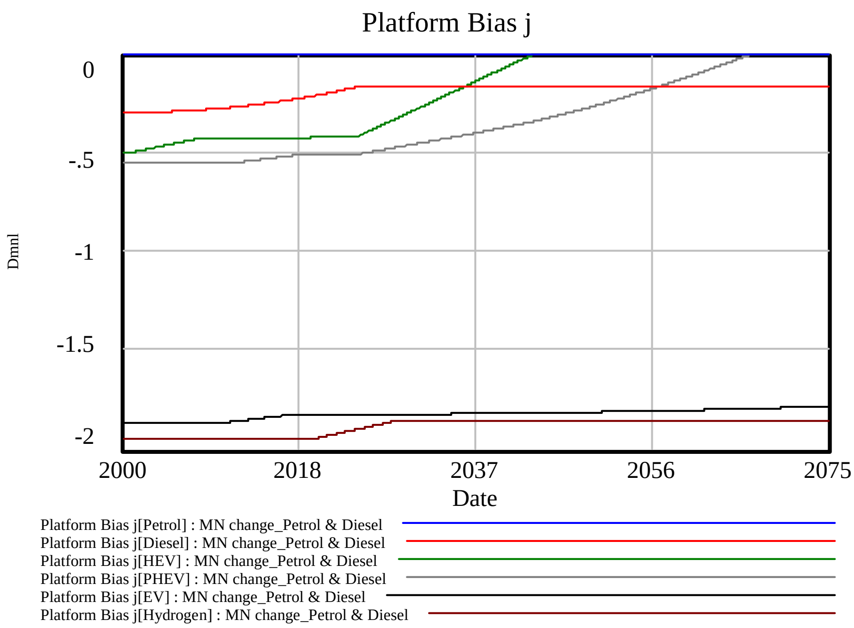

Figure 7-32 Policy intervention on petrol and diesel vehicle model number – consumer biases

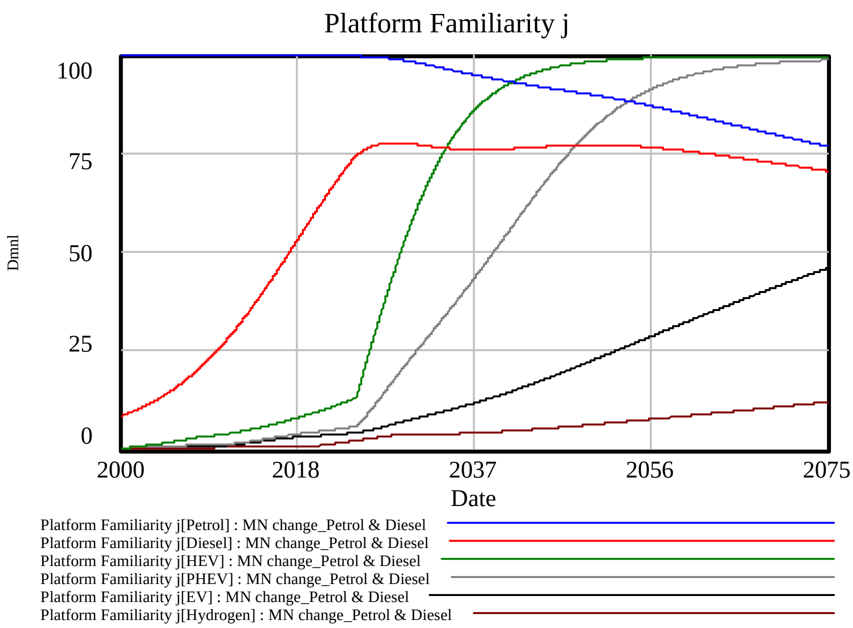

Figure 7-33 Policy intervention on petrol and diesel vehicle model number – consumer familiarity

However, for alternative powertrains with high consumer biases and low consumer familiarity level, such as EVs and hydrogen vehicles, such measurement is not as effective. Especially for consumer biases, the reinforcing forces to reduce the negative consumer attitude towards EVs and hydrogen vehicles has not been triggered by the policy.

7.6.2 Interventions on vehicle utility

Improving the vehicle utility is a common aim for policy implementation for AFV adoption. Since this key variable contains all tangible vehicle attributes that are determinant to consumer evaluation process, interventions around vehicle utility are the most direct way to encourage more consumers to choose one powertrain. Common policy interventions that improve the utility of the powertrains include financial incentives to reduce vehicle purchase price (Sierzchula et al., 2014, Gallagher and Muehlegger, 2011, Rudolph, 2016, Mueller and de Haan, 2009), extra refuelling infrastructure to mitigate consumers' range anxiety (Meyer and Winebrake, 2009, Struben, 2006, Franke and Krems, 2013, Coffman et al., 2017), and incentives for reduction of the operating costs of the powertrain.

According to the extreme condition scenarios where the utility of EV powertrain was altered to its optimal value, interventions that depend solely on improvement of vehicle utility are not efficient to boost up the adoption of alternative powertrains that does not have high consumer familiarity and little consumer biases (Figure 7-17). In the extreme condition scenario where the consumer biases were reduced prior to EV utility intervention, intense EV utility improvement has achieved significant market share increase compared to the scenario with only reduction in consumer biases (Figure 7-25). This finding indicates that interventions on vehicle utility can be effective only if the powertrain does not suffer from low consumer familiarity and high consumer biases.

In reality, the degree of utility change through policy interventions is relatively low if the consumer preferences associated with each vehicle attribute are kept constant during the adoption. Take the Australian market for example, to achieve a 7.5% vehicle utility change in EV in year 2025 requires providing AUD4236 incentives to purchase price or adding 1045 charging stations in populated areas, which are already considered as relatively strong policy enforcement. It is unrealistic to increase the utility of one powertrain to the same degree as the extreme condition scenario described in Section 7.5.1 in real world. In addition, the extreme condition scenario also has permanent improvement of EV utility. However, the powertrain utility changes in reality are not always permanent and often last only for a period. For instance, it is common to provide financial incentives for alternative powertrain during the early stage of the powertrain adoption with the policy beginning to phase out after a period of time (Sierzchula et al., 2014, Gallagher and Muehlegger, 2011, Rudolph, 2016, Mueller and de Haan, 2009). Therefore, it is reasonable to deduce that temporary AFV promoting policies that solely focus on utility change based on improving the vehicle performance may not be effective, especially when the alternative powertrain has high consumer biases and low consumer familiarity, such as EV and hydrogen vehicles.

7.6.3 Interventions on consumer attitudes and opinions

Key variables that depict the attitudes and opinions of consumers are not subjected to direct changes and can only be changed via dynamics within the model. For key variable platform bias, its values are determined by generic marketing that are based on the sales revenue of the powertrain. Therefore, it is reasonable to assume that by providing more funding for marketing, consumer biases against a powertrain can be reduced further. In addition, combined marketing effect of traditional buying criteria with ecological motivations (Johan, 2011), and targeted educational campaigns and social marketing (Hae-Kyong et al., 2000, Roger et al., 2016), are all effective in reducing the misconceptions within the market. Specific marketing to reduce consumer biases as listed above would be more effective than the regular marketing based on the sales revenue. For consumer familiarity, although marketing can help accumulate consumer familiarity of one powertrain, its majority accumulation is via the word of mouth endogenous feedback. Therefore, this key variable is more difficult to intervene through external forces.

As variables that depict the system with not much external interventions, the natural dynamics and changes in variables consumer biases and familiarities lie in the demographics of vehicle consumers. The changes in consumer demographics characteristics are significant in understanding the shifts in variables like consumer biases and familiarities in AFV adoption, more specifically, the age or generation of vehicle consumers. In the base scenario, the consumer attitudes and preferences are largely based on the 2016 survey results, which are answered by a panel that is more leaning towards the elder groups in the population (see Table 5-2 in Section 5.3). In the discrete choice model, it has been proven that the age of consumers and their attitudes towards AFVs are strongly associated (Section 5.6.2). Younger consumers are more likely to have positive attitudes towards AFV powertrain (Liao et al., 2017) and have higher awareness of AFV powertrain than older generations (Timmons and Perumal, 2016). For these younger consumers, the main obstacle of AFV adoption is their strong preferences towards vehicles with a cheaper price tag. Therefore, it is intuitive to deduct that the consumer attitudes are likely to shift towards the direction that favours AFV adoption because the current young generations who are constrained by their purchase abilities will become the majority of vehicle consumers and be less sensitive to the high purchase price of AFVs due to their age growth and life status change. The natural shifts in consumer biases and familiarities due to changes in consumers' age and generations are worth further investigation as well.

Similarly, consumer preferences, as an important part in the determining the overall vehicle utility in the evaluation stage, can also shift due to changes in consumer demographics during the course of AFV adoption. Specifically, with growing vehicle market under emerging economy or increasing awareness in environmental issues, vehicle consumers' preferences are highly likely to change according to economy transitions (Andreasen, 1984, Roger et al., 2016). The increase of specific vehicle utility may also be achieved by the natural or intervened shifts in consumer preferences.

In Section 7.6, the possible policy interventions for promoting the adoption of AFVs were discussed. Interventions based on key model variables were put into realistic perspectives and their potential influences on the adoption performances of different alternative powertrains under distinctive adoption specifics were investigated. In the next section, a general discussion on the findings of the system dynamics model will be performed.

7.7 Discussion

Based on various tests on the system dynamics model, this section summarizes the insights from the system dynamics model and provides a discussion on the research findings. These findings are categorised into three groups: dynamics of consumer biases and attitudes, influences of key variables, and competitions between powertrains. In the following sub-sections, findings in each category are discussed. Based on real-world context, implications of such findings to policy establishment are also addressed.

7.7.1 Dynamics of consumer attitudes and biases

Dynamic feedback on key variables in consumer choices enable the investigation of the main research question in this thesis: what are the implications of changes in consumer attitudes and preferences to AFV adoption? Among all key variables that have been identified, the dynamics for consumer familiarity and consumer biases can best address the consumer behaviour and psychosocial changes within the consumer decision-making process.

For consumer familiarity, previous research has intensively investigated the reinforced relationship between adoption rates and consumer familiarity accumulation (Struben and Sterman, 2008, Lee et al., 2013, Struben, 2006, Keith, 2012b). This simulation model follows the guidance of previous literature to build the familiarity accumulation dynamics where consumer familiarity builds up through marketing and word-of –mouth effects. Spillover in marketing funding within similar powertrains, i.e. electrified powertrains have a slight spillover between each other during familiarity accumulation through marketing advertisements. Model simulation in this research has suggested that the consumer familiarity as a key variable is critical to the adoption of alternative powertrains. Since the variable is largely depend on the endogenous feedback within the system, it can become the most prominent obstacles of AFV adoption.

For platform biases, the model first discovered consumer biases through market survey and the embedded choice modelling. In the literature, misconceptions of consumers towards new technologies/products are also addressed (Meeran et al., 2017, Hae-Kyong et al., 2000), especially for environmentally friendly innovations such as AFVs (Green et al., 2014). However, it has yet to be included in a dynamic simulation model and its implications to adoption behaviour has to be investigated. The model has looked into the dynamics around consumer attitudes and its implications to the adoption of AFVs. The added dynamics around platform bias has generated significant behaviour improvement in AFV adoption. Test on such dynamic hypothesis revealed that the reinforcing dynamics between consumer biases against alternative fuel powertrains and their adoption rates acts as a driving force in AFV diffusion process into the vehicle market. The dynamics structure on platform biases has provided a more comprehensive picture for AFV adoption studies. Later scenario tests on various key variables become more reliable because of the well-rounded viewpoint of the system. The establishment of the dynamics structure around consumer biases has also provided additional measurements for potential interventions on the adoption of AFVs.

Apart from consumer familiarity and consumer biases, another variable that depicts consumer attitudes and preferences is the consumer preferences associated with different vehicle attributes in consumer's evaluation stage. This variable is set as static in the base scenario, but it can be dynamic in the extreme condition scenarios. In the work done by Lachaab et al. (2006), the variance in consumer preferences associated with product attributes over time has been observed. The possibilities of consumer preferences changing were also mentioned in previous literature (Andreasen, 1984). The arrangement of consumer preferences as a changeable variable in the extreme condition scenarios provides an opportunity to investigate the implications of changes in consumer preferences to the adoption paths of AFVs.

7.7.2 Influences of key variables

With the dynamics around consumer familiarity and biases, the model presents a comprehensive view of AFV adoption. The influences of all key variables in the system are lucidly explored. Through extreme condition scenarios of EV adoption based on different variables, key variables that focus on consumer attitudes and opinions are found to be more influential in promotion of EV market share. Interventions that only focus on promoting the performances of situational variables can hardly make an impact on the performances of variables that determines consumers' attitudes and opinions. For more recent alternative powertrains that usually suffer from high consumer biases and low consumer familiarity level, the key to increase of their projected market shares is to focus on changing consumer's attitudes and opinions.

Another observation through the extreme condition scenarios is that extreme setting of joint key variables provides superior results in boosting adoption rates than isolated interventions. It is intuitive to understand that joint interventions are able to generate stronger driving forces for AFV adoption. This hybrid policy instalment was also confirmed in previous literature (Silvia and Krause, 2016, Bakker and Jacob Trip, 2013, Supple, 2007) .

To summarize, the key to successful interventions for AFV adoption is to is to trigger the self-sustained reinforcing feedback that drives the model. For powertrains that lack consumer familiarity and have high consumer biases, interventions have to focus on changing the consumer attitudes and opinions first before improving the performances of situational variables. Combined intervention approaches are found to generate better effects to the adoption then isolated interventions. This model has provided insights and guidance for wisely choose interventions for promoting AFV adoption.

7.7.3 Competitions between powertrains

The system dynamics model in this research includes a variety of powertrains. Although the extreme condition scenarios did not involve interventions for key variables in every powertrain, the dynamics between different powertrains can still be observed and analysed. These observed dynamics between powertrains can provide additional insights for external intervention implementation and paint the picture of future vehicle market landscape in Australia and possible other markets.

The most prominent dynamics that was observed between powertrain is the competition among alternative fuel powertrains. In the extreme condition scenarios of EV powertrain, the uprises in projected market share of EV always lead to corresponding market share drops of the HEV and PHEV powertrain and further suppression on the adoption of hydrogen vehicles. It has been revealed that more recent powertrains with relatively lower adoption rates are most likely to endure market loss caused by increases in projected market shares of other powertrains. Especially in a market environment that has a diverse vehicle makes and powertrains, the competition between alternative powertrains has become a significant hurdle for AFV adoption (Tran, 2012). Based on this finding, focused policy interventions on single powertrains can generate more satisfied results in enhancing the adoption process.

7.8 Summary

This chapter implemented the system dynamics model that was constructed and formulated in previous chapters. A model calibration was performed to finalize the values of intangible model constants. With results from the model calibration, the simulation model base scenario was performed. The specific dynamics of each key variable in the simulation model were also investigated. Later in the chapter, the extreme condition scenarios of EV adoption based on single key and multiple key variables were conducted. Based on the extreme condition scenarios, possible policy interventions were addressed with real-world context. Finally, a discussion section that summarized the findings in the system dynamics model and implications of such findings was provided.

Chapter 8 Conclusion

The final chapter of the thesis presents a conclusion of the work. It starts with a review of the entire thesis. Contents of each chapter are summarized and recapped. Next, based on the research questions proposed at the end of Chapter 2, a summary of the key findings of the work is presented. Implications of the work are then discussed in two aspects: structural contributions and practical implications. Limitations of this research and directions for future works are presented subsequently with a final concluding remarks in the end.

8.1 Review of the research

The main objective of the research is to investigate the implications of changes in consumer attitudes and preferences on AFV adoption from a holistic and dynamic viewpoint. Based on the research objective, a combined modelling approach has been developed in this research. By incorporating discrete choice modelling with a system dynamics model, the research is able to quantitatively capture individuals' preferences during vehicle purchases while holistically depict the timely feedback and dynamics between different stakeholders in AFV diffusion process. The Australian vehicle market is selected as case study for its diverse and purely market-driven environment.

Following the iterative steps of system dynamics modelling and the procedures of discrete choice modelling, the research was conducted in the following three stages:

- ❖ Stage one: Dynamic hypotheses identification and preliminary dynamics model development

In Chapter 4, a theoretical foundation about consumer choices in AFV adoption was established by revisiting literature in consumer decision-making process and innovation diffusion theory (Section 4.1). Key variables and their dynamics involved in consumer choices, specifically consumer awareness, vehicle availability and model variety, and vehicle evaluation, were identified based on the theoretical foundation (Section 4.2). Using these key variables as guidance, a market observation based on historical data was conducted (Section 4.3). Based on historical trends identified from the market observation and hypotheses derived from theoretical foundation, a preliminary system dynamics model structure was constructed in Section 4.4. Since this preliminary model structure is purely based on previous literature and the market observation, only dynamics around tangible variables such as vehicle performance, and the number and variety of AFV models were developed. Dynamics in intangible variables in consumer choices such as consumer preferences and consumer familiarity have been remained unclear at this stage.

❖ Stage two: Discrete choice modelling and market survey

In order to acquire more information about intangible variables in consumer choices, the discrete choice model was executed in Chapter 4. A market survey embedded with a stated choice experiment was designed and implemented in the subsequent Chapter 5. The market survey delivered qualitative information about key variable consumer familiarity. Its results also reflected the dynamics that were identified in the previous chapter. Most importantly, data collected by the stated choice experiment was fitted into a discrete choice model. The discrete choice model provided valuable quantitative information about consumer preferences against different vehicle attributes. The best model fit also explored the influences of consumer demographics to consumer preferences (Section 5.6.2). Based on choice modelling and survey results, one additional key variable in the system, consumer biases, was revealed (Section 5.7.1); the values of consumer preference associated with different vehicle attributes were acquired (Section 5.6); additional insights about the dynamics of vehicle model variety and dynamics of vehicle performance were drawn (Section 5.7.2 and Section 5.7.4).

❖ Stage three: Research model construction, implementation, and scenario tests

With quantitative data derived and new dynamic structures about platform biases from the discrete choice modelling and market survey, in Chapter 6, the thesis proceeded to the integration of the system dynamics model and the discrete choice model. A new choice model specification that is more suited to the system dynamics model was developed (Section 6.1). Based on such integration, the final structure of the system dynamics model was established (shown in the causal loop diagram in Figure 6-1). Formulations of each key feedback loop were presented (Section 6.3). Finally, in Chapter 7, the system dynamics model simulation was implemented. A model calibration based on historical data was conducted (Section 7.2). The base scenario was derived based on the calibrated model (Section 7.4). Extreme condition scenarios to investigate the influences of key variables in the model were conducted (Section 7.5). Possible interventions were simulated in scenario tests based on various key variables (Section 7.6). Lastly, main findings of the system dynamics model were summarized and discussed (Section 7.7).

8.2 Key findings of the research

In this section, key findings of the research are summarized in accordance with the research questions proposed in Chapter 2. Recall from Section 2.6, the proposed research questions were:

- What are the dynamics of consumer attitudes and preferences in AFV adoption process?
- What are the implications of the changes in consumer attitudes and preferences to the adoption AFV?
- What are the potential interventions to promote AFV adoption based on a dynamic and holistic system viewpoint?

In this section, the research questions are answered sequentially.

8.2.1 Dynamics identified in consumer attitudes and preferences

Three key variables that depict the consumer attitudes and preferences in AFV adoption were identified in the thesis: consumer familiarity towards different powertrains in consumer information searching stage, consumer biases associated with different powertrains in consumer evaluation stage, and consumer preferences linked with different vehicle attributes in consumer evaluations.

Consumer familiarity depicts consumers' awareness of the powertrain and determines the possibilities of a powertrain entering in consumers' consideration sets for evaluation. During the course of market penetration, the powertrain gains consumer familiarity mainly by the word of mouth effect accompanied by generic marketing. The greater the consumer familiarity around the powertrain, the more likely for consumers to include the powertrain within their consideration sets for evaluation stage, which leads to greater powertrain popularity to generate more consumer familiarity around the powertrain. This reinforced dynamic was widely recognized in previous works by Struben and Sterman (2008), Shepherd et al. (2012), Shepherd (2014). In this study, the dynamics of consumer familiarity has been further investigated. It has been found that the consumer familiarity, as an endogenously driven model variable, poses significant impediments to the adoption of AFV and is difficult to increase based purely on improving the vehicle utility or providing more vehicle models in the market (Section 7.5.1).

Consumer biases representing consumers' negative perceptions around a particular powertrain were found to have heavy influences on the decision-making of vehicle consumers. From attitudinal questions of the market survey (Section 5.4.1) and the discrete choice modelling (Section 5.6), consumer biases were identified and quantified. In the simulation model, the values of consumer biases against each powertrain in 2016 were derived from the discrete choice modelling. Using these values as benchmarks, dynamics around consumer biases were built to allow gradual reduction naturally during the adoption process of the powertrain (Section 6.3.4).

The last dynamic worth-noting is the consumer preferences that are associated with different vehicle attributes and help determine the results of consumer decisions in the evaluation stage. Consumer preferences are normally treated as static coefficients in discrete choice modelling (Liao et al., 2017). Although consumer preferences were kept static during the model base scenario, they were allowed to change during the scenario tests. The model variable vehicle utility, which is determined jointly by consumer preferences and vehicle performance, was treated as one variable in the model scenario tests (Section 7.5.1, 7.5.3 and 7.5.4) and discussion on potential policy intervention (Section 7.6.2). Optimizations of utility can be achieved by improvement of vehicle performance, or shifts in consumer preferences, or both. This kind of flexibility has allowed the modeller to observe the possibility of consumer preferences shifts.

In addition to the reinforced dynamic mentioned previously, succession in consumer generation accompanied by general economic development (Saunders and Saker, 1994) and changes in consumers' life status (Andreasen, 1984, Mathur et al., 2003) can also lead to changes in consumer attitudes and preferences. As awareness in environmental issues and fuel dependency increases, the younger generations are exposed in a social environment that has more emphases on environmentally friendly products (Kanchanapibul et al., 2014, Yadav and Pathak, 2016). This can lead to the younger generation become more accepting of alternative fuel powertrains. In the discrete choice model, age of the respondents and their biases towards alternative powertrains are positively correlated, which also suggests that younger respondents have more positive opinions about alternative powertrains than elder respondents. As the generation changes in society, the adoption of AFVs are subject to change as well. In this study, although the dynamics of consumer attitudes due to generation change are not specifically investigated, the dynamic structure in consumer attitudes and preferences of the simulation model has presented the implications of changeable consumer attitudes and preferences and provided a feasible basis to further investigation of such dynamics due to changes of consumer generation.

8.2.2 Implications of changes in consumer attitudes and preferences

Dynamics in consumer attitudes and preferences have made significant impacts on the adoption of AFVs. The reinforcing feedback relationship between consumer attitudes and preferences and powertrain market shares enhances the overall reinforcing dynamics in the process of AFV adoption. Especially, consumer familiarity and consumer bias, have been identified as the two key variables that can significantly affect the adoption performances of different powertrains.

Alternative powertrains that are introduced relatively late and share less similarities with traditional powertrains often have low consumer familiarity levels and high consumer biases. In the Australian market context, powertrains that fit under this condition are pure electric and hydrogen. In the extreme condition scenarios, EV adoption performance was increased the most based on reduction of EV consumer biases (Figure 7-21 in Section 7.5). The significant improvements in the performances of all key variables and the projected market share of EV have indicated that the consumer attitudes, specially consumer familiarity and bias, are critical in successful adoption of alternative powertrains. Enhancements in the performances of consumer attitudes and preferences can strengthen the driving forces of the adoption process and consequentially improve the performances of other key variables in the model. In scenarios that optimize the EV utility or the number of EV models, EV projected market share did not show substantial changes, and performances in consumer familiarity and bias around EV did not improve either (Section 7.5.1). This suggests that when the performance of consumer attitudes and preferences are low, adoption of alternative powertrain are not likely to succeed by only improving situational variable, such as vehicle utility and model availability.

Different from powertrains that are more recent and less similar with ICE powertrains, alternative powertrains that are more mature have relatively higher consumer familiarity and less consumer biases. In Australia, such powertrains are HEVs and PHEVs. Due to their similar driving and refuelling experiences, projected market shares of HEV and PHEV have achieved significantly superior level than that of EV and hydrogen vehicle. In Section 7.5.3, extreme optimizations of subjective variables such as EV utility and model number were conducted after optimization of consumer attitudes and preference performances. The results showed that, when an alternative powertrain has high consumer familiarity and low consumer bias, extreme optimization in vehicle utility can considerably boost up the market share of the powertrain. This means that, for powertrains that already have relatively high consumer familiarity levels and low consumer biases, increasing the vehicle utility can effectively enhance their adoption performances. In such cases, vehicle utility becomes a feasible way to promote the adoption of AFVs. Apart from improvements on vehicle performance, shifts in consumer preferences that may be due to changes in consumer generations should also be considered.

The dynamics in consumer attitudes and preferences significantly affected the adoption paths of alternative powertrains. Generally, the adoption of AFVs is under heavy influence of the performances of the two model variables, consumer familiarity and consumer biases against powertrains. Especially for powertrains that are lack of consumer familiarity and are penalized by high consumer biases, successfulness of their adoption depends on whether the performance of consumer attitudes and preferences can be improved.

8.2.3 Potential interventions for promoting AFV adoption

Based on theoretical foundations, the market observation, a market survey, and a discrete choice model, the dynamic model that depicts the AFV adoption in Australia has been established. Analyses and extreme condition scenarios based on the dynamic model have identified several characteristics within the process of AFV adoption: significant dynamics around consumer attitudes and preferences, heavily reinforced global dynamics, and competition between alternative powertrains. Based on these characteristics, potential interventions for promoting AFV adoption are drawn.

The first characteristic of AFV adoption is the significant influence of consumer attitudes and preference. As summarized in the Section 8.2.2, the substantial influences of the key variables i.e. consumer familiarity and bias towards the powertrain, provide insightful guidelines for potential interventions to promote the adoption of AFVs. In summary, for alternative powertrains that are lack in consumer familiarity and have high consumer biases, interventions based solely on situational variables are not sufficient for improving the adoption of AFVs.

It is found that lack of knowledge around alternative powertrains are closely linked with negative perceptions towards alternative powertrains (Burgess et al., 2013), Therefore, it is reasonable to argue that educational campaigns to raise awareness of alternative powertrains and to inform the population about the potential benefits of the powertrains can be an effective way to correct consumers' biases around certain alternative powertrains. In real-world context, the effectiveness of interventions around consumer attitudes and preferences can also be observed. For instance, in Norway, where the annual EV market share is the highest globally, it was identified that technology myths and perceived risks could be a major barrier for zero-emission vehicles (Carranza et al., 2013). Awareness actions were launched early in the 1990's to educate consumers about EVs' potential benefits and correct misunderstanding (Carranza et al., 2013). In the study done by Figenbaum et al. (2015), it was also stated that frequent media coverage and vivid public discourse on electrification in transportation sector had positive effects on the diffusion of EV powertrain in Norway. Even though the EV utility in Norway can be more preferable because of its heavy incentives, the effects of subjective factors in the adoption process is non-negligible. In the extreme condition scenario where the EV utility is extremely optimized, the projected market share of EV is still low. This result also supports the finding that consumers' acquired knowledge of EVs over two decades in the Norwegian market has accelerated the sales of EVs (Figenbaum, 2017).

The second characteristic of AFV adoption is the heavily reinforced global dynamics in AFV adoption. In the dynamic model, four key dynamic feedback loops and their influences on the adoption of AFVs have been identified and investigated. The key variables within each loop are: consumer familiarity around powertrain, number of powertrain vehicle models, vehicle utility, and consumers' biases towards powertrain. This research has identified that all four key variables have reinforced relationships with

AFV adoption and therefore construct the reinforced global dynamics around AFV adoption.

The reinforced global dynamics leads to the fact that any successful adoption of alternative powertrain relies heavily on the early stage of the adoption. It is crucial for any powertrain to have enough relative advantages compared to traditional powertrains in order to trigger the endogenous drive for self-sustained diffusion in the vehicle market. To this end, interventions need to focus on supporting the powertrains to achieve self-sustained adoption by considering the intensity, duration, timing, and combination of the interventions. It is intuitive to only consider the intensities and durations of interventions when designing a policy. However, in the extreme condition scenarios where only situational variables were optimized, despite maximized intensities in the scenarios, the results in promoting AFV adoption were not ideal. It is important to consider the progression of the diffusion process and come up with efficient policies for increasing the market share of an alternative powertrain. For instance, the extreme condition scenario on EV utility made significant impact on the adoption path of EVs after EV consumer bias was reduced (Section 7.5.3). Compared with optimization based solely on EV utility, timing and the combination of the measurements have led to a distinct difference in EV adoption performance.

The last characteristic of AFV adoption is the competition between alternative powertrains, which can significantly impede the adoption of AFV. The dynamic model has revealed that once the adoption of one alternative powertrain got improved, the projected market share of other powertrains would be negatively affected. Especially for more recent powertrains, due to their relatively low consumer familiarity level and high consumer biases, successful adoption of more matured powertrains can induce more fierce competitions between more recent powertrains and therefore create additional difficulties for their adoption. In the scenario where the traditional powertrains are eliminated from the market, the additional market space will soon be filled by the most mature alternative powertrains in the market (Section 7.6.1). More recent alternative powertrains, especially those with relatively low consumer familiarity and high consumer biases, have little chance of competing with the more matured alternative powertrains and gain more market share under the new market landscape. The finite market space and fierce competitions between emerging powertrains are becoming a hurdle to the adoption of AFVs. Therefore, it is reasonable to argue that targeted interventions that focus on improving the relative advantages of one alternative powertrain can be more effective to promote its adoption rather than more generic measurements to promote all AFV powertrains.

8.3 Contributions and implications of the research

The contribution and implications of the research are discussed in this section. The contribution and implications are summarized in two aspects: structural and practical. In structural aspect, the research adopts a combined modelling approach and emphasizes significant dynamic structures in AFV adoption. In the practical perspective, the dynamic simulation based the Australian vehicle market provides general insights for AFV adoption that can be applied in other markets globally.

8.3.1 Dynamics identified using combined modelling approach

This research adopts a combined modelling approach to construct a quantitative model based on real-world consumer preferences data with a holistic and dynamic viewpoint. The static consumer preferences and attitudes precisely derived from the discrete choice model is expanded within time dimension in the system dynamics model, which allows timely feedback and dynamics. Furthermore, system dynamics simulations under different scenario conditions provided great visualization for the influences of key variables. This hybrid modelling approach combines the advantages of two modelling techniques and achieved comprehensive depiction of AFV adoption.

This approach allows the model to reveal and incorporate significant dynamics that were not discussed by existing studies, such as consumer biases against powertrains and number of vehicle models offered by powertrains. Especially, the inclusion of dynamics around consumer attitudes in the research better reflected societal changes over time in the lengthy adoption process of AFVs. Such dynamics has generated significant model behaviour changes. The importance of considering dynamics in consumer attitudes to studies of AFV adoption is confirmed in this research.

8.3.2 Implications of the Australian vehicle market case study

The research is conducted using the Australian market as the case study. Although the Australian vehicle market is small in size, high diversity in both vehicle makes and vehicle powertrains has created intricate dynamics between different powertrains. Its mature market environment with no external policy interventions provided a purely market-driven context for simulation models.

The simulation model derived from the Australian vehicle market is able to simulate the AFV adoption process with no interference of policy interventions and project the AFV market share based on market-driven dynamics. It provides the researcher opportunities to analyse the organic adoption performance of different powertrains without artificial interference while also has the ability to provide an empty canvas for various policy tests. Because of the characteristics of the Australian vehicle market, the model can provide insights more generally to vehicle markets that are similar in market complexity but are larger in size and are more characterized by policy interventions.

The projected AFV adoption paths in the base scenario of the simulation model suggest that with no external interventions, traditional powertrains such as petrol and diesel would still be the dominant players in the future landscape of the vehicle market. Alternative powertrains that share more similarities with theses traditional powertrains, i.e. the hybrid powertrains, have gained considerable market shares over the simulation projection time frame. However, for pure alternative powertrains, i.e. electric and hydrogen vehicles, due to their low consumer familiarity and high consumer biases, the adoption is unsuccessful. The base scenario portrays the AFV adoption paths in a market that is market-driven and relies on imports for vehicle model release and vehicle technological development.

To generalize this finding, the adoption of AFV could be challenging based on findings of this simulation model. Interventions that focus to only improve the vehicle utility can be ineffective if the powertrain suffers from negative consumer attitudes. In addition, with low consumer familiarity and high consumer biases, the adoption of more recent powertrain can suffer from more fierce competition from the more matured alternative powertrains. The relative advantages of more recent powertrains in the aspects of both vehicle performance and consumer attitudes under no external interventions are insufficient in order to trigger a self-sustained adoption, even when traditional powertrains such as petrol and diesel are removed from the market.

8.4 Research limitations and future work directions

As stated by Hannon et al. (1995), “we never solve all our problems and challenges, we move from solution to the next challenge.” Accordingly, limitations of this research can present opportunities and directions for further research.

First, in the simulation model that utilizes a combined modelling technique, more focus was put into the system dynamics model than the discrete choice model. In the discrete choice model, although valuable quantitative information around generic consumer preferences was acquired and applied, more specific consumer preferences based on respondents’ demographics that were also derived from the choice model has not been fully utilized. The best model fit of the discrete choice model explored and revealed additional information about consumer groups and distribution in consumer tastes. However, for clarity of dynamics formulations, neither these characters in the discrete choice model, nor interesting demographic insights about survey respondents were incorporated in the final dynamics model. Although the elimination of consumer demographics in the final simulation model does not affect the model’s ability to answer the research questions, inclusion of such characteristics in the model would bring additional insights around policies targeted at specific consumer groups. Further work in fuller integration of the system dynamics model and the discrete choice model can bring more dimensions, such as consumer demographics and spatial information to the current model.

Second, the research model has incorporated endogenous dynamics structures in the subjective factors during consumer choices in vehicle powertrain selection. The accumulation loop of consumer familiarity and the reduction loop of consumer biases have added dynamic and holistic perspectives to the current model. However, changes in consumer preference coefficients are still treated as an external factor instead of an endogenous dynamic feedback. Because changes in consumer preferences are usually affected by factors on larger scale such as economy growth and social awareness changes (Roger et al., 2016) that can also involve different generations of consumers (Andreasen, 1984), the system dynamics model boundary can broadened to include such factors in the model. Furthermore, the model can be expanded to include more variables as endogenous such as fuel price, the price development of new vehicles, and vehicle production delay. For the purpose of this model, these variables are either exogenous or excluded from the model boundary. However, including such variables as endogenous feedback can definitely provide a more comprehensive picture of the AFV adoption process. For further work, similar endogenous dynamics like consumer familiarity and biases can be created around consumer preferences coefficients. The model boundary can be expanded to include more endogenous feedback loops in future simulation model.

Finally, input data for the simulation model can be further replenished for future research. Specially, historical data collected in the Australian market for this research are in the timeframe from 2000 to 2014. Although the dynamics of emerging powertrains and competitions within the market can be undoubtedly observed, a longer timeframe might provide more insights on the emerging of diesel powertrains and diminish of LPG vehicles. In addition, a second stated choice experiment to capture consumer preferences at a future time point can bring additional data to model the potential shifts in coefficients of consumer preferences. Furthermore, the model built on the Australian vehicle market case study can also be applied to other vehicle markets. To utilize this model to study other vehicle markets, the historical input data and specific coefficients needs to be changed. It would be interesting to discover insights from other vehicle markets where the market condition and consumer preferences are different from the Australian case study. Future work that incorporates longer timeframe or vehicle markets in countries other than Australia can provide more accuracy to the current simulation model and potential additional insights about the plateaued and failed AFV adoption paths.

The current model provides a comprehensive yet concise picture of the dynamics around consumer subjective factors in AFV adoption, while the future model can include broader dimension and details and provide more specific suggestions for AFV adoption.

8.5 Concluding remarks

In summary, this research has investigated the implications of changes in consumer attitudes and preferences on AFV adoption, using a combined modelling technique with system dynamics modelling and discrete choice modelling. The work has demonstrated that considering changes in consumer choices and preferences is necessary in understanding and forecasting AFV adoption, and wisely taking advantage of such dynamics can facilitate the future adoption of alternative powertrains.

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Appendix A Survey Questionnaires

Section 1

1. Please check the level of experience you had with the following alternative fuel vehicles.

	I have not heard of it before	I have heard of it, but not very familiar with it	I have researched about this type of car	I have driven this type of car	I currently own one or I use to own one
Diesel vehicles					
Hybrid electric vehicles					
Electric vehicles					
Plug-in hybrid electric vehicles					
Hydrogen vehicle					

Question 2-5 (Please only display the alternative fuels that were not selected as "I have not heard of before" in question 1)

Please note: You can put the same rating to different fuel technologies if you think they are at the same level.

2. Please **rate** fuel efficiency of the following vehicle fuel technologies (1 being very low in fuel-efficiency and 5 being very high in fuel-efficiency).

Petrol	○ 1	○ 2	○ 3	○ 4	○ 5
Diesel vehicle	○ 1	○ 2	○ 3	○ 4	○ 5
Hybrid electric vehicle	○ 1	○ 2	○ 3	○ 4	○ 5
Electric vehicle (EV)	○ 1	○ 2	○ 3	○ 4	○ 5
Plug-in hybrid electric vehicle (PHEV)	○ 1	○ 2	○ 3	○ 4	○ 5
Hydrogen vehicle	○ 1	○ 2	○ 3	○ 4	○ 5

3. Please **rate** how you feel about the following vehicle fuel technologies in terms of environmental impact (1 being the least environmentally friendly and 5 being very environmentally friendly).

Petrol	○ 1	○ 2	○ 3	○ 4	○ 5
Diesel vehicle	○ 1	○ 2	○ 3	○ 4	○ 5
Hybrid electric vehicle	○ 1	○ 2	○ 3	○ 4	○ 5
Electric vehicle (EV)	○ 1	○ 2	○ 3	○ 4	○ 5
Plug-in hybrid electric vehicle (PHEV)	○ 1	○ 2	○ 3	○ 4	○ 5
Hydrogen vehicle	○ 1	○ 2	○ 3	○ 4	○ 5

4. Please **rate** how confident you are in buying/driving the following vehicle fuel technologies (1 being not confident at all and 5 being very confident).

Petrol	○ 1	○ 2	○ 3	○ 4	○ 5
Diesel vehicle	○ 1	○ 2	○ 3	○ 4	○ 5
Hybrid electric vehicle	○ 1	○ 2	○ 3	○ 4	○ 5
Electric vehicle (EV)	○ 1	○ 2	○ 3	○ 4	○ 5
Plug-in hybrid electric vehicle (PHEV)	○ 1	○ 2	○ 3	○ 4	○ 5
Hydrogen vehicle	○ 1	○ 2	○ 3	○ 4	○ 5

5. Please **rate** the driving range of the following vehicle fuel technologies (1 being very poor driving range and 5 being adequately long driving range).

Petrol	○ 1	○ 2	○ 3	○ 4	○ 5
Diesel vehicle	○ 1	○ 2	○ 3	○ 4	○ 5
Hybrid electric vehicle	○ 1	○ 2	○ 3	○ 4	○ 5
Electric vehicle (EV)	○ 1	○ 2	○ 3	○ 4	○ 5
Plug-in hybrid electric vehicle (PHEV)	○ 1	○ 2	○ 3	○ 4	○ 5
Hydrogen vehicle	○ 1	○ 2	○ 3	○ 4	○ 5

Section 2

6. What was the fuel type of your most recently purchased vehicle?

- Petrol
- Diesel
- Hybrid electric
- Pure electric
- Plug-in hybrid electric
- Liquefied Petroleum Gas (LPG)

7. What was the make and model of your most recently purchased vehicle?

Please include the year, make, model and transmission in your answer. For example, 2010 Toyota Corolla SX manual

8. Please rate the importance of the following features in making you decision during your most recent vehicle purchase.

	Unimportant	Somewhat Unimportant	Neutral	Somewhat Important	Very Important
Price					
Operating cost					
Environmentally friendly					
Reliability/ low maintenance					
Car size/ class/ body type					
Performance					
Safety					
Brand					
Storage/ cargo space					
Engine capacity					
Transmission					

Aesthetics/appearance					

9. Please rank the importance of the following information sources during your most recent vehicle purchase. (4 being the most important and 1 being the least important)

Online reviews ○ 1 ○ 2 ○ 3 ○ 4
Vehicle dealer ○ 1 ○ 2 ○ 3 ○ 4
Friends and family ○ 1 ○ 2 ○ 3 ○ 4
Newspaper, radio and TV ○ 1 ○ 2 ○ 3 ○ 4

If there is any information source you think is very important that is not on the list above, please specify.

10. Please rank the following vehicle body styles based on your preferences during your latest vehicle purchase. (4 being the most preferred and 1 being the least preferred)

Sports/Coupe ○ 1 ○ 2 ○ 3 ○ 4
Hatch/Wagon ○ 1 ○ 2 ○ 3 ○ 4
Sedan ○ 1 ○ 2 ○ 3 ○ 4
SUV/People mover ○ 1 ○ 2 ○ 3 ○ 4

11. Have you considered vehicles that used fuel sources other than petrol during your latest vehicle purchase?

- Yes
- No

(If yes, ask question 10. If no, skip to question 12)

12. What fuel type(s) did you include in your final selection of models during your most recent vehicle purchase?

- Diesel vehicle
- Hybrid electric vehicle
- Electric vehicle (EV)
- Plug-in hybrid electric vehicle (PHEV)
- Liquefied Petroleum Gas (LPG)

13. If your latest purchased vehicle were available in model variants that use alternative fuel. How willingly would you choose the model with following alternative fuel? (1 being the least possible and 5 being the most possible)

Diesel vehicle	○ 1	○ 2	○ 3	○ 4	○ 5
Hybrid electric vehicle	○ 1	○ 2	○ 3	○ 4	○ 5
Electric vehicle (EV)	○ 1	○ 2	○ 3	○ 4	○ 5
Plug-in hybrid electric vehicle (PHEV)	○ 1	○ 2	○ 3	○ 4	○ 5
Hydrogen vehicle	○ 1	○ 2	○ 3	○ 4	○ 5

Section 3

(First page)

In this section, we will show you a sequence of choice scenarios, each contain 6 vehicles for sale. You should select the car that you are most likely to buy as if you were making purchase decision for your latest purchased car, assuming they are the only available choices on the market.

Each choice scenario will contain 6 vehicles using different powertrains: petrol, diesel, hybrid-electric, plug-in hybrid electric, pure electric and hydrogen. Each vehicle provided in the choice scenarios contains 5 vehicle features: purchase price, car size, annual fuel cost, fuel availability and driving range.

Note that some of the options are likely to be vehicles you have not seen in the current market, but may become available in the future. You should respond as if they were available today.

(Second page)

Here is some information about the six powertrains and the five vehicle features used in the choice scenarios. You can also find the information when place your cursor to the words in the first column and second row of the question table.

The description of the powertrains is provided below:

- **Petrol vehicles**: vehicles use petrol fuel.
- **Diesel vehicles**: vehicles use diesel fuel.
- **Hybrid electric vehicles (HEV):** vehicles use both petrol and electricity as propulsion. Electricity for propulsion comes from the built-in battery that requires no recharge. The vehicles can be refueled in petrol stations as petrol vehicles.

- **Plug-in hybrid vehicles (PHEV):** vehicles use both petrol and electricity as propulsion. Electricity for propulsion comes from the rechargeable battery of the vehicle. The vehicles can be refueled in petrol stations as petrol vehicles or recharged in electric vehicle charging stations.
- **Pure electricity vehicles (EV):** vehicles use only electricity as propulsion. The vehicles have rechargeable batteries act as the only source for driving power. The vehicles can be recharged in electric vehicle charging stations.
- **Hydrogen vehicles:** vehicles use only hydrogen as propulsion. The vehicles have fuel tanks used for containing liquid hydrogen as fuel. These vehicles can be recharged in charging stations that provide hydrogen fuel.

The description on the vehicle features is provided below:

- **Purchase price**: the final price paid for the vehicle in Australian dollars, including all taxes and fees.
- **Car style:** the style of the car. A sports/coupe is generally smaller in size, commonly a two-door style with little cargo space. A hatch/wagon style car has a rear door that swings upward to provide access to cargo area. The size of this style of car may vary, however, it generally is smaller than a standard SUV style. A sedan style car normally comes in a three-box configuration that has separate compartments for engine, passenger and cargo. This style of cars has 4 doors and can seat 4/5 people comfortably. A SUV/people mover style car can seat 5 or more people with relatively large cargo space.
- **Annual fuel cost**: the annual cost for fuelling the vehicle in Australian dollar.
- **Fuel availability**: the availability of fuel. For petrol, diesel and hybrid electric vehicles, the fuel availability is set to100%. For vehicles that require refueling other than petrol or diesel, i.e. pure electric vehicles and hydrogen vehicles, the fuel availability is the percentage of available refueling stations for electricity and hydrogen to the number of current

petrol/diesel stations. A 15% fuel availability for EVs means the number of electric recharging stations equals to 15% of nowadays petrol/diesel stations.

- **Driving range**: the range of a vehicle can travel with a full tank/fully charged battery. The driving range of petrol, diesel, hybrid electric and plug-in hybrid electric vehicles are described as more than 600km, which is more than enough of most people's daily driving distance.

(Question 14 to 29 presents one of the six sets of choice scenarios in the survey)

14	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$98,000	$33,000	$85,000	$111,000	$85,000	$59,000
Car size	 SUV/People mover	 Hatch/Wagon	 SUV/People mover	 Sedan	 Sports/Coupe	 Hatch/Wagon
Annual fuel cost	$2400	$1200	$1200	$1100	$500	$2400
Fuel availability	100%	100%	100%	100%	65%	15%
Driving range	>600 km	>600 km	>600 km	>600 km	600 km	300 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

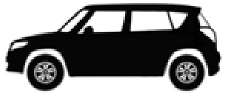
15

	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$20,000	$72,000	$20,000	$59,000	$59,000	$33,000
Car size	 Sedan	 Sports/Coupe	 Sports/Coupe	 SUV/People mover	 Sedan	 Hatch/Wagon
Annual fuel cost	$800	$1200	$1200	$700	$900	$2400
Fuel availability	100%	100%	100%	100%	90%	90%
Driving range	>600 km	>600 km	>600 km	>600 km	600 km	400 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

16	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$46,000	$111,000	$98,000	$46,000	$98,000	$33,000
Car size	 Sedan	 Hatch/Wagon	 Hatch/Wagon	 SUV/People mover	 Sports/Coupe	 Sedan
Annual fuel cost	$3200	$2400	$2400	$1100	$500	$1200
Fuel availability	100%	100%	100%	100%	65%	65%
Driving range	>600 km	>600 km	>600 km	>600 km	450 km	600 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

17	Powertrain type					
	Petrol Vehicle	Diesel Vehicle	HEV	PHEV	EV	Hydrogen Vehicle
Purchase price	$72,000	$98,000	$46,000	$59,000	$98,000	$111,000
Car size	 SUV/People mover	 Hatch/Wagon	 Sedan	 Sports/Coupe	 Hatch/Wagon	 Sedan
Annual fuel cost	$3200	$600	$2400	$900	$700	$2400
Fuel availability	100%	100%	100%	100%	40%	90%
Driving range	>600 km	>600 km	>600 km	>600 km	150 km	500 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

18	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$98,000	$59,000	$46,000	$20,000	$59,000	$85,000
Car size	 Sedan	 Hatch/Wagon	 Sedan	 Hatch/Wagon	 SUV/People mover	 SUV/People mover
Annual fuel cost	$3200	$1800	$1800	$500	$500	$2000
Fuel availability	100%	100%	100%	100%	90%	90%
Driving range	>600 km	>600 km	>600 km	>600 km	450 km	600 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

19	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$72,000	$111,000	$72,000	$46,000	$33,000	$20,000
Car size	 Hatch/Wagon	 Sports/Coupe	 SUV/People mover	 Sedan	 Sedan	 Sports/Coupe
Annual fuel cost	$3200	$1800	$1800	$500	$1100	$2000
Fuel availability	100%	100%	100%	100%	90%	40%
Driving range	>600 km	>600 km	>600 km	>600 km	600 km	500 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

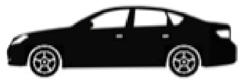
20	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$85,000	$98,000	$111,000	$20,000	$72,000	$20,000
Car size	 Sports/Coupe	 SUV/People mover	 SUV/People mover	 Sedan	 Hatch/Wagon	 Hatch/Wagon
Annual fuel cost	$2400	$1200	$1800	$900	$500	$1200
Fuel availability	100%	100%	100%	100%	90%	65%
Driving range	>600 km	>600 km	>600 km	>600 km	450 km	500 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

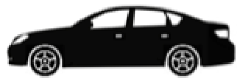
21	Powertrain type					
Powertrain type	**Petrol Vehicle**	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$33,000	$46,000	$20,000	$72,000	$20,000	$98,000
Car size	 Hatch/Wagon	 Sports/Coupe	 SUV/People mover	 Sedan	 Sedan	 SUV/People mover
Annual fuel cost	$3200	$600	$1200	$1100	$700	$1200
Fuel availability	100%	100%	100%	100%	15%	90%
Driving range	>600 km	>600 km	>600 km	>600 km	450 km	600 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

22	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$46,000	$72,000	$72,000	$20,000	$85,000	$59,000
Car size	 Hatch/Wagon	 Sedan	 Hatch/Wagon	 Hatch/Wagon	 Sedan	 Sedan
Annual fuel cost	$1600	$600	$600	$700	$1100	$1200
Fuel availability	100%	100%	100%	100%	40%	65%
Driving range	>600 km	>600 km	>600 km	>600 km	300 km	400 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

23	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$98,000	$59,000	$59,000	$98,000	$111,000	$33,000
Car size	 Hatch/Wagon	 Sports/Coupe	 Sedan	 Sports/Coupe	 SUV/People mover	 SUV/People mover
Annual fuel cost	$2400	$2400	$600	$700	$900	$2000
Fuel availability	100%	100%	100%	100%	15%	65%
Driving range	>600 km	>600 km	>600 km	>600 km	150 km	300 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

24	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$46,000	$46,000	$59,000	$111,000	$59,000	$85,000
Car size	 Sports/Coupe	 Sedan	 Sports	 Sedan	 Hatch/Wagon	 Sports/Coupe
Annual fuel cost	$800	$2400	$2400	$900	$1100	$1600
Fuel availability	100%	100%	100%	100%	15%	40%
Driving range	>600 km	>600 km	>600 km	>600 km	150 km	500 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

25	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$59,000	$20,000	$72,000	$59,000	$72,000	$46,000
Car size	 Sports/Coupe	 Sedan	 Hatch/Wagon	 Sports/Coupe	 Sports/Coupe	 SUV/People mover
Annual fuel cost	$1600	$1800	$1200	$1100	$900	$1600
Fuel availability	100%	100%	100%	100%	90%	65%
Driving range	>600 km	>600 km	>600 km	>600 km	600 km	300 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

26	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$20,000	$20,000	$98,000	$85,000	$46,000	$72,000
Car size	 Hatch/Wagon	 Sports/Coupe	 Sedan	 Sports/Coupe	 SUV/People mover	 Sports/Coupe
Annual fuel cost	$2400	$1200	$2400	$900	$500	$1200
Fuel availability	100%	100%	100%	100%	90%	15%
Driving range	>600 km	>600 km	>600 km	>600 km	300 km	400 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

27	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$72,000	$111,000	$85,000	$33,000	$72,000	$46,000
Car size	 Sedan	 Hatch/Wagon	 SUV/People mover	 SUV/People mover	 Sedan	 Sports/Coupe
Annual fuel cost	$2400	$2400	$600	$700	$700	$2000
Fuel availability	100%	100%	100%	100%	15%	15%
Driving range	>600 km	>600 km	>600 km	>600 km	300 km	400 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

28	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$111,000	$111,000	$111,000	$98,000	$46,000	$72,000
Car size	 SUV/People mover	 SUV/People mover	 Sports/Coupe	 SUV/People mover	 Hatch/Wagon	 SUV/People mover
Annual fuel cost	$1600	$600	$1800	$500	$1100	$2400
Fuel availability	100%	100%	100%	100%	15%	65%
Driving range	>600 km	>600 km	>600 km	>600 km	600 km	300 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

29	Powertrain type					
	Petrol Vehicle	**Diesel Vehicle**	**HEV**	**PHEV**	**EV**	**Hydrogen Vehicle**
Purchase price	$85,000	$59,000	$33,000	$46,000	$20,000	$98,000
Car size	 SUV/People mover	 SUV/People mover	 Hatch/Wagon	 Hatch/Wagon	 Sports/Coupe	 Sports/Coupe
Annual fuel cost	$800	$1200	$600	$700	$900	$2400
Fuel availability	100%	100%	100%	100%	90%	40%
Driving range	>600 km	>600 km	>600 km	>600 km	150 km	500 km
Please choose your most preferred vehicle within the set as if you were making decisions for your latest vehicle purchase	○	○	○	○	○	○

Section 4

General information

1. How many cars are owned in your household?

- 1
- 2
- 3
- 4
- 5
- More than 5

2. Approximately, how many kilometres do you drive in a typical week?

- Less than 100kms
- 100kms to 300kms
- 301kms to 500kms
- More than 500kms

3. Which age group are you in?

- Younger than 20
- 20-29
- 30-39
- 40-49
- 50-59
- 60-69
- 70 and over

4. What is your gender?

- Male
- Female

5. Which of the following best describes your weekly household income range?

- Less than AUD 299
- AUD 300 to 599
- AUD 600 to 999
- AUD 1,000 to 1,499
- AUD 1,500 to 2,499
- AUD 2,500 to 3,499
- AUD 3,500 to 4,999
- More than AUD 5,000

6. Which of the following best describes your highest achieved education level?

- Some secondary education
- Graduated high school
- Some university Education
- 2 year university or trade school degree
- 3 or 4 year university degree (bachelors)
- Master’s degree
- Doctoral degree

7. What is the size of your household?

- 1
- 2
- 3
- 4
- 5
- More than 5

8. What is your postcode?

Appendix B System Dynamics Model Coding

Fleet Turnover

Vehicles 0 to 4 years i[Powertrain]= INTEG (Vehicle Sales i[Powertrain]-Vehicle 0 to 4 years Retirement i[Powertrain]-Vehicle Aging i[Powertrain], "Initial Installed Base Vehicles 0 to 4 years i"[Powertrain])
Units: Vehicles

> "Initial Installed Base-Vehicles 0 to 4 years i"[Powertrain]= Pass and SUV Market Size j[Powertrain]*(Aging Time Period*Vehicle 9 years above Retirement Fraction *(1+Aging Time Period*Vehicle 5 to 8 years Discard Fraction))/((2+Aging Time Period *Vehicle 5 to 8 years Discard Fraction)*Aging Time Period*Vehicle 9 years above Retirement Fraction +1)

Units: Vehicles
Initial installed base of new vehicles given the total fleet size

Vehicles 5 to 8 years i[Powertrain]= INTEG (Vehicle Aging i[Powertrain]-Vehicle 5 to 8 years Retirement i[Powertrain]-Vehicle Aging 2 i[Powertrain],"Initial Installed Base-Vehicles 5 to 8 years i"[Powertrain])
Units: Vehicles

> "Initial Installed Base-Vehicles 5 to 8 years i"[Powertrain]= IF THEN ELSE (SW Initial Stock in Equilibrium = 1, Vehicles 0 to 4 years i[Powertrain]/(1+Aging Time Period*Vehicle 5 to 8 years Discard Fraction) , Aging Time Period*Pass and SUV Market Size j[Powertrain]/Vehicle Lifetime)

Units: Vehicles
Initial installed base of vehicles 5 to 8 years given the total fleet size

Vehicles 9 years above i[Powertrain]= INTEG (Vehicle Aging 2 i[Powertrain]-Vehicle 9 years above Retirement i[Powertrain], "Initial Installed Base-Vehicles 9 years above i"[Powertrain])
Units: Vehicles

> "Initial Installed Base-Vehicles 9 years above i"[Powertrain]=IF THEN ELSE (SW Initial Stock in Equilibrium = 1, Vehicles 5 to 8 years i[Powertrain]/(Aging Time Period*Vehicle 9 years above Retirement Fraction) , Pass and SUV Market Size j[Powertrain]*(Vehicle Lifetime-2*Aging Time Period)/Vehicle Lifetime)

Units: Vehicles
Initial installed base of vehicles 9 years above, given the total fleet size

Aging Time Period=4
Units: Year
The time period to divide different ages of vehicles in the fleet

Vehicle Aging i[Powertrain]=Vehicles 0 to 4 years i[Powertrain]/Aging Time Period
Units: Vehicles/Year
Rate of new vehicle aging

Vehicle Aging 2 i[Powertrain]=Vehicles 5 to 8 years i[Powertrain]/Aging Time Period
Units: Vehicles/Year
Rate of vehicle 5 to 8 years aging

Vehicle Sales i[Powertrain]=Platform Demand j[Powertrain]
Units: Vehicles/Year
Annual sales of new vehicles, by powertrain

Platform Demand j[PowertrainTo]= SUM (Vehicle Discards i[Powertrain!]*(1+Market Growth Rate)*Share ij[Powertrain!, PowertrainTo])
Units: Vehicles/Year
Total demand of powertrain j per year. PowertrainTo ensures powertrain j is selected

Market Growth Rate= 0.022
Units: Dmnl
Allow for market growth in the system. Based on historical data.

Share ij[Powertrain, Petrol]=Petrol Share i[Powertrain]
Share ij[Powertrain, Diesel]=Diesel Share i[Powertrain]
Share ij[Powertrain, HEV]=HEV Share i[Powertrain]
Share ij[Powertrain, PHEV]=PHEV Share i[Powertrain]
Share ij[Powertrain, EV]=EV Share i[Powertrain]
Share ij[Powertrain, Hydrogen]=Hydrogen Share i[Powertrain]
Units: Dmnl
Share of platform i drivers choosing platform j given current level of consumer utility and familiarity.

Vehicle Discards i[Powertrain]=Vehicle 0 to 4 years Retirement i[Powertrain]+Vehicle 5 to 8 years Retirement i[Powertrain]+Vehicle 9 years above Retirement i[Powertrain]
Units: Vehicles/Year
Total number of vehicles exiting the market every year, assumed to be equal to annual new vehicle sales to keep the fleet constant

Vehicle 0 to 4 years Retirement i[Powertrain]=Vehicles 0 to 4 years i[Powertrain]*New Vehicle Discard Fraction
Units: Vehicles/Year
Vehicle 0 to 4 years that got discarded every year
New Vehicle Discard Fraction= 0.001
Units: Dmnl/Year
The fraction of new vehicles got discarded every year

Vehicle 5 to 8 years Retirement i[Powertrain]=Vehicles 5 to 8 years i[Powertrain]*Vehicle 5 to 8 years Discard Fraction
Units: Vehicles/Year
Vehicle 5 to 8 years that got discarded every year
Vehicle 5 to 8 years Discard Fraction=0.05
Units: Dmnl/Year
The fraction of vehicles 5 to 8 years got discarded every year

Vehicle 9 years above Retirement i[Powertrain]=Vehicles 9 years above i[Powertrain]*Vehicle 9 years above Retirement Fraction
Units: Vehicles/Year
Vehicles 9 year above that retires every year
Vehicle 9 years above Retirement Fraction=0.3
Units: Dmnl/Year
The fraction of vehicle 9 years above that retires per year

Installed Base i[Powertrain]= Used Vehicles i[Powertrain] + Vehicles 0 to 4 years i[Powertrain]
Units: Vehicles
Total number of vehicles on the road, by powertrain

Used Vehicles i[Powertrain]=Vehicles 5 to 8 years i[Powertrain] + Vehicles 9 years above i[Powertrain]
Units: Vehicles
Total number of used vehicles on the road, by powertrain

Initial Installed Base i[Powertrain]="Initial Installed Base-Vehicles 0 to 4 years i"[Powertrain]+"Initial Installed Base-Used Vehicles i"[Powertrain]
Units: Vehicles
Total initial installed base of all vehicles, by powertrain

"Initial Installed Base-Used Vehicles i"[Powertrain]="Initial Installed Base-Vehicles 5 to 8 years i"[Powertrain]+"Initial Installed Base-Vehicles 9 years above i"[Powertrain]
Units: Vehicles
Total initial installed base of used vehicles, by powertrain

"Platform From/To ij"[Powertrain, PowertrainTo]= Vehicle Discards i[Powertrain]*Shareij[Powertrain, PowertrainTo]
Units: Vehicles/Year
Number of vehicles from powertrain i switching to j every year.

Platform Introduction

Platform Introduced j[PowertrainTo]= INTEG (Introduction Trigger j[PowertrainTo], IF THEN ELSE (Time < Platform Introduction Date j[PowertrainTo], 0, 1))
Units: Dmnl
Indicator that is equal to 1 when platform is introduced

Introduction Trigger j[PowertrainTo]=IF THEN ELSE (Time < Platform Introduction Date j[PowertrainTo], 0, (1-Platform Introduced j[PowertrainTo])/TIME STEP)
Units: Dmnl/Year
Platform introduced trigger

Platform Introduction Date j[Petrol]= Petrol Introduction Date
Platform Introduction Date j[Diesel]= Diesel Introduction Date
Platform Introduction Date j[HEV]= HEV Introduction Date
Platform Introduction Date j[PHEV]= PHEV Introduction Date
Platform Introduction Date j[EV]= EV Introduction Date

Platform Introduction Date j[Hydrogen]= Hydrogen Introduction Date
Units: Year
Year of introduction of the platform

Petrol Introduction Date= GAME (0)
Units: Year

Diesel Introduction Date= GAME (0)
Units: Year

HEV Introduction Date= GAME (1)
Units: Year

PHEV Introduction Date= GAME (12)
Units: Year

EV Introduction Date= GAME (10)
Units: Year

Hydrogen Introduction Date= GAME (20)
Units: Year

Market Share and Consumer Choices

Affinity ij[Powertrain, PowertrainTo]=Familiarity ij[Powertrain, PowertrainTo]*EXP Utility j[PowertrainTo] *Vehicle Model Effect on Consumer Choice j[PowertrainTo]
Units: Dmnl
Combined effect of familiarity, utility, bias and model variety

Petrol Share i[Powertrain]=IF THEN ELSE (Affinity ij[Powertrain, Petrol] =0 , 0 , ZIDZ(Affinity ij[Powertrain, Petrol] , Logit Denominator i[Powertrain]))
Units: Dmnl
Share of platform i drivers choosing petrol platform

Diesel Share i[Powertrain]=IF THEN ELSE (Affinity ij[Powertrain, Diesel] =0, 0 , ZIDZ(Affinity ij[Powertrain, Diesel] , Logit Denominator i[Powertrain]))
Units: Dmnl
Share of platform i drivers choosing diesel vehicles

HEV Share i[Powertrain]=IF THEN ELSE (Affinity ij[Powertrain, HEV] =0 , 0 , ZIDZ(Affinity ij[Powertrain, HEV] , Logit Denominator i[Powertrain]))
Units: Dmnl
Share of platform i drivers choosing HEVs

PHEV Share i[Powertrain]=IF THEN ELSE (Affinity ij[Powertrain, PHEV] =0 , 0 , ZIDZ(Affinity ij[Powertrain, PHEV] , Logit Denominator i[Powertrain]))
Units: Dmnl
Share of platform i drivers choosing PHEVs

EV Share i[Powertrain]=IF THEN ELSE (Affinity ij[Powertrain, EV] =0 , 0 , ZIDZ(Affinity ij[Powertrain, EV] , Logit Denominator i[Powertrain]))
Units: Dmnl
Share of platform i drivers choosing EVs

Hydrogen Share i[Powertrain]=IF THEN ELSE (Affinity ij[Powertrain, Hydrogen] =0, 0, ZIDZ(Affinity ij[Powertrain, Hydrogen] , Logit Denominator i[Powertrain]))
Units: Dmnl
Share of platform i drivers choosing hydrogen vehicles

Logit Denominator i[Powertrain]
=IF THEN ELSE(Affinity ij[Powertrain, Petrol]=0 , 0, Affinity ij[Powertrain, Petrol])+IF THEN ELSE(Affinity ij[Powertrain, Diesel]=0 , 0 , Affinity ij[Powertrain, Diesel])+IF THEN ELSE(Affinity ij[Powertrain, HEV]=0 , 0 , Affinity ij[Powertrain, HEV])+IF THEN ELSE(Affinity ij[Powertrain, PHEV]=0 , 0 , Affinity ij[Powertrain, PHEV])+IF THEN ELSE(Affinity ij[Powertrain, EV]=0 , 0 , Affinity ij[Powertrain, EV])+IF THEN ELSE(Affinity ij[Powertrain, Hydrogen]=0 , 0, Affinity ij[Powertrain, Hydrogen])
Units: Dmnl
Total affinities of drivers of platform i across all possible platforms j

Familiarity Build-up

Familiarity ij[Powertrain, PowertrainTo]=IF THEN ELSE(SW Endogenous Familiarity=0 , Exogenous Familiarity Value ,Average Familiarity ij[Powertrain, PowertrainTo])
Units: Dmnl
Current level of familiarity of drivers of platform i with platform j.

Exogenous Familiarity Value=1
Units: Dmnl [0,1,0.1]
Default value of the familiarity (1 means full familiarity)

SW Endogenous Familiarity=1
Units: Dmnl [0,1,1]
Switch to use model structure to track familiarity

Average Familiarity ij[Powertrain, PowertrainTo]=IF THEN ELSE(Platform Introduction Date j[Powertrain]>Time , 0 , IF THEN ELSE (Powertrain=PowertrainTo , 1 , MIN(1, ZIDZ(Cumulative Familiarity ij[Powertrain, PowertrainTo] , Installed Base i[Powertrain]))))
Units: Dmnl
Average familiarity of platform i with platform j. Range from 1 to 0.

Cumulative Familiarity ij[Powertrain, PowertrainTo]= INTEG (Familiarity Gain from Sales ij[Powertrain, PowertrainTo]+Familiarity Increase ij[Powertrain, PowertrainTo]-Familiarity Forget ij[Powertrain, PowertrainTo]-Familiarity Lose from Discards ij[Powertrain, PowertrainTo],Initial Familiarity ij[Powertrain, PowertrainTo])
Units: Vehicles
Cumulative familiarity measured in drivers of platform i with j

Initial Familiarity ij[Powertrain, PowertrainTo]= IF THEN ELSE(PowertrainTo=Petrol, Initial Installed Base i[Powertrain] , 0)+IF THEN ELSE(PowertrainTo=Diesel :AND: Powertrain=Diesel , Initial Installed Base i[Powertrain] , 0)

Units: Vehicles
Initial value of cumulative familiarity in 2000. Petrol has full familiarity. Diesel's familiarity equals to its fleet size in 2000. Other powertrains have zero cumulative familiarity

Familiarity Gain from Sales ij[Powertrain, PowertrainTo]=SUM(Familiarity Swaps[PowertrainFrom!, Powertrain, PowertrainTo])
Units: Vehicles/Year
Increase in familiarity from sales, familiarity moves from platform i to j with drivers shift from platform i to j.

Familiarity Swaps [PowertrainFrom, Powertrain, PowertrainTo]="Platform From/To ij"[PowertrainFrom, Powertrain]*IF THEN ELSE(PowertrainTo=Powertrain , 1 , Average Familiarity ij[PowertrainFrom, PowertrainTo])
Units: Vehicles/Year
PowertrainFrom: the previous platform Powertrain: the platform we buy PowertrainTo: the platform about which we trace familiarity A consumer that switches to a technology will take familiarity of 1.

"Platform From/To ij"[Powertrain, PowertrainTo] =Vehicle Discards i[Powertrain]*Share ij[Powertrain, PowertrainTo]
Units: Vehicles/Year
Number of vehicles from powertrain i switching to j every year

Familiarity Increase ij[Powertrain, PowertrainTo]=MAX(0 , (1-Average Familiarity ij[Powertrain, PowertrainTo])*Total Exposure to Platform ij[Powertrain, PowertrainTo]*Installed Base i[Powertrain])
Units: Vehicles/Year
Increase in familiarity from social exposure.

Total Exposure to Platform ij[Powertrain, PowertrainTo]=Total Social Exposure to Platform ij[Powertrain, PowertrainTo]+Total Marketing Exposure j [PowertrainTo]
Units: Dmnl/Year
Total exposure equals to the sum of social and marketing exposure.

Marketing exposure

Total Marketing Exposure j[PowertrainTo]=Marketing Effectiveness * Total Marketing Spending j[PowertrainTo]
Units: Dmnl/Year
Total marketing exposure equals to the marketing effectiveness times the total marketing spending.

Marketing Effectiveness=3.131e-05
Units: Dmnl/million [0,0.0001,1e-05]
Effectiveness of advertising activities in reducing the gap to full familiarity with platform per million dollars spend. The value of this parameter is estimated from calibration

Total Marketing Spending j[PowertrainSpillTo]= SUM (Total Marketing Spending ij[PowertrainFrom!, PowertrainSpillTo])
Units: million/Year

Total Marketing Spending ij[PowertrainFrom, PowertrainSpillTo]=IF THEN ELSE(SW Marketing Spillover=1 , Platform Marketing Spending j[PowertrainFrom]*Familiarity Exposure Spillover Matrix ij[PowertrainFrom, PowertrainSpillTo], Platform Marketing Spending j[PowertrainFrom]* Powertrain Matrix[PowertrainFrom, PowertrainSpillTo])
Units: million/Year
If the marketing spillover switch is on, the total marketing spending will spill to similar powertrains.

Powertrain Matrix[PowertrainFrom, PowertrainSpillTo]=
1, 0, 0, 0, 0, 0;
0, 1, 0, 0, 0, 0;
0, 0, 1, 0, 0, 0;
0, 0, 0, 1, 0, 0;
0, 0, 0, 0, 1, 0;
0, 0, 0, 0, 0, 1;
Units: Dmnl
Powertrain matrix is for dividing marketing spending by platform.

Familiarity Exposure Spillover Matrix ij[PowertrainFrom, PowertrainSpillTo]=
1, 0, 0, 0, 0, 0;
0, 1, 0, 0, 0, 0;
0, 0, 1, 0.25, 0.1, 0;
0, 0, 0.25, 1, 0.5, 0;
0, 0, 0.1, 0.5, 1, 0.1;
0, 0, 0, 0, 0.1, 1;
Units: Dmnl
Familiarity spillover of marketing exposure. Marketing funding spend in one powertrain can create spillover to similar powertrains.

SW Marketing Spillover=1
Units: Dmnl [0,1,1]
Switch for marketing spillover

Platform Marketing Spending j[PowertrainTo]=IF THEN ELSE (Platform Introduction Date j[PowertrainTo]>Time , 0 , Regular Marketing Spending i[PowertrainTo]+Spending by Platform j[PowertrainTo])
Units: million/Year
Platform marketing spending is the sum of regular marketing spending that is in proportion to sales revenue and the additional marketing spending by platform.

Regular Marketing Spending i[Powertrain]=Revenue j[Powertrain]/Dollars per Million*Marketing Fraction of Revenue
Units: million/Year
Regular spending on marketing by platform

Dollars per Million=1e+06
Units: $/million
Amount of dollars in one million

Marketing Fraction of Revenue=0.005
Units: Dmnl [0,1,0.005]
Revenue fraction of OEMs dedicated to marketing on a regular basis

Spending by Platform j[Powertrain]=Marketing spending[Powertrain]*PULSE (Marketing spending START[Powertrain], Marketing spending DURATION[Powertrain])
Units: million/Year
Additional marketing spending to promote powertrain. The initial marketing spending during powertrain introduction.

Marketing spending[Powertrain]=0, 0, 86.6933, 50.3285, 50, 91.2284
Units: million/Year
Marketing spending DURATION[Powertrain]=0,0,8,8,8,10
Units: Year
Marketing spending START[Powertrain]=0,0,0,11,9,19
Units: Year
The marketing spending at the introduction of each powertrains are estimated in calibration.

Social exposure
Total Social Exposure to Platform ij[Powertrain, PowertrainTo]=Exposure from Drivers j[PowertrainTo]+Exposure from NonDrivers ij[Powertrain, PowertrainTo]
Units: Dmnl/Year
Effective strength of a contact with both drivers of the platform j and non-drivers of the platform i to promote the platform j.

Exposure from Drivers j[PowertrainTo]=Effective Contact Rate Drivers*Probability of Contact with Drivers j[PowertrainTo]*1
Units: Dmnl/Year
Effective strength of a contact with a driver of the platform j. Measures the effective rate of reducing the gap to full familiarity with platform j per year.

Exposure from NonDrivers ij[Powertrain, PowertrainTo]=Effective Contact Rate Drivers*Probability of Contact with Drivers j[Powertrain]*Average Familiarity ij[Powertrain, PowertrainTo]
Units: Dmnl/Year
Effective strength of a contact of population i with a non-driver of the platform j. Measures the effective rate of reducing the gap to full familiarity with platform j per year.

Probability of Contact with Drivers j[PowertrainTo]=Installed Base i[PowertrainTo]/SUM (Installed Base i[PowertrainTo!])
Units: Dmnl
Probability of a random contact with the driver of platform j.

Effective Contact Rate Drivers=0.111521
Units: Dmnl/Year
Average strength of contacts with drivers to build the familiarity with the platform. Calculated as the rate of reducing the gap to full familiarity per year. This is one of the parameters that is estimated through calibration.

Familiarity Lose from Discards ij[Powertrain, PowertrainTo]=Average Familiarity ij[Powertrain, PowertrainTo]*Vehicle Discards i[Powertrain]
Units: Vehicles/Year
Lose in familiarity due to vehicle discard. Vehicle discards is equal to the sum of vehicle discards of all vehicle age groups. More details about vehicle discards are introduced in vehicle turnover module.

Familiarity Forget ij[Powertrain, PowertrainTo]=SW Forgetting*Linear Effect of Exposure on Forgetting ij[Powertrain, PowertrainTo]*Normal Forget Rate Phi*Cumulative Familiarity ij[Powertrain, PowertrainTo]
Units: Vehicles/Year
Lose in familiarity due to consumer forgetfulness.

Linear Effect of Exposure on Forgetting ij[Powertrain, PowertrainTo]=MIN(1 , MAX(0 , Epsilon*Social Exposure Offset+0.5-Epsilon*Total Exposure to Platform ij[Powertrain, PowertrainTo]))
Units: Dmnl
Forgetting trigger that is equal to 1 when the effective rate of gap reduction to full familiarity is less than or equal to the minimum required level to offset forgetting

Epsilon=20
Units: Year
Multiplier for the difference between actual and minimum rate of reduction of the gap to full familiarity. The value is chosen to generate at least 1 when the difference is 0.

Normal Forget Rate Phi=0.025
Units: Dmnl/Year
Fractional rate of forgetting familiarity per year

Social Exposure Offset=0.05
Units: Dmnl/Year
Minimum required level of effective rate of gap reduction to full familiarity to offset forgetting.

SW Forgetting=1
Units: Dmnl [0,1,1]
Switch for familiarity forgetting dynamic

Vehicle Utility

EXP Utility j[PowertrainTo]=IF THEN ELSE (Platform Introduction Date j[PowertrainTo]>Time, 0, EXP (Utility j[PowertrainTo]+ Platform Bias j[PowertrainTo]))
Units: Dmnl
Exponent of the utility of a vehicle in platform j. If the platform hasn't been introduced, then 0.

Utility j[Powertrain]=Utility Proxy j[Powertrain]* (1 - SW Utility Change * STEP (Utility Change Rate j[Powertrain] , Utility Change Time))
Units: Dmnl
Vehicle utility that allows potential global change. Set up for scenario tests.

SW Utility Change=1
Units: Dmnl [0,1,1]
Switch for vehicle utility change.
Utility Change Rate j[Powertrain]=0,0,0.1,0.1,0.1,0
Units: Dmnl
Global vehicle utility change rate.
Utility Change Time=25
Units: Year
The time when global vehicle utility starts to change (early13, 11; late 25)

Utility Proxy j[PowertrainTo]= IF THEN ELSE (Platform Introduced j[PowertrainTo] , (U1 Purchase Price j[PowertrainTo]+U2 Operating Cost j[PowertrainTo] +U3 Fuel Availability j[PowertrainTo] +U4 Driving Range j[PowertrainTo]), Min Utility)
Units: Dmnl
Utility of a vehicle of platform j. Endogenous without external interference. The vehicle utility has four parts: purchase price, operating cost, fuel availability, and driving range.

Min Utility=-3
Units: Dmnl
Preventing utility from over float.

U1
U1 Purchase Price j[PowertrainTo]=Purchase Price j[PowertrainTo]*Purchase Price Weight/1000
Units: Dmnl
Utility component of purchase price.

Purchase Price Weight=-0.028
Units: Dmnl*Vehicles/$
Value is derived from discrete choice model

Purchase Price j[PowertrainTo]= MSRP j[PowertrainTo]*(1 - SW Purchase Price Reduction * STEP (Purchase Price Reduction j [PowertrainTo], Utility Change Time))
Units: $/Vehicles
The effective upfront cost of a vehicle when purchased by consumer.

SW Purchase Price Reduction=0
Units: Dmnl [0,1,1]
Switch for price reduction
Purchase Price Reduction j[PowertrainTo]=0,0,0,0,0,0
Units: Dmnl
The percentage of price reduction of each powertrain. Set up for scenario tests.
Utility Change Time=25
Units: Year
Utility change time for scenario tests. Early or late scenarios. 13 or 25.

MSRP j[PowertrainTo]=Vehicle Cost j[PowertrainTo]*(1+Mark up)
Units: $/Vehicles
The MSRP (manufacturer's suggested retail price) of a vehicle, by platform

Mark up= 0.1
Units: Dmnl
The mark up margin for vehicle manufacturers

Vehicle Cost j[PowertrainTo]=Alternative Incremental Cost j[PowertrainTo]+Vehicle Base Cost
Units: $/Vehicles
The overall cost of manufacturing a vehicle, by platform

Vehicle Base Cost= INTEG (-Vehicle Base Cost Reduction, Initial Vehicle Base Cost)
Units: $/Vehicles
Initial Vehicle Base Cost=66800
Units: $/Vehicles
Using 45000 as the petrol base price. this price is not changed through time. However, inflation is considered. 45000 AUD in 2000 equals 66800 in 2014.

Vehicle Base Cost Reduction= IF THEN ELSE (Vehicle Base Cost>Base Cost threshold, (Vehicle Base Cost-Base Cost threshold) *Vehicle Base Cost Reduction Rate, 0)
Units: $/(Year*Vehicles)
In order to create a smooth goal seeking, 0.3 is selected to make sure the base price will drop to 45000 around 2014.
Vehicle Base Cost Reduction Rate=0.3
Units: Dmnl/Year
Base Cost threshold=45000
Units: $/Vehicles

Alternative Incremental Cost j[Powertrain]= INTEG (-Alternative Cost Reduction j[Powertrain], Initial Incremental j[Powertrain])
Units: $/Vehicles
Initial Incremental Cost [Powertrain]=0, 4500, 7000, 12000, 13500, 30000
Units: $/Vehicles
Incremental cost by powertrain at the time of introduction. Petrol does not have incremental cost.

Alternative Cost Reduction j[Powertrain]=Alternative Cost Reduction Rate j[Powertrain]*Alternative Incremental Cost j[Powertrain]
Units: $/(Year*Vehicles)
A smooth curve for alternative cost reduction.
Alternative Cost Reduction Rate j[PowertrainTo]=0, 0.075, 0.1, 0,0,0
Units: Dmnl/Year
The price change rate here were based on historical alternative vehicle price.

Revenue j[PowertrainTo]=MSRP j[PowertrainTo]*Platform Demand j[PowertrainTo]
Units: $/Year
Revenue from sales by platform.

Platform Demand j[PowertrainTo]=SUM (Vehicle Discards i[Powertrain!] *(1+Market Growth Rate)*Share ij[Powertrain!, PowertrainTo])
Units: Vehicles/Year
Total demand of powertrain j per year. PowertrainTo ensures powertrain j is selected

U2
U2 Operating Cost j[PowertrainTo]=Annual Operating Cost j[PowertrainTo]*Operating Cost Weight/100
Units: Dmnl
Utility component of operating cost.

Operating Cost Weight=-0.0372
Units: Dmnl*Year*Vehicles/$
Value is derived from discrete choice model

Annual Operating Cost j[PowertrainTo]=Vehicle Travel per Year i[PowertrainTo]* Kilometre Unit Converter *(Operating Cost per 100km Petrol j[PowertrainTo]+ Operating Cost per 100km Diesel j[PowertrainTo]+ Operating Cost per 100km HEV j[PowertrainTo]+ PHEV Travel Distance Petroleum Percentage*Operating Cost per 100km PHEV p j [PowertrainTo]+(1-PHEV Travel Distance Petroleum Percentage)*Operating Cost per 100km PHEV e j[PowertrainTo]+Operating Cost per 100km EV j[PowertrainTo]+Operating Cost per 100km Hydrogen j[PowertrainTo])
Units: $/(Year*Vehicles)
Annual fuel cost by platform. PHEV powertrain operating cost is consist of two parts, one due to petro driving, the other due to electric driving.

PHEV Travel Distance Petroleum Percentage=0.33
Units: Dmnl
The percentage of PHEV travel distance using petrol fuel. Could be used to define how PHEV utilizes petrol and electricity. This variable is used to for GHG missions audit and operating cost audit.

Vehicle Travel per Year i[Powertrain]=13716
Units: km/Vehicles/Year
The average annual vehicle travel distance. Based on ABS Survey of motor vehicle use 9208.0

Kilometre Unit Converter=0.01
Units: hundred km/km
Kilometre unit convert

Operating cost is equal to fuel price times fuel efficiency. Fuel price and fuel efficiency are introduced later.

Operating Cost per 100km Petrol j[PowertrainTo]=IF THEN ELSE (PowertrainTo=Petrol, Fuel Price r[PF]*"Fuel Efficiency of New Vehicles by Platform-Fuel v"[Pef], 0)
Units: $/hundred km
Operating cost of a petrol vehicle

Operating Cost per 100km Diesel j[PowertrainTo]=IF THEN ELSE (PowertrainTo=Diesel, Fuel Price r[DF]*"Fuel Efficiency of New Vehicles by Platform-Fuel v"
[Def] , 0)
Units: $/hundred km

Operating Cost per 100km HEV j[PowertrainTo]=IF THEN ELSE (PowertrainTo=HEV, Fuel Price r[PF]*"Fuel Efficiency of New Vehicles by Platform-Fuel v"[Hef], 0)
Units: $/hundred km

Operating Cost per 100km PHEV e j[PowertrainTo]=IF THEN ELSE (PowertrainTo=PHEV, Fuel Price r[EF]*"Fuel Efficiency of New Vehicles by Platform-Fuel v"[PHEVe], 0)
Units: $/hundred km

Operating Cost per 100km PHEV p j[PowertrainTo]=IF THEN ELSE (PowertrainTo=PHEV, Fuel Price r[PF]*"Fuel Efficiency of New Vehicles by Platform-Fuel v"[PHEVp], 0)
Units: $/hundred km

Operating Cost per 100km EV j[PowertrainTo]=IF THEN ELSE (PowertrainTo=EV, Fuel Price r[EF]*"Fuel Efficiency of New Vehicles by Platform-Fuel v"[EVef], 0)
Units: $/hundred km

Operating Cost per 100km Hydrogen j[PowertrainTo]=IF THEN ELSE (PowertrainTo=Hydrogen, Fuel Price r[HF]*"Fuel Efficiency of New Vehicles by Platform-Fuel v"[Hyef], 0)
Units: $/hundred km

U3
U3 Fuel Availability j[PowertrainTo]=Fuel Availability j[PowertrainTo]*Fuel Availability Weight
Units: Dmnl
Utility component of fuel availability.

Fuel Availability Weight=0.0068
Units: Dmnl
Value is derived from discrete choice model

Fuel Availability j[Petrol]=100
Fuel Availability j[Diesel]=100
Fuel Availability j[HEV]=100
Fuel Availability j[PHEV]=100
Fuel Availability j[EV]=MIN(Available Public Infrastructure f[EStation]/Ideal Infrastructure*100, 100)
Fuel Availability j[Hydrogen]=MIN((Available Public Infrastructure f[HyStation])/Ideal Infrastructure*100,100)
Units: Dmnl
Fuel availability is regarded as 100% for petrol, diesel, HEV and PHEV.

Ideal Infrastructure=6000
Units: Stations
Based on the number of petrol stations.

Available Public Infrastructure f[Infrastructure]= INTEG (Change rate f[Infrastructure]+Exogenous Infrastructure f[Infrastructure], Initial Infrastructure Availability f[Infrastructure])
Units: Stations
Available public infrastructure equals to initial exogenous infrastructure and endogenous infrastructure growth.
Initial Infrastructure Availability f[Infrastructure]=6000, 5000, 0, 0
Units: Stations
Initial stations

Exogenous Infrastructure f[Infrastructure]=Station per Year f[Infrastructure]
Units: Stations/Year
Additional rate of introduction of new stations
Station per Year f[Infrastructure]= GAME (Extra Stations[Infrastructure]*PULSE (Extra Stations START[Infrastructure], Extra Station DURATION[Infrastructure]))
Units: Stations/Year
Extra Station DURATION[Infrastructure]=15
Units: Year
Extra Stations[Infrastructure]=0,0,20,10
Units: Stations/Year
Extra Stations START[Infrastructure]=0,0,10,20
Units: Year

Change rate f[PStation]=0
Change rate f[DStation]=0
Change rate f[EStation]= MAX ((Ideal Station Number f[EStation]-Available Public Infrastructure f[EStation])/Station Construction Time, 0)
Change rate f[HyStation]=MAX ((Ideal Station Number f[HyStation]-Available Public Infrastructure f[HyStation])/Station Construction Time, 0)
Units: Stations/Year
Change rate for petrol and diesel is assumed as constant.

Station Construction Time=1
Units: Year
It is assumed that the time for station construction is 1 year.

Ideal Station Number f[PStation]=Ideal Stations per Vehicle f[PStation]* (Perceived installed base v[Pef]+Perceived installed base v[Hef]+Perceived installed base v [PHEVp])
Ideal Station Number f[DStation]= Ideal Stations per Vehicle f[DStation]*Perceived installed base v[Def]
Ideal Station Number f[EStation]=Ideal Stations per Vehicle f[EStation]*(Perceived installed base v[PHEVe] +Perceived installed base v[EVef])
Ideal Station Number f[HyStation]= Ideal Stations per Vehicle f[HyStation]*Perceived installed base v[Hyef]
Units: Stations

Ideal Stations per Vehicle f[Infrastructure]= 0.00043, 0.00043, 0.0639,0.00092
Units: Stations/Vehicles
The ideal number of stations per vehicle. Value for powertrains like petrol and diesel are based on the current petrol station to petrol fleet ratio (2016 data: 6000stations/14115057 petrol vehicles including trucks). For electricity, the ideal ratio is based on the current Norway data (2016 to be exact) since Norway has the highest station numbers and it is assumed that this country's EV adoption is not affected by lack of EV stations (8521/133.26k). For hydrogen, the number is from the simulation in paper "Modelling technology diffusion of complementary goods: The case of hydrogen vehicles and refuelling infrastructure" by P.E. Meyer and J.J.Winebrake.

Perceived installed base v[Powertrain EF Audit]=(Installed Base delay 1[Powertrain EF Audit]+Installed Base delay 3[Powertrain EF Audit]+Installed Based delay 2[Powertrain EF Audit])/3
Units: Vehicles

Installed Base delay 1[Powertrain EF Audit]= DELAY FIXED (Installed Base v[Powertrain EF Audit] , 1 , Installed Base v[Powertrain EF Audit])
Units: Vehicles
Installed Based delay 2[Powertrain EF Audit]=DELAY FIXED(Installed Base v[Powertrain EF Audit] , 2 , Installed Base v[Powertrain EF Audit])
Units: Vehicles
Installed Base delay 3[Powertrain EF Audit]= DELAY FIXED (Installed Base v[Powertrain EF Audit] , 3 , Installed Base v[Powertrain EF Audit])
Units: Vehicles

U4
U4 Driving Range j[PowertrainTo]= (Driving Range j[PowertrainTo]/100)*Driving Range Weight j[PowertrainTo]
Units: Dmnl
Utility component of driving range.

Driving Range Weight j[Petrol]=0
Driving Range Weight j[Diesel]=0
Driving Range Weight j[HEV]=0

Driving Range Weight j[PHEV]=0
Driving Range Weight j[EV]=0.1339
Driving Range Weight j[Hydrogen]=0.1339
Units: Dmnl*Vehicles/km
Coefficients for driving range. Parameter values equal to zero for powertrain petrol, diesel, HEV, and PHEV since this is an alternative specific attribute.

Driving Range j[PowertrainTo]=Driving Range by Platform i[PowertrainTo]
Units: km/Vehicles

Driving Range by Platform i[Petrol]="Driving Range by Platform-Fuel v"[Pef]
Driving Range by Platform i[Diesel]="Driving Range by Platform-Fuel v"[Def]
Driving Range by Platform i[HEV]="Driving Range by Platform-Fuel v"[Hef]
Driving Range by Platform i[PHEV]="Driving Range by Platform-Fuel v"[PHEVp] +"Driving Range by Platform-Fuel v"[PHEVe]
Driving Range by Platform i[EV]="Driving Range by Platform-Fuel v"[EVef]
Driving Range by Platform i[Hydrogen]="Driving Range by Platform-Fuel v"[Hyef]
Units: km/Vehicles
Driving range by platform

"Driving Range by Platform-Fuel v"[Powertrain EF Audit] ="Energy Capacity by Platform-Fuel v"[Powertrain EF Audit]/("Average FE by Platform-Fuel v"[Powertrain EF Audit]*Kilometre Unit Converter)
Units: km/Vehicles
Driving range by platform-fuel

"Energy Capacity by Platform-Fuel v"[Powertrain EF Audit] ="Initial Energy Capacity by Platform-Fuel v"[Powertrain EF Audit] *(1+ SW Capacity Improvement * STEP (Energy Capacity Improvement Level v[Powertrain EF Audit] , Utility Change Time))
Units: petrol liter equivalent/Vehicles
Energy capacity by platform-fuel, allow improvement over time in scenario tests.

SW Capacity Improvement=0
Units: Dmnl [0,1,1]
Switch for possible improvement of energy capacity of the vehicle
Energy Capacity Improvement Level v [Powertrain EF Audit] =0, 0, 0, 0, 0, 0, 0
Units: Dmnl
The improvement of energy capacity of vehicles, set up for scenario test.

"Initial Energy Capacity by Platform-Fuel v"[Pef]=Initial Energy Capacity Petrol
"Initial Energy Capacity by Platform-Fuel v"[Def]=Initial Energy Capacity Diesel
"Initial Energy Capacity by Platform-Fuel v"[Hef]=Initial Energy Capacity HEV
"Initial Energy Capacity by Platform-Fuel v"[PHEVp]=Initial Energy Capacity PHEV p
"Initial Energy Capacity by Platform-Fuel v"[PHEVe]=Initial Energy Capacity PHEV e
"Initial Energy Capacity by Platform-Fuel v"[EVef]=Initial Energy Capacity EV
"Initial Energy Capacity by Platform-Fuel v"[Hyef]=Initial Energy Capacity Hydrogen
Units: petrol liter equivalent/Vehicles

Initial Energy Capacity Petrol=60
Units: petrol liter equivalent/Vehicles
Tank capacity multiplies energy unit

Initial Energy Capacity Diesel=Initial Diesel Tank Cap*Fuel Unit Converter Diesel
Units: petrol liter equivalent/Vehicles
Initial Diesel Tank Cap=60
Units: Liter/Vehicles
The tank size of a diesel vehicle
Fuel Unit Converter Diesel=1.155
Units: petrol liter equivalent/Liter
https://epact.energy.gov/fuel-conversion-factors

Initial Energy Capacity HEV=50
Units: petrol liter equivalent/Vehicles

Initial Energy Capacity PHEV p=45
Units: petrol liter equivalent/Vehicles

Initial Energy Capacity PHEV e=Initial PHEV FE e*Initial PHEV eRange* Kilometre Unit Converter*Fuel Unit Converter Electric
Units: petrol liter equivalent/Vehicles
Initial PHEV eRange=54
Units: km/Vehicles
The initial driving range of PHEV on pure electric driving force
Initial PHEV FE e=19
Units: kwh/hundred km
The initial fuel efficiency of PHEV on max charge (full on battery mode) Mitsubishi Outlander.
Fuel Unit Converter Electric=0.1123
Units: petrol liter equivalent/kwh
https://www.afdc.energy.gov/fuels/fuel_comparison_chart.pdf. 3.786 ple/33.7kwh

Initial Energy Capacity EV=Initial EV eRange*Initial EV FE*Kilometre Unit Converter*Fuel Unit Converter Electric
Units: petrol liter equivalent/Vehicles
Initial EV eRange=200
Units: km/Vehicles
Initial driving range of pure EV
Initial EV FE=19
Units: kwh/hundred km

Initial Energy Capacity Hydrogen=Initial Hydrogen Tank Cap*Fuel Unit Converter Hydrogen
Units: petrol liter equivalent/Vehicles
Initial Hydrogen Tank Cap=5.63
Units: Kg/Vehicles
Tank size of a hydrogen vehicle
Fuel Unit Converter Hydrogen=3.786
Units: petrol liter equivalent/Kg
https://www.afdc.energy.gov/fuels/fuel_comparison_chart.pdf. 3.786 ple/ 1 kg

Fuel Price and Fuel Efficiency

Fuel Price
Fuel Price r[Fuel]= Fuel Price Proxy r[Fuel]*(1 + SW Fuel Price Change * STEP (Fuel Price Change Level r[Fuel], Utility Change Time))
Units: $/petrol liter equivalent

SW Fuel Price Change=0
Units: Dmnl [0,1,1]
Switch for fuel price change
Utility Change Time=25
Units: Year
The time when utility starts to change (early13, 11; late 25)
Fuel Price Change Level r[Fuel]=0, 0, 0, 0
Units: Dmnl
Fuel price change level, set up for scenario tests.

Fuel Price Proxy r[PF]= Petroleum Fuel Price r[PF]/Fuel Unit Converter Petrol
Fuel Price Proxy r[DF]=Petroleum Fuel Price r[DF]/Fuel Unit Converter Diesel
Fuel Price Proxy r[EF]=Electric Fuel Price/Fuel Unit Converter Electric
Fuel Price Proxy r[HF]=Hydrogen Fuel Price/Fuel Unit Converter Hydrogen
Units: $/petrol liter equivalent

Fuel Unit Converter Petrol=1
Units: petrol liter equivalent/Liter

Fuel Unit Converter Diesel=1.155
Units: petrol liter equivalent/Liter
https://epact.energy.gov/fuel-conversion-factors

Fuel Unit Converter Electric=0.1123
Units: petrol liter equivalent/kwh
https://www.afdc.energy.gov/fuels/fuel_comparison_chart.pdf 3.786 ple/33.7kwh

Fuel Unit Converter Hydrogen=3.786
Units: petrol liter equivalent/Kg
https://www.afdc.energy.gov/fuels/fuel_comparison_chart.pdf 3.786 ple/ 1 kg

Petroleum Fuel Price r[PF]
= INTEG (Petroleum Fuel Price Rate r[PF], Initial Price Petroleum Fuel r[PF])
Petroleum Fuel Price r[DF]
= INTEG (Petroleum Fuel Price Rate r[DF], Initial Price Petroleum Fuel r[DF])
Units: $/Liter
Initial Price Petroleum Fuel r[PF]=1.235
Initial Price Petroleum Fuel r[DF]=1.31
Units: $/Liter

Petroleum Fuel Price Rate r[PF]
=Price Change Rate Petroleum[PF] * Petroleum Fuel Price r[PF]
Petroleum Fuel Price Rate r[DF]
=Price Change Rate Petroleum[DF] * Petroleum Fuel Price r[DF]
Units: $/Liter/Year

Price Change Rate Petroleum[PF]=PULSE (0 , 16) * 0.0185
Price Change Rate Petroleum[DF]=PULSE (0 , 16) * 0.0207
Units: Dmnl/Year
Based on historical data.

Electric Fuel Price= INTEG (Electric Fuel Price Rate, Initial Price Electric Fuel)
Units: $/kwh
Initial Price Electric Fuel=0.04
Units: $/kwh
Fuel price at the simulation start time. this value has already considered the effect of inflation. The price is calculated as 2014 equivalent. Initial price is based on the adjusted electricity price (national wholesale average based on aer.gov.au) in 2010.

Electric Fuel Price Rate=Price Change Rate Electricity * Electric Fuel Price
Units: $/kwh/Year

Price Change Rate Electricity=0.08*PULSE (10 , 4) + 0.25* PULSE(14 , 2)
Units: Dmnl/Year
Based on annual data of Australian Energy Regulator (aer.gov.au), the average increase of electricity price from 2010 to 2014 is estimated as 0.08. In 2014, the electricity price has risen to 0.56 AUD/kwh. The price keeps fluctuating after 2014 (in a growing trend), the price has risen to 0.92 AUD/kwh and is expected to continue to increase. So the second stage of annual price increase is estimated as 0.25. The price change after 2016 is not important to the scope of this model.

Hydrogen Fuel Price= INTEG (Hydrogen Fuel Price Rate, Initial Price Hydrogen Fuel)
Units: $/Kg
Initial Price Hydrogen Fuel=15
Units: $/Kg

Hydrogen Fuel Price Rate=Price Change Rate Hydrogen * Hydrogen Fuel Price
Units: $/(Year*Kg)

Price Change Rate Hydrogen=0
Units: Dmnl/Year

Fuel Efficiency
"Average FE by Platform-Fuel v"[Pef]
= XIDZ ("Cumulative FE of Vehicle by Platform-Fuel v"[Pef], Installed Base i[Petrol], "Fuel Efficiency of New Vehicles by Platform-Fuel v"[Pef])
"Average FE by Platform-Fuel v"[Def]
= XIDZ ("Cumulative FE of Vehicle by Platform-Fuel v"[Def], Installed Base i[Diesel], "Fuel Efficiency of New Vehicles by Platform-Fuel v"[Def])
"Average FE by Platform-Fuel v"[Hef]

=XIDZ ("Cumulative FE of Vehicle by Platform-Fuel v"[Hef], Installed Base i[HEV], "Fuel Efficiency of New Vehicles by Platform-Fuel v"[Hef])
"Average FE by Platform-Fuel v"[PHEVp]
=XIDZ ("Cumulative FE of Vehicle by Platform-Fuel v"[PHEVp], Installed Base i[PHEV], "Fuel Efficiency of New Vehicles by Platform-Fuel v"[PHEVp])
"Average FE by Platform-Fuel v"[PHEVe]
=XIDZ ("Cumulative FE of Vehicle by Platform-Fuel v"[PHEVe], Installed Base i[PHEV], "Fuel Efficiency of New Vehicles by Platform-Fuel v"[PHEVe])
"Average FE by Platform-Fuel v"[EVef]
=XIDZ ("Cumulative FE of Vehicle by Platform-Fuel v"[EVef], Installed Base i[EV], "Fuel Efficiency of New Vehicles by Platform-Fuel v"[EVef])
"Average FE by Platform-Fuel v"[Hyef]
=XIDZ ("Cumulative FE of Vehicle by Platform-Fuel v"[Hyef], Installed Base i[Hydrogen], "Fuel Efficiency of New Vehicles by Platform-Fuel v"[Hyef])
Units: petrol liter equivalent/hundred km
Average fuel efficiency in installed base by platform by fuel type

"Cumulative FE of Vehicle by Platform-Fuel v"[Pef]
= INTEG ("Increase in FE by Platform-Fuel v"[Pef]-"Decrease in FE by Platform-Fuel v"[Pef], "Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[Pef]*Installed Base i[Petrol])
"Cumulative FE of Vehicle by Platform-Fuel v"[Def]
= INTEG ("Increase in FE by Platform-Fuel v"[Def]-"Decrease in FE by Platform-Fuel v" [Def],
"Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[Def]*Installed Base i[Diesel])
"Cumulative FE of Vehicle by Platform-Fuel v"[Hef]
= INTEG ("Increase in FE by Platform-Fuel v"[Hef]-"Decrease in FE by Platform-Fuel v"[Hef], "Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[Hef]*Installed Base i[HEV])
"Cumulative FE of Vehicle by Platform-Fuel v"[PHEVp]
= INTEG ("Increase in FE by Platform-Fuel v"[PHEVp]-"Decrease in FE by Platform-Fuel v"[PHEVp], "Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[PHEVp]*Installed Base i[PHEV])
"Cumulative FE of Vehicle by Platform-Fuel v"[PHEVe]
= INTEG ("Increase in FE by Platform-Fuel v"[PHEVe]-"Decrease in FE by Platform-Fuel v"[PHEVe], "Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[PHEVe]*Installed Base i[PHEV])
"Cumulative FE of Vehicle by Platform-Fuel v"[EVef]
= INTEG ("Increase in FE by Platform-Fuel v"[EVef]-"Decrease in FE by Platform-Fuel v"[EVef], "Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[EVef]*Installed Base i[EV])
"Cumulative FE of Vehicle by Platform-Fuel v"[Hyef]
= INTEG ("Increase in FE by Platform-Fuel v"[Hyef]-"Decrease in FE by Platform-Fuel v"[Hyef], "Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[Hyef]*Installed Base i[Hydrogen])
Units: petrol liter equivalent*Vehicles/hundred km
*Cumulated fuel efficiency by platform by fuel type (ple/100km)*vehicles*

"Decrease in FE by Platform-Fuel v"[Pef]="Average FE by Platform-Fuel v"[Pef]*Vehicle Discards i[Petrol]

"Decrease in FE by Platform-Fuel v"[Def]="Average FE by Platform-Fuel v"[Def]*Vehicle Discards i[Diesel]
"Decrease in FE by Platform-Fuel v"[Hef]="Average FE by Platform-Fuel v"[Hef]*Vehicle Discards i[HEV]
"Decrease in FE by Platform-Fuel v"[PHEVp]= "Average FE by Platform-Fuel v"[PHEVp]*Vehicle Discards i[PHEV]
"Decrease in FE by Platform-Fuel v"[PHEVe]= "Average FE by Platform-Fuel v"[PHEVe]*Vehicle Discards i[PHEV]
"Decrease in FE by Platform-Fuel v"[EVef]= "Average FE by Platform-Fuel v"[EVef]*Vehicle Discards i[EV]
"Decrease in FE by Platform-Fuel v"[Hyef]= "Average FE by Platform-Fuel v"[Hyef]*Vehicle Discards i[Hydrogen]
Units: petrol liter equivalent*Vehicles/(Year*hundred km)

Fuel Efficiency Improving Rate v [Powertrain EF Audit]
=IF THEN ELSE (SW Calibrate FE=1, IF THEN ELSE (Ideal Fuel Efficiency v[Powertrain EF Audit]<"Fuel Efficiency of New Vehicles by Platform-Fuel Proxy v"[Powertrain EF Audit] , (Ideal Fuel Efficiency v[Powertrain EF Audit]-"Fuel Efficiency of New Vehicles by Platform-Fuel Proxy v"[Powertrain EF Audit])/Fuel Efficiency Improving Time,0) , 0)
Units: petrol liter equivalent/ (Year*hundred km)
Assume the fuel efficiency improvement is linear. if the ideal efficiency is reached, the rate turns 0. 3 is selected to derive a smooth decline towards the ideal fuel efficiency in 2014-2016

SW Calibrate FE=1
Units: Dmnl [0,1,1]
Switch for FE historical improvement

Fuel Efficiency Improving Time=3
Units: Year

"Fuel Efficiency of New Vehicles by Platform-Fuel v"[Powertrain EF Audit]
= "Fuel Efficiency of New Vehicles by Platform-Fuel Proxy v"[Powertrain EF Audit]
*(1-SW FE Improvement*STEP (FE Improvement level v[Powertrain EF Audit] , Utility Change Time))
Units: petrol liter equivalent/hundred km

SW FE Improvement=0
Units: Dmnl [0,1,1]
Switch for fuel efficiency improvement
FE Improvement level v[Powertrain EF Audit]=0, 0, 0, 0.1, 0.1, 0, 0
Units: Dmnl
Set up for scenario tests

"Fuel Efficiency of New Vehicles by Platform-Fuel Proxy v"[Powertrain EF Audit]
= INTEG (Fuel Efficiency Improving Rate v[Powertrain EF Audit], "Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[Powertrain EF Audit])
Units: petrol liter equivalent/hundred km

Ideal Fuel Efficiency v[Powertrain EF Audit]=7, 6.93, 5, 5.5, 2.134, 2.134, 3.597
Units: petrol liter equivalent/hundred km
The ideal fuel efficiency of each powertrain.

"Increase in FE by Platform-Fuel v"[Pef]= "Fuel Efficiency of New Vehicles by Platform-Fuel v"[Pef]*Platform Demand j [Petrol]
"Increase in FE by Platform-Fuel v"[Def]="Fuel Efficiency of New Vehicles by Platform-Fuel v"[Def]*Platform Demand j [Diesel]
"Increase in FE by Platform-Fuel v"[Hef]="Fuel Efficiency of New Vehicles by Platform-Fuel v"[Hef]*Platform Demand j[HEV]
"Increase in FE by Platform-Fuel v"[PHEVp]="Fuel Efficiency of New Vehicles by Platform-Fuel v"[PHEVp]*Platform Demand j[PHEV]
"Increase in FE by Platform-Fuel v"[PHEVe]="Fuel Efficiency of New Vehicles by Platform-Fuel v"[PHEVe]*Platform Demand j[PHEV]
"Increase in FE by Platform-Fuel v"[EVef]="Fuel Efficiency of New Vehicles by Platform-Fuel v"[EVef]*Platform Demand j[EV]
"Increase in FE by Platform-Fuel v"[Hyef]="Fuel Efficiency of New Vehicles by Platform-Fuel v"[Hyef]*Platform Demand j[Hydrogen]
Units: Vehicles*petrol liter equivalent/hundred km/Year

"Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[Pef]= Initial Petrol Energy Efficiency
"Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[Def]= Initial Diesel Energy Efficiency
"Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[Hef]= Initial HEV Energy Efficiency
"Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[PHEVp]= Initial PHEV Energy Efficiency p
"Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[EVef]= Initial EV Energy Efficiency
"Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[Hyef]= Initial Hydrogen Energy Efficiency
"Initial Energy Efficiency by Platform-Fuel(ple/100km) v"[PHEVe]= Initial PHEV Energy Efficiency e
Units: petrol liter equivalent/hundred km
Initial fuel efficiency with united unit (ple/100km) by platform by fuel type

Initial Petrol Energy Efficiency=Initial Petrol FE
Units: petrol liter equivalent/hundred km
Initial fuel efficiency of petrol vehicles in ple unit
Initial Petrol FE=11
Units: petrol liter equivalent/hundred km

Initial Diesel Energy Efficiency=Fuel Unit Converter Diesel*Initial Diesel FE
Units: petrol liter equivalent/hundred km
Initial fuel efficiency of diesel vehicles in ple unit
Initial Diesel FE=9
Units: Liter/hundred km

Initial HEV Energy Efficiency= Initial HEV FE
Units: petrol liter equivalent/hundred km
Initial fuel efficiency of HEV vehicles in ple unit
Initial HEV FE=6.5
Units: petrol liter equivalent/hundred km

Initial PHEV Energy Efficiency p=Initial PHEV FE p
Units: petrol liter equivalent/hundred km
Initial petroleum fuel efficiency of PHEV vehicles in ple unit
Initial PHEV FE p=5.5
Units: petrol liter equivalent/hundred km
The initial petroleum fuel efficiency of PHEV when the battery is fully drained (full on petrol mode). Mitsubishi Outlander

Initial PHEV Energy Efficiency e=Fuel Unit Converter Electric*Initial PHEV FE e
Units: petrol liter equivalent/hundred km
Initial electricity fuel efficiency of PHEV vehicles in ple unit
Initial PHEV FE e=19
Units: kwh/hundred km
The initial fuel efficiency of PHEV on max charge (full on battery mode) Mitsubishi Outlander

Initial EV Energy Efficiency= Fuel Unit Converter Electric*Initial EV FE
Units: petrol liter equivalent/hundred km
Initial fuel efficiency of EV vehicles in ple unit
Initial EV FE=19
Units: kwh/hundred km

Initial Hydrogen Energy Efficiency= Fuel Unit Converter Hydrogen*Initial Hydrogen FE
Units: petrol liter equivalent/hundred km
Initial fuel efficiency of hydrogen vehicles in ple unit
Initial Hydrogen FE= 0.95
Units: Kg/hundred km
Hyundai website 9.5g hydrogen can drive 1 kilometre
https://www.hyundai.com/worldwide/en/eco/ix35-fuelcell/highlights

Consumer Biases

Platform Bias j[PowertrainTo]= GAME (MIN ((Platform Bias Proxy j[PowertrainTo] + SW Platform Bias Intervention * STEP (Platform Bias Intervention j[PowertrainTo], Platform Bias Change Time j[PowertrainTo])), 0))
Units: Dmnl
Platform biases that allow intervention for scenario tests.

SW Platform Bias Intervention=1
Units: Dmnl [0,1,1]
Switch for platform intervention

Platform Bias Change Time j[PowertrainTo]=0,0,0,0,0,0
Units: Year
The time when the bias intervention kick in early: 0,0,2,13,11,22 or 25/ late 0,0,25,25,25,0

Platform Bias Intervention j[PowertrainTo]=0, 0, 0, 0, 0, 0
Units: Dmnl
Set up in scenario tests

Platform Bias Proxy j[PowertrainTo]= INTEG (-Bias Reduction Rate j[PowertrainTo], Initial Platform Bias j[PowertrainTo])
Units: Dmnl
Endogenous platform bias.
Initial Platform Bias j[PowertrainTo]=0, -0.303803, -0.50117, -0.553295, -1.87681, -1.9573
Units: Dmnl
Initial bias consumers hold against powertrains. The values are estimated from calibration.

Bias Reduction Rate j[PowertrainTo]
=IF THEN ELSE (SW Platform Bias Dynamic=0, 0 , IF THEN ELSE(Platform Bias Proxy j[PowertrainTo]>=0 , 0 , (Platform Marketing Spending j[PowertrainTo]*(1-SW Bias Marketing Spill)+Total Marketing Spending j[PowertrainTo]*SW Bias Marketing Spill)*Marketing effectiveness on bias correction))
Units: Dmnl/Year
The bias reduction rate because of marketing strength. SW bias marketing fund =1 marketing fund spill also works for bias reduction.

SW Platform Bias Dynamic=1
Units: Dmnl [0,1,1]
Switch to link marketing effect with bias reduction

SW Bias Marketing Spill=0
Units: Dmnl [0,1,1]
We assume bias reduction are only affected by platform marketing with no spillover

Marketing effectiveness on bias correction=-0.000113619
Units: Dmnl/million [-1e-05,-0.001,1e-05]
The marketing effectiveness on bias correction. The value is estimated from calibration.

Total Marketing Spending j[PowertrainSpillTo]= SUM Total Marketing Spending ij[PowertrainFrom!, PowertrainSpillTo])
Units: million/Year

Number of Vehicle Models

Vehicle Model j[PowertrainTo]=INTEGER (Vehicle Model Proxy j[PowertrainTo]) + SW MN Change * STEP (Model Number Change j[PowertrainTo] , MN Change Time j[PowertrainTo])
Units: Models
Vehicle model number that allow exogenous interventions for scenario tests.

SW MN Change=1
Units: Dmnl [0,1,1]
Switch for model number change
MN Change Time j[PowertrainTo]=0, 0, 0, 0, 0, 0
Units: Year
Intervention time for model number, late or early in scenrioa tests
Model Number Change j[PowertrainTo]=0, 0, 0, 0, 0, 0
Units: Models
Intervention change level, 134 or 67 models.

Vehicle Model Proxy j[PowertrainTo]= ACTIVE INITIAL (IF THEN ELSE (Market share three year average i[PowertrainTo]<=Vehicle model parameter 1, (Vehicle Model parameter a*(Market share three year average i[PowertrainTo]-Vehicle model parameter 1)^2 +Vehicle model parameter 2)*Unit Correction, Vehicle model parameter 2*Unit Correction), Initial MN Value j[PowertrainTo])
Units: Models
This relationship was derived from historical data. (all powertrains in AUS: petrol, diesel, Electric and hybrid, LPG fuelled) The equation is a polynomial equation of degree 2, the function will change to the constant once the maximum value is reached.
Initial MN Value j[PowertrainTo]=369, 28, 1, 1, 1, 1
Units: Models
The initial value for model number.

Market share three year average i[Powertrain]= (Market share Delay 1 i[Powertrain]+Market share Delay 2 i[Powertrain]+Market share Delay 3 i[Powertrain])/3
Units: Dmnl

Market share Delay 1 i[Powertrain]
=DELAY FIXED (Market share i[Powertrain], 1, Market share i[Powertrain])
Units: Dmnl
Market share Delay 2 i[Powertrain]
=DELAY FIXED (Market share i[Powertrain], 2, Market share i[Powertrain])
Units: Dmnl
Market share Delay 3 i[Powertrain]
=DELAY FIXED (Market share i[Powertrain], 3, Market share i[Powertrain])
Units: Dmnl

Vehicle model parameter 1=73.2692
Units: Dmnl
Vehicle model parameter 2=369.386
Units: Dmnl

Vehicle Model parameter a = (1-Vehicle model parameter 2)/(Vehicle model parameter 1^2)
Units: Dmnl

Vehicle Model Effect on Consumer Choice j[PowertrainTo]
=IF THEN ELSE (Vehicle Model j[PowertrainTo]<1 , Point1 Y Minimal Effect , 0)+IF THEN ELSE(1 <= Vehicle Model j[PowertrainTo] :AND: Vehicle Model j[PowertrainTo] < Sufficient Vehicle Model Number, Vehicle Model Constrain Factor a * LN(Vehicle Model Constrain Factor b * Vehicle Model j[PowertrainTo]/Unit Correction) , 0)+IF THEN ELSE(Vehicle Model j[PowertrainTo]>=Sufficient Vehicle Model Number, 1 , 0)
Units: Dmnl [0,1]
A logarithm function is chosen to represent the vehicle model effect on consumer choice

Point1 X=1
Units: Dmnl
Point1 Y Minimal Effect=0.140622
Units: Dmnl [?,?,0.01]
Point2 X Sufficient Vehicle Number=120
Units: Dmnl [?,?,1]
Point2 Y=1
Units: Dmnl

Vehicle Model Constrain Factor a
= (Point1 Y Minimal Effect-Point2 Y)/ LN((Point1X/Point2 X Sufficient Vehicle Number))
Units: Dmnl

Vehicle Model Constrain Factor b
= EXP((Point2 Y*LN(Point1 X)-Point1 Y Minimal Effect*LN(Point2 X Sufficient Vehicle Number))/(Point1 Y Minimal Effect-Point2 Y))
Units: Dmnl

Sufficient Vehicle Model Number
=Point2 X Sufficient Vehicle Number*Unit Correction
Units: Models
Sufficient number of vehicle models in the market to satisfy consumer needs

Unit Correction=1
Units: Models
Unit correction between dmnl and models