A combined multi-criteria and system dynamics methodology for mid-term planning of light duty vehicle fleets

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توانا بود هر که دانا بود

ز دانش دل پیر برنا بود

Capable is the one who is enlightened

Happiness from wisdom will arise

Ferdowsi, Persian Poet

Abstract

Defining policies to shape the future development of transportation systems is a considerable challenge, especially in a framework of sustainable development. With the intent of contributing to the process, this dissertation aims at developing a Multi-Criteria Decision Analysis (MCDA) framework for the mid-term evolution of individual vehicle fleets in the context of a country or large region, considering both conventional fuel and alternative fuel-technologies. The proposed methodology combines multi-criteria decision making with system dynamics, consisting of three main phases.

The first phase regards the MCDA model. Its development started with a comprehensive literature review, identifying a list of alternatives (alternative fuel-technology vehicles) and decision objectives and attributes. On the technologies, besides the current technologies, there are several other becoming available, such as hybrid, fuel cell, Plug-in Hybrid (PHEV), and Battery Electric Vehicle (BEV). Regarding the decision framework, the five final attributes selected for the MCDA analysis are: Acceptance, Emissions to atmosphere, Transition cost, Risk of technology development, and Availability of Fuel Supply (AOFS). As for the concrete decision making technique, the Multi-Attribute Utility Theory (MAUT) was chosen. Then, a multi-stage screening process was applied; starting with a Pareto Optimality (PO) screening approach, followed by a Data Envelopment Analysis (DEA) based screening and a Tradeoff Weights (TW) screening procedure, in order to eliminate those alternatives that do not seem to be interesting under any decision preference scenario. The outcome is a screened list of alternatives that can be discussed with a decision maker as planning target for a Light-Duty Vehicle (LDV) fleet.

For the second phase of the methodology, a system dynamics model was developed, to analyze the co-evolution of the refueling infrastructure and vehicle sales through time. The developed model enables the estimation of more precise transition costs for each of the screening alternatives that had resulted from phase 1.

An iterative procedure between phases 1 and 2 was developed in the third phase, ensuring that the developed multi-criteria analysis framework will be re-applied for comparing all the alternatives, with the updated transition costs from phase 2, as a way to identify an updated screening set of alternatives. The new alternatives from the screening process are then analyzed through the system dynamics model, and the updated transition costs for these will be calculated. This iterative analysis will continue until there is no new alternative in the screening set, and thus the phase 1- phase 2 iterative process has converged.

The applicability and value of the whole method were verified through the application to Portugal as a case study. It was shown that the method can be made operational, and the coupling of the multi-criteria analysis with the system dynamics model results in a significantly different set of “potentially best alternatives” than the consideration of the multi-criteria analysis alone.

Resumo

Moldar o desenvolvimento futuro dos sistemas de transportes é um desafio de grande complexidade, especialmente num contexto de desenvolvimento sustentável. Com a intenção de contribuir para o processo, esta dissertação teve como objetivo o desenvolvimento de um quadro de decisão multi-critério (MCDA) para a evolução, individuais a médio prazo, de frotas de veículos, no contexto de um país ou de uma região grande, considerando tanto os combustíveis convencionais como tecnologias baseadas em energias alternativos. A metodologia proposta combina técnicas de decisão multi-critério com um modelo de dinâmica de sistemas, e consiste em três fases principais.

A primeira fase diz respeito ao modelo MCDA. O desenvolvimento deste modelo começou com uma ampla revisão da literatura, com o objetivo de identificar uma lista de alternativas (tecnologias de propulsão alternativas), objetivos e atributos. Sobre as tecnologias, além das tecnologias atuais, há várias outras tecnologias em vias de se tornarem disponíveis, tais como híbrida, pilhas de combustível, híbrida "plug-in" (PHEV) e veículo eléctrico de baterias (BEV). Em relação ao quadro de decisão, os cinco atributos finais selecionados para a análise MCDA são: atratividade, emissões para a atmosfera, custo da transição, risco de desenvolvimento de tecnologia, e disponibilidade de fornecimento de combustível (AOFS). Quanto à técnica concreta para MCDA, foi a escolhida a Teoria da Utilidade Multi-Atributo (MAUT). Em seguida, foi aplicado um processo de triagem multi-etapa, começando com uma abordagem de Análise de Pareto, seguida de um processo de DEA (Data Envelopment Analysis) e de um procedimento de TW (Tradeoff Weights), a fim de eliminar as alternativas que parecem não ser interessantes sob qualquer cenário de preferências. O resultado é a uma lista de alternativas selecionadas que podem ser discutidas com o decisor.

Para a segunda fase do método, foi desenvolvido um modelo de dinâmica de sistemas, para analisar a co-evolução das vendas de veículos e da infra-estrutura de reabastecimento, ao longo do tempo. O modelo desenvolvido permite a estimação mais precisa dos custos de transição para cada uma das alternativas da lista que resulta da fase 1.

Na terceira fase foi desenvolvido um processo iterativo entre as fases 1 e 2, garantindo que o quadro de análise multi-critério desenvolvido seja novamente aplicado para comparar todas as alternativas, com os custos de transição atualizados da fase 2, a fim de identificar um conjunto novo conjunto de alternativas potencialmente melhores. As novas alternativas são definidas como os "shares" resultantes do modelo de dinâmica de sistemas. Esta análise iterativa fase 1 / fase 2 continua até que não surja qualquer nova alternativa, caso em que o processo iterativo terá convergido.

A aplicabilidade e utilidade de todo o método foi verificada através da aplicação a Portugal como um estudo de caso. Mostrou-se que o método pode ser tornado operacional, e o acoplamento da análise multi-critério com o modelo de dinâmica de sistemas resulta num conjunto final de “potenciais soluções” melhor do que aquele que se obteria por exclusiva consideração da análise de multi-critério.

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List of Acronyms and Abbreviations

ACAP – Associação Automóvel de Portugal (Portuguese automobile retail association)

AHP - Analytic Hierarchy Process

AOFS - Availability Of Fuel Supply

BAU - Business As Usual

BEV - Battery Electric Vehicle

CH2 - Compressed Hydrogen

CNG - Compressed Natural Gas

DA - Decision Analysis

DEA - Data Envelopment Analysis

DICI - Direct Injection Compression Ignition engine

DISI - Direct Injection Spark Ignition engine

DME - DiMethyl Ether

EEA - European Environment Agency

U.S. EIA – U.S. Energy Information Administration

ELECTRE - ELimination Et Choix Traduisant la REalité

FCEV - Fuel-Cell Powered Electric Vehicle

FC-NR - Fuel Cell with No-Reformer

FCV - Fuel Cell Vehicle

FC-WR - Fuel Cell With Reformer

FTD - Fischer-Tropsch Diesel

GDI - Gasoline Direct Injection

GHG - Green House Gases

GWP - Global Warming Potential

HDV - Heavy-Duty Vehicle

HEV - Hybrid Electric Vehicle

HRT - Heavy-Rail Transit

HT - Human Toxicity

ICE - Internal Combustion Engine

ICT - Information and Communication Technologies

IEA - International Energy Agency

LCA - Life Cycle Analysis

LDV - Light-Duty Vehicle

LH2 - Liquefied Hydrogen

LNG - Liquefied Natural Gas

LPG - Liquefied Petrol Gas

LRT - Light-Rail Transit

MADM - Multiple Attribute Decision Making

MAUT - Multi-Attribute Utility Theory

MCDA - Multi-Criteria Decision Analysis

MCDM - Multiple Criteria Decision Making

MODM - Multiple Objective Decision Making

NGV - Natural Gas Vehicle

OECD - Organisation for Economic Co-operation and Development

OEM - Original Equipment Manufacturers

PHEV - Plug-in Hybrid Electric Vehicle

PISI - Port Injection Spark Ignition engine

PROMETHEE - Preference Ranking Organization METHod for Enrichment Evaluation

SD - System Dynamics

TLCC - Total Life Cycle Cost

TMC - Toyota Motor Company

TRL - Technology Readiness Level

TTW - Tank-To-Wheel

WBCSD - World Business Council for Sustainable Development

WTT - Well-To-Tank

List of Symbols

α	The coefficient of fleet gap filling (difference of the number of vehicles to the saturated level);
β	A set of parameters that relate variables to probabilities;
β_j	The logit coefficient for attribute j;
β_n	The coefficient sensitivity of the customer for n choice factors;
γ_1	The importance of technology share in the total fleet on familiarity of individuals;
γ_2	The impact of word-of-mouth contacts with drivers of that AFV on its familiarity;
γ_3	The forgetfulness impact of the familiarity of the drivers with AFV;
ε_{ni}	The impact of all unobserved factors that affect the person's choice to alternative *i* for person *n*;
ρ	A corresponding vector of coefficients of the observed variables;
A^i	Alternative i;
AAT	The average annual travel in km;
AFE_i	The average fleet efficiency of vehicles using technology option i;
AVL	The average lifetime of the light duty vehicle;
C_f	The amount of consuming fuel f;
CC	The capital cost of a fuel station;
$d_{i,r}$	The number of vehicles' discards for technology option i, in region r;
DR	The annual discount rate;
ESI	Energy Security Index;
$ESMC$	Energy Security Market Concentration;
f	The function relating the fuel station entrance with the profitability of fuel stations;
F_i	The familiarity of individuals with technology i;
$FC_{i,r}$	The total consumption of fuel used by a vehicle using technology option i in region r;
$FCO_{r,f}$	The number of fuel stations of fuel f, in region r that are dropped;
FP_f	The price of fuel f;
$FSE_{r,f}$	The station entrance for fuel f, in region r;
$FSIC_{r,f}$	The fuel Station for fuel f in construction planning in region r;
ASL	The average lifetime of a fuel station;
$FSP_{r,f}$	The fuel stations for fuel f, in planning phase in region r;
$FCost$	The Annual Fuel cost;
G_r	The gap between current vehicle ownership and the saturation level in region r;
GtT	The gap to target in terms of "share of AFV in the LDV fleet";
HHI	Herfindhal Hirschman Index;
i	An index for different powertrain options;
I	The total number of vehicle technology options;
$ICost$	The purchase price of the vehicle;
IDM	The initial diesel marketing;
IFP_f	The incentive for price of fuel *f*;

IFS_f The incentive for fuel stations of fuel *f;*

IHM The initial hybrid marketing;

$IVPP_t$ The incentive for purchase price of technology *t*;

M The trade-off factor in terms of euro/share of AFV in the LDV fleet;

M_{diesel} The Marketing with diesel vehicle;

$M_{diesel1}$ The changes in diesel marketing since 1990;

$M_{diesel2}$ The changes in diesel marketing since 1995;

$M_{diesel3}$ The changes in diesel marketing since 2000;

M_i The marketing factor for technology i;

M_{hybrid} The Marketing with hybrid vehicle;

$\mathrm{M}_{\mathrm{hybrid1}}$ The changes in hybrid marketing since 2005;

MRCost The annual Maintenance and Repair Cost;

$NFS_{r,f}$ The number of available fuel stations for fuel f, in region r;

OMC The operation and maintenance cost of a fuel stations;

$P_{i,t}$ The Probability that consumer will choose a given technology i in year t;

P_{ni} The probability with which person n chooses alternative i;

$PFS_{r,f}$ The profitability of a station for fuel f in region r;

POP_r The size of population in region r;

$PU_{i,r}$ The perceived utility of technology i, in region r;

PVExpenses The present value expenses;

r An index for the region r;

r_i Political risk rating of country i;

RPFS The reference for profitability of fuel station;

$s_{i,r}$ The number of vehicles' sales for technology option i, in region r;

s_n A vector of characteristics of person n;

$S_{i,f}$ The share of each supplier i in the market of fuel f;

$SIP_{r,f}$ The rate of fuel stations in planning for fuel f, in region r;

$Sop_{i,r}$ The share of purchase for technology option i in each region r;

SVO The saturated vehicle ownership of the case study;

TPES Total Primary Energy Consumption;

TSL The time to select the location for the fuel station;

TTC The total transition cost;

TTCFC The time for the construction of a fuel station;

$u_{i,r,n}$ The characteristic of each technology i, in region r, and for variant choice factor n;

$U_{i,t}$ The consumer utility for vehicle i in year t;

$U_{i,r}$ The nominal utility of each technology i in region r;

U_{ni} The Utility that person n obtains from choosing alternative i;

v_j The value vector for each sub-attribute j;

V The aggregated function for evaluation of alternative;

$V_{i,r}$	The number of vehicles for technology option i, in region r;
w_j	The weight vector of sub-attribute j;
$x_{i,j,t}$	The value of attribute j for vehicle i in year t;
x_{ni}	A vector of attributes of the other alternatives (other than i) faced by person n;
z_{ni}	A vector of observed variables relating to alternative *i* for person *n*;

Chapter 1 - Introduction

Nowadays, it is well understood that the transportation sector is an important component of the economy impacting on development and the welfare of populations. When transportation systems are efficient, they provide economic and social opportunities and benefits that result in positive multipliers effects such as better accessibility to markets, employment and additional investments.

Among the available modes of transportation such as road, rail, air and maritime, the dominant mode of passenger transportation is the car, likely fuelled by the general people's desire to have greater mobility and flexibility. The high reliance on the use of the car as a means of passenger transportation across the world has resulted in increased congestion and pollution in many urban areas and on many major transport arteries. On the other hand, the road and other vehicle support infrastructure represent a very considerable investment from societies. This justifies that the design and planning of transportation modes, vehicle fleets and associated infrastructure be treated with great attention and methodological care, only enhanced by the energy paradigm challenges of this time.

1.1. Historical evolution of road transportation

Humans' first means of transportation were walking and swimming. The domestication of animals introduced a new way to lay the burden of transportation on more powerful creatures. Humans were enabled to ride the animals for higher speed and duration, and heavier loads could be hauled. Inventions such as the wheel helped a more efficient transportation through the introduction of vehicles. The Persian, Egyptian, Greek and Roman empires built stone-paved roads basically to allow armies to move quickly, but this brought benefits in economic and social terms as well ([1]). Until the Industrial Revolution, land transportation remained slow and costly, and production and consumption were located as close to each other as feasible.

The Industrial Revolution in the 19th century saw a number of inventions which fundamentally affected transportation. The development of a practical, efficient steam engine and its application to industry and transportation caused a great leap for industrialization. Its application was virtually limitless, and it was responsible for lifting industries from infancy to adolescence ([2]).

After the introduction of private cars in the early years of the 20^{th} century, the technological development in the internal combustion engine started at a significant pace, with the adoption of multi-valve and overhead camshaft engines, hydraulic brakes, automatic transmission, and the fuel injection system.

A turbocharger is a forced induction device used to allow more power to be produced from an engine of a given size. General Motors manufactured the first turbocharged production cars in 1962 with the Turbo Jetfire engine used in the Oldsmobile Jetfire. A turbocharged engine aimed at delivering more power than a naturally aspirated engine because the turbine forces more intake air, proportionately more fuel, into the combustion chamber than if atmospheric pressure alone is used ([3]).

Direct Injection appears to be the next generation of fuel injection for gasoline engines. The reasons for this technology are legislative, and also include market requirements that drive the need for reduced fuel consumption, while at the same time, meet the increasingly stringent exhaust emissions regulations. Mitsubishi in Japan was first to release a production Gasoline Direct Injection (GDI) engine in 1996, which reportedly delivered 15 to 40 percent better fuel efficiency than an indirect multi-port injected engine. The engine also put out 10 percent more torque and met all emission requirements, including the ones for oxides of nitrogen (NO_x) which are especially tough to meet [4].

On what regards the evolution of fuel use in private passenger transportation, the first European attempts at a diesel powered passenger car resulted in the development of the Citroen "Rosalie" Diesel around 1933. In 1995, the share of diesel cars in passenger fleets in the EU was around 17% ,and this has increased to 28% at 2009, with a significant annual growth of 3.6% in this period ([5]).

More recently, hybrid electric vehicles, which use an internal combustion engine (generally gasoline or diesel engines) and electric batteries to power the vehicle entered the market. This introduction was in 1997; by the end of December 2011, more than 4.5 million hybrid electric vehicles have been sold worldwide, led by Toyota Motor Company (TMC). In May 2012, cumulative TMC hybrid vehicle sales passed 4 million, with significant progress from the sale of a one million vehicles in 2007 ([6]). It is worth mentioning that despite this rapid growth, in 2009, their share in vehicle sale in Europe is still as low as 0.4% ([7]).

The first generations of Plug-in Hybrid Electric Vehicles (PHEVs) and mass-produced Battery-Electric Vehicles (BEVs) are currently being introduced into the market. These are becoming very attractive vehicles especially after the Nissan Leaf, the first full electric vehicle obtained the highest grade in the contest of the Car of the Year in 2011. Currently, industry and governments have defined ambitious targets for both PHEVs and BEVs as the car manufacturers Nissan and Renault plan to reach a joint yearly production capacity of half a million vehicles by 2015 ([8][9]).

1.2. Passenger transportation trends

Transportation demand depends on many factors, including economic activities. As shown on figure 1, there is a significant correlation between the economic growth and passenger and freight transportation growth. The figure 1 also shows the noticeable impact of the international economic crisis started in 2008 on both freight transportation and GDP in EU-27 countries. It is worth mentioning that the passenger transportation demand seems to be less affected by the crisis than the freight demand ([10]).

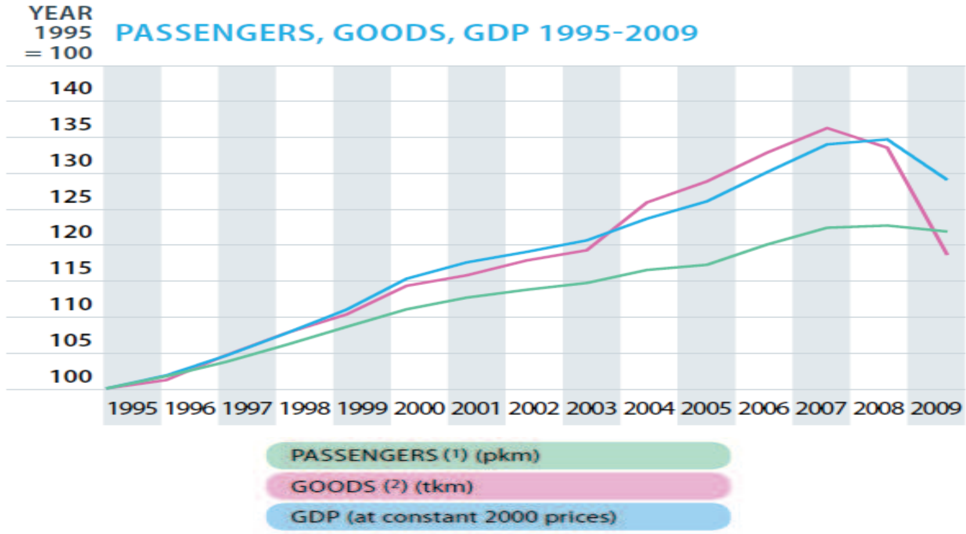


Figure 1: Trends for GDP, passengers and goods transportation in the EU-27, 1995-2009 ([10])

Focusing on the passenger transportation, it is worth reviewing the historical trends for market share of each passenger transportation mode in Europe during the last few decades (figure 2). The trends show a gradual relative shift from using buses and trains towards passenger cars and airplanes, even if they seem to be all growing in absolute terms. It should be noticed that several parameters can affect the market share of each transportation mode. For example, the market share of private cars depends on individual income, cost of fuel, density and quality of the road network, etc. The market share of railways and buses depends on the car ownership index, fares of competitive modes (e.g., bus, railways, and airplanes) and travel time.

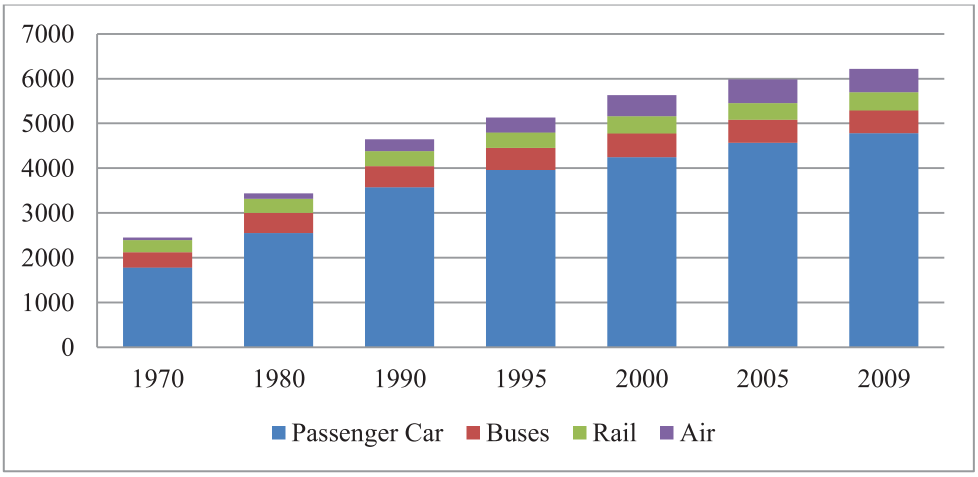


Figure 2: Passenger transportation by mode in billion pkm for EU-27 ([10], [11])

As it is clear from figure 2, private cars contribution to the passenger transportation is significant and has slowly increased from 73% to 76.9% since 1970. Besides, it can be seen that after the initial rapid growth, the rate of increase in demand for passenger transportation has slowed (Table I).

Table I: Average annual change by transportation mode (% per year)

	Passenger Car	Buses	Rail	Air
1970-80	3,7%	2,6%	1,3%	8,4%
1980-90	3,4%	0,6%	0,8%	7,8%
1990-00	1,7%	1,1%	1,3%	6,1%
2000-09	1,2%	-0,3%	0,6%	1,0%

Considering the reduction in the growth rate of passenger transportation demand, the passenger cars still account for the highest average annual growth. In fact, despite the crisis effect, the private passenger transportation still rises annually by 0.4% since 2008 ([10]).

In Portugal, according to the EU statistics ([10]), passenger cars account for 85.2% of total passenger transportation in 2008. That has increased from 81.9% since 2000. Moreover, the number of registered passenger cars is around 4 million, and the ownership rate is 415 cars per 1000 inhabitants, slightly below the average of 470 for EU-27 countries (ERF, [12]).

In 2009, the vehicle sales in the Portuguese market had a significant decrease in various segments, reflected in light passenger vehicle sales (-24.5%), but in 2010 it showed a recovery with increases of 38.8% (from 161013 in 2009) in the segment of light passenger vehicles sales (ACAP, [13]).

1.3. Energy and CO_2 Trends

According to the IEA report, transportation, in 2007 accounted for more than half the oil used worldwide and nearly 26% of energy-related CO_2 emissions. From 1971 to 2007, global transportation energy use rose steadily by between 2% to 2.5% annually. This has been mainly driven by rising population and incomes (IEA, [8]). Focusing on the passenger transportation, it was reported that it accounts for more than half (60-70% in the US, and 55% in Canada) of the global transportation energy use (IEA, [14]).

In 2009, the main sources of fuels for road transportation in Portugal were gasoline, diesel and LPG (Table II).

Table II: Fuel consumption in road transportation in tons of oil equivalent in Portugal

	2009	2010[(a)]
LPG	33300	31714
Gasoline	1528672	1479410
Diesel	4544948	4646134
Biodiesel	3874	4183

[(a)] Provisional data (Source: DGEG [15])

The transportation sector in Europe contributed with more than 25% of EU-27 GHG emissions in 2008 (1271 Mt CO_2 eq.), representing an increase of 17% since 1995 (954 Mt CO_2 eq.). The historical trend outlines an annual growth of around 1.8% for GHG emissions resulting from transportation (EEA, [16]). In Portugal, the share of Transportation in total GHG emissions was almost 22% in 1990, an increase of more than 30% in 2008. Besides, these statistics also show that in Europe, road transportation, as the major contributor, accounts for more than 70% of GHG emissions resulting from the transportation sector in 2008, while this value for Portugal is around 78% ([16]).

Focusing on the passenger cars, it was reported that passenger cars accounted for 7710 kton of CO_2 emissions in 2005, this representing 11% of the total CO_2 emissions in Portugal in that year ([17] Portugal, 2007). Considering, the significant share of road transportation in GHG emissions and its growth rate, it is inevitable to investigate the projection studies.

1.4. Visions ahead for the transportation sector

According to a study by the World Business Council for Sustainable Development ([18]), the transportation energy use in 2030 will be about 80% higher than in 2002 (see figure 3). It should be noted that the projected share of fuel consumption by light-duty vehicles is significant comparing to the other modes of transportation.

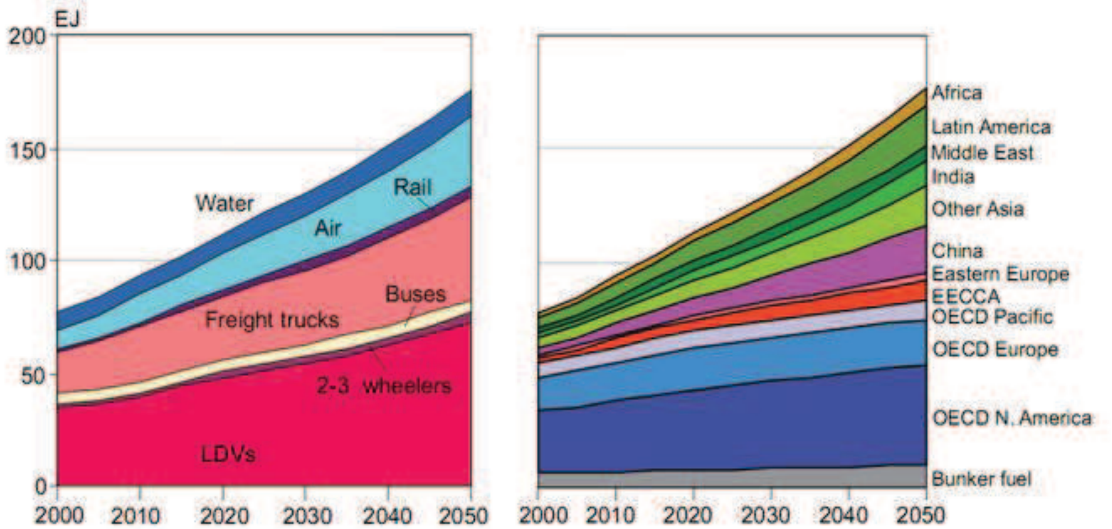


Figure 3: Projection of transportation energy use by region and mode (source: WBCSD [18]).

According to another projection by ExxonMobil ([19]), oil will continue to lead as a source for transportation fuels in the decades to come. However, European energy demand in the transportation sector is anticipated to be flat, with oil declining from 2005 to 2030, as a result of energy efficiency measures, new technologies, renewable energy policies and other factors.

In terms of the GHG emissions, the CO_2 emissions from passenger cars are projected to reach about 13500 Kton of CO_2 in 2020, a value that is 75% higher than its level in 2005 ([17]).

Considering the findings of projection studies, energy demand and GHG emissions for passenger road transportation will increase significantly in the next few decades. The major unfavorable impact of GHG emissions is the increase in the speed of global warming that can cause serious damages such as the sea level rise.

Besides there are other critical consequences associated with the increase of fuel needs for transportation, such as the security of fuel supply. The high dependency of transportation on petroleum, with over 95% of fuel being either gasoline or distillate fuels such as diesel, kerosene or jet fuel, raises obvious concerns. Several issues such as the limited available fossil fuel resources, hardly predictability of their price, uneven distribution of the oil in the world, and instability in the Persian Gulf area as one of the main geographical sources of oil (28.4% in 2010 (U.S. DOE [20]) attract the attention of policy makers.

Therefore, the future development of transportation systems is one of the most challenging issues in the framework of sustainable development, considering the impact of GHG emissions and also the security of fuel supply. There are several available measures that can be adopted in order to tackle the above issues, and they can be categorized into the two main groups: measures on the "supply side" and "demand side" measures. Measures on the demand side include:

- travel demand management (through urban planning, mobility management, lifestyle change and increased use of Information and Communication Technologies (ICT));
- efficient driving (through efficient patterns of driving and carpooling).

On the other hand, possible measures on the supply side are:

- promoting more sustainable traveling modes (increased use of public transport and slow modes, but also changes in how modes are utilized);
- improving vehicle efficiency (primarily through adopting new technology powertrains).
- changes in the fuels used by the vehicles to renewable or cleaner fossil ones.

The focus of this research is on private passenger road transportation. Considering the fact that according to the U.S. EIA projections, vehicle ownership is expected to double worldwide, with most of the increase occurring in non-OECD countries over the next two decades, it becomes crucial to investigate alternative powertrain technologies and the challenges ahead for their adoption.

Generally, these options can be categorized as alternative fuels and engines. Alternative engines range from hybrid vehicles (using an electric battery for additional power) and full battery-powered to fuel cell-electric (where the electricity is produced from a chemical reaction between hydrogen and oxygen). In terms of alternative fuels, there are many more possibilities including biofuels (ethanol, biodiesel, and methanol), Compressed Natural Gas (CNG), Liquefied Natural Gas (LNG), hydrogen (compressed or liquefied) and electricity.

Gone are the days when consumers just wanted speed and power. Performance is still a priority, but vehicle makers also need to make sure that they incorporate measures not only to improve fuel economy but also lower exhaust emissions.

In fact, one the main drivers of the interest on alternative fuels is the increasing concern for the environmental impacts of passenger cars. Different environmental problems however motivate different solutions. If climate change is the main concern, reduction of greenhouse gases emissions is the answer. However, some non-fossil alternative fuels such as biodiesel causes small levels of greenhouse gases but on the other hand significant amounts of local emissions (particulate matter and nitrogen oxides). In urban areas with air quality problems, the use of alternative fossil fuels such as Liquified Petrol Gas (LPG) and natural gas may be a more reasonable option. Figure 4 schematically shows the relation between local emissions and global effects for the most commonly used fossil (diesel, petrol, LPG and natural gas) and non-fossil fuels (biodiesel, ethanol - E85 and E95 and biogas).

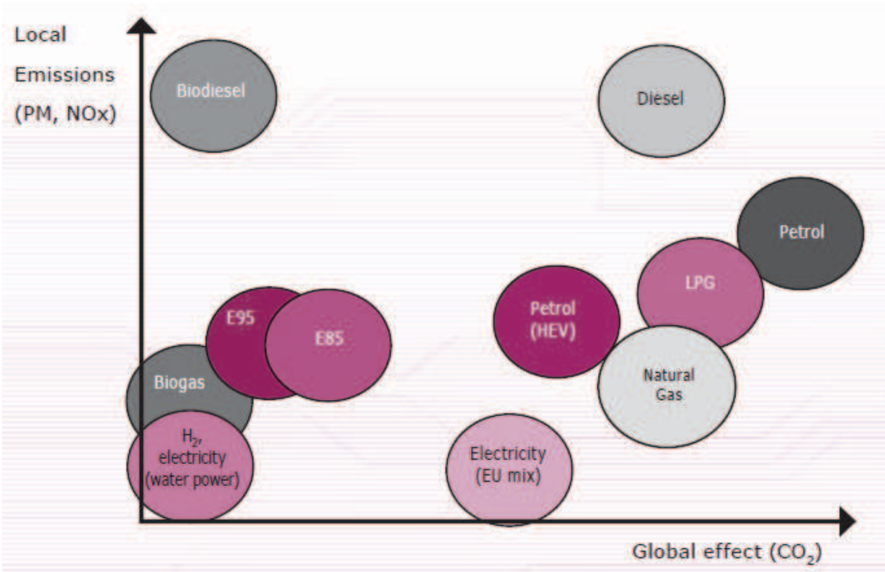


Figure 4: Local emissions in relation to global effects, for different fuels (source: Birath and Sjölin [21])

In addition to these major factors, other factors such as cost, quality, reliability, and lifetime of the powertrain, drive the need for advanced powertrain technologies. These factors play an important role for decision makers to justify their decisions for supporting a specific alternative fuel-technology powertrain. In fact, considering the limited available budgets to support specific alternative fuel-technology vehicles, and also the specific pros and cons of each option for each specific region, decision makers face a critical choice problem regarding the alternative fuel-technology powertrains.

The most used alternative fuel in the world is Ethanol. Brazil and USA have dominated ethanol production and its use, and the two countries together were responsible for 88% of world ethanol production (86 billion liters) in 2010, with the United States alone producing 57% of the world's total (REN21, [22]).

On the other hand, in Europe the production and use of biodiesel is far more developed than ethanol. The expansion of biodiesel in the EU has been truly remarkable with production increasing from 1.93 Mt in 2004 to over 3 Mt in 2005 (UNICAMP, [23])).

More recently, the interest toward adopting hybrid, Plug-in hybrid vehicles (PHEVS) and Battery Electric vehicles (BEVs) has increased substantially, mostly in the USA, China, France and Spain ([8]). BEVs can provide three important benefits: zero emissions of any kind from the vehicle; the possibility to run on an energy source that produces almost zero greenhouse gases; and continued efficiency gains compared to ICE vehicles. PHEVs offer a compromise between pure BEV and ICE vehicles, incorporating both systems. These vehicles are more complex than EVs and are likely to be somewhat less efficient, but they preserve the long driving range offered by ICEs and also offer the flexibility to use either electricity or liquid fuels.

1.5. Policy Context

Many countries have defined targets of shares for AFVs in the mid-term and have implemented or are implementing incentives to achieve those targets. One early example was natural gas vehicles. The use of natural gas vehicles (NGVs), first introduced in Italy in the mid-1930s as an alternative to gasoline-powered vehicles, began spreading to other countries as early as 1940 ([24]). Especially after the energy crisis of the 1970s, NGVs have been promoted by governments in both developed and developing countries as a cleaner alternative to gasoline and diesel vehicles, and also to reduce dependence on foreign oil.

It is estimated that the number of NGVs in use worldwide by the end of 2011 had grown to 15.2 million (NGV Global [25]). According to the same statistics, NGVs have been most successful in the Middle East and Latin America, especially in countries that lack a high capacity to refine oil (Table III). On another estimate, Global NGV sales are expected to rise at a compound annual growth rate (CAGR) of 7.9% to reach 19.9 million vehicles by 2016 (Pike Research [9]).

Table III: Number of Natural Gas vehicles by countries (source: NGV Global , 2011 [25])

Country	Number of Vehicles	% of Total NGVs Worldwide
Iran	2,859,386	18.82%
Pakistan	2,850,500	18.76%
Argentina	1,900,000	12.50%
Brazil	1,694,278	11.15%
India	1,100,000	7.24%
China	1,000,000	6.58%
Italy	779,090	5.13%
Ukraine	390,000	2.57%
Columbia	348,747	2.30%
Thailand	300,581	1.98%

In an article by Yeh ([24]), the adoption of natural gas vehicles (NGVs) in eight countries (Argentina, Brazil, China, India, Italy, New Zealand, Pakistan, and Iran) was compared. New Zealand presents a unique case in what regards the impact of the amount and timing of incentives on the NGV market. In fact, by the mid-1980s, it already had a very successful NGV market as a result of government incentives, loan programs (such as a 100% loan for vehicle conversion), and targets to promote the adoption of NGVs. By 1985, NGVs in New Zealand had a little more than 10% of the market share; Original Equipment Manufacturers (OEM) vehicles were being imported from Japan, Australia, and Europe. However, afterwards policy and political changes led the government to withdraw favorable NGV loan conditions in 1985, and the NGV market eventually disappeared.

In recent years, governments of numerous countries have promoted industrial-scale production and use of liquid biofuels (including ethanol and biodiesel). The policy to promote biofuels is being justified by their supposedly positive effects on climate, energy, and agricultural policy goals. Some argue that an increased use of biofuels could contribute to sustainable development by reducing greenhouse-gas emissions and the use of non-renewable resources, though this is disputed and seems to depend heavily on the type and "production history" of the biofuel.

In the EU, the Renewable Energy Directive (2009/28/EC) ([26]) has set an overall binding target to source 20% of the EU energy needs from renewables such as biomass, hydro, wind and solar power by 2020. As part of the overall target, each member state has to achieve at least 10% of their transport fuel consumption from renewable sources (including biofuels).

In 2006, total transfers in support of biofuels associated with policies of the EU and the Member States were around € 3.7 billion (see table IV). This is probably a gross underestimate of the total amount of support provided, as many subsidies are under-reported.

Table IV: Support for ethanol and biodiesel in the European Union in 2006 (source: Kutas et al, [27])

	Units	Ethanol	Biodiesel
Total transfers	millions €	1290	2436
Support per liter consumed	€ / liter	0.74	0.50
Support per gigajoule (GJ)	€ / GJ	35	15
Support per liter of petrol or diesel equivalent	€ / liter equivalent	1.10	0.55

Currently, policies including biofuel production subsidies, tax exemptions, mandatory minimum share in total transport fuel obligations, and blending mandates continue to support liquid biofuels for use in the transport sector. Biofuel obligations and mandates are in place in at least 46 countries at the national level and 26 states and provinces since 2012. Blending mandates now exist in at least 23 countries at the national level and in 26 states/provinces (Table V).

Table V: National and State/Provincial Biofuel Blend Mandates in selected countries (source: REN21[22])

Country	Mandate
Brazil	E18–25 and B5
Canada	National: E5 and B2. Provincial: E5 and B3–5 in British Columbia; E5 and B2 in Alberta; E7.5 and B2 in Saskatchewan; E8.5 and B2 in Manitoba; E5 in Ontario
China	E10 in nine provinces
Germany	E10
Portugal	Mandatory incorporation of biofuels for the years 2011–2020, growing up to 10% (in energy content) by 2020 and the mandatory incorporation of biofuel for substitute gasoline of 2.5% (minimum % in energy content) for the period 2015–2020; B7 by 2010
Spain	Mandate for biofuel blend: 6.2% currently, 6.5% for 2012 and 2013;
United Kingdom	B4
United States	National: The Renewable Fuels Standard 2 (RFS2) requires 36 billion gallons of renewable fuel to be blended annually with transport fuel by 2022

Governments are also paying an increasing attention to biofuel sustainability and environmental standards. Several government and non-governmental codes of practice have been implemented. For example, the EU has a strict condition in place for imported biofuels, and the U.S. 2011 Renewable Fuels Standard mandates that foreign-grown feedstock comply with the “renewable biomass” provisions within the law (REN21 [22]).

Policies to support electric vehicle deployment are also starting to appear, although such policies do not necessarily require or imply that the electricity used will be renewable. Several countries have announced targets that together would result in more than 20 million BEVs operating by 2020, i.e., around 2% of light-duty vehicle stocks (REN21 [22]). To reach the defined target, each country defined their own incentive packages for users and private sectors. Table VI provides a summary of relevant incentive packages in selected markets.

Table VI: Comparison of EV/PHEV-related policies in several countries (source IEA [8])

Country	Sales Target	Fiscal incentives	Other comments
China	500 000 cars by end of 2011	Up to USD 8 800 per Vehicle	Incentives available in 12 Chinese cities
France	Up to 2 million stock by 2020; 50 000 purchase order for government Fleet	USD 6 300 (EUR 5 000) tax credit per vehicle	Total funding of USD 1.9 billion (EUR 1.5 billion) includes funding for , battery production and four million recharging points by 2020
Japan	About 1 million sales by 2020 (based on 20% share of LDV sales target)	Up to USD 14000 (JPY 1.3 million) per vehicle	Fiscal incentives can change frequently
Germany	1 million total stock by 2020	No direct incentives at this time	USD 350 million (EUR 285 million) for infrastructure development and battery R&D
Spain	250 000 sales by 2014	Up to USD 7 500 (EUR 6000) per vehicle	Primary focus on Madrid, Barcelona, Seville
United Kingdom	1.5 million stock by 2020	Up to USD 7500 (GBP 5000) per vehicle	Total funding of USD 375 million (GBP 250 million) for low-carbon transport
United States	1 million stock by 2015	Up to USD 7500 per vehicle	US DOE providing R&D funding and grants of over USD 2 billion

1.6. Motivation for the research

The future development of transportation systems is one of the most challenging issues in a framework of sustainable development. Considering the impact of projections in terms of GHG emissions and security of fuel supply, a wide range of possible options for passenger cars can be defined. These are options either using an alternative engine or alternative fuels like biofuels, or a combination of both (such as hydrogen-fuel cell). There are significant differences in terms of their impacts on GHG emissions, local pollution and fuel source availability, but also different requirements in terms of costs and incentives. There is currently a lack of comprehensive analysis methodologies for assessing the effects of each alternative fuel-technology vehicle in terms of pre-described attributes, to compare them and to assist designing policies.

There is thus a need for an integrated framework to assess the influence of different supportive policies to enable decision makers to choose the most effective plan(s).

1.7. Objectives and Research Questions

1.7.1 Objectives of the research

The research described in this dissertation aims at developing a multi-criteria decision making framework for comparing options for the mid-term evolution of individual vehicle fleets in the context of a country, either the current vehicles or alternative fuel-technology ones. As there is no absolute frontrunner technology considering all important attributes such as emission reduction, improvement of fuel availability and transition cost, policy makers are in urgent need of an aiding tool that can provide justifiable reasons for identifying the "best" policy in a given geographical and socio-economic context.

The envisioned users of this multi-criteria decision making tool are the policy makers of a region or a country, or whoever intends to perform an evaluation in the perspective of the general interest of the society, rather than in the specific perspective of an interest group. This framework will enable the identification of the most promising alternative fuel/technology options for passenger road transportation, in order to tackle issues such as global warming and oil supply uncertainties.

Moreover, the policy maker needs support on the important attributes that can be affected by the choice between alternative fuel/technology vehicles. It is essential for him/her to incorporate the interests of all related parties such as individuals, manufacturing companies, environmentalists and so on. Policy makers also require scientific support for identifying parameters that can potentially affect the adoption of AFVs. Considering budget limitations, it is crucial for him/her to recognize the most effective supports to the users and investors in order to leverage the market toward the intended solutions. Obviously, the amount of transition costs and duration of support for each alternative fuel vehicles are critical factors for decision makers, which may also affect the choice of the options to support.

One of the main goals of this research is to develop a framework using system dynamics, to analyze the requirements of a successful transition for the adoption of alternative fuel vehicles. This tool should support the analysis of the co-evolution of the refueling infrastructure and AFV sales, and should have the potential to support the decision maker regarding the impact of supportive plans.

Another critical issue for the policy makers is the impact of transition cost analysis on the decision making regarding the AFVs and how much it can affect the identification of the most promising alternative fuel/technology options. In this study, the purpose is to investigate an integrated approach to be able to incorporate the results from transition analysis into the multi-criteria decision making process. The applicability of the developed method in this thesis was tested by using Portugal as a case study.

1.7.2. Research Questions

To guide this work, a set of research question was defined based on the main problem characterized in the previous sections, and they are addressed along the work. Two central general research questions were identified for this study:

1. *How to identify the preferred alternative for fuel/technology drivetrains, in a multi-criteria analysis environment (assuming these alternatives are available)?*

Considering that the most likely situation is that none of the options can maximize all the important criteria, decision makers should be informed on how to identify the alternative for fuel/technology drivetrains that presents better trade-offs regarding their preferences. This multi-criteria perspective will enable the decision maker to include his/her preferences using a trade-off analysis approach.

2. *How do transitional issues affect the decisions regarding the adoption of alternative fuel vehicles?*

There are numerous discussions on the effect of the transitional issues on the choice between alternative fuel vehicles. This study tries to analyze the transition period for the adoption of alternative fuel-technology vehicles and to identify the most important transitional factors that can potentially affect the result of the decision. In the end it is intended to assess if the inclusion of the systems dynamics model in the Multi-Criteria Decision Analysis (MCDA) process results in added value or not.

1.8. Structure of Thesis

The research started by trying to understand the main issues around the development of a multi-criteria decision aid tool for alternative fuel-technology vehicles. This was formalized by a review of the context of the problem and the identification of the key research questions, the scope of the research and the main assumptions, as reported in sections 1.7 and 1.8.

Chapter 2 deals with the literature review and overall vision of the work. A detailed bibliographic review on existing approaches for comparing vehicle fleet options is reported in the first section of chapter 2. This review covers the Life Cycle Analysis (LCA) approach, vehicle's choice models and decision making techniques. This review is followed by a brief presentation of the three phases of this research including a multi criteria analysis, a transition analysis and an integrated analysis. The last subchapter discusses the expected results from each phase the research.

The focus of chapter 3 is on the first phase of this research that aims at developing a multi criteria analysis approach for alternative fuel technology vehicles. The problem was structured at the beginning of this chapter in a way that a first step is the identification of alternatives. It follows by the identification of the objectives according to the decision maker's interests. Afterward, a methodology is proposed to identify the relevant attributes that represent the general interests of the decision makers when deciding about alternative fuel-technology vehicles. For this, a process involving a comprehensive literature review followed by a discussion with decision makers is presented in chapter 3. To reach the final attributes, not only the interest of the policy maker, but also the interest of individuals was considered. After identifying the attributes, the process follows to quantify the attributes for each AFVs. Both the methodology and its application are described in section 3.2. Regarding the decision making technique, and based on a literature review on available approaches, MAUT (Multi-Attribute Utility Theory) was selected for this study, mainly because it could enable the decision maker to clearly express preferences over tradeoffs. In order to facilitate the process of decision making among alternatives, a screening procedure was developed that can help the DM to concentrate on a smaller set of alternatives that (very likely) contains the best alternative. The full description of the methodology is explained and illustrated using data from Portugal in sections 3.3 and 3.4.

After identifying the preferred AFV, it is clear that a movement away from a petroleum-based system to one of alternative fuel-technology drivetrains requires many changes or decisions to occur in parallel. For instance, not only would vehicle manufacturers need to offer AFVs for sale, but the fuel would need to be produced and distributed to a network of fuel stations sufficiently dense to supply the vehicles. In addition, the successful development of such alternatives may require changes to the current legislative and taxation frameworks.

Considering the importance of analyzing the transition for the adoption of AFVs, a System Dynamics (SD) approach was applied to investigate the relation between the development of the refueling infrastructure and the AFV sales. The model was then improved by adding an optimization module in order to estimate the relevant transition cost for the alternatives in the screening set. A complete description of the model and its results is discussed in chapter 4, which has a case study application of the methodology for Portugal.

After identifying the transition cost for each alternative of the screening set using the system dynamics model, it was noticed that there are significant differences between the result of SD models and the initial estimation. Therefore, it seems necessary to investigate the possibility of inputting this outcome in the multi-criteria comparison framework. Accordingly, in chapter 5 an iterative procedure was proposed to use this information to update the inputs to the multi-criteria comparison framework. Then, the developed multi-criteria comparison framework was re-applied for comparing all the alternatives combining up to four technologies in order to identify the updated screening set of alternatives. The new alternatives in the screening set are defined as the new targets for system dynamics model and the relevant transition costs will be calculated. This iterative analysis continues until there is no new alternative in the screening set. This approach is explained thoroughly in section 5.1 and the outcomes for Portugal are presented in section 5.2.

The general key findings and achievements of the research, and the discussion over the results for Portugal and future steps for this research, are presented in chapter 6.

Chapter 2 - Research strategy and phases

2.1. Introduction

The research described in this dissertation aims at developing a multi-criteria framework for the evaluation of alternative fuel/technology options for light-duty vehicles, in a mid-term horizon. Such a framework is intended to assist policy makers and governments to take sufficiently in advance, informed and sound decisions regarding the next twenty years, concerning the development of infrastructures, including the establishment of incentives. The framework is developed for reasonably large geographic areas (countries or regions), in the perspective of "the society's interest".

The alternatives to be considered for choice range from the expected evolution of current combustion technologies (gasoline and diesel engines) to technologies that are under development and nearing the maturing phase, as the electric and the hydrogen fuel-cell vehicles. Since many of the developers of these technologies are asking for public support, it is important to identify "which one or which combinations do better suit the public interest".

The next critical step for developing a multi criteria decision aid framework is to identify the objectives that can represent not only the interest of the Decision Maker (DM), but also the interest of individuals. To assess the significance of alternatives and make value tradeoffs between the different objectives, it is necessary to identify a measurement procedure for each objective. We refer to such a measurement as an attribute.

Before presenting a brief description of the first phase of the multi-criteria decision framework, a literature review of the approaches on vehicle fleet planning is presented and the choice of the research methods justified.

2.2. Brief survey on existing methods for comparing vehicle fleet options

As a result of reviewing many articles in the context of comparing vehicle fleet options, it was well understood that one of the most popular approaches on comparing alternative fuel-technology vehicles is the Life Cycle Analysis (LCA). A true LCA tries to assess consequences related to alternative fuel-technology vehicles. It examines every stage of a product's life cycle, from raw materials acquisition, through manufacturing, distribution, use, reuse/recycling and final disposal. This review starts with reviewing the fundamentals of LCA, followed by some of the applications on assessing alternative fuel technology vehicles including the Total Life Cycle Cost (Cardullo [28]) and the Societal Life Cycle Cost (Ogden [29]). Furthermore, this review highlights the key attributes that are usually considered crucial for policy makers.

2.2.1. Literature on Life Cycle Analysis and its application on Alternative Fuel-Technology Vehicles

There are several ways on how to assess alternative fuel/technology vehicles and Life Cycle Analysis is one of the most popular approaches. There has been significant efforts to compare vehicle fuels and vehicle technologies on a full LCA, "cradle-to-grave" basis, including the GREET Model (Wang [30]), Total Life Cycle Cost (TLCC) analysis (Cardullo [28]) and Societal Life Cycle Cost (Ogden [29]).

Life cycle assessment is a "cradle-to-grave" approach for assessing industrial systems. "cradle-to-grave" begins with the gathering of raw materials from the Earth, to create the product, and ends at the point when all materials are returned to the Earth. LCA evaluates all stages of a product's life from the perspective that they are interdependent, meaning that one operation leads to the next. LCA enables the estimation of the cumulative environmental impacts resulting from all stages in the product life cycle, often including impacts not considered in more traditional analyses (e.g., raw material extraction, material transportation, ultimate product disposal, etc.). Figure 5 illustrates the possible life cycle stages that can be considered in an LCA and the typical measured inputs and outputs (SAIC [31]).

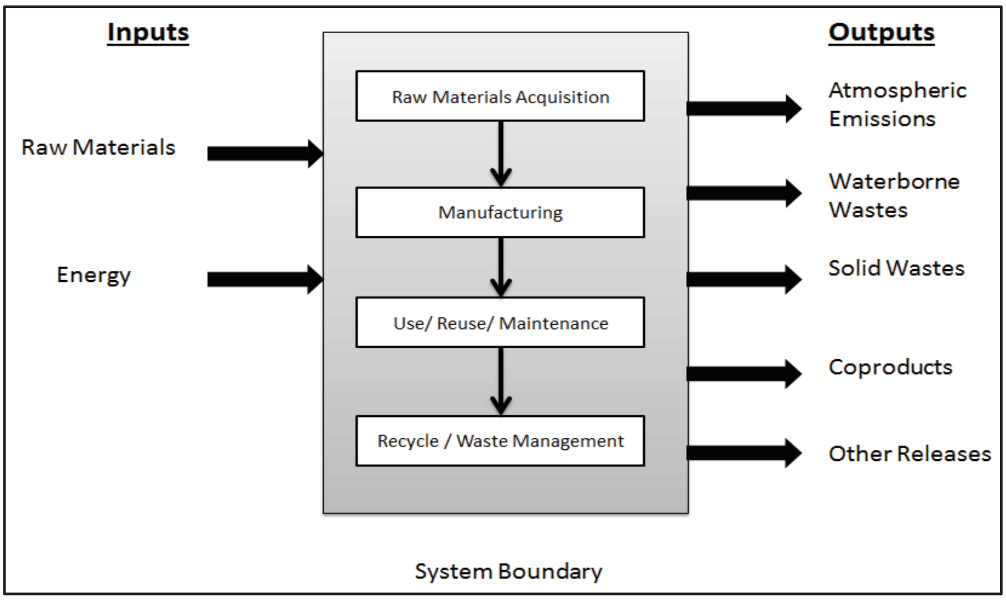


Figure 5: Life Cycle Stages (source: EPA, [32])

A typical LCA consists of four stages: a) Goal Definition and Scope; b) Inventory Analysis; c) Life Cycle Impact Assessment; and d) Interpretation, as defined by the International Standardisation

Organisation: 1997 Environmental Management – Life Cycle Assessment – Principles and Framework (ISO 14040 [33]). Figure 6 illustrates each stage of a typical LCA and the linkage between them.

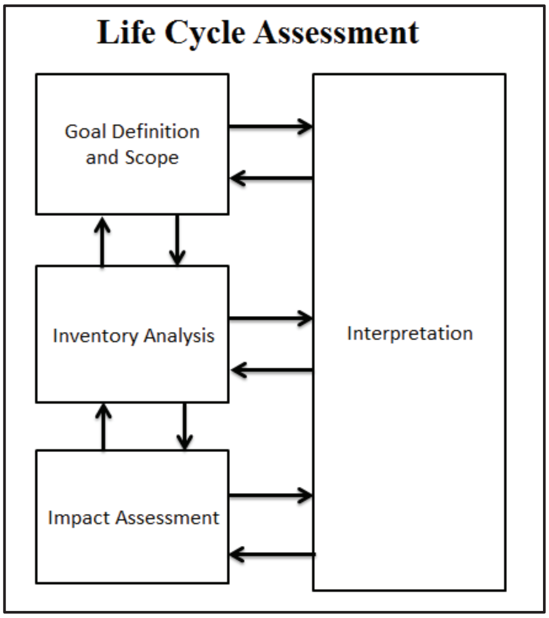


Figure 6: Life Cycle Assessment Framework (source: Forbes et al, [34])

By adopting a holistic approach, LCAs avoid the problem of changing environmental impacts. This is to say that any positive and negative impacts through a products life system are combined to produce a net impact; the significance of these impacts becomes apparent when comparing various vehicle and fuel combinations.

Goal and Scope Definition

The goal of an LCA study shall explicitly state the intended application, the reasons for carrying out the study and the intended audience – ISO 14041 ([33]). The scope of the LCA defines the system boundaries. In theory a full LCA would include all upstream and downstream processes associated with the production and use of the vehicles and vehicle fuels. For the purpose of the study by Finnegan, ([35]), the vehicle fuels and vehicles are compared on a full LCA, "cradle-to-grave" basis. It becomes clear to see that two separate cycles exist (see figure 7):

- fuel cycle
- vehicle cycle

The cycles are linked and define the system boundaries, together with the stages to be considered in the Inventory Analysis. The fuel cycle consists of six stages (F1-F6), and the vehicle cycle contains four stages (V1-V4). Both cycles can be used descriptively to document each stage within the life cycle of any fuel and vehicle combination. This includes the life cycle of traditional and alternative fuels. Within each stage the emissions are analyzed. At any given stage (e.g., F4), a detailed analysis is available, together with a breakdown of the percentage contribution the stage makes to the overall LCA.

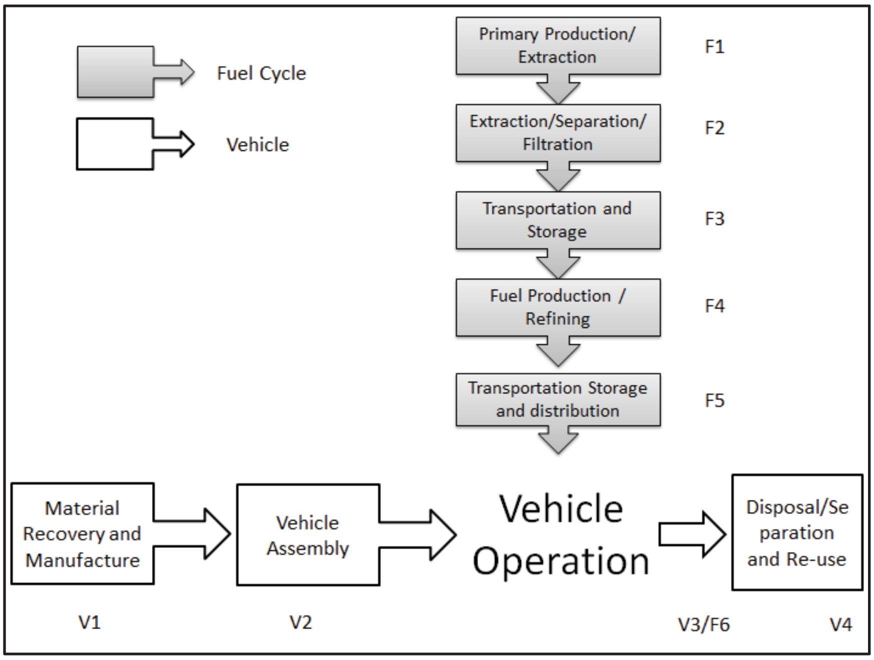


Figure 7: LCA Fuel and Vehicle Cycle (source: Finnegan [35])

Other LCA studies have produced fuel and vehicle cycles, the first of these models being the GREET Model 1.5a, (Wang ([30]) (figure 8)).

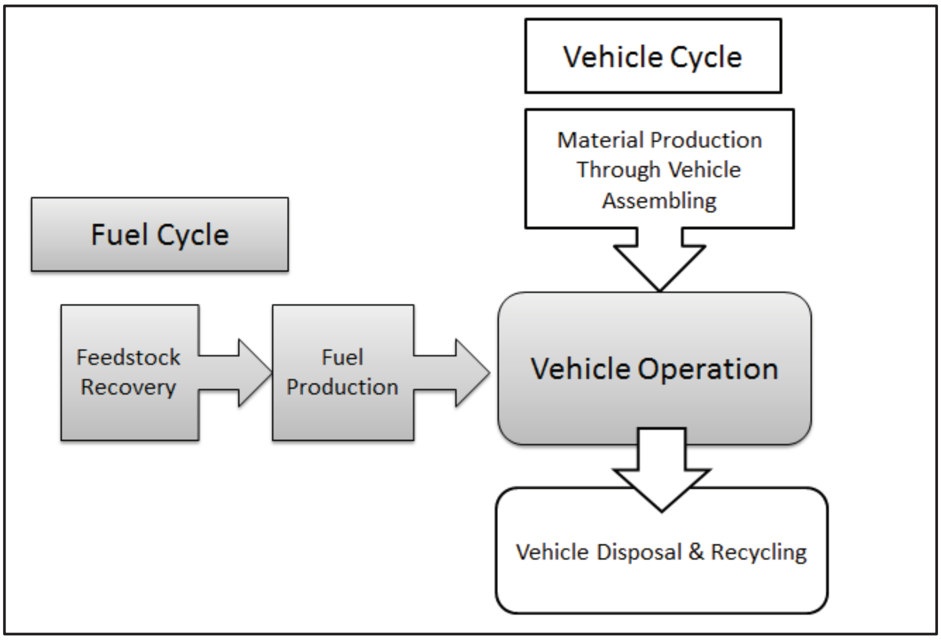


Figure 8: LCA GREET Model 1.5a (source: Wang [30])

To-date GREET is the most widely used LCAs model, from a transportation point of view, in America, with a European version currently being under preparation. Other LCA studies world-wide use the model as a template for their own work - see General Motors, et al., ([36], [37]), Bandivadekar A., et al., ([38]), Ahlvik P., and Brandberg A., ([39]), Hackney J., and R. de Neufville, ([40]), Maclean et al., ([41]), Tahara K., et l., ([42]), Delucchi ([43]).

Inventory Analysis

Inventory Analysis gathers data on the environmental burdens associated with the product. An inventory is simply a listing of how much energy or material is used during the life cycles and how much waste is generated. In order to draw comparisons and allow an interpretation, LCA relates each environmental burden to the same functional unit, e.g., per giga-joule (GJ) of final product, where this typically is a fuel.

Impact Assessment

With many LCAs a conclusion can be reached on completion of the Inventory Analysis. However, for more complex LCAs, it becomes necessary to assess the environmental burdens. Typically, the burdens are grouped, and estimations are made of their individual contribution to that particular environmental impact. This process is referred to as "characterization". It allows the most significant burden to be identified. For example, the burdens of concern of a case study could be the environmental impacts of Global Warming Potential (GWP) and Human Toxicity (HT), and in particular their impact on public health. For this LCA, emissions classification occurs by assessing global and local air quality: (1) Greenhouse Gas (GHG) emissions, which contribute to GWP; and (2) Local Air Quality (LAQ) emissions, which contribute to HT. The emissions from each stage are summed over their life cycle followed by an identification of the major and minor contributors to the overall emission output. Energy classification is based upon the total energy use throughout the life cycle.

Interpretation

Throughout an LCA, it is necessary to revise the scope of the study by considering the results emerging from the inventory analysis and impact assessment. Interpretation is used to identify gaps in the data, redirect stages and modify initial goals and system boundaries. Prioritization is needed to assess the environmental impacts and to decide upon the most important category on which to base the assessment.

After reviewing the fundamental background of life cycle analysis, it is important to review the major studies of application of this approach to alternative fuel vehicles.

An article by Cardullo [28] summarizes a TLCC (Total Life-Cycle Cost) model which was developed to take into account the various factors involved in both individual and societal policy decision making. A true total life-cycle cost analysis is an examination of all costs and benefits, including direct (from resource extraction through useful life to disposal or recycling) and indirect (from societal or environmental impacts not internalized in the market) costs.

This TLCC model (figure 9) was designed to provide a tool for an economic comparative analysis of urban passenger vehicle technologies, in an easy to use "desktop" package. The model operates in a linked spreadsheet environment using the Workbook feature of Microsoft Excel®. Each model spreadsheet deals with a specific analytical element of the life-cycle cost analysis. The relationships used are primarily based on work done at the Jet Propulsion Laboratory (JPL) for the U. S. Department of Energy ([44]).

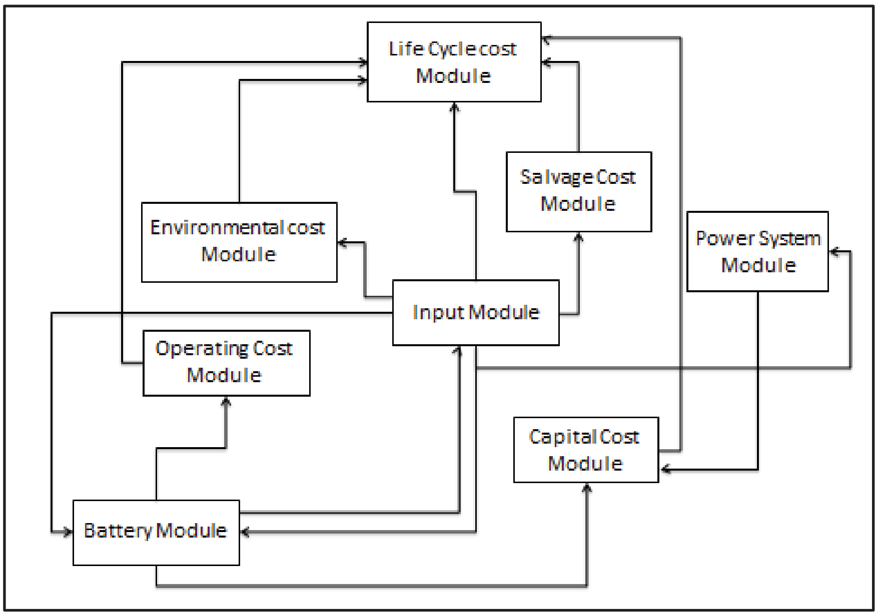


Figure 9: Total Life Cycle Cost Model (source: Cardullo [28])

This TLCC is capable of analyzing the total life cycle costs, including elements that were not considered in former models such as environmental externalities, costs, parametric analysis of battery technologies, impact of alternative fuels, and parametric analysis of advanced conventional vehicle technologies. This model also employs an iterative design procedure for the analysis of conceptual vehicle designs in terms of propulsion system component and power to weight ratio to meet a prescribed set of performance parameters, and it incorporates the ability to analyze buses, vans, and passenger cars with a wide variety of propulsion systems. Other advantages include the fact that this model considers various driving cycles and can easily be expanded to include additional modules such as market penetration, research and development policy alternatives, total fuel cycle cost elements, and international factors and markets. The major related factors for vehicle cost estimation in this TLCC model are listed in Table VII.

Table VII: Main relevant components for cost estimation of AFVs

Main Components	**Components**
Initial Costs	Basic vehicle, Engine, Electric Transmission, Motor, Controller, Engine Transmission, Battery, Fuel Cell, Fuel Tanks
Operating Costs	Replacement batteries, Replacement Fuel Cells, Repairs & Maintenance, Replacement Tires, Insurance, Garage, Parking, Tolls, Title Registration, License, Fuel, Interest
Salvage Value	Vehicle, Battery, Fuel Cells
Environmental Externalities	Hydrocarbons, Carbon Dioxide, Nitrogen Oxide

Cardullo was also planning to pursue the research by incorporating some other fleet-related costs, such as Infrastructure Costs, Energy Security, Domestic Economic Viability and International Competitiveness([28]). A critical finding from reviewing the result of the TLCC model is that the benefits of alternative fuel vehicles are tied to early introduction and use (market penetration) of these vehicles.

A more comprehensive review of the studies adopting the LCA approach is presented in Table VIII.

According to Delucchi ([45]), it is clear that there are numerous factors which can potentially affect the comparison of different pathways. Therefore several factors were selected to characterize the works that were surveyed, including:

- *region*; the country or region covered by the analysis can affect the results (mainly due to the feedstock characterization and already existing infrastructure);
- *time Frame*: the target year of the analysis;
- *transport modes*: the types of passenger transport modes included- LDVs = light-duty vehicles, HDVs = heavy-duty vehicles, LRT = light-rail transit, HRT = heavy-rail transit
- *vehicle drivetrain type*: including ICEVs (Internal Combustion-Engine Vehicles), HEVs (Hybrid-Electric Vehicles - vehicles with an electric and ICE drivetrain), BPEVs (Battery-Powered Electric Vehicles), FCEVs (Fuel-Cell Powered Electric Vehicles);
- *fuels*: fuels carried and used by motor vehicles - FTD (Fischer-Tropsch diesel), CNG (Compressed Natural Gas), LNG (Liquefied Natural Gas), CH2 (Compressed Hydrogen), LH2 (Liquefied Hydrogen), DME (Dimethyl Ether);
- *feedstock*; the feedstock from which the fuels are made;
- *vehicle energy use modeling*: the models or assumptions used to estimate vehicular energy use (which is a key part of fuel cycle CO_2 emissions), and the drive cycle over which fuel usage is estimated (if applicable).
- *vehicle lifecycle*: the lifecycle of materials and vehicles, the lifecycle includes raw material production and transport, manufacture of finished materials, assembly of parts and vehicles, maintenance and repair, and disposal;
- *green House Gases* (GHGs): the pollutants that are included in the analysis of CO_2-equivalent emissions,
- *infrastructure*: the life cycle of energy and materials used to make and maintain infrastructures, such as roads, buildings, equipment, rail lines, and so on. (in most cases, emissions and energy used with the construction of infrastructure are small comparing to emissions and energy used with the land use of transportation fuels);
- *price effects*: this refers to the relationships between prices and equilibrium final consumption of a commodity (e.g., crude oil) and an “initial” change in supply of or demand for the commodity or its substitutes, due to the hypothetical introduction of a new technology or fuel.

Table VIII: Summary characterization of previous studies (updated based on Delucchi [45])

Study	GM-ANL U.S. **(General Motors,et al** [36]**)**	GM-LBST Europe **(General Motors et al.**[37]**)**	MIT 2035 **(Bandivadekar A., et al.,** [38]**)**	EcoTraffic **(Ahlvik P., and Brandberg A.,** [39]**)**	ADL **(Hackney J., and R. de Neufville,** [40]**)**	CMU **(Maclean H. L., et al.,** [41]**)**	Japan **(Tahara K., et l.,** [42]**)**	LEM **(Delucchi (**[43]**)**
Region	North America	Europe	Based on U.S. Data	Weighted to Europe	United States	United States	Japan	Multi-Country
Time Horizon	Near term (about 2010)	2010	2035	Between 2010 and 2015	1996 baseline, future scenarios	Near term	Near term	Any year from 1970 to 2050
Vehicle type	LDV (Light-duty Vehicle)	LDV (European Mini-Van)	LDV (Mid-sized passenger car)	LDVs (generic small passenger car)	Subcompact cars	LDV (Mid-sized sedan)	LDV (generic small passenger car)	LDVs, HDVs, buses, LRT, HRT, minicars,
Vehicle drivetrain	ICEVs, HEVs, FCEVs, BEVs	ICEVs, HEVs, FCEVs	ICEVs, HEVs, FCEVs, BEVs	ICEVs, HEVs, FCEVs	ICEVs, HEVs, FCEVs, BEVs	ICEVs, HEVs, FCEVs	ICEVs, HEVs, FCEVs, BEVs	ICEVs, HEVs, FCEVs
Fuels	Gasoline, diesel, naptha, FTD, CNG, Methanol, Ethanol,	Gasoline, diesel, naptha, FTD, CNG, LNG Methanol, Ethanol,	Gasoline, diesel, FTD, CNG, Methanol, CH2,	Gasoline, diesel, FTD, CNG, LNG Methanol, Ethanol,	Gasoline, diesel, naptha, FTD, CNG, Methanol, Ethanol,	Gasoline, diesel, naptha, FTD, CNG, LNG Methanol, Ethanol,	Gasoline, diesel, FTD, CNG, Methanol, CH2,	Gasoline, diesel, FTD, CNG, LNG, Methanol, Ethanol,

	CH2, LH2, Electricity	CH2, LH2	Electricity	DME CH2, LH2	CH2, LH2, Electricity	CH2, LH2	Electricity	DME CH2, LH2
Primary resource for Fuel Production	Crude oil, coal, crops, lingo-cellulosic biomass, renewable nuclear power	Crude oil, NG, coal, crops, lingo-cellulosic biomass, waste, renewable nuclear power	Crude oil, NG, lingo- cellulosic biomass, renewable nuclear power	Crude oil, coal, lingo-cellulosic biomass, waste	Crude oil, coal, crops, lingo-cellulosic biomass, renewable nuclear power	Crude oil, NG, coal, crops, lingo-cellulosic biomass, waste, renewable nuclear power	Crude oil, NG, renewable nuclear power	Crude oil, coal, lingo-cellulosic biomass, waste
Vehicle Energy Use Modeling	GM simulator,	GM Simulator,	MIT simulator,	Advisor (NREL simulator),	GM simulator,	GM Simulator,	MIT simulator,	Advisor (NREL simulator),
Drive Cycle	U.S. combined city/highway driving	European drive cycle	U.S. combined city/highway driving	New European Drive Cycle	U.S. combined city/highway driving	European drive cycle	U.S. combined city/highway driving	New European Drive Cycle
Fuel LCA	GREET Model	LBST E2I/O Model and database	GREET Model	Literature review	GREET Model	LBST E2I/O Model and database	Literature review	Literature review
Vehicle Life cycle	Not included	Not included	Detailed literature review and analysis	Not included	Not included	Not included	Detailed literature review and analysis	Not included
GHGs	CO_2,	CO_2,	CO_2,	None (Energy Efficiency study only)	CO_2,	CO_2,	CO_2,	None (Energy Efficiency study only)

	CH4, N2O [IPCC] (others as non-GHGs)	CH4, N2O [IPCC]	CH4 [IPCC]		CH4, N2O [IPCC] (others as non-GHGs)	CH4, N2O [IPCC]	CH4 [IPCC]	
Infrastructure	Not included	Not included	Not included	Not included	Not included	Not included	Not included	Not included
Price Effects	Not included	Not included	Not included	Not included	Not included	Not included	Not included	Not included

In addition to the studies presented in table VIII, there is a more comprehensive approach which is called "Societal Life Cycle Cost approach". It compares alternative automotive engine/fuel options not only based on the vehicle first cost (assuming large-scale mass production), fuel costs (assuming a fully developed fuel infrastructure), and damage costs for emissions of air pollutants and greenhouse gases, but also externality costs for oil supply security as assessed over the full fuel cycle (Ogden [29]). According to this definition, the societal LCC can be defined as follows:

Societal LCC ($/vehicle) = vehicle first cost + the present value of lifetime costs (fuel + non-fuel operation and maintenance + full fuel cycle air-pollutant damages + full fuel cycle GHG emission damages + oil supply insecurity).

A major finding of this study was that most advanced options would not be competitive on a LCC cost basis without internalizing externalities associated with air-pollutant and GHG damages and oil supply insecurity risks. But when such externalities are internalized, most advanced options offer lower LCCs than typical new cars, for which externalities account for about half of the LCC under base-case conditions.

There are several advantages in following LCA for comparing AFVs. First of all, it is very convenient to study the impacts from each stage of the fuel cycle in terms of emissions, energy, etc. Besides, a detailed analysis is available, together with a breakdown of the percentage contribution that each stage makes to the overall LCA.

Ideally, the purpose of the LCAs is to analyze and assess the changes in a system considering its entire life cycle. In practice, however, most of the studies do not specify or analyze a policy, but just assume (implicitly) that one simple and narrowly defined set of activities replaces another (Delucchi, [45]).

Besides, there are some other critical concerns about these approaches. First, the decision maker's preferences could be a decisive factor in the comparison process, which cannot be incorporated in the above methodologies. Second, these methods are dependent on the accuracy of the collected data and the low quality of data may result in considerable uncertainty of the conclusions. And finally, in order to have a comprehensive assessment of alternative fuel vehicles, it is crucial to incorporate not only technical parameters but also other points of view, including issues related to social sciences, politics, and ethics.

This review revealed that there are two key different perspectives to tackle the evaluation of alternative fuel-technology vehicles:

- a policy maker's perspective
- a user's perception

In general, the focus of policy makers is on universal issues such as GHG emissions and the security of fuel supply. This approach is adequate when the target is to incorporate the stakeholder's or national-wide DM's concern in the decision making process. On the contrary, looking from the users' perspective requires different analysis, in which the focus is more on vehicle characteristics such as the initial cost, safety and performance.

In the following section (3.1.2), a review on vehicle choice models will enable us to identify the most critical factors on alternative fuel technology vehicle's comparison from an individual's viewpoint.

Considering the diverse set of critical attributes and their potentially diverse characteristics, naturally leads us to a multi criteria analysis. This was our main motivation to apply a Multiple Criteria Decision Making (MCDM) approach in this study. In the following section (2.1.2), some general concepts from decision analysis will be introduced, and some key methods will be briefly presented.

2.2.2. Literature on vehicle choice parameters

An important issue in LDV fleet planning is to understand the perspective of individuals in choosing their forthcoming car. It is crucial to consider the most relevant attributes that represent the interests of individuals in the Multi Criteria Decision Aid framework. This review on vehicle choice models will provide valuable information about a rather complete list of choice parameters that matter for individuals. Besides, it assists us in obtaining awareness on the importance of vehicle characteristics, such as the initial cost and fuel consumption, on the user's decision.

Traditionally, economists and market researchers have been interested in identifying the factors that affect consumers' car buying behaviors, and have developed various models of vehicle type choice to estimate market share. The purpose of a research by Choo and Mokhtarian ([46]) was to explore the impact of travel attitude, personality, lifestyle, and mobility factors on vehicle type choices. They first studied key literature related to vehicle type choice models and vehicle use models. Afterwards they identified the characteristics of their sample and defined a vehicle classification for their study. They reviewed several studies, spanning two decades. Six papers (Lave and Train, [47]; Manski and Sherman, [48]; Berkovec and Rust,[49]; Berkovec, [50]; Kitamura, et al.,[51]; Mannering, et al.,[52]) introduce disaggregate discrete-alternative models such as multinomial logit and nested logit for vehicle type choice. A summary of their survey is presented in tables IX and X.

Table IX: Review on vehicle choice models – Part 1 (source: Choo and Mokhtarian, [46])

Reference	**Lave and Train ([47])**	**Manski and Sherman ([48])**	**Berkovec and Rust ([49])**
Data Location (Year)	7 U.S. cities (1976)	U.S. (1976)	U.S. (1978)
Sample Size	541 new car buyers	1,200 single-vehicle or two-vehicle households	237 single-vehicle households
Model Type	Multinomial logit model of vehicle type purchased	Multinomial logit model of vehicle holdings	Nested logit model of vehicle holdings
Dependent Variable	10 vehicle classes - subcompact - sports - subcompact-A - subcompact-B - compact-A - compact-B - intermediate - standard-A - standard-B - luxury	Chosen alternative plus 25 alternative makes/models/ vintage (randomly selected from 600 vehicle types)	Upper level: vehicle age groups - new (1977-78) - mid (1973-76) - old (1967-72) Lower level: 5 vehicle classes - subcompact - compact - intermediate - standard - luxury/sports
Explanatory Variables Tested	Vehicle attributes - purchase price - operating cost - no. of seats - weight - horsepower to weight Primary driver attributes - age - education Household (HH) attributes - no. of household members - income - no. of vehicles - vehicle miles traveled	Vehicle attributes - purchase price - operating cost - no. of seats - weight - luggage space - acceleration time - vehicle age - turning radius - braking distance - noise level - scrappage rate - transaction-search cost - foreign/domestic Household attributes - no. of household members - no. of workers - income - age - education - location (city or not)	Vehicle attributes - purchase price - operating cost - no. of seats - vehicle age - turning radius - horsepower to weight - transaction cost - manufacturer Household attributes - no. of household members - income - age
Significant Results	- purchase price /income (−) - weight*age (+) - no. of household members (+, for subcompact and subcompact A) - no. of vehicles (+)	- purchase price (−) - no. of seats (+) - vehicle weight and age (+) - acceleration time (+) - luggage space (+) - scrappage rate (−) - transaction-search cost (−) - operating cost and low income HH (−)	- purchase price (−) - operating cost (−) - no. of seats (+) - vehicle age (−) - turning radius in urban (−) - horsepower to weight (+) - transaction cost (+)

Note: the sign in parentheses means a positive or a negative effect on the choice of the associated vehicle type.

Table X: Review on vehicle choice models – Part 2 (source: Choo and Mokhtarian, [46])

Reference	Berkovec ([50])	Kitamura, et al. ([51])	Mannering, et al. ([52]))
Data Location (Year)	U.S. (1978)	South Coast (Los Angeles) metropolitan area (1993)	U.S. (1993 to 1995)
Sample Size	1,048 households	1,898 households	654 households buying new vehicles
Model Type	Nested logit model of vehicle holdings	Multinomial logit model of vehicle holdings (most recent vehicle for multi-vehicle households)	Nested logit model of vehicle purchased
Dependent Variable	Upper level: No. of vehicles (0, 1, 2, and 3) Lower level: 131 vehicle classes and vintages - 10 years (1969-1978) - 13 vehicle classes each year: (domestic) subcompact, compact, sporty, intermediate, standard, luxury, pickup truck, van, and utility vehicle; (foreign) subcompact, larger, sports, and luxury - all models before 1969	6 vehicle classes - 4-door sedan - 2-door coupe - van/wagon - sports car - sports utility - pickup truck	Upper level: Vehicle acquisition type - cash, non-cash (lease, finance) Lower level: Chosen alternative plus 9 alternative makes and models (randomly selected from 175 vehicle types)
Explanatory Variables Tested	Vehicle attributes - purchase price - operating cost - no. of seats - shoulder room - proportion of makes/models in class to total makes/models - new or used Household attributes - no. of household members - income	Primary driver attributes - age - gender - education - employment status - acquisition decision - commute distance Household attributes - no. of household members - no. of workers - no. of vehicles - income - type (single, group) Residence attributes - accessibility (auto, transit) - residential density	Vehicle attributes - purchase price - operating cost - passenger side airbag - horsepower - turning radius - vehicle reliability - vehicle residual value - vehicle size: two-seater, mini-compact, pickup, subcompact, compact, mid-sized, large, minivan, SUV Household attributes - income Brand loyalty - consecutive purchases
Significant Results	- purchase price (−) - no. of seats (+) - proportion of makes/models in class to total make/models (+)	- age (+, for 4-door, 2-door, and van/wagon) - male (− , for all but pickup) - college degree (+, for 4-door) - no. of household members (+, for van/wagon) - income (+, for SUV) - transit accessibility (+, for 4-door)	- purchase price/income (−) - passenger side airbag (+) - horsepower (+) - vehicle residual value (+) - consecutive purchases (+)

Note: the sign in parentheses means a positive or a negative effect on the choice of the associated vehicle type.

Many of the studies reviewed for this report use disaggregate discrete choice models (multinomial logit and nested logit) for the vehicle type choice, and vehicle and household characteristics are mainly considered as explanatory variables in the models. Not surprisingly, the most common variable is vehicle price, which is significant across all the models. After the review, Choo and Mokhtarian ([46]) developed a multinomial logit model for vehicle type choice to estimate the joint effect of the key variables on the probability of choosing each vehicle type. They identified a list of explanatory factors that matter for the choice of vehicle. These factors can be grouped as Vehicle attributes (such as Purchase price, Operating cost, Number of seats, Horsepower to weight ratio, Acceleration time, and Vehicle age), Driver attributes (such as Age and Education), and Household attributes (such as Number of household members, Income, Number. of vehicles, and Vehicle miles traveled).

The key results of their analysis are as follows:

- Those who have a strong attitude toward living in high density region are more likely to drive small cars, while those who are workaholics or do not enjoy personal vehicle travel for short distance are less likely to choose small cars. Those who have higher household incomes are also more likely to choose mid-sized cars, but are even more likely to drive luxury cars and SUVs.
- Similar to the previous studies on vehicle type choice, demographic characteristics are also related to vehicle type choice. The respondent's age is negatively associated with driving small or sports cars and SUVs, and drivers of pickups and large cars tend to be less-educated than drivers of the other vehicle types. Household income is positively related to expensive cars such as luxury cars and SUVs, while personal income is negatively related to small cars. Clearly, the number of people under age 19 in a household is strongly positively associated with minivans, and the number of people aged 65 or older in a household is positively related to larger cars such as luxury cars.

This review provides significant information about the key attributes from the perspective of individuals. Although according to tables IX and X, there is a broad range of variables that are checked/tested to represent the interest of people, it seems possible to choose some variables as decision making attributes based on the fact that their importance for individuals is higher than others.

2.2.3. Literature on Decision Making techniques applied to Energy Policies

From the very beginning of this research, it was decided to consider the planning for alternative fuel technology vehicles as a decision making problem. Therefore, we have reviewed some relevant methods in decision analysis studies for our research domain.

As mentioned in Huang et al [53], decision analysis (DA) was first applied to study problems in oil and gas exploration in the 1960s and its application was subsequently extended from industry to the public sector.

Energy and environmental (E&E) issues are often quite complex and conflict with multiple objectives. These issues generally involve many sources of uncertainty, a long time frame, capital intensive investments and a large number of stakeholders with different views and preferences, making the application of DA methods particularly suitable (Huang et al [53]).

Applications cover a wide range of topics such as alternatives facing the utility industry, energy technology choice, synthetic-fuel policy, commercialization of solar photovoltaic systems, and management of nuclear waste, acid-rain control, and environmental-impact assessments. A survey of different types of DA techniques was first proposed by Huang et al, [53]. This classification was then refined by Zhou ([54]). They classified DA methods into three main groups as shown in figure 10: single objective decision making (SODM) methods, MCDM methods, and decision support systems (DSS).

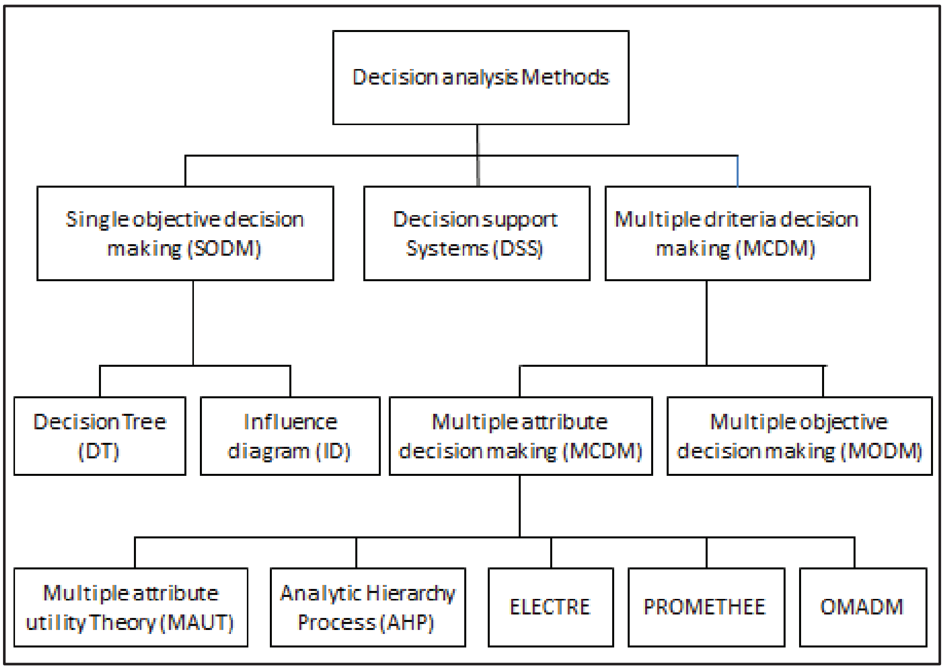


Figure 10: Classification of decision analysis methods (source: Zhou [54])

SODM comprises a class of methods for evaluating the available alternatives with uncertain outcomes under a single objective situation. A classical approach is the decision tree (DT). Another approach, the influence diagram (ID), provides a simpler and more compact representation of decision problems (Howard, and Matheson [55]).

As this research aims at incorporating several criteria in the decision making process, it is crucial to review the methods categorized as Multiple Criteria Decision Making (MCDM) techniques.

MCDM allows decision makers to choose or rank alternatives on the basis of an evaluation according to several criteria. Decisions are made based on trade-offs or compromises among a number of criteria that are in conflict with each other. Multiple objective decision making (MODM) and multiple attribute decision making (MADM) are the two main branches of MCDM.

MODM methods are multiple objective mathematical programming models in which a set of conflicting objectives is optimized and subjected to a set of mathematically defined constraints. The purpose is to choose the ‘‘best’’ among all the alternatives. A special case of MODM is the multiple objective linear programming (MOLP) where the objective functions and constraints are linear functions.

In the case of this research, the goal in general is to identify a set of most preferred alternatives, rather than one best alternative; thus, despite the interesting feature of MODM methods, it is more important to review MADM techniques with further detail.

MADM refers to making decisions by evaluating and prioritizing all the alternatives that are usually characterized by multiple conflicting attributes. Figure 10 shows the more popular MADM methods in E&E studies. Multiple attribute utility theory (MAUT) allows decision makers to consider their preferences in the form of multiple attribute utility functions. This general approach was introduced by Keeney and Raiffa [56], who tried to transform scores at any level into utility functions. In a simple case where there is no hierarchical structure and no interactions between attributes, an alternative would have utility $\sum_i w_i . u_i(x_i)$, where the x_i is typically normalized to a range from the worst to best possible values, and u_i ranging from 0 to 1 reflects the decision maker's attitude towards risk within attribute i. A special case of MAUT is multiple attribute value theory (MAVT) where there is no uncertainty in the consequences of the alternatives.

In the case of a single decision maker who is able to clearly express preferences over gambles and clear tradeoffs for specific levels of achievement across dimensions, this approach facilitates rational choices in the sense that the course of action with the highest expected utility would also be the most preferred alternative consistent with the axioms of decision theory.

The analytic hierarchy process (AHP) (Saaty [57]), and its extension (the Analytic Network Process) is a family of approaches that use pairwise comparisons of criteria, based on making how much more important one is than the other (this is generally thought to be simple, and can be flexible when multiple stakeholders are involved). AHP and ANP can function even with incomplete or inconsistent inputs, by using matrix algebra (involving either eigenvalue-based or similar calculation methods, (Ishizaka and Lusti [58]), to produce weights, overall scores, and measures of consistency. In a more recent article, Saaty et al, [59], give an overview on the main criticisms on the AHP approach, and reply to those criticisms. One of the most critical concerns with illegitimate changes in the ranks of the alternatives is called rank reversal, and can lead to change in the chosen alternative. But this debate is obviously out of the scope of this study (Belton, [60]).

Outranking approaches ELECTRE (Elimination and Choice Expressing Reality) and PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) are methods that essentially involve holding various "votes" across the different dimensions. The range of possible scores for different alternatives is considered within each dimension, to derive alternatives that can be combined across the dimensions. The relative scope of an alternative on a specific dimension is thus a function of how well it compares against the set of other alternatives. Then weights are applied across dimensions to come up with an overall attractiveness for each alternative, which may be interpreted as a level of confidence or agreement or in other ways. Variations on outranking methods have used fuzzy intervals for weights or performance scores, in which outputs can be thought of as probabilistic and dependent on how results of a voting process on various dimensions and across dimensions can change as different values are assumed. In contrast to MAUT, the scores calculated with these two voting-type methods are not usually aimed to identify a single correct answer, but rather to drive a deliberative process between multiple stakeholders (Huang et al, [61]).

Other multiple attribute decision making (OMADM) methods such as the conjunctive and disjunctive methods (TOPSIS) are also popular in practice.

Decision Support Systems (DSS) are interactive, flexible and adaptable software systems that integrate models, databases and other decision aiding tools, and package them in a way that decision makers can use (Turban [62]). A DSS supports the solution of complex and unstructured decision problems that are difficult to handle. In traditional DSS, the users must often depend on their expertise and knowledge in order to choose the appropriate parameters and models. Recent advances in artificial intelligence have led to the development of intelligent DSS that provide more flexibility to the users in dealing with different situations, by incorporating a knowledge base that contains heuristic knowledge from the domain experts.

Considering the features of all the above methods and the aim of this research, aiming at developing a multi-criteria decision making framework, a MAUT approach was selected for this study, mainly because it could enable the decision maker to clearly express preferences and tradeoffs. This approach facilitates rational choices in the sense that the course of action with the highest expected utility would also be the most preferred alternative consistent with the axioms of decision theory.

2.3. Research Phases

Understanding the advantages and limitations of the methods proposed in the literature, the method developed pursued in this work has been structured in three main phases. In this section the approach developed for each of these phases is briefly presented (details are left for the next chapters):

- Phase 1: Initial Multi-Criteria Analysis
- Phase 2: Transition Analysis
- Phase 3: Iterative integrated Analysis

The relation between these phases is shown in figure 11. Initially, a list for available alternative fuel technology options is prepared. This step is followed by identifying the objectives that can better represent the interests of policy makers as well as the interests of individuals. For this purpose, a set of measurable attributes was identified to help us in computing value tradeoffs between achieving relatively more or less on the different objectives. Options on alternative fuel technologies are analyzed in a multi-criteria analysis framework during the first phase of the approach. A set of best alternatives is then identified using a sequential screening approach.

In the second phase, a System Dynamics (SD) approach is applied to analyze the evolution over time of the fleet composition, and to obtain better estimates of some of the attributes used in the MCDA framework of phase 1. This model is used to simulate the co-evolution of the light duty vehicle fleet and the fuel stations, based on the projections about the prices of vehicles and fuels. An optimization module was added to the model in order to assess the impact of different supportive policies. This model is used to estimate the transition costs associated to each alternative of the screening set. The detailed description on how the system dynamics technique was applied for the transition analysis of the AFV adoption is presented in chapter 4.

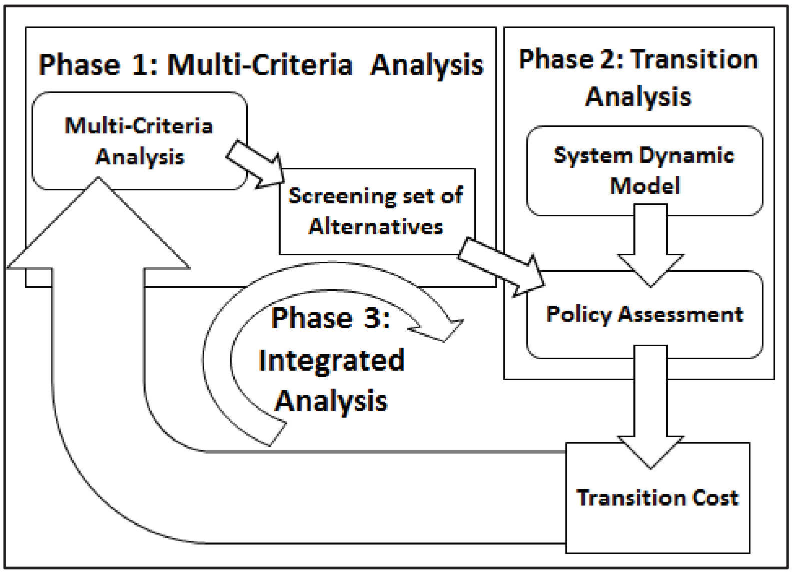


Figure 11: Research phases and their interconnections

After identifying the transition costs of each alternative, the updated information on these costs can be used as an input to the multi-criteria analysis (Phase 3). The next paragraphs provide a more detailed description of each phase.

2.3.1. Phase 1 - Multi-Criteria Analysis

2.3.1.1. Multi-criteria comparison framework

The multi-criteria comparison framework developed in this work performs an analysis based on the following items:

- a list of possible alternative fuel-technology vehicles, such as conventional gasoline and diesel cars, hybrid vehicles and plug-in hybrid vehicles;
- a set of objectives, translated through attributes including vehicle cost, engine efficiency and fuel price

The first stage of this approach was the identification of the alternatives. In this study, it has been decided to define the alternatives as the possible combinations of shares of each fuel-technology for the light-duty vehicle passenger fleet in each year of the horizon. For example, a fleet combination of 25% of vehicles with internal combustion engine using gasoline, plus 25% of vehicles with diesel engine, plus 25% of hybrid electric vehicle, plus 25% of plug-in hybrid vehicles would be a possibility and therefore constitutes a decision alternative.

The second stage will be the identification of the decision objectives, and also classifying the attributes that reflect the objectives. In order to identify these objectives and attributes, several studies have been reviewed. A detailed presentation of this review analysis can be found in section 3.1.3.

A multi criteria decision aid method, MAUT, was chosen to identify the utility of alternative fuel technology vehicles in each selected attribute. Because poor scores in an attribute can be compensated by high scores in another attribute, MAUT is part of a group of MCDA techniques known as “compensatory” methods. Then the procedure pursues by applying a sequential screening process to identify the screening set of alternatives (Figure 12).

2.3.1.2. Sequential Screening

For the basic MCDA problem of choosing the most preferred alternative, it is useful for a decision maker to start by eliminating those alternatives that do not seem to be interesting. This procedure is often called “screening”. Screening helps by allowing the DM to concentrate on a smaller set that (very likely) contains the best alternative. In this work, a multi-stage process was used, starting with a Pareto Optimal (PO) approach, followed by a Data Envelopment Analysis (DEA) based screening and a Trade-off Weights (TW) procedure. Compared to using a single stage screening, this sequential screening procedure seems to be a rather powerful technique (Chen et al.,[63]).

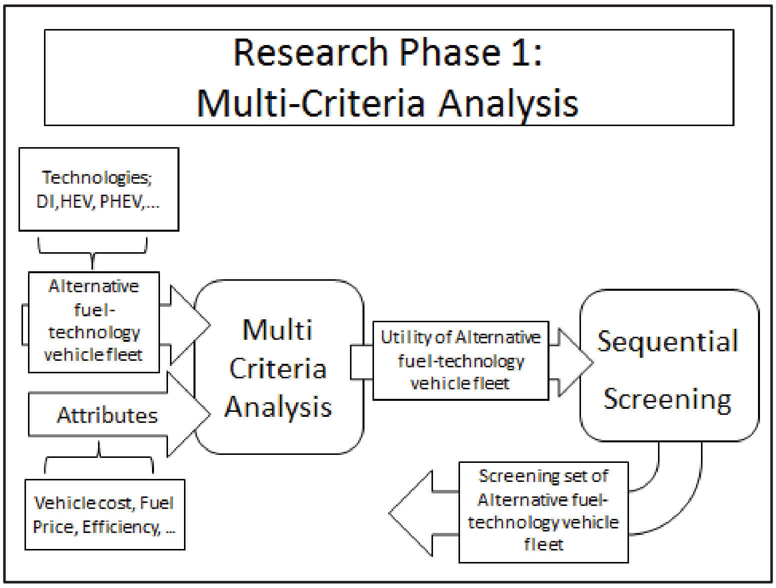


Figure 12: Research Phase 1 - Multi-Criteria Analysis

The output of this phase is a “screened” set of alternatives that provide a higher value over the other alternatives, in a multi-criteria comparison perspective. Each of these alternatives can be chosen as the target for alternative fuel technology vehicle planning of the case study that was used to provide national-level information for the Multi-Criteria comparison.

2.3.2. Phase 2 - Transition Analysis

In the second phase of this study, a System Dynamics approach was applied to analyze the bi-directional interaction between the development of the fuel stations network and vehicle sales. This second phase of the approach has two components; Constructing the System Dynamics (SD) model and Policy Assessment. In the end it produces an updated estimate of some parameters need to achieve a successful implementation of the technology, with emphasis on the transition costs.

2.3.2.1. System Dynamics Model

System dynamics is an approach to interpret the combinatorial complexity of problematic behaviors of a system, which often involve multiple stakeholders, dynamic interacting feedbacks, nonlinearities and time delays. The model developed in this research is based on a previous model that has been developed by Struben at MIT ([64]). A more detailed description of the parameters and feedbacks of the SD model can be found in section 4.2.

It was decided to formulate the model using the VENSIM software. VENSIM is one of several commercially available programs that facilitate the development of continuous simulation models known as system dynamics models. Compared with competing programs, VENSIM is extraordinarily powerful yet inexpensive [65].

We need to design a reliable model - one that matches observed behaviors and is able to effectively support decision making. One of the key-steps of system dynamics models is model calibration, necessary in building a reliable model. In this case, to calibrate the model parameters, we need to collect the historical data for the evolution of light duty vehicles for any given case study (Figure 13).

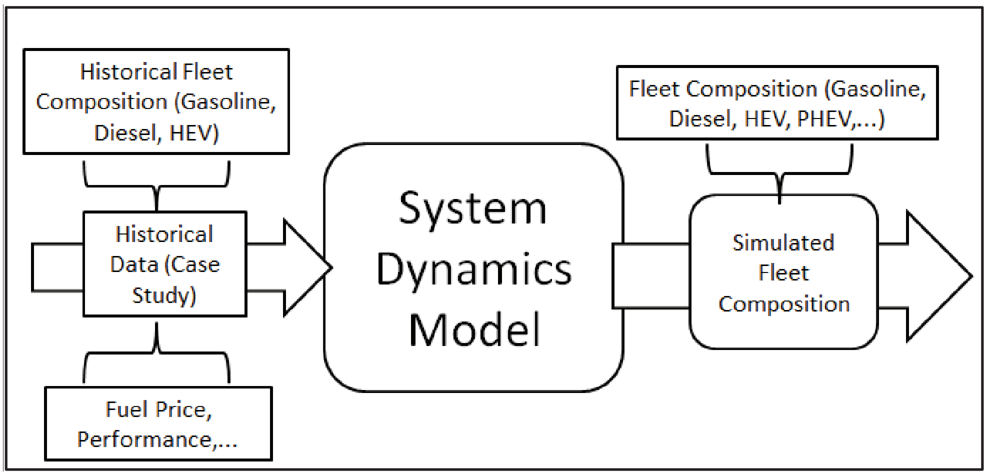


Figure 13: Research Phase 2 – System Dynamics Model

The output of this component is a calibrated SD model to simulate the evolution of the light-duty passenger fleet. Afterwards, a policy assessment module was added to the model, to estimate the transition cost incurred to reach a predefined target (share of alternative fuel vehicles).

2.3.2.2. Policy Assessment

After calibrating the developed System Dynamics model, it will be necessary to estimate the transition costs for the alternatives obtained in the first phase of the multi-criteria analysis. For this purpose, a policy assessment module was added, to support the estimation of the transition cost for a selected alternative fleet combination, for a certain case study.

In this research, the transition cost is defined as the sum of all the discounted incentives required for the transition to take place. These incentives can be either for the initial cost of the vehicle, for the fuel cost or for the fuel stations.

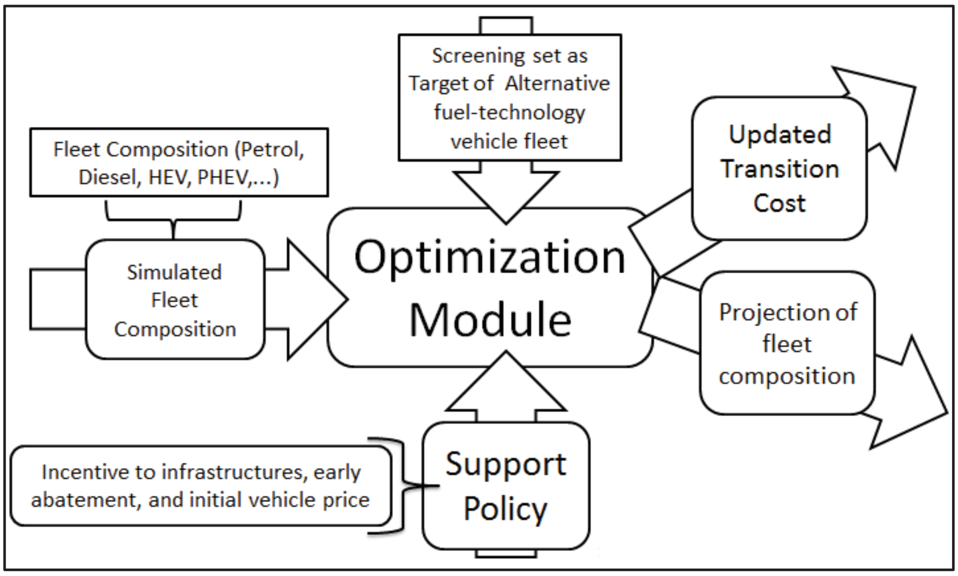


Figure 14: Research Phase 2 – Policy Assessment

The simulated fleet composition is the projection of fleet which can be optimized considering the screening set as the target of alternative fuel-technology vehicle fleet, with the least amount of incentives. The major output of this phase is an updated estimation of the transition costs that can be used to update the results of the multi-criteria comparison in the third phase of this approach.

2.3.3. Phase 3 - Integrated Analysis

The main purpose of the third phase of the approach is to integrate the results of its first and second phases. The need for this third phase is justified by the fact that the attributes for the "potentially best" alternatives may have changed after phase two (system dynamics model). Theoretically, with the new and more realistic values of the attributes (mainly the transition cost), an alternative that had previously been selected for the set of potentially best after phase 1 may after all prove to be not attractive. This procedure thus includes reapplying the developed multi-criteria comparison method of phase 1, using the updated estimated transition costs for screening the set of alternatives. Phase 3 thus essentially consists of a sequence of iterations between phase 1 and phase 2 until convergence is reached, Figure 15 shows the proposed procedure to integrate the different components forming this method.

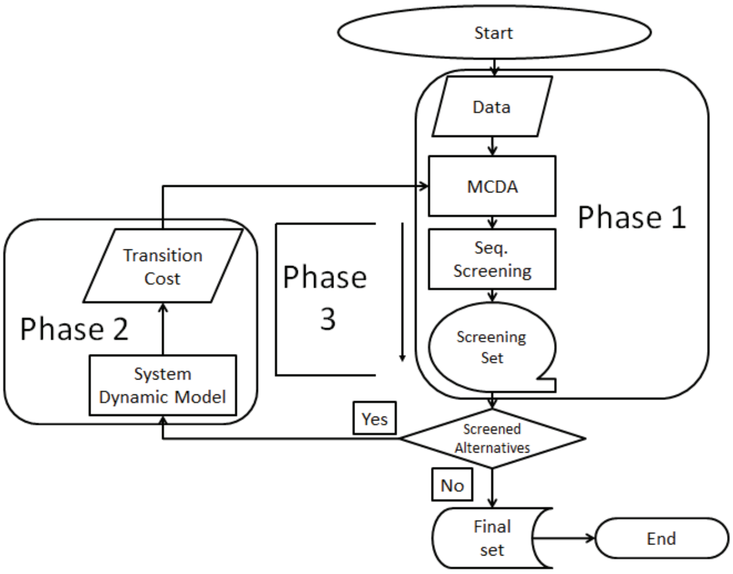


Figure 15: Integrated approach and its three phases

As it was mentioned earlier, this procedure starts with inputting the data to the MCDA module. Applying a sequential screening procedure, a set of screened set of alternatives will be identified. It would be necessary to identify the transition cost for each of the screened alternatives and then reapply the MCDA with the updated information. If new alternatives showed up in the screened set, this iteration must continue, otherwise, the final set of alternatives has been identified and the procedure has converged. A more detailed discussion on the applied procedure and its results is presented in chapter 5.

2.4. Summary of the method architecture

This research aims at developing a multi-criteria comparison framework for alternative fuel technology vehicles. As briefly described in this chapter, this approach has three phases including a multi-criteria analysis, a transition analysis and an integrated analysis.

The first phase of the approach aims at characterizing alternative fuel vehicles. To achieve this goal, a set of alternatives and attributes should be identified. The outputs of this phase are a matrix of values for each alternative with respect to each attribute. Then, a sequential screening approach is applied in order to compare the alternatives according to their impact in each attribute. The outcome includes a set of alternatives that have superior impacts, considering a multi criteria comparison approach (figure 12).

The second phase of the approach tries to investigate the transition for the adoption of alternative fuel vehicles. We have decided to use a System Dynamics approach in order to capture the effect of bi-directional interactions between the development of the fuel stations network and vehicle sales. Another goal of this phase is to estimate the transition cost for each screening alternative that resulted from the first phase. Thus an optimization module was added to compute what supportive incentives are required for the adoption of that specific alternative (figures 13 and 14).

The third phase is an integrated analysis framework designed to incorporate the updated transition cost estimation in the multi criteria comparison context. When the iterative process described in section 2.2.3 has converged, the output will be a final set of alternatives and their estimated transition costs. These alternatives can be used by the decision makers to support the definition of a target for the fleets of light-duty passenger vehicles in 2030.

Chapter 3 - Phase 1: Multi Criteria Analysis

3.1. Introduction

The first phase of this study aims at developing a multi criteria framework that can identify and evaluate alternatives with respect to attributes representing a pre-defined set of decision objectives. As a first step in terms of methodological development of the work, we have reviewed the previous studies on assessing alternative fuel technology vehicles. A comprehensive review on existing methods for comparing vehicle fleet options was presented in section 2.1.

This review started with a very popular approach on comparing alternative fuel-technology vehicles the Life Cycle Analysis (LCA). A true LCA tries to assess consequences related to alternative fuel-technology vehicles. It examines every stage of a product's life cycle, from raw materials acquisition, through manufacturing, distribution, use, reuse/recycling and final disposal. In fact, there are several advantages in following LCA for comparing AFVs, including the convenience of studying the impacts from each stage of the fuel cycle in terms of emissions, energy, etc. On the other hand, there are some other critical concerns about these approaches. First, decision maker's preferences could be a decisive factor in the comparison process, being different to incorporate in the above methodologies. Second, these methods are dependent on the accuracy of the collected data which may result in considerable uncertainty of the conclusions. And finally, in order to have a comprehensive assessment of alternative fuel vehicles, it is crucial to take into account not only technical parameters, but also other factors including issues related to social sciences, politics, and ethics. In fact, the major outcome of this review was getting familiar with the key attributes that are crucial for policy makers.

In order to enhance the inclusiveness of the study, we need to consider the most relevant attributes that represent the interests of individuals in a Multi Criteria Decision Aid content. Therefore, a review on vehicle choice parameters was conducted and the outcome was a list of techno-economic factors that matters for vehicle choice by users. Although there is a broad range of variables that are checked/tested to represent the interests of people, it seems promising to choose some variables as decision making attributes based on the fact that their importance for individuals is more significant than others.

From the very beginning of this research, it was decided to consider the planning for alternative fuel technology vehicles as a decision making problem. The result of the review on decision analysis methods resulted in the selection of a MAUT approach, mainly because it allows the decision maker to clearly express preferences over tradeoffs. This approach facilitates rational choices in the sense that the course of action with the highest expected utility would also be the most preferred alternative consistent with the axioms of decision theory.

After having performed a comprehensive literature survey, we have worked on structuring the problem, and on identifying the alternatives and attributes. This resulted in the model presented in section 3.1. Afterwards the adopted methodology, that includes the multi criteria comparison and screening approach, is presented thoroughly (section 3.2).

In order to test the developed method, Portugal has been selected as a case study. The results and the discussion of this case close the chapter (section 3.3).

3.2. Model Specification

We start here by defining an overall methodology to achieve the objectives set for this discussion. We also aim at carefully structuring the problem, and defining its boundaries and key aspects. This is obviously a first step to help the design of models. Model building is here viewed as a very dynamic process, having several iterations, general discussions and the definition of alternatives and criteria.

3.2.1. Problem Structuring

In order to identify the most relevant issues and also to ensure that the study covers all applicable participants, we here followed a CAUSE checklist [66]:

C – *Criteria*: represent the decision maker(s) or other stakeholders' points of view. There are two main approaches to determine the set of criteria or attributes. We can take a top-down approach that is compatible with 'value focused thinking' where criteria are built in a hierarchical structure, known as 'value tree', leading from primary goals to main (fundamental) objectives, which in turn are further broken down to specific criteria [56]. The bottom-up approach supports 'alternative-focused thinking', where criteria are identified through a systematic process, and may subsequently be grouped in broader categories. In both cases, a rational set of attributes presents the following properties:

- *Value relevance*: attributes are linked to fundamental goals of the stakeholders enabling them to specify preferences.
- *Understandability*: the concept behind each attribute is clear and there is a common interpretation about the preferred direction of the alternatives' performances.

- *Measurability*: the performance of alternatives can be expressed on either a quantitative or a qualitative measurement scale.

- *Completeness*: the set of attributes attempts to cover all important aspects of the problem considered while still being concise and effective.

- *Non-redundancy*: no two attributes reflect the same concept as another, thus avoiding double-counting and over-attributing importance of a single feature.

A – *Alternatives*: are usually thought of as 'given', in the sense that they are a priori and strictly defined. However, alternatives may result from the systematic exploration of the possibilities and options chased in the decision situation considered. An example is available alternative fuel technology powertrain for mid-size vehicles.

U – *Uncertainties*: such as future oil price, annual passenger transport demand and future cost of technologies. These uncertainties can be handled by different methods such as parametric sensitivity analysis and scenario analysis, to study various possible values of the uncertain parameters.

S – *Stakeholders*: or decision maker(s) such as government, local users of the system (current and potential) involved in the decision situation; their perspective on the decisions, and how this will be taken into account.

E – *Environmental factors and constraints*: refers to all those parameters defining the decision context. They may include legislative or cultural aspects, which may broaden or limit the scope of the analysis and impose boundaries in the decision making procedure. Some examples of these constraints are GHG emissions and available investment funding.

In this work, we have followed the CAUSE approach to help problem structuring, starting with the identification of the alternatives, presented in the next section.

3.2.2. Identification of Alternatives

Considering the definition of alternatives proposed by the CAUSE approach, and based on a comprehensive literature review, a list of alternatives and attributes has been prepared to be used as a foundation for the model developed in this study. The focus was then on building a model to be used as a framework for the evaluation of alternatives. Regarding the alternatives, numerous combinations of alternative fuels and technologies exist that can be used in light-duty vehicles. Several fuels such as ethanol, methanol, CNG, LPG, biodiesel, hydrogen, electricity as well as gasoline and diesel, have been investigated. On technologies, beside the current common technologies (the port injection spark ignition engine (PISI), and the direct injection compression ignition engine (DICI)), several other technologies for mid-size light duty vehicles exist, such as the direct injection spark ignition engine (DISI), Hybrid-PISI, Hybrid-DICI, Fuel Cell with reformer (FC-WR) and with no-reformer (FC-NR), Plug-in Hybrid (PHEV), and Battery Electric Vehicle (BEV). In table XI, the possible combinations of fuels/technologies identified for the future engines are presented.

Besides conventional fuels such as gasoline, diesel, LPG and CNG, several other fuels can are becoming available to be used. Methanol (methyl alcohol) is an alternative fuel made from woody plant fiber, coal or natural gas. As a motor fuel, it is mixed with gasoline to produce M85 (85% methanol and 15% gasoline). It can be used either in combustion engines or Fuel-Cell With Reformer (FC-WR) engines. A Fuel-cell with No Reformer (FC-NR) requires hydrogen to run. A blend of up to 85% ethanol fuel and 15% gasoline by volume is called E85 and currently used by flex-fuel vehicles. Another blend fuel is B20 which has 20% biodiesel and 80% petrodiesel. More recently, electricity (re)emerged as a very interesting option to be used as a vehicle power source.

Table XI: Combinations of fuel - engine technology options for light duty vehicles

	PISI	DISI	DICI	FC-NR	FC-WR	Hybrid-PISI	Hybrid-DICI	PHEV	BEV
Gasoline	■	■			■	■		■	
Diesel			■				■		
LPG	■								
CNG	■								
Methanol (M85)	■				■				
Hydrogen	■			■					
Ethanol (E85)	■	■							
Bio-Diesel (B20)			■						
Electricity								■	■

After defining the fleet of alternative fuel technology vehicle as the alternative in this study, the decision variables are naturally the shares of each fuel-technology combination in a LDV fleet. The decision variables are: [x_1 x_2 …. x_n], where x_i (i= 1,2, … , n) is the share of each alternative fuel-technology in a light duty vehicle fleet, with $\sum_i x_i = 1.0$

Since the share of a given variable can is a variable of continuous nature (potentially taking any real value between 0 and 1), the problem would become a continuous one, with an infinite number of alternatives. To overcome this difficulty, a discretization of these alternatives was considered to decrease the calculation time and to render results more useful. Therefore the possible values of the share of each technology were restricted to the following values: 0%, 25%, 33.3%, 50%, and 100%. Complementarily, it was decided that each decision alternative can combine a maximum of four different technologies.

3.2.3. Structuring the Objectives and the Attributes

As it was mentioned above, when using the CAUSE checklist, there are two main approaches to determine the set of objectives. In this research, a top-down approach was adopted as a way to identify the fundamental objectives, that can be organized as a value tree. A value tree decomposes the overall objective of an evaluation into operational objectives, which can be more easily employed to assess the performance of decision alternatives.

Given our focus on alternative fuel technology options for light duty vehicles, the objectives of this research were considered as ([29], [38] [67] and [68]):

i) to minimize the influence of the use of energy on climate change;

ii) to maximize the satisfaction of car owners;

iii) to maximize the security of energy supply;

iv) to minimize investment costs;

v) to maximize the local air quality.

After identifying the fundamental objectives, literature review of the literature was performed, first to identify the most common attributes in those studies and second to check if they are sufficient to cover all the objectives of the current decision making problem. The result of this review is presented in tables XII and XIII, while the attributes have been classified in four main categories: expenses to users; emissions; performance of vehicle; and security of fuel supply (shown on top of the columns). These tables gave us a better understanding about whether or not each attribute implicitly (I) or explicitly (E) has been considered in that study.

Table XII: review on attributes for assessing alternative fuel vehicles – Part 1 (E – Explicit, I: Implicit)

sources	**Expenses for the vehicle owner**			**Emissions**					**Performance of vehicle**										**Security of fuel supply**
	Purchase Cost	O&M Cost	Fuel Cost	CO_2 Emission from Fuel Cycle	CO_2 Emission from Vehicle Operation	Local Air pollution	Global CO_2	GHG Emission from Manufacturing/disposal	Fuel Economy (MPG or L/100Km)	Range	Acceleration Time (0-100 Km/h)	Power - Power to Weight	Energy of manufacturing and disposal	Energy Use - Well to Tank	Energy Use - Tank to Wheel	Refueling Time	Safety	Reliability	Resource availability (Oil Supply insecurity)
[47] Lave and Train	E	E	E									E							
[48] Manski and Sherman	E	E	E								E								
[49] Berkovec and Rust	E	E	E									E							
[50] Berkovec	E	E	E																
[69] Ewing	E	E	E		E				E	E	E				E	E			
[67] Edwards, et al.	E	E	E	E	E	E	E	E	E	I	I			E	E	E	I	I	I
[70] Brownstone	E		E		E	I			E	E	E					E			
[51] Kitamura, et al.	E	E	E																
[52] Mannering, et al.	E	E	E									E						E	
[68] MacLean and Lave,	E	E	E	E	E	E	E		E	E	I	I					E	I	E

Table XIII: review on attributes for assessing alternative fuel vehicles – Part 2 (E – Explicit, I: Implicit) (Continued)

sources	Expenses for the vehicle owner			Emissions					Performance of vehicle										Security of fuel supply
	Purchase Cost	O&M Cost	Fuel Cost	CO_2 Emission from Fuel Cycle	CO_2 Emission from Vehicle Operation	Local Air pollution	Global CO_2	GHG Emission from Manufacturing/disposal	Fuel Economy (MPG or L/100Km)	Range	Acceleration Time (0-100 Km/h)	Power - Power to Weight	Energy of manufacturing and disposal	Energy Use - Well to Tank	Energy Use - Tank to Wheel	Refueling Time	Safety	Reliability	Resource availability (Oil Supply insecurity)
[29] Ogden, et al.	E	E	E	E	E	E	E		E			I					I		E
[71]Yacobucci	E	E	E		E					E		E			E		E		I
[72] Goedecke	E	E	E	E	E	E	E	I	E	I	I	I							E
[73] Brinkman et al.				E	E	E	E	E						E	E			I	
[74] Waegel, et al.	E	E	E	E	E	I	E		E	E							I		I
[75] TIAX				E	E	E	E		E					E	E				
[76] Bandivadekar	E		E	E	E	I	E	E	E		E		E		E		I	I	I
[77] Taylor				E	E	E	E		E	I	I	I		E	E				I
[38] Bandivadekar, et al.,	E		E	E	E		E	E	E	I		E		E	E			I	I
[78]Yang, et al.			I	E	E	I	E		E					E	E				
[79] Grahn and Williander	E		E	E	E		E		E	E					E				
[80] Gunnarsson	E			E	E		E		E	I	I	E		E	E			I	
[81] Baptista, et al.				E	E	E	E	E	E				E	E	E				

Based on the review on the attributes used to compare alternative fuel vehicles, it was easy to identify the most common attributes. These attributes are the purchase price, the fuel price and the vehicle fuel economy, and the emissions from the vehicle. Based on this list of attributes, and following the 'value focused thinking' approach, a 'value tree' was prepared (figure 16).

The value tree shows how the objectives are linked to attributes and eventually to sub-attributes or performance measures. This value tree for evaluating alternative fuel technology options for a LDV fleet presents higher-order objectives at the left of the hierarchy ultimately linked to sub attributes at the right. The important issue is that following the top-down approach, we have been able to identify factors at a lower level (to the right), and these should be a reasonable representation of the set on the left. Besides, according to [82], a consistent set of attributes must be:

- able to discriminate among the alternatives and to support their comparison;
- complete, to include all goals;
- operational and meaningful.

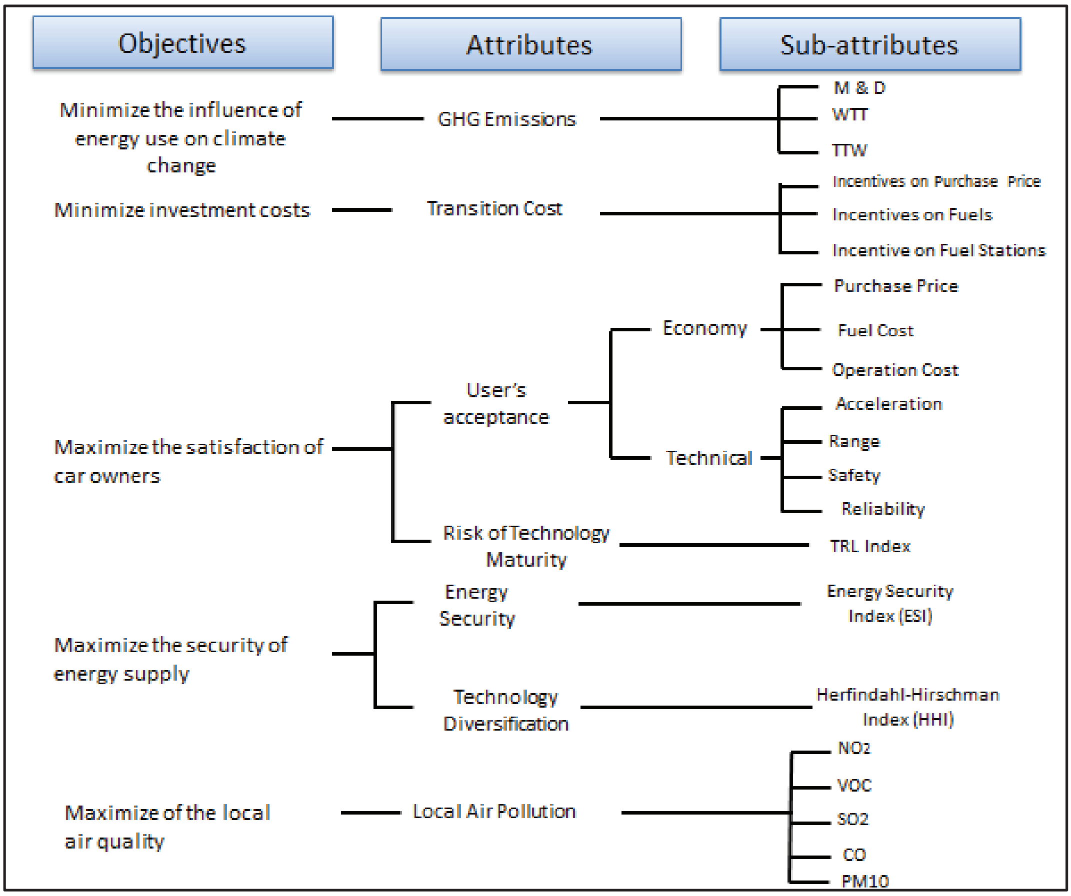


Figure 16: Value tree hierarchy for the selection of attributes

After identifying the key attributes, it seemed logical to group some objectives whose attributes were of the same category. These were the cases of "minimize the influence of the use of energy on climate change" and "maximize the local air quality", which were both translated through the attribute "emissions to Atmosphere"; and of "energy security" and "technology diversification", which were both translated through the attribute "Availability of fuel supply" (figure 17). There were thus five final attributes for the MCDA analysis: Acceptance, Emissions to atmosphere, Transition cost, Risk of technology development, and Availability of Fuel Supply (AOFS).

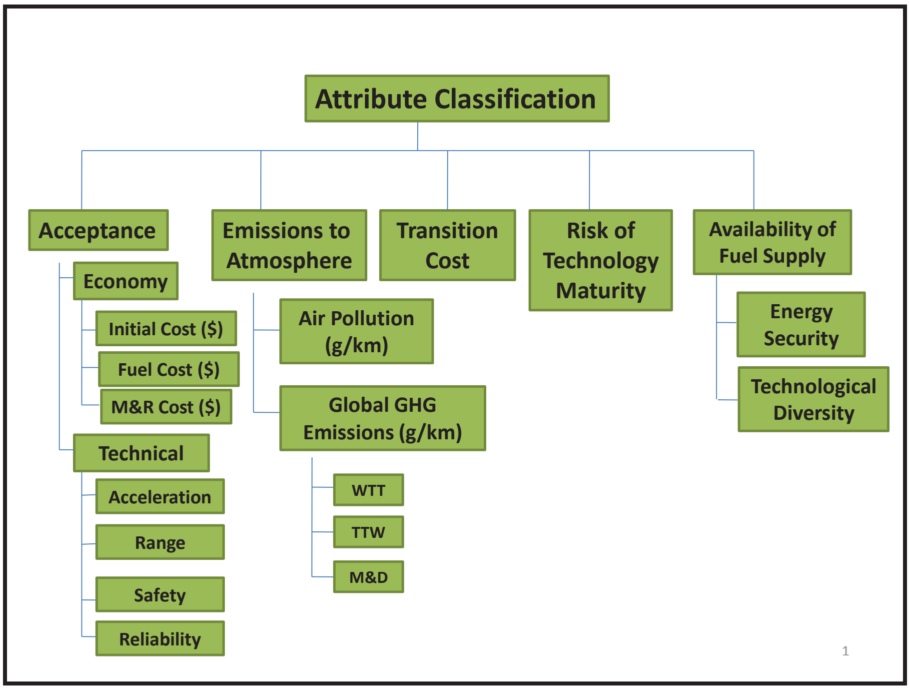


Figure 17: Classification of attributes for alternative fuel-technology vehicles

After classifying the attributes, a detailed description of how to measure alternatives with respect to each of these attributes is presented in the following paragraphs. These also show how the different detailed attributes were merged into the 5 representative ones.

Acceptance

Regarding user's "acceptance", two factors are considered in this work: the vehicle lifetime cost or expenditures and its performance. In order to compare the alternative technologies in terms of lifetime costs, all the costs including the Initial Cost, Maintenance and Repair (MR) Cost and Fuel Cost should be taken into account. The fuel cost is based on the assumption that a fully developed fuel infrastructure is available for all the fuels. In this research, alternatives will be compared based on their Present Value Expenses defined as follows:

$$PVExpenses = ICost + \sum_t \left(\frac{FCost+MRCost}{(1+DR)^{t-1}}\right) \quad (1)$$

Here, *ICost* is the purchase price of the vehicle, *FCost* is the annual fuel cost, and the *MRCost* is the annual maintenance and repair cost.

Besides, *DR* is the annual discount rate and the summation is for the whole lifetime of each vehicle. In the base scenario, it is assumed that *DR* = 8%, the average lifetime of each vehicle is 15 years, with an annual average of 15 000 km.

The data used for calculating the present expenses of each technology was collected from several sources ([38], [71], [72], [74], [76], [79], [80], [83], [84], [85])) and is presented in table LX of Appendix 1.

As there is a significant dispersion of values in the literature especially for the initial price, a set of values representative of this distribution were identified as low, likely and high. In Appendix 1, table LX presents the findings, considering the fact that the "likely" value was identified, assuming 50% as a confidence level (meaning that the specific value can be assumed as a representative for 50% of reviewed references), while the low and high value are simply the lowest and highest values referred by the references.

Besides the vehicle expenses, users are willing to compare different technologies based on their performance characteristics, such as acceleration, range, safety and reliability. For this sub-attribute, the assessment is more a relative one, with respect to the base technology (current gasoline-ICE), rather than an absolute one ([67]).

As presented earlier, in this study we applied the MAUT approach to aggregate the sub-attributes into the main attribute. We noticed that the reasonable weights that can be adopted for aggregating the two sub-attributes of "*Economy*" and "*Technical*" depend on the case study and the preference of the consumers on the vehicle's expenses and its performance. For this work, the values considered for the weights were 40% for *"Economy"* and 60% for *"Technical"*.

Emissions to Atmosphere

"Emissions", have been categorized into two main groups: Green-House Gas (GHG) and Air Pollutants (non-GHG Emissions). The approach taken consisted in comparing the alternatives with their damage cost resulting from GHG and non-GHG emissions. Coefficient factors were based on the results of ([86]) to find the overall damage cost of different pollutants. Information on GHG Emissions for different technologies was obtained from a significant literature review ([67], [68], [67], [69], [74], [38], [41], and [87]). Regarding the Air Pollution data, several articles have been reviewed ([67], [68], [72], [73], [75], [81] and [88]).

Similar to cost estimation, there is, in the literature a significant distribution of values on emissions from vehicles. Therefore a set of low, likely and high values for that distribution were identified and are reported in table LXI, in Appendix 2. A summary of projected data on air pollution resulting from WTW and Material of AFVs in 2030 is presented in table LXII of Appendix 2.

Transition Cost

As for most of the alternatives there will be a need for renovating the fuel supply infrastructures, this attribute allows the comparison of technologies according to the required investment. Relevant data was gathered from several sources ([68], [85] and [89]). The initial estimation for the transition cost of pure technology alternatives after normalization is presented in table LXIII of appendix 3.

In a later phase of this research (chapter 4) , focus will be put on the issue of the transition period, the aim being to incorporate other transitional costs such as incentives for motivating people to choose specific fuels/technologies.

Risk of Technology Development

There exists a considerable risk related to the maturity of the proposed technologies. These technologies are under development and will indeed take a considerable amount of time to become mature for commercial production and application. The Technology Readiness Level (TRL) is a measure used by some United States government agencies and many of the world's major companies, to assess the maturity of an evolving technology prior to incorporating that technology into a system or subsystem. Generally, when a new technology is first invented or conceptualized, it is not suitable for immediate application. Instead, new technologies are usually subjected to experimentation, refinement, and increasingly realistic testing. Once the technology is sufficiently proven, it can be incorporated into a system/subsystem.

By reviewing the literature, the TLR value of different technologies was found for a mid-term horizon ([67], [85], and [90]).

Availability of Fuel Supply

Besides the above issues, availability of fuel supply also became recently a key issue for decision makers. It will be tackled in this work by considering two parameters: energy security and technological diversity. In order to quantify the "energy security", the methodology suggested by [91] will be applied to evaluate the security of energy supply in different countries:

$$\mathrm{ESI}_{\mathrm{price}} = \sum_{\mathrm{f}} \left[\mathrm{ESMC}_{\mathrm{pole-f}} * {}^{\mathrm{C_f}}/_{\mathrm{TPES}}\right] \tag{2}$$

where ${}^{\mathrm{C_f}}/_{\mathrm{TPES}}$ is the share of the fuel mix and $\mathrm{ESMC}_{\mathrm{pole-f}}$ is the energy security market concentration of the targeted market for fuel f.

In order to calculate $\mathrm{ESMC}_{\mathrm{pole-f}}$, the following equation is used:

$$\mathrm{ESMC_{pole}} = \sum_i [r_i * S_{i,f}^2] \tag{3}$$

where r_i is the political risk rating of country i, and $S_{i,f}$ is the share of each supplier i in the market of fuel f ($S_{i,f}$ varies from 0 to 100 percent).

As r_i ranges from 1 to 3, the worst possible level of political stability leads to tripling the country's contribution to ESMC and the best possible level (1.0) does not affect the country's contribution. A more detailed discussion on the calculation of the energy security market concentration for each fuel is presented here, for the case of Portugal.

Oil Based Fuels

Portugal imports oil and related products mainly from 4 countries, namely Algeria, Nigeria, Libya and Saudi Arabia ([92]). The information regarding the political risk rating for these sources was obtained from a report by the PRS Group Statistics, ([93]). So, the ESMC will be calculated for oil based fuels, by equation 3 above.

Natural Gas Based Fuels

According to the latest report on natural gas statistics in Portugal ([92]), Nigeria and Algeria are the main suppliers of natural gas. The same reference was used for information on risk rating factors. The ESMC for Natural Gas based fuels was calculated, applying equation 3 above.

Biofuels

There seems to be a very high potential for domestic biofuel production in Portugal. According to a study on the environmentally-compatible bioenergy potential of EU members ([94]), Portugal has in fact a potential of producing 4.1 MtOE of bioenergy in 2030, from domestic sources including agriculture, forestry and wastes. In the "base scenario", it was assumed that the production capacity will reach 50% of the potential in 2030. In order to identify the related demand of fossil fuels for the production of biofuels, the EROI (Energy Return On Investment) factor was applied ([95], [96]). Another simplifying assumption was that the production capacity for each of these biofuels is the same. The excess demand should be supplied by import. Following the current trend, it was assumed that all the additional required biofuels will be provided from Brazil.

Electricity

In practical terms, Portuguese power generation will evolve in the time horizon of this study, but the focus of this study is to examine the impacts of alternatives on the defined attributes.

The National Renewable Energy Action Plan [97] for Portugal provides a projection for the diffusion of renewable energy sources in different sectors including power generation. This projection was adopted for the base scenario analysis. According to the NREAP, Portugal aims at achieving a share of 60% of renewable energy in the electricity sector. However, for the purposes of the NREAP, the share in the electricity sector will correspond to 55.3%, since it is necessary to account for pumped production in the gross final energy.

Conservatively,, in this study, the value of 55% was chosen as the share of renewable energy in power generation for Portugal in 2030, while the impact of considering a higher value will be evaluated in the section on sensitivity analysis. Besides that, in the situation that the domestic power generation capacity was not sufficient to meet the demand, the additional demand should be imported from Spain. Accordingly, the ESMC for Electricity was calculated using equation 3.

Regarding the technological diversity in the vehicle fleet, the "HHI" (Herfindahl-Hirschman Index) was applied as it is a commonly accepted measure of market concentration ([98]). In order to compare the diversity of alternative technology/fuel options in an LDV fleet, the HHI is calculated by the sum of the squares of the market share of each alternative fuel/technology in the market. Finally, these two parameters (for energy security and technological diversity) are aggregated in order to assess the alternatives from the point of availability of fuel supplies. 3.3. Decision Methodology

As it was mentioned earlier in section 2.1.3 and based on a comprehensive literature review, the MAUT approach was selected for this study, mainly because it could enable the decision maker to clearly express preferences over tradeoffs. In the following section, a more detailed description of the applied decision methodology will be presented.

In order to facilitate the process of decision making among alternatives, a common approach is to eliminate those alternatives that do not seem to be interesting ([99]). This procedure is often called “screening”. Screening helps by allowing the DM to concentrate on a smaller set that (very likely) contains the best alternative.

3.3.1. A Multi Criteria Decision Framework

In order to provide support to decision makers in their search for satisfactory solutions in a multi-criteria perspective, it is necessary to construct a Multi Criteria Decision Aid (MCDA) model to represent decision maker preferences and value judgments. Such preference models contain two primary components:

- preferences in terms of each distinct attribute, i.e., models describing the relative significance or attractiveness of achieving different levels of performance for each identified attribute;

- an aggregation model, i.e., a model allowing cross-attribute comparisons (such as trade-offs), in order to combine preferences across attributes.

As it was discussed before, a very popular approach in this context, the Multi-Attribute Utility Theory (MAUT) was chosen for this research, mainly because it easily incorporates the decision maker's preferences. The basic goal of MAUT is to replace available information by "utility values" allowing the comparison of alternatives ([100]).

Regarding the methodology to aggregate the several attributes, there are two main approaches: additive and multiplicative aggregation. The main advantages of the additive approach are simplicity and the independence to outliers. But, an undesirable feature of an additive aggregation is the full compensability it implies: poor performance in some indicators can be compensated by sufficiently high values of other indicators. On the other hand, multiplicative aggregation is a less compensatory approach.

In an article by Stewart [101], a number of simulation studies are reported in which this is an assessment of the effects on preference ordering of using additive rather than multiplicative aggregation under conditions of mutual utility independence. It appears that errors introduced by using the additive model were in general extremely small for realistic ranges of problem settings, and they were in any case considerably smaller than those introduced by incorrect modeling of partial utility functions.

After structuring a basic MCDA model and understanding the DM preferences, a global model to aggregate those preferences and solve a specific problem (choose, rank or sort) may be constructed. A typical example is the linear additive value function that can be expressed as:

$$V\,(A^i) = \sum_{j \in Q} w_j . v_j(A^i) \qquad (4)$$

where V(Ai) is the aggregated evaluation of alternative Ai, v_j is the value vector for each sub-attribute j, and the w_j the weight vector of sub-attribute j for the aggregation process.

In this model, in order to aggregate the values of sub-attributes, e.g., to determine the value of the attribute "Acceptance", the equation 4 was applied, aggregating the value of vehicle expenses and vehicle performance.

3.3.2. Screening

For the basic MCDA problem of choosing the best alternative, it is useful for a DM to start by eliminating those alternatives that do not seem to be interesting ([99]). This procedure is often called "screening". In practical terms, screening is any process that reduces a larger set of alternatives to a smaller set that (most likely) contains the best choice. Figure 18 illustrates the relation between Screening, Sorting and Choice.

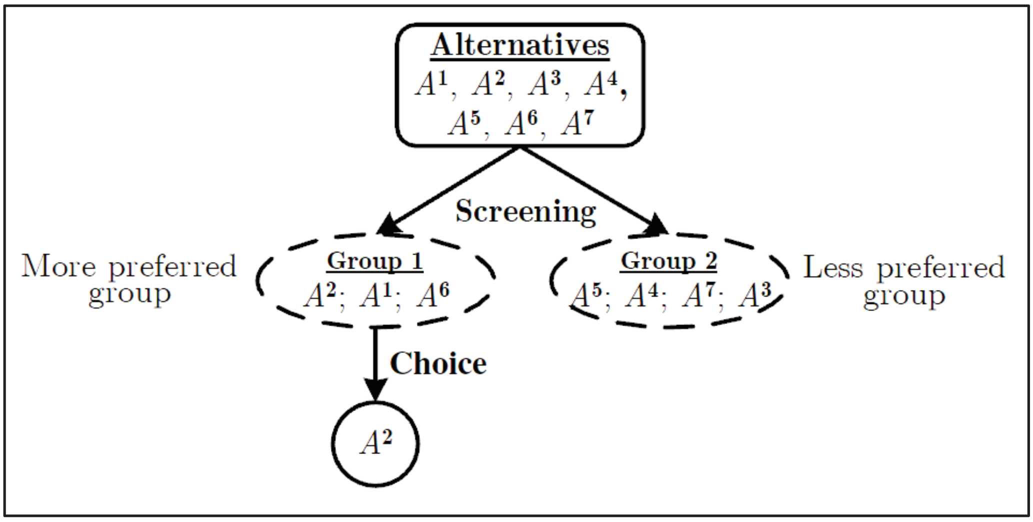


Figure 18: The Relationship among Screening, Sorting and Choice (source: [63])

Several methods can be adopted as a screening tool such as the Pareto Optimal (PO) approach and Data Envelopment Analysis (DEA). As we have decided, in this study, to adopt a a multi-stage screening process, we now briefly review these methods.

Pareto Optimality (PO) Based Screening

Pareto optimality is widely used in economics and in many other fields. It provides a very useful definition of optimality in MCDA as it can be interpreted as taking into account multiple aspects (attributes) for attempting overall optimality. The concept of Pareto optimality in MCDA as expressed by Chen [102] and the procedure he suggests, were applied in this research.

Data Envelopment Analysis (DEA) Based Screening

Data Envelopment Analysis (DEA) is a technique used to measure the relative efficiency of a number of similar units performing essentially the same task. DEA was first put forward in [103] with the basic DEA model, called CCR (after Charnes, Cooper and Rhodes, [103]). CCR assumes that each unit operates with "constant-returns-to-scale". The basic purpose of DEA is to determine which units are efficient and which are not; in MCDA, these can be regarded as non-dominated and dominated alternatives, respectively. Thus, the DEA based screening approach is structured around the following steps:

- identify the preference direction (positive or negative) for each attribute;
- apply a DEA model (usually CCR) to identify dominated alternatives;
- remove dominated alternatives.

It is worth mentioning that several drawbacks for the DEA approach have been identified by Berg [104] , such as:

- results are sensitive to the selection of inputs and outputs;
- poor capability for characterizing the best specification;
- the number of efficient alternatives on the frontier tends to increase with the number of inputs and output variables.

Aspiration Levels (AL) Based Screening

Aspiration-level based screening techniques are techniques using preferred or acceptable consequence levels of the attributes to identify better alternatives (the name was proposed by Lotfi [105]). Techniques such as Goal Programming ([106]), Compromise Programming ([107]) and the Reference Point Approach ([108]) can be regarded as the inspirations of aspiration-based screening. To introduce these methods, Chen [63] classifies them into two categories, simple linguistic methods and distance-based techniques.

Simple linguistic screening techniques use linguistic expressions on attributes as constraints, eliminating alternatives that do not satisfy these constraints. The advantage of this method is that expressions are simple and there are fewer model parameters to specify.

Distance-based screening employs a measure of distance between an alternative and some reference point (ideal alternative or aspiration level) as an index to screen out the alternatives that are too far away.

A more detailed description of these techniques can be found in Chen [63].

To screen alternatives, two options are available to the DM:

- First, the DM can reset one or several aspiration levels. This is useful when the DM is not sure about his aspiration level. Updated nearest nondominated alternatives (maybe the same, maybe not) are obtained based on these aspiration levels. Then only these nearest alternatives remain for further consideration, and all others are screened out.

- Second, if the DM prefers not to express aspiration levels, he/she can request a set of "neighboring" alternatives based on single aspiration levels. All alternatives other than these "neighboring" ones are then screened out.

Tradeoff Weights (TW) Based Screening

Finally, TW based screening techniques are related to research areas such as sensitivity analysis ([108, 109,110]) and potential optimality ([111], [112]). Chen [102], reorganized these methods and put forward a systematic screening method, Tradeoff Weights (TW) based screening, that underlies the existence of tradeoff weights. The method works as follows:

- check the validity of the linear additive preference function assumption;
- obtain the preference functions and values for each alternative;
- for each alternative apply Mathematical Programing to examine the optimality potential (the mathematical program proposed by Geoffrion [113], can be used to determine whether that alternative is potentially optimal);
- keep only the potential optimal alternatives.

As it was mentioned earlier, in this work, a multi-stage screening process was applied, starting with a PO screening approach, followed by a DEA based screening and a TW procedure. This seems to be a rather powerful sequential screening technique ([63]).

In order to apply the DEA screening approach, the Efficiency Management System (EMS) ([114]) tool has been adopted.

For the DEA approach, instead of one model configuration, three combinations of input-outputs have been analyzed in order to lower the sensitivity of results on the selection of inputs and outputs. Details on these three input-output combinations are presented in Appendix 4. The inputs and outputs should be selected appropriately so as to express the performance of alternatives. Variables considered to be desirable are normally treated as outputs, and those considered to be undesirable are treated normally as inputs ([115]).

Regarding the TW procedure, a simple linear programming model has been developed in Microsoft Excel. The objective function is defined to check if the overall utility of a certain alternative would become superior than any other alternative with a feasible set of weighting parameters. Basically, the weighting factors are bounded to be non-negative and lower than 100%.

Moreover, the following conditions have been added to the mathematical model used in exploring the potential optimality of alternatives:

- the lower limit of weights for each attribute is 10%, as a way to remove the alternatives that are extremely weak in one attribute;
- the higher limit of weights for each attribute is 50%, thus avoiding excessive biased weighting of a specific attribute.

3.4. Results and Discussion

3.4.1. Base Scenario

This phase of the research aims at developing a multi-criteria decision aid model, to identify the utility values of each alternative, for each group of attributes. Then, a multi-stage screening approach is adopted to identify the screening set of alternative fuel/technology vehicles. In this research, an M file has been developed in MATLAB environment to estimate the utility of alternatives in the five key attributes according to the presented formulation (section 3.2.3.). It also enabled us to remove the dominated alternatives. As mentioned before, in order to estimate the efficiency of the alternatives based on DEA approach, the EMS tool has been used. Finally, according to the TW procedure, it is important to check the potential optimality of the alternatives, what was done using the Excel Solver.

To illustrate the approach, Portugal was chosen as a case study. The key factors describing the base scenario are the following:

- annual travelled distance = 15000 Km;
- discount rate = 8%;
- GHG damage cost = 20 Euro/tonne-CO_2 Eq;
- average vehicle lifetime = 15 years;
- Number of passenger light-duty vehicle = 5365000 (PNAC [116]).

Figure 19 shows the results of analyzing the pure alternative fuel technology vehicle fleets in a multi criteria comparison perspective.

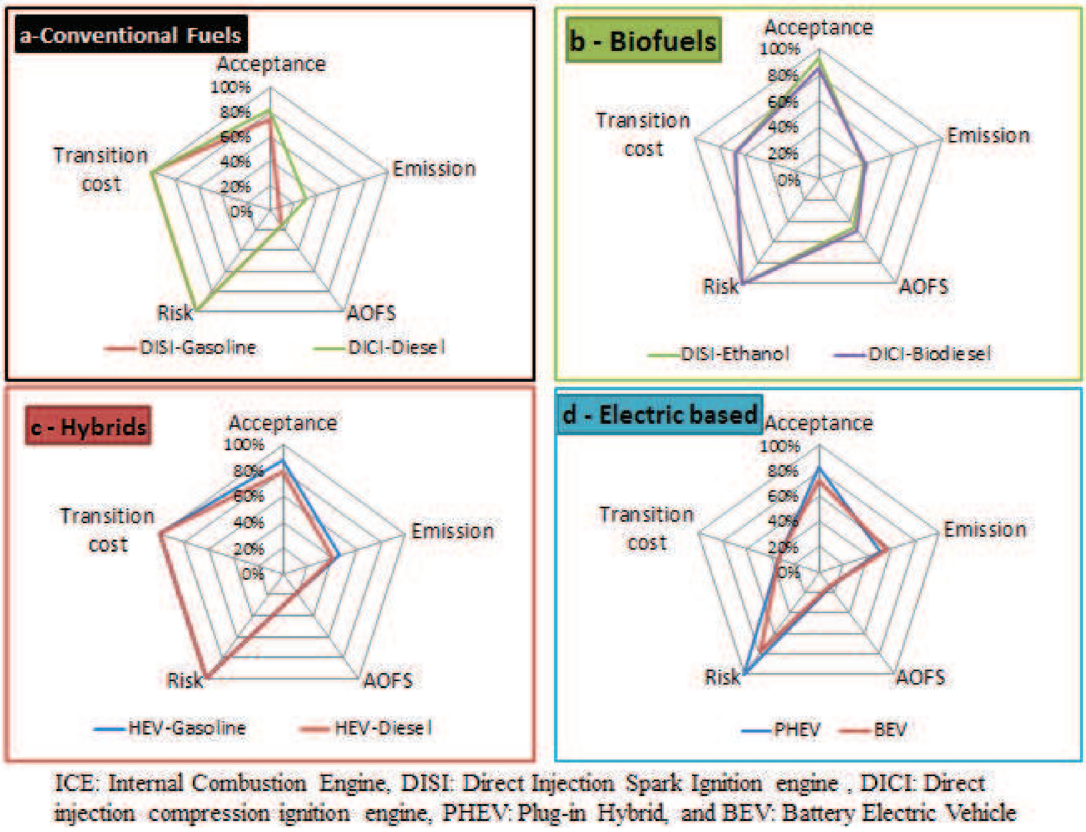


Figure 19: Multi-Attribute evaluation of pure technology alternatives: 19-a) alternatives using conventional fuels, 19-b) alternatives using biofuels, 19-c) hybrid technologies, 19-d) electric based alternatives

The results illustrate the value of pure technology alternatives for each of the five attributes. In all attributes, the value of 100% means higher *acceptance for users*, lower *total emissions*, lower *transition cost*, lower *risk of technology maturity* and higher *availability of fuel supply*. It should be noted that, as presented in figures 16-17, the *acceptance* of each technology involves two parameters which are the lifetime cost of the vehicle and its performance. The AFV that holds the lowest lifetime cost was assigned 100%, while the AFV that shows the best performance was assigned 100%.

With respect to *emissions*, we have considered the damage cost from GHG emissions and local air pollutions and the alternative option with lowest damage cost got 100% in this comparison. According to the *transition cost*, the alternative that requires zero incentives was assigned 100%. Regarding the risk of technology maturity, conventional technologies obtained the highest value in the TRL measure and 100% (figure 19). And finally, the 100% value in the availability of fuel supply corresponds to an alternative where the total required fuel is produced domestically and also the vehicle technologies are satisfactorily diverse.

As it was expected, and according to figure 19, alternatives using conventional fuels obtain a good score not only in *transition cost* and *risk*, but also in *acceptance*. This happens mainly because of the low necessary investment in fuel stations, the low risk in technology maturity, the good technical performance and the low present value expenses. Besides, biofuel based alternatives achieve high value in *availability of fuel supply* mainly because of a high capacity of domestic production in Portugal. Hybrid based alternatives got a superior grade in *emissions, acceptance and transition cost*, essentially because of low present value expenses and limited necessary investment. Besides, as the technology is already mature, hybrid based alternatives achieve a superior grade in risk evaluation. And finally, the electric based alternatives show a good score in emissions, when compared to other options, primarily because of low emission intensity of the Portuguese power sector. In contrast, the low value of electric based alternatives in terms of acceptance and transition costs, seems to be the major challenge for the adoption of these alternatives.

As it was mentioned earlier, in this study the alternatives are the passenger light duty vehicle fleets with the combination of up to four alternative fuel technology vehicles in the fleet. In the base scenario, this number was 3213. Figure 20 shows the changes in the number of alternative in the screening set after each phase of screening.

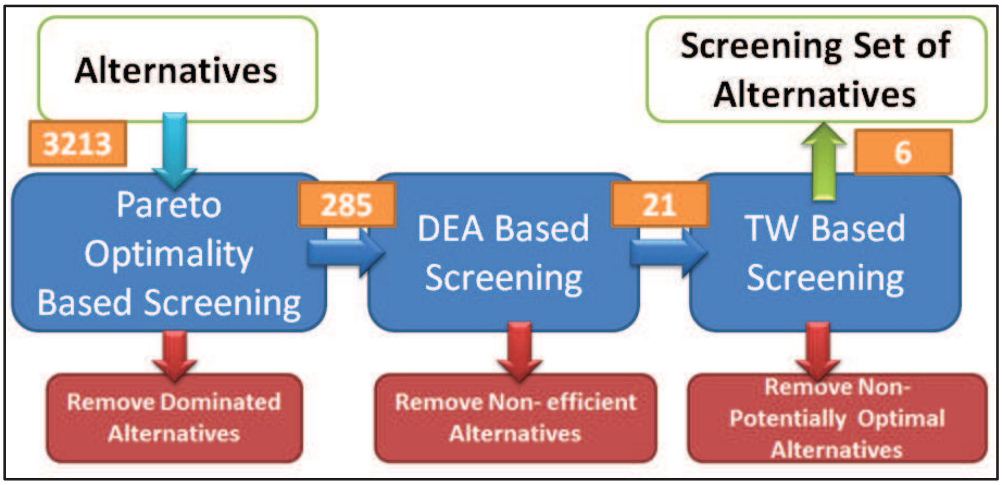


Figure 20: changes in the number of alternatives after applying the sequential screening approach

Then the proposed sequential screening approach was applied in order to identify the screening set of alternatives. After applying the PO screening approach, we got 285 alternatives. Then, the DEA based screening was adopted and the outcome set includes 21 alternatives. Finally, the TW procedure assists us to identify the initial screening set of alternatives which have six alternatives.

The initial screening set of alternatives for the case of Portugal is presented in Table XIV. Each alternative specifies the share of each technology in the light-duty passenger vehicle in Portugal at 2030.

Table XIV: Initial screening set of alternatives for Portugal in the base scenario at 2030

	DISI-Ethanol	DICI-Biodiesel	HEV-Gasoline	HEV-Diesel	PHEV	BEV
Alternative 1				100%		
Alternative 2			50%	50%		
Alternative 3		33.3%	33.3%	33.3%		
Alternative 4	25%	25%	25%	25%		
Alternative 5		25%	25%	25%	25%	
Alternative 6		25%	25%	25%		25%

In overall, table XIV shows that the technology with the highest appearance in almost all of the screening alternatives, when compared to other technologies, is hybrid-diesel, followed by hybrid-gasoline and biodiesel. Considering the potential uncertainty in several factors, it was decided to analyze the sensitivity of some of the most critical parameters. As it was mentioned before, another interesting benefit of this approach is to have a list of alternatives that can be discussed with the decision maker and obviously, to choose between these options, more information about the decision maker's attitude is necessary.

3.4.2. Parametric sensitivity analysis

After applying the developed methodology to the multi-criteria problem, the impact evaluation of several key parameters on the final results is necessary. In this step, four parameters have been chosen among many other factors mainly because of their potential impacts on the results. These parameters include share of renewable electricity, GHG damage cost, oil price and annual average travel.

Share of Renewable Electricity

Based on a [97], in the base scenario of this study, the "share of renewable electricity" in 2030 could reach 55%. As it is one of the key factors that could play an important role to enhance the advantage of using an electric based technology, there are several justifications to invest significantly on renewable power generation, increasing this share even more ([117]). Therefore, it seems critical to do an investigation on clarifying the impact of improving the share of renewable electricity from (55% to 70%) on the final sets.

GHG Damage Cost

"GHG damage cost" is another important factor that potentially can affect the multi criteria comparison results. In this study, the coefficient for GHG damage cost are based on the results of ([86]), but there are serious discussions on increasing this cost to 50 Euro/tonne-CO_2 Eq when compared to 20 Euro/tonne-CO_2 Eq (IEA [14], BLUE Map scenario).

Oil price

The other key factor is the "oil price" and its impact on the price of other fossil based-fuels. IEA [14], analyzed a situation in which oil price may rise up to USD 120/bbl by 2050; Thus, in this study, it was assumed that by 2030, the price of gasoline and diesel, in a high oil price scenario, could reach 2.1 €/liter and 1.7 €/liter, respectively.

Annual Average Travel

According to a study conducted by the European Conference of Ministers of Transports ([118]) in 2003, demand for passenger transportation is driven by not only the technological drivers (such as high speed cars), but also by economic factors (such as an increase in purchasing power). Therefore, in this dissertation, it was decided to investigate the impact of changing the average yearly car travelled distance from 15000 km to 20000 km.

First, the distinct impact of changing each of the above four parameters should be investigated. The new screening sets of alternatives are presented in tables XV to XVIII, respectively. The first interesting outcome is that increasing the boundary of the solution space such as higher share of renewable and higher annual average travel increases the number of alternatives in the screening set. On the other hand, imposing strict limitations including higher GHG damage cost and oil price, either keeps the same alternatives or reduces the number of screening alternatives.

As expected, the higher the share of renewable electricity production; the lower the emissions will be from PHEVs and BEVs. Therefore, the situation in which the share of renewable electricity increases from 55% to 70%, shows that the share of PHEVs and BEVs in the screening set are clearly increased when compared to screening alternatives in the base scenario (Table XV).

Table XV: Screening set of alternatives for Portugal - Share of Renewable Electricity: 70% from 55% in the base scenario

	DISI-Ethanol	DICI-Biodiesel	HEV-Gasoline	HEV-Diesel	PHEV	BEV
Alternative 1				100%		
Alternative 2					100%	
Alternative 3						100%
Alternative 4			50%	50%		
Alternative 5					50%	50%
Alternative 6		25%	25%	25%	25%	
Alternative 7		25%	25%	25%		25%
Alternative 8			25%	25%	25%	25%

Let us, consider the situation where the GHG damage cost jumps to 50 from 20 Euro/tonne-CO_2 Eq in the base scenario, which may happen due to an increased penalty regarding the impacts of GHG emission. As expected, in this scenario the solutions tend to shift s to less GHG emitting technologies. Table XVI shows the share of biofuels (Ethanol and biodiesel) with a significant growth.

Table XVI: Screening set of alternatives for Portugal - GHG Damage cost: 50 from 20 Euro/tonne-CO_2 Eq in the base scenario

	DISI-Ethanol	DICI-Biodiesel	HEV-Gasoline	HEV-Diesel	PHEV	BEV
Alternative 1				100%		
Alternative 2	50%	50%				
Alternative 3	33%	33%		33%		
Alternative 4	25%	25%	25%	25%		

Another key factor that should be analyzed is the price of oil and the related fuels including gasoline and diesel. According to US DOE/EIA [119], several factors can potentially increase the price of oil including a large demand for liquid fuels in the non-OECD nations resulting from economic growth in that region.

Reviewing the screening set of alternatives in table XVII, it seems that the impact of higher oil price is insignificant. This can be justified by the fact that it will affect only the performance of alternatives on fuel price and related user's acceptance, which is only a small part of the whole Multi Criteria decision aid framework.

Table XVII: Screening set of alternatives for Portugal - Gasoline Price: 2.1 from 1.6 Euro/liter in the base scenario

	DISI-Ethanol	DICI-Biodiesel	HEV-Gasoline	HEV-Diesel	PHEV	BEV
Alternative 1				100%		
Alternative 2			50%	50%		
Alternative 3		33.3%	33.3%	33.3%		
Alternative 4	25%	25%	25%	25%		
Alternative 5		25%	25%	25%	25%	
Alternative 6		25%	25%	25%		25%

The other important factor is the annual average travel. Considering the list of screening alternatives in Table XVIII, it seems that the only difference is the enclosure of the second alternative.

Table XVIII: Screening set of alternatives for Portugal - Annual average travel: 20000 from 15000 km in the base scenario

	DISI-Ethanol	DICI-Biodiesel	HEV-Gasoline	HEV-Diesel	PHEV	BEV
Alternative 1				100%		
Alternative 2		50%		50%		
Alternative 3			50%	50%		
Alternative 4		33%	33%	33%		
Alternative 5	25%	25%	25%	25%		
Alternative 6		25%	25%	25%	25%	
Alternative 7		25%	25%	25%		25%

After analyzing each of these parameters, individually, it seems useful to examine situations where more than one parameter change. In figure 21 the variables including "share of renewable electricity" and "annual average travel" are maintained in their base values, while in figure 22 "GHG damage cost" and "oil price" are kept in their initial values.

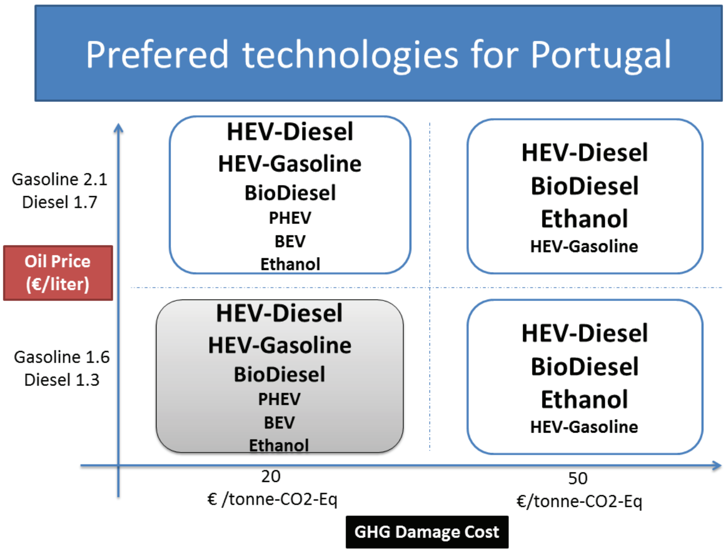


Figure 21: Sensitivity of high oil price and High GHG damage cost on initial screening set of alternatives

In figure 22, each box presents the list of alternative technologies and their size is associated with their share in the screening set of alternatives. For example, the dark box in the down-left corner is associated with the base scenario and according to table XIV, the technologies with highest occurrences are Hybrid-diesel and Hybrid-gasoline, followed by biodiesel.

The box on the down-right corner characterizes the sensitivity analysis for GHG damage cost. Besides, it presents the information in table XVI, showing that the technologies with highest share in the screening alternatives are Hybrid-diesel, biodiesel and ethanol.

The box on the top-left corner shows the sensitivity analysis of oil price, and according to table XVII, the impact on overall screening alternatives is unimportant.

Finally, the box on the top-right corner, signifies the situation of high GHG damage cost (50 €/tonne-CO_2-Eq from a base value of 20 €/tonne-CO_2-Eq) and high oil price (gasoline price at 2.1 €/liter from 1.6 €/liter). The technologies with highest share in the screening alternatives are Hybrid-diesel, biodiesel and ethanol.

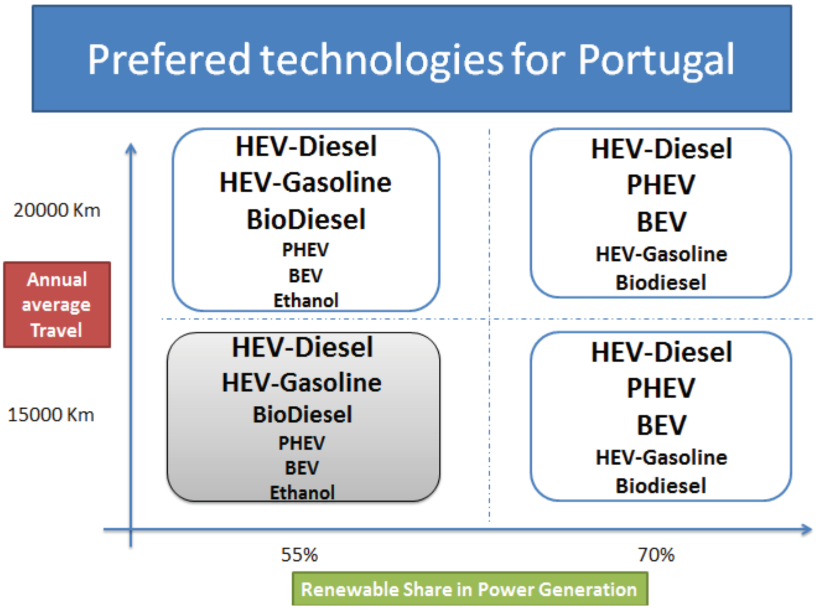


Figure 22: Sensitivity of high renewable penetration in power generation and high annual travel demand on initial screening set of alternatives

Similar to the figure 21, in figure 22 each box presents a list of alternative technologies and their size is associated with their share in the screening set of alternatives.

The box in the down-left corner is the base scenario, while the one in the down-right corner is the sensitivity analysis for the share of renewable in power generation. The result of analyzing the impact of higher annual average travel is presented in the top-left box, showing that the changes from the base are unimportant.

Finally, the box on the top-right corner shows the results of a situation where the share of renewable electricity is 70% and the annual average travel has increased to 2000 km. This demonstrates that Hybrid-diesel, PHEV and BEV technologies tend to have the highest share in the list of screening alternatives. This is mainly due to better performance of these technologies in terms of emissions and fuel availability.

Chapter 4 – Phase 2: Transition analysis

In recent years, significant policy attention has been given to the adoption of alternative fuel technology vehicles. Unfortunately, most previous efforts to encourage widespread adoption of alternative fuel vehicles have been largely unsuccessful. Examples include the failed attempt to significantly increase the percentage of (local) zero emission vehicles in California as well as the recognition that petroleum displacement has fallen far short of the Energy Policy Act ([120]) goal of 10% by the year 2000, and also of 30% displacement by the year 2010 ([121]).

Changing the fuels of personal transportation vehicles is a daunting challenge in any region of the world. Fleets of light duty vehicles have been firmly rooted in the petroleum-based, internal-combustion technology, including not only the vehicle systems and refueling infrastructure but also the vehicle maintenance and parts, as well as fuel production and distribution. Because of this, a movement away from a petroleum-based system to one of alternative fuel-technology drivetrains requires many changes or decisions to occur in parallel. For instance, not only would vehicle manufacturers need to offer Alternative Fuel Vehicles (AFVs) for sale, but the alternative fuel would need to be produced and distributed to a network of fuel stations sufficiently dense to supply the vehicles. In concomitance, the successful development of such alternatives may require changes to the current legislative and taxation frameworks. The greatest challenge of this transition process is to get all the critical elements spatially and temporally aligned (Melendez, [122]).

Therefore the complexities of the transport sector are probably a major cause for the current difficulties in changing the situation. The transport sector is a very dynamic system and like other complex systems exhibits path dependencies and lock-in effects. Furthermore policies and plans involve costs and benefits that can occur over long periods of time. Risk, uncertainty, path dependency, lock-in effects and irreversibility are also associated with technological change (Ramjerdi and Brundell-Freij, [123]).

To maximize the likelihood of a successful transition for an alternative fuel technology vehicle, it is vital to have a good understanding of the complex forces that have contributed to previously unsuccessful transition attempts, as these forces will inevitably still be active in any attempt to displace gasoline and diesel based vehicles. The barriers that are more often referred in the literature are (Melendez, [122]):

- unavailability of alternative fuel refueling infrastructures;
- high costs of constructing refueling infrastructures;
- relatively low oil prices;
- poor perceived or actual performance of AFVs (safety, power, range, reliability, etc.);
- high costs of purchasing AFVs (when compared with conventional vehicles);
- lack of customer awareness and market acceptance;
- lack of economic incentives;
- lack of AFV service and maintenance training and technicians;
- availability of alternative fuels;
- poor properties of alternative fuels.

The main known methodologies that address the important elements of a dynamic transition for alternative fuel vehicles will be presented and discussed in the next section.

4.1. Literature review of LDV fleet analysis models

Analyzing the evolution of Light Duty Vehicles (LDVs) is a puzzling task, which must account for two different perspectives:

- *Bottom-up*; which corresponds to individuals' decisions on their vehicle and how it might evolve considering the introduction of alternative fuel-technology vehicles. The main focus is on how economic and technical characteristics of a vehicle can affect the vehicle choice of individuals.
- *Top-Down*; which represent the broad view on the LDV fleets. It is basically concentrated on how global factors such as vehicle scrappage rate, incentives and fuel station coverage will affect the rate of vehicle sale and discard.

Therefore, it seems crucial to survey the most popular methods that have been investigated to capture the individuals' decisions on vehicle choice. The purpose is to identify the pros and cons of these methods and choose the most appropriate model for this study.

Then, in order to develop a model to investigate the transition of alternative fuel vehicles, it is necessary, to review the applicable methods. Reviewing the literature, it was found that the most common tools are: the MARKAL model ([124], [125], [126]), the Transitional Alternative Fuels and Vehicles (TAFV) model ([127], [128]), the HyTRANS model ([129], [130]), Agent-Based modeling (ABM) ([131], [132]) and System Dynamics approach ([64], [123]).

4.1.1. Literature Review on vehicle choice models

Before identifying the proper methodology for analyzing the transition of AFVs, we review approaches on how to simulate the individuals' vehicle choices and identify their preferences on vehicle's attributes. Therefore, we focus on the most popular choice models and their characteristics.

In a recent review, Greene ([133]) examined 20 studies that applied various approaches for vehicle choice modeling. The studies span a wide range of model formulations, data sources, premises and estimation methods (table XIX). He was interested in analyzing the findings of the papers on the value consumers assign to fuel economy. In table XIX, the column on the right presents the estimated value for Willingness-To-Pay (WTP) as the percentage of discounted Present Value (PV). The WTP parameter represents the economic equivalence that individuals are eager to pay for 1 unit improvement in fuel economy.

Table XIX: Summary of Consumers' Evaluation of Fuel Economy Improvements

Authors	Model Type	Data / Time	WTP as % of Discounted Present Value
[134] Arguea, Hsiao & Taylor (1994)	Hedonic Price	U.S., 1969 to 1986	3% to 46%
[135] Berry, Levinsohn & Pakes (1995)	NMNL	Aggregate US, 1971-1990	<1% Non-significant
[136] Goldberg (1995)	NMNL	U.S. CES, 1983- 1987	
[137] Brownstone, Bunch, Golob & Ren (1996)	NMNL Stated & Revealed Preference	CA Survey, 1993	-420% to 402%
[138], [139] Goldberg (1996, 1998)	NMNL	U.S. CES, 1984-1990	Consumers "not myopic"
[70] Brownstone, Bunch & Train (2000)	Mixed NMNL Stated & Revealed Preference	CA Survey, 1993	132% to 147%
[140] Bento, Goulder, Henry, Jacobsen & von Haefen (2005)	NMNL Survey	U.S. 2001	No direct estimate but MPG insensitive to price of gasoline
[141] Feng, Fullerton & Gan (2005)	NMNL	CES, U.S., 1996- 2000	0.03% to 1.3%
[142] Espey & Nair (2005)	Hedonic Price	U.S., 2001	109%
[143] Dasgupta, Siddarth and Silva-Risso (2007)	NMNL Survey	CA, 1999-2000	15%
[144] Train & Winston (2007)	Mixed NMNL Survey	U.S.,2000	1.3% Non-significant
[145] McManus (2007)	Hedonic Price	U.S., 2002	90%
[146] Gramlich (2008)	NMNL	Aggregate U.S., 1971-2007	287% to 823%
[147] Sawhill (2008)	Mixed NMNL	Aggregate U.S., 1971-1990	140%, range of -360% to 1,410%
[148] Klier and Linn (2008)	Logit	Aggregate U.S., 1970-2007	Very approximately 69%
[149] Cambridge Econometrics (2008)	Mixed logit	UK survey, 2004 to 2009	196% but uncertain of estimate. Authors contacted for clarifications.
[150] Alcott & Wozny (2009)	Mixed NMNL	Aggregate U.S., 1999-2008	25%
[151] Fifer & Bunn (2009)	Hedonic Price	State of Maine, 2007	Cars: 25% Lt. Trucks: 16%
[152] Fan & Rubin (2009)	Hedonic Price	U.S., 1996-2005	Cars: 52%, Pickups: 283% SUVs: 44%, Vans: 240%
[153] Vance & Mehlin (2009)	NMNL	Germany, Aggregate New Car Sales	Approximately 1,000%

This review reveals that some studies estimate consumers' willingness to pay (WTP) for automotive attributes using the hedonic price model (Arguea, Hsiao & Taylor, [134]; Espey & Nair, [142]; Fifer & Bunn, [151]; Fan & Rubin, [152]); while other studies applied discrete choice models (Goldberg, [136]; McManus,

[145]; Train, and Winston, [144]). The hedonic price model needs data that includes prices of automobiles, while a discrete choice model requires survey data that reveals consumers' discrete choices. Both approaches perform equally well in estimating the marginal value of an attribute of vehicles. The hedonic model has the advantage of using more detailed data information than the discrete choice model. A large portion of the automobile market provides thousands of observations of vehicle prices and attributes, while surveys are confined to a few hundreds of observations of consumers' choice. Discrete Choice Models have several variants such as the Multinomial logit model (MNL), the nested multinomial logit model (NMNL), the Mixed nested multinomial logit (Mixed NMNL).

The Hedonic Model

In order to estimate a demand function for fuel economy, Fan ([154]) estimated a hedonic demand regression for the state of Maine in 2007. A hedonic model is a non-market valuation approach that decomposes the price of a good into separate component attributes to determine the price of each attribute. This model was adopted in order to estimate consumers' valuations of automobile attributes, such as vehicle class, weight, horsepower, fuel economy, performance, and luxury features. Besides, he explored the impact of demographic factors on consumers' valuations of automotive fuel economy.

In a heterogeneous goods market, people value each characteristic of a product. A hedonic price model provides the capability to estimate implicit prices of these characteristics. This type of models is a widely used approach to non-market valuation in the field of environmental economics that was originally used to estimate the value of environmental amenities and other attributes of housing. Using this model, people can indirectly observe the monetary trade-offs in the differentiated goods market with respect to a marginal change of a specific characteristic of differentiated products. An automobile is one of these products, and its various characteristics create a distinction among vehicles. Automobile consumers' valuations of each characteristic of a vehicle can be obtained through the observable transactions in the automobile market using a hedonic price model.

A first-stage hedonic model typically estimates implicit prices, of component characteristics of goods. In the automobile market, the utility of an automobile depends on consumers' valuations of all attributes such as safety, vehicle class, vehicle weight, horsepower, fuel economy, manufacturers, performance, and luxury features. A second-stage hedonic model describes the demand function of a specific attribute under the income constraint (Champ et al. [155]). This model can also examine the impact of demographic factors on consumers" demands for a specific attribute.

Considering the fact that the main purpose of a hedonic model is to estimate consumers' valuations of automobile attributes, such as vehicle class, weight, horsepower, fuel economy, performance, and luxury features, this approach is limited to be applied for simulating the individual's vehicle choice.

For example, there is a general assumption associated with hedonic price models that attributes are constant when examining the implicit price of a specific attribute. In reality, other attributes, such as vehicle size, vehicle weight, and horsepower might be correlated with fuel economy. In other words, multi-collinearity is a major problem which implies that the implicit price of an attribute is unstable and will vary greatly among different sample tests.

Besides, the results reported by Fan ([154]) are only based on a static analysis when studying fuel economy and introducing social benefits. It was assumed that consumers value fuel savings at the current fuel economy level. In practice, however, automotive fuel economy changes during vehicles' lifetime, and fuel economy can also be affected by the maintenance of automobiles. When social benefits are addressed, this author ignored the change of externality costs and benefits from increasing fuel economy across time, during the life cycle of vehicles. These static assumptions may produce some errors in the calculation of lifetime fuel savings.

Discrete choice models

Another group of vehicle choice models are discrete choice models. Discrete choice models were developed by Daniel McFadden in the 1970s. His work (e.g. McFadden [156]) introduced viable techniques for estimating a complete characteristics-based discrete choice model of demand (Ben-Akiva, and Lerman, [157]). Basically, discrete choice models are statistical procedures that model choices made by people among a finite set of alternatives. The models have been used to examine, e.g., the choice of which car to buy, which mode of transport (car, bus, rail) to take to work, among numerous other applications. Discrete choice models take many forms. The most popular approaches applied for vehicle choice are Multinomial logit model (MNL), the nested multinomial logit (NMNL) model and the Mixed nested multinomial logit (Mixed NMNL). All these models share the features described below.

The Choice Set is the set of alternatives that are available to a person. For a discrete choice model, the choice set must meet three requirements (Train, ([158]):

1. The set of alternatives must be *exhaustive*, meaning that the set includes all possible alternatives. This requirement implies that the person necessarily does choose an alternative from the set.
2. The alternatives must be *mutually exclusive*, meaning that choosing one alternative means not choosing any other alternatives. This requirement implies that the person chooses only one alternative from the set.
3. The set must contain a *finite* number of alternatives. This third requirement distinguishes discrete choice analysis from regression analysis in which the dependent variable can (theoretically) take an infinite number of values.

Defining Choice Probabilities

A discrete choice model specifies the probability with which a person chooses a particular alternative, with the probability expressed as a function of observed variables that relate to the alternatives and the person. In its general form, the probability with which person n chooses alternative i is expressed as:

$$P_{ni} = G(x_{ni}, x_{nj} \forall j \neq i, s_n, \beta) \quad (5)$$

where

x_{ni} is a vector of attributes of alternative i faced by person n,

$x_{nj} \forall j \neq i$ is a vector of attributes of the other alternatives (other than i) faced by person n,

s_n is a vector of characteristics of person n, and

β is a set of parameters that relate variables to probabilities .

In the vehicle choice example, the attributes of vehicles (x_{ni}), such as vehicle cost, performance and the characteristics of consumer (s_n), such as annual income, age, and gender, can be used to calculate choice probabilities.

Consumer Utility

Discrete choice models can be derived from utility theory. It is useful for three reasons:

1. it gives a precise meaning to the probabilities P_{ni}
2. it contributes to identify the alternative model specifications.
3. it provides the theoretical basis for calculation of changes in consumer surplus (compensating variation) from changes in the attributes of the alternatives.

$U_{ni}$is the utility (or net benefit or well-being) that person n obtains from choosing alternative i. The behavior of the person is toward maximizing the utility; therefore person n chooses the alternative that provides the highest utility. The utility that the person obtains from choosing an alternative is decomposed into a part that depends on variables that the researcher observes and a part that depends on variables that the researcher does not observe. In a linear form, this decomposition is expressed as:

$$U_{ni} = \rho z_{ni} + \varepsilon_{ni} \quad (6)$$

where

z_{ni} is a vector of observed variables relating to alternative *i* for person *n,* and a function of alternative attributes x_{ni}, and the attributes of the person, s_n:

ρ is a corresponding vector of coefficients of the observed variables, and

ε_{ni} captures the impact of all unobserved factors that affect the person's choice.

The Multinomial Logit Model (MNL) estimates the probability $P_{i,t}$ that the modeled consumer will choose a given technology i in year t based on the vehicle attributes according to the equation:

$$P_{i,t} = \frac{\exp(U_{i,t})}{\sum_{i=1}^{I} \exp(U_{i,t})} \tag{7}$$

where,

$U_{i,t}$ is the consumer utility for vehicle i in year t;

I is the total number of vehicle technology options.

The core equation of the model represents the utility the consumer derives from the attributes of the vehicle and the equation coefficients (β_j) represent the consumer's relative weighting of each attribute. In other words, the consumer utility derived from selecting technology i in year t is:

$$U_{i,t} = \sum_j \beta_j . x_{i,j,t} \tag{8}$$

where,

β_j is the logit coefficient for attribute j and

$x_{i,j,t}$ is the value of attribute j for vehicle i in year t

A standard multinomial logit model is not always suitable, since it assumes that there is no correlation in unobserved factors over alternatives. This lack of correlation translates into a particular pattern of substitution among alternatives that might not always be realistic in a given situation. This pattern of substitution is often called the Independence of Irrelevant Alternatives (IIA) property of standard logit models.

In the situation that the number of new vehicle models is large, the IIA property of the MNL model may be an important restriction in modeling new vehicle choices. The larger the number of elemental alternatives, the more likely will a particular make-model be closely related to one subset of make-models than it is to some other subset of make-models. A number of models have been proposed to allow correlation over alternatives and more general substitution patterns such as nested multinomial logit (NMNL) and mixed logit models. The NMNL model captures correlations between alternatives by partitioning the choice set into 'nests' while the mixed logit model allows any form of correlation and substitution patterns.

McFadden ([159]) demonstrated that, under certain conditions, the IIA property of the MNL model could be relaxed in such a way as to accommodate correlations among elemental alternatives in a given subset or nest, while maintaining the IIA restriction across nests. Thus, elemental alternatives in a given nest need not satisfy the IIA restriction but alternatives in one nest are assumed to be independent of alternatives in other nests.

McCarthy and Tay, [160] tried to develop and estimate nested multinominal logit (NMNL) models of new vehicle demands where the lower level of the nest represents make/model choice and the upper level models the fuel efficiency of vehicles. The nested logit structure provides a potential improvement over the commonly used multinomial logit model (MNL). The NMNL structure relaxes this constraint by allowing correlated disturbances among alternatives in a given subset or nest. For their analysis, they assumed that fuel efficiency separates the make-models and define three nests of vehicles: high, medium and low fuel efficiency vehicles. By this criterion, they were assuming that make-models in each fuel efficiency nest have similar unobserved characteristics and, accordingly, are correlated. Make-models across vehicle nests, however, are assumed to have unobserved attributes that are uncorrelated. Figure 23 depicts the nested structure that they adopted (McCarthy and Tay, [160]), which identifies fuel efficiency as the upper branch and make-model choice as the lower branch.

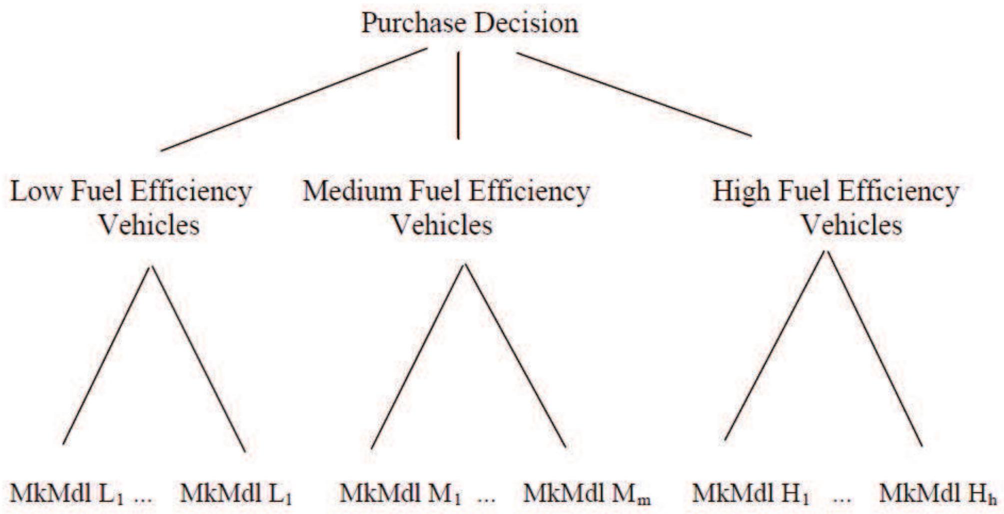


Figure 23: Nested Logit Model for Fuel Efficiency and Make-Model Choices (source: McCarthy and Tay, [160])

Their results indicate that females, minorities, and residents in more densely populated areas exhibit higher demands for fuel efficient vehicles. On the other hand, higher income households and individuals older than 45, prefer less fuel efficient vehicles.

As expected, increases in the expected maximum utility associated with the make-model choice in a fuel efficiency category increase the demand for that fuel efficiency type. Furthermore, since the coefficient lay in the open unit interval, the results are consistent with random utility maximization and a nested logit structure.

As it was mentioned before, there is another solution for the issue of the IIA property of standard logit models, which is to apply a mixed multinomial logit model. This model was used by Train and Hudson, [161], to estimate customers' choices. This model reflects the importance that customers place on each vehicle attribute when choosing among vehicles. The model explicitly accounts for the fact that different customers value attributes differently. In particular, for each attribute, the distribution of values across customers is estimated. These estimates indicate the amount that customers are willing to pay, on average, for each attribute, as well as the variance in individual customers' values around this mean.

Besides, the mixed logit model can serves as the basis for the forecasting model. The user of the model specifies the vehicles that are assumed to be available, as well as the attributes of each vehicle. Market shares are calculated from the mixed logit models of customer choice. Separate forecasts are provided under the assumption that customers receive extra information about ICEVs, EVs, and HVs, and under the alternative assumption that customers do not receive this information. The difference in the two sets of forecasts provides an indication of how such information can affect market shares.

Considering the limitation of the hedonic model explained thoroughly in the initial part of this section, and the fact that the main purpose of this model is to estimate consumers' valuations of automobile attributes, such as fuel economy, it was decided in this work to consider the discrete choice models as the approach for vehicle choice modeling.

As presented earlier, the nested logit models generally require a comprehensive survey to be able to identify the logit coefficient of the utility function. The unavailability of the disaggregated historical information on fuel economy, vehicle purchase price for the case study, led us to choose the standard logit model for this study. Considering the limited number of new vehicles, the importance of an unfavorable IIA property of the MNL model is insignificant.

4.1.2. Literature Review of transition analysis models

The most common tools and approaches that were applied to analyze the transition for alternative fuel technology vehicles are: the MARKAL model, the Transitional Alternative Fuels and Vehicles (TAFV) model, the HyTRANS model, Agent-Based modeling (ABM) and System Dynamics approaches.

MARKAL

MARKAL (short for MARKet ALlocation) is a popular energy/economic model, in use at over 50 countries. MARKAL is built on the General Algebraic Modeling System (GAMS), an optimization framework (Brook, Kendrick, & Meeraus, [124]). It uses optimization techniques to find the least cost combination of energy technologies to meet energy and emissions related constraint sets (Johnson, [125]; Seebregts, [126]). MARKAL considers a simplifying assumption of perfect foresight about energy prices and technological progress. Perfect foresight is an extreme assumption (it is impossible to achieve), which limits the value of MARKAL results. The latest evolution of MARKAL, introduced in 1999, is called TIMES ("The Integrated Markal-Efom System) (Seebregts, [126]).

TAFV Model

The TAFV (Transitional Alternative Fuels and Vehicles) model was the result of a first attempt in the mid-1990's to characterize how the United States' market for AFVs might change from one based on new technologies available only at a higher-cost and lower-volume, to a world with more mature technologies offered at lower cost and wider scale (Leiby and Rubin, [127], [128])

The TAFV model simulates the use and cost of alternative fuels and vehicles over the time period of 1996 to 2010. It was designed to examine the transitional period for the adoption of alternative fuels and vehicles, considering possible barriers related to infrastructural needs and production scale. The model takes into account the dynamic linkages between vehicle and fuel production capacity and government investments, and considers the impacts of increasing scale and expanding retail fuel availability on the effective costs to consumers.

Besides, it explores the effectiveness of current policies authorized under EPACT and the Alternative Motor Fuels Act of 1988 ([162]), as well as potential policies including fleet vehicle purchase mandates, fuel subsidies, and tax incentives for low greenhouse gas emitting fuels, that would be necessary for this transition to happen (Leiby and Rubin, [163])

HyTRANS

HyTRANS (short for Hydrogen TRANSition) is a model being developed by the Oak Ridge National Laboratory (ORNL) that addresses various elements of the hydrogen transition (Greene, [129]). It covers hydrogen generation, delivery, vehicle production, consumer choice and hydrogen usage relying on a number of other established models including GREET for GHG emissions, H2A for hydrogen production and delivery, and others.

The model is a dynamic, non-linear optimizing market simulation that runs through 2050. It seeks to maximize producer profitability and consumer welfare. It outputs projections on hydrogen fuel costs, vehicle technology penetration and cumulative costs (Greene [130])

Agent-Based Models (ABM)

Agent-based modeling (ABM) is a technique for studying the interactions among many autonomous and heterogeneous decision makers. It has been used often in recent years to model the transition of passenger vehicle fleets to AFVs because of its ability to capture both spatial and temporal patterns (Sullivan et al, [131], Pellon et al., [132]).

ABM starts with agent (buyer, dealers, government) preferences and basic behavior rules and allows them to interact, thus projecting into the future and looking for collective responses (market penetration), that may or may not be optimal.

Sullivan et al, ([131]) developed an agent based simulation to characterize the penetration of new vehicles into the marketplace under a variety of consumer, economic and policy conditions. The model comprises four classes of decision makers: consumers, government, fuel producers and vehicle producers/dealers. The agents, virtual decision makers in software, interact with one another and the environment (especially economic) based on their individual needs and/or organizational objectives. Briefly, in each cycle (one month) consumers review the status of their driving mileage, fuel costs, and whether or not it is time to buy another car. If it is determined that there is a need to change driving mileage or buy a car, they act in a way to remain at least budget neutral and meet their driving needs and model preferences. In that study, agents could choose from twelve models of vehicles produced by three OEMs. At the end of each cycle, car dealers review sales and revenues and adjust the prices of used cars based on virtual market supply and demand. The government monitored fuel use and carbon emissions and vehicle introductions and implements policies (fuels, vehicle tax incentives, etc.) to meet pre-established objectives. Finally, fuel producers provide fuels for automotive and change prices both exogenously (petroleum induced gasoline price shock) and endogenously (competition between two fuel types).

The model was developed to address the general question of how do new technologies migrate into their appropriate marketplaces, and in particular the vehicle marketplace. Of special interest to these authors was the penetration of the PHEV into the U. S. auto marketplace. They applied several validation scenarios to the model to assure that it was sufficiently representative of a real marketplace to the PHEV market penetration question.

In another study, a prototype of a spatially explicit and socially embedded agent based model was introduced to study the adoption of the plug-in hybrid vehicle (PHEV) technology under a variety of scenarios (Pellon et al., [132]). Agent-based decision support system was adopted to decide whether or not to buy a PHEV by weighing environmental benefits and financial considerations (based on their personal driving habits, their projections of future gas prices, and how accurately they estimate fuel costs), subject to various social influences such as social diffusion of an innovation. Proof-of-concept results are presented to illustrate the types of questions that could be addressed by such a model, and how they may help to support decisions of policy-makers and/or vehicle manufacturers. For example, their results indicate that simple web-based tools for helping consumers to more accurately estimate relative fuel costs could dramatically increase PHEV adoption.

The results of the study illustrate the types of questions that could be addressed by an agent based model, assessing how much consumers are willing to pay for a PHEV in exchange for forecasted savings in fuel costs and/or perceived environmental benefits. Such simulations could be used to help policy-makers and/or vehicle manufacturers in understanding what types of policies or features may have the most effect on the adoption of the PHEV technology.

System Dynamics models

Another interesting approach is system dynamics, a technique that has been the focus of some recent studies on the adoption of AFVs.

A dynamic, behavioral, spatial framework using System Dynamics was developed by Struben at MIT (Struben, [64]). This tool has been developed to explore the co-evolutionary dynamics between infrastructure supply and vehicle demand. The paper explores in-depth the dynamics resulting from local demand-supply interactions with strategically located fuel-station entrants. This model was applied to develop targeted entrance strategies for alternative fuels in transportation. Besides, the roles of other powerful positive feedbacks arising from scale and scope economies, R&D, learning by doing, driver experience, and word of mouth were discussed.

After this research, several studies have been adopting this general methodology. For example, Ramjerdi and Brundell-Freij ([123]) tried to analyze the Swedish market using the system dynamics approach. Their findings suggest that government should set policies that are directly related to objectives rather than selecting the technology.

4.2. Model setup

In this study, the methodology developed by Struben ([64]) was adopted as the basis for development of the phase 2 analysis.

This model is built based on the assumption that the adoption of new vehicles is generated by consumer awareness and learning through feedback from driving experience, word-of-mouth, and marketing. Therefore, consumer acceptance of a new technology is a critical factor for the successful diffusion and sustained adoption of AFVs. Besides it examines the dynamics of vehicle and fuel infrastructures under heterogeneous socio-economic/demographic conditions. Modifications introduced enable the model to calculate the average fleet fuel efficiency. Besides, in order to estimate the total incentive required to reach a target, an optimization module was added.

The core model, the most important parameters and the interaction between those parameters are now presented. Also, it is useful to identify the most important feedbacks and understand their impacts on the system.

Considering the dynamic characteristics of the fleet evolution of light duty vehicles, some important feedbacks need to be identified. Basically, there are two types of feedbacks: reinforcing and balancing. In a reinforcing (or positive) feedback loop, the increase in a particular parameter in the loop tends to lead to a further increase in that parameter through something akin to a "snowball" effect. Reinforcing loops tend to accelerate change and result in exponential growth in the absence of other counteracting forces. Balancing (or negative) feedback loops, on the other hand, tend to counteract change. Balancing loops arise when an initial increase in one parameter in the loop tends to lead to a subsequent decrease in that same parameter, all else being equal. In the absence of other dynamics, a balancing loop will tend to result in an exponential decline of the parameters in the loop. The interaction of multiple reinforcing and balancing loops govern the behavior of any complex system.

4.2.1. Main positive feedbacks

As it was mentioned before, one of the most important characteristics of a system dynamics approach is the capability of capturing feedback impacts in the model. In this study, the model considers two key reinforcing (positive) feedbacks: "fuel station evolution" and "familiarity", as illustrated in figure 24.

Reinforcing feedback 1: "Familiarity"

The first key reinforcing feedback illustrated in figure 24 addresses social behavior of customers facing a new technology (alternative fuel-technology vehicle). When introducing a new technology, there is a limited familiarity with it, and this can significantly affect the user's choice. But factors such as marketing and communication with the owners of those new vehicles (word of mouth) could be the main instruments of increasing the familiarity of people with the new vehicles. This positive impact will result in an increase of the perceived utility of alternative fuel-technology vehicles, followed by an increase in vehicle sales. The more AFVs in the market, the more customers will get familiar with them.

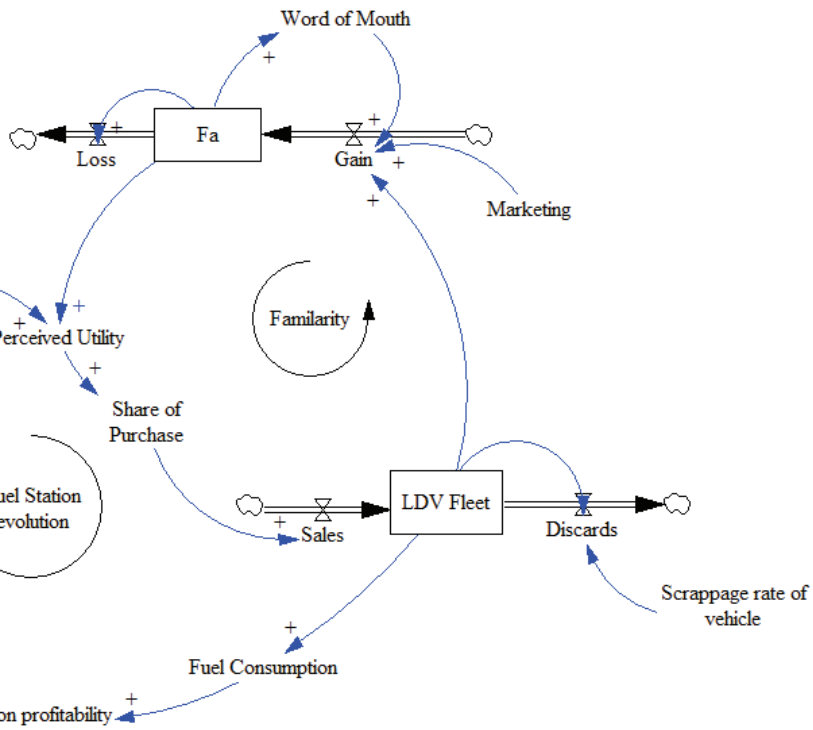


Figure 24: Main positive feedbacks

To characterize how this reinforcing loop work, we have studied the relations between the parameters in the loop and identified their mathematical formulation.

It was noted that, perceived utility is a critical factor on the share of purchase for different technologies, which depends on familiarity and nominal utility of technologies. This relation is formulated as follow:

$$PU_{i,r} = F_i \times U_{i,r} \tag{9}$$

where:

$PU_{i,r}$ is the perceived utility of technology I, in region r.

F_i is the familiarity of individuals with technology i; and

$U_{i,r}$ represents the nominal utility of each technology i in region r.

As an assumption, the $Sop_{i,r}$ (share of purchasing technology i, in region r) depends only on the perceived utility of each technology and the higher perceived utility, the higher the share of that technology option will be:

$$Sop_{i,r} = \frac{PU_{i,r}}{\sum_i \sum_r PU_{i,r}} \tag{10}$$

As presented in equation 9, another important fact that directly affects the value of the perceived utility is the familiarity of individuals with the vehicle. "Familiarity" captures the emotional processes through which drivers gain enough information about a technology. Everyone is familiar with ICE, so $F_{ICE} = 1.0$, while $F_i = 0$ for those completely unfamiliar with technology i and therefore such individuals do not even consider such a vehicle for their decision. In this study, familiarity relates with marketing, share of technology in vehicle fleet, word of mouth and forgetfulness:

$$\frac{dF_i}{dt} = M_i + \gamma_1 * \frac{\sum_r V_{i,r}}{\sum_i \sum_r V_{i,r}} + \gamma_2 * F_i - \gamma_3 * F_i \tag{11}$$

where:

F_i is the familiarity of individuals with technology i;

M_i is the marketing factor for technology i;

$\gamma_1$represents the importance of technology share in the total fleet on familiarity of individuals;

$V_{i,r}$ is the number of vehicles for technology option i, in region r;

γ_2 captures the impact of word-of-mouth contacts with drivers of that AFV on its familiarity;

γ_3 is related with the forgetfulness of the familiarity of the car buyers with AFV.

The values of the social parameters (γ_1, γ_2 and γ_3) needs to be estimated through the calibration process. Presumably, the initial step after building up this model is to gather information for calibrating the model with data of the case study.

According to equation 9, the nominal utility is another important factor for calculating the perceived utility. Following the discussion on vehicle choice modeling in section 4.1.1, the next critical part of the model is about how to simulate the user's preferences for vehicle choice. The unavailability of the disaggregated historical information on fuel economy, vehicle purchase led us to choose a standard logit model in order to estimate the nominal utility of each technology:

$$U_{i,r} = \sum_n \beta_n \times u_{i,r,n} \tag{12}$$

where:

$U_{i,r}$ represents the nominal utility of each technology i in region r,

β_n illustrates the coefficient sensitivity of the customer for n choice factors;

$u_{i,r,n}$ is the characteristic of each technology i, in region r, and for variant choice factor n.

Considering the review on important vehicle choice parameters presented in section 2.1.2, five characteristics have been chosen, including vehicle purchase price, fuel cost, performance, range and fuel station coverage. These are the most common parameters in tables IX and X presented in chapter 2.

Since for the development of this research we need to investigate the impact of station coverage on the annual sales of alternative fuel vehicles, it seems necessary to consider the geographical distribution of the fuel stations. In fact, it was also assumed that the fuel station coverage in each region will impact the annual sales of AFV in that region alone and not in the others. This will reduce the error of assuming similar station coverage in the whole are of the case study (thus avoiding the "flaw of averages"). For the case study of this thesis (Portugal), it was decided to include 5 main sub-regions: Norte, Centro, Lisboa e vale do Tejo, Alentejo and Algarve.

In fact, in order to identify valid coefficients representing the sensitivity of the customer for each choice factor, it was decided to calibrate the model with the available historical data and identify the case-dependent values for each coefficient.

Reinforcing feedback 2: "Fuel Station Evolution"

The second reinforcing feedback is the heart of the dynamic interdependence between fuel station coverage and vehicle demand. Considering an increase in the number of alternative fuel vehicles (such as the ethanol E85 vehicle), the relative fuel consumption and the profitability of fuel stations will increase, this leading to a higher investment on fuel stations. An increase in the total number of fuel stations will improve their coverage. The overall impact is the increase in the vehicle utility, followed by Vehicle Sales and Total Vehicles.

This reinforcing dynamics has the potential to lead to an exponentially increasing number of alternative fuel vehicles and fuel stations. The balance will be reached through the parameter "Station Profitability": the lower the Station Profitability is, the lower is the likelihood that other station owners will enter the market, this resulting in no additional fuel stations.

Focusing on the formulating part of "fuel station evolution", the fuel consumption is the main factor affecting the station profitability. Total fuel consumption depends on the annual average travel, fleet average fuel efficiency and road fleet of vehicles using that fuel:

$$FC_{i,r} = AAT * AFE_i * V_{i,r} \tag{13}$$

where:

$FC_{i,r}$ is the total consumption of fuel used by a vehicle using technology option i in region r;

AAT is the average annual travel in km;

AFE_i represents the average fleet efficiency of vehicles using technology option i.

The profitability of fuel stations depends on many factors including the capital and operating cost of fuel stations, fuel delivered, fuel price and the number of available fuel stations:

$$PFS_{r,f} = \left(\frac{FP_f * FC_{i,r}}{NFS} - \frac{CC}{ASL} - \frac{OMC}{NFS}\right) \Big/ \left(\frac{CC}{ASL} + \frac{OMC}{NFS}\right) \quad (14)$$

where:

$PFS_{r,f}$ represents the profitability of a station for fuel f in region r;

FP_f is the price of fuel f;

NFS is the number of available fuel stations;

CC is the capital cost of a fuel station;

ASL is the average station lifetime;

OMC is the operation and maintenance cost of a fuel stations.

If the profitability of a fuel station goes over the reference profitability, the investment on fuel stations will grow, causing the fuel station entrance to increase:

$$FSE_{r,f} = f\left(\frac{PFS_{r,f} - RPFS}{RPFS}\right) \quad (15)$$

where:

$FSE_{r,f}$ represents the station entrance for fuel f, in region r;

f is the function relating the fuel station entrance with the profitability of fuel stations; and

RPFS is the reference for profitability of fuel station.

In order to identify the shape of the *f* function, we need to check the values in the higher and lower extremes. Rationally, if $PFS_{r,f} \leq RPFS$, there would be no investment and therefore no fuel station entrance. Presumably, the sales of vehicle will cause the fuel consumption to grow. It will motivate the profitability of fuel stations to increase, as expressed in equation 14. Therefore, PFS can go above $RPFS$ which will be the sign for investors. In this situation, if the absolute value of "$PFS_{r,f} - RPFS$" becomes very large, it will definitely attract more investors comparing to the low value of "$PFS_{r,f} - RPFS$". Therefore, the shape of the *f* function could be as it is shown in figure 25. In this study, the reference for fuel station profitability was assigned as 10% (Struben, [164]).

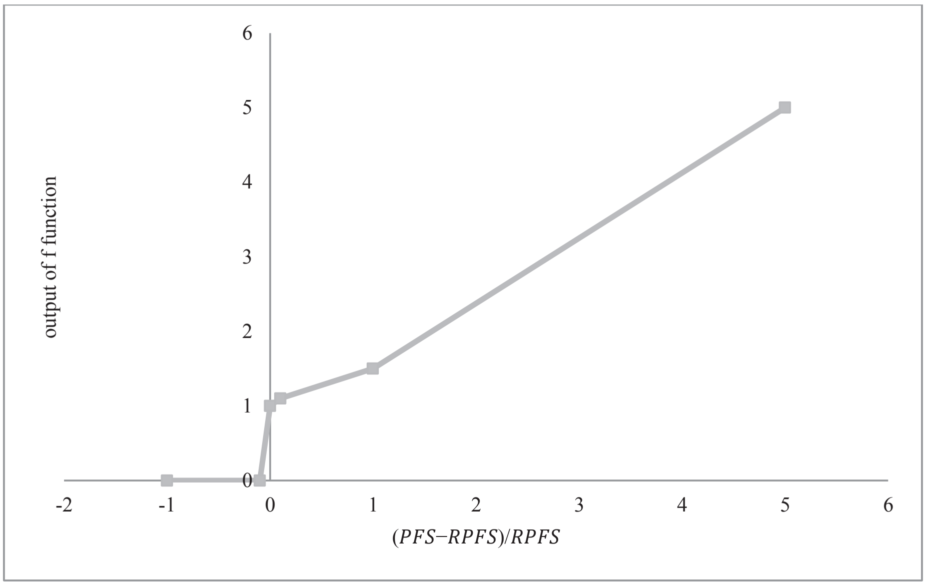


Figure 25: General shape of the *f* function

The detailed discussion on the relation between fuel station entrance and the number of fuel stations is presented later (equations 21-25), but for the moment, the relation between the number of fuel stations and the coverage of fuel stations should be characterized. Obviously with more fuel stations on the ground, the coverage of fuel station will increase, as follows:

$$FSC_i = \frac{\sum_r NFS_{r,f}}{\sum_i \sum_r NFS_{r,f}} \tag{16}$$

As discussed above, concerning the nominal utility of a vehicle (equation 12), fuel station coverage is a key parameter, having the potential to affect the vehicle choice results.

4.2.2. Main negative feedbacks

In addition to the reinforcing feedbacks discussed in the previous section, there are two main balancing feedbacks in the model.

Balancing feedback 1: "Fleet Saturation"

There exists a saturation level of vehicle ownership that is basically the maximum number of vehicles per population or household. This level is mainly conditioned by economic factors such as GDP and the household income (figure 26). With the increase in sales, the gap with the saturation level will tend to decrease. Therefore, it will lower the sales until the vehicle ownership reaches the saturation level.

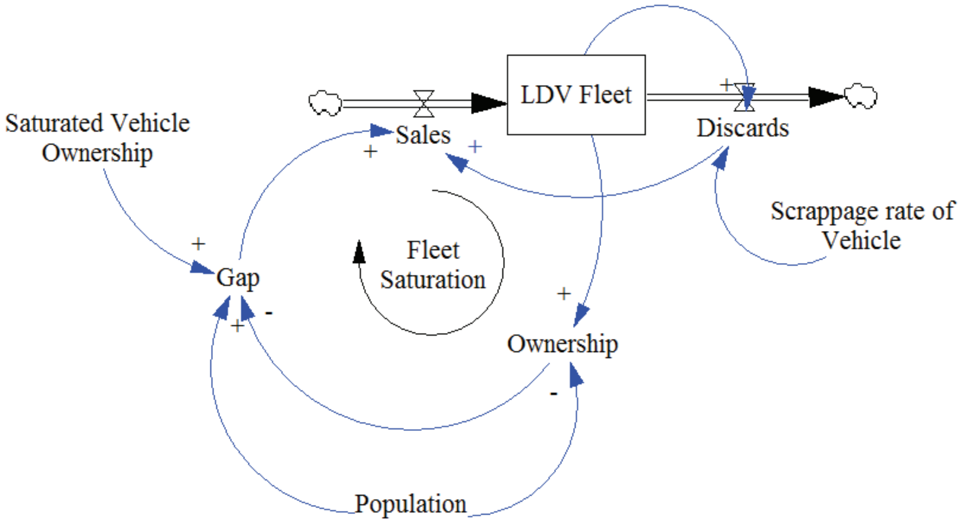


Figure 26: Balancing feedback "Fleet Saturation"

To characterize quantitatively, we need to start with the fleet turnover model. The total number of vehicles (V), accumulates new vehicle sales, (s), less discards, (d), i.e.;

$$\frac{dV_{i,r}}{dt} = s_{i,r} - d_{i,r} \tag{17}$$

where:

$V_{i,r}$ is the number of vehicles for technology option i, in region r;

$s_{i,r}$ is the number of vehicles' sales for technology option i, in region r;

$d_{i,r}$ is the number of vehicles' discards for technology option i, in region r;

r is an index for the region; and

i is an index for different powertrain options.

Total discards depend directly on the number of vehicles in the fleet, and are inversely proportional to the average vehicles lifetime. Total discards are here defined as the share of the vehicle fleet that reaches the end of their life. The inverse of average lifetime of light duty vehicles is named as scrappage rate in this study.

$$d_{i,r} = \frac{V_{i,r}}{AVL} \tag{18}$$

where:

$V_{i,r}$ is the number of vehicles for technology option i, in region r; and

AVL is the average lifetime of the light duty vehicle.

Total sales contain initial and replacement purchases, while the initial sales share depend on the gap between current vehicle ownership and the saturation level of vehicle ownership (the maximum number of vehicles per population). This saturation level is mainly characterized by economic factors such as GDP and the household income. As a simplifying assumption, the replacement purchase is equal to the number of vehicle's discard (basically anyone who sells his/her car, will get a substitute). Therefore, the total sales will be:

$$s_{i,r} = Sop_{i,r} * (\alpha * G_r + d_{i,r}) \tag{19}$$

where:

$Sop_{i,r}$ is the share of purchase for technology i in each region r;

α is the coefficient of fleet gap filling (difference of the number of vehicles to the saturated level); and

G_r is the gap between current vehicle ownership and the saturation level in region r;

It should be noted that α is a case study specific parameter within a (0,1) boundary. If its value approaches 1, it means that the income of the individuals is growing and the gap with the saturation level will be filled soon, while on the other hand, if α is near to zero, it means that it will take longer for the society to reach the saturation level of vehicle ownership.

G_r, which is the gap between current vehicle ownership and the saturation level in region r, can be estimated as follows:

$$G_r = POP_r * SVO - \sum_i V_{i,r} \tag{20}$$

where:

POP_r is the size of population in region r;

SVO is the saturated vehicle ownership of the case study.

Balancing feedback 2: "Station Saturation"

Another balancing feedback arises from the fact that the profitability of investments on fuel/charging stations will decrease as the number of stations in the market increases (figure 27).

While an increase in the number of fuel stations helps to increase the utility of the alternative fuel vehicles, it also has a counter-balancing effect that is seen through the Saturation of Stations in this loop. Based on equation 14, the saturation of fuel stations will happen when the "Number of available Fuel Station" (NFS) goes up and results in lowering the profitability of investment on fuel stations. This will lead to a reduction of the number of fuel stations (mainly because of the aging impact of stations), thus resulting in a balancing feedback.

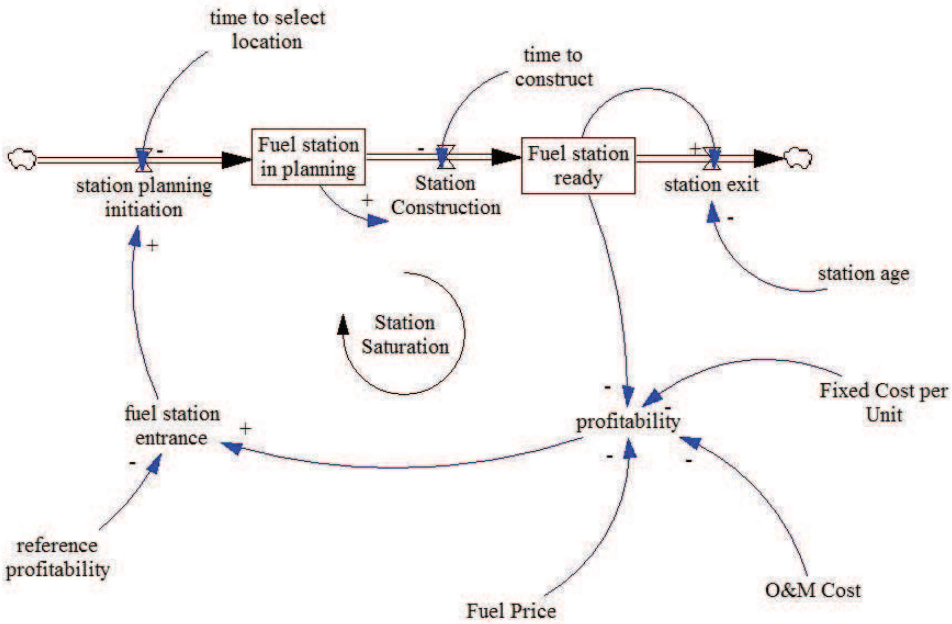


Figure 27: Balancing feedback "Station Saturation"

The initiation rate of fuel station in planning depends on many factors such as the fuel station entrance and time to select the location;

$$SIP_{r,f} = \frac{\mathrm{FSE}_{\mathrm{r,f}}}{TSL} \quad (21)$$

where:

$SIP_{r,f}$ represents the rate of fuel stations in planning for fuel f, in region r; and

TSL is the time to select the location for the fuel station.

According to (Struben, [164]), it was assumed that the TSL is 1 year. The number of fuel stations in planning accumulates the stations in planning (SIP), less the fuel stations in a construction phase:

$$\frac{dFSP_{r,f}}{dt} = SIP_{r,f} - FSIC_{r,f} \quad (22)$$

where:

$FSP_{r,f}$ represents the fuel stations for fuel f, in planning phase in region r; and

$FSIC_{r,f}$ represents the fuel Station for fuel f in construction phase in region r;

The number of fuel stations in the construction phase depends on the number of fuel stations in planning on the time for construction;

$$FSIC_{r,f} = \frac{FSP_{r,f}}{TTCFS} \tag{23}$$

where:

TTCFC is the time for the construction of a fuel station.

According to (Struben, [164]), the *TTCFC* is 2 year. Moreover, the number of functional fuel stations accumulates the stations that are being constructed, less the stations that reaches their lifetime:

$$\frac{dNFS_{r,f}}{dt} = FSIC_{r,f} - FCO_{r,f} \tag{24}$$

where,

$FCO_{r,f}$ is the number of fuel stations that are dropped.

The number of fuel stations that reach their lifetime threshold depends on the number of available fuel station and fuel station lifetime:

$$FCO_{r,f} = \frac{NFS_{r,f}}{ASL} \tag{25}$$

where,

ASL is the average lifetime of a fuel station. In this study 20 years was assumed as the lifetime of a fuel station (Struben, [164]).

4.3. Model calibration

When a model is structurally complete and simulates properly, its calibration is done to find the values of parameters that make the model generate behavior curves (results) that best fit the real data of the known history. Calibration of a model can be partially done by comparing the model behavior with time series data collected in the "real world". The model parameters selected for tuning during the calibration are the following:

- M_i: Marketing factor for technology i (equation 11);
- β_n: The vehicle choice coefficients (equation 12);
- AVL: Average vehicle lifetime of the light duty vehicle (equation 18);
- α: The coefficient of fleet gap filling (equation 19).

4.3.1. Historical data

In order to calibrate the model, real data is essential. For this purpose, in the case study of Portugal, the historical data for the evolution of gasoline, diesel and hybrid vehicles for the Portuguese fleet shown in figure 28, were found in (ACAP, [13]). Data regarding the fuel price was obtained from statistics provided by DGEG [15].

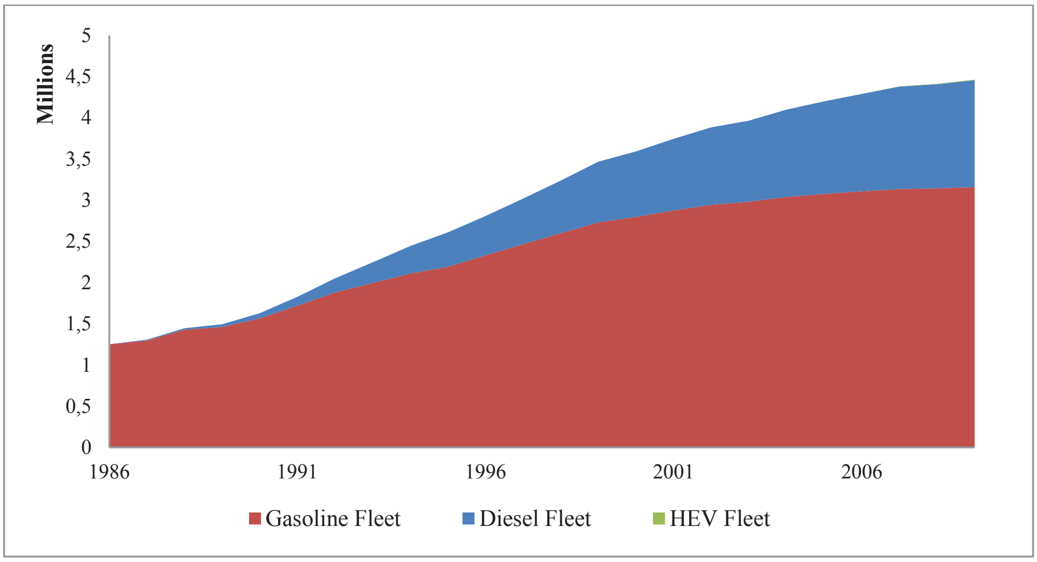


Figure 28: Historical data for light duty passenger fleet in Portugal

In the VENSIM software [165], the optimization module can be used to calibrate the model and estimate the parameters. In order to use it, it is necessary to define the "payoff" concept. The payoff is the indicator reported at the end of the simulation, numerically calculating the difference between the real data and simulation results. After defining the payoff, the optimization module will select a value for each calibration parameter within a predefined range (Appendix 3) and run the whole model in order to maximize the payoff. The combination of values of these selected parameters that minimizes the difference between the results of the simulation and the real historical data are stored in the optimization control file.

4.3.2. Sequence of calibration hypotheses

As one of the major purposes of this model is to learn from the adoption of new technologies (in this case diesel cars), we needed to investigate some hypotheses regarding the characteristics of the marketing factor. This analysis was developed in several phases. This was due to the fact that the results obtained with the initial hypothesis were rather poor. The sequence of hypotheses tried and respective results obtained were as follows:

a) *TRIAL 1: Marketing Factor constant over time, similar for Diesel and Hybrid*

First, it was assumed that the marketing factor is constant (time-independent) and similar for diesel and Hybrid technologies. This has implicit that the consumer is sensible to the techno-economic characteristics of the product but not to the "name" of the product itself. The calibration values returned by VENSIM for the key parameters are presented in table XX.

It should be noted that all the values make physical sense, such as the average vehicle life and negative values for the purchase cost and the fuel cost coefficients. According to table XX, during this period (1986-2009) in average 5% of the gap with saturation vehicle ownership level was compensated by the new vehicle sales, annually. Besides, it is interesting to note that the absolute value for the fuel cost and the performance coefficient is very low and the most important parameters for vehicle choice are purchase price, range and fuel station coverage.

Table XX: Calibration values on TRIAL 1 based on historical data for Portugal (1986-2009)

	AVL	α	β				
			Purchase Price	Fuel Cost	Range	Performance	fuel station coverage
TRIAL 1	8.33	0.05	-9.00	-0.01	2.59	0.01	0.48

Focusing on equation 11, which relates the social parameters with the familiarity of individuals with each technology, the calibration step assists us to identify the values of the parameters (table XXI).

Table XXI: Calibrated results for familiarity-related factors in TRIAL 1

	M_{Diesel}	M_{Hybrid}	γ_1	γ_2	γ_3
TRIAL 1	0.16	0.16	0.1	0.01	0.2

Considering the marketing factor, it means that at a constant rate, every year, around 16% of people got familiar with diesel technology because of the marketing impact. In fact, the first feeling from this finding is that these values seem to be relatively low for diesel vehicle and relatively high for hybrid vehicles. The value of γ_1=0.1 represents the impact of vehicle share on familiarity, while γ_2= 0.01 reflects the low impact of word of mouth on familiarity growth. In this hypothesis γ_3= 0.2 means that every year 20% of the familiarity (in that year) is lost due to forgetfulness, this being a rather significant value.

It worth mentioning that, it was assumed that the familiarity of individuals with gasoline car is 100% and constant. As a result, the sales of gasoline cars are only indirectly affected by the sales of diesel and hybrid vehicle. When the interest toward diesel cars increase, the sales of gasoline car will drop and vice versa. The comparison between the results of the calibration and real data is shown in figures 29 to 31. It is obvious that there are significant differences between simulated values and real data for diesel and hybrid fleet. Therefore, it seems necessary to separate the marketing factor for diesel and hybrid technologies.

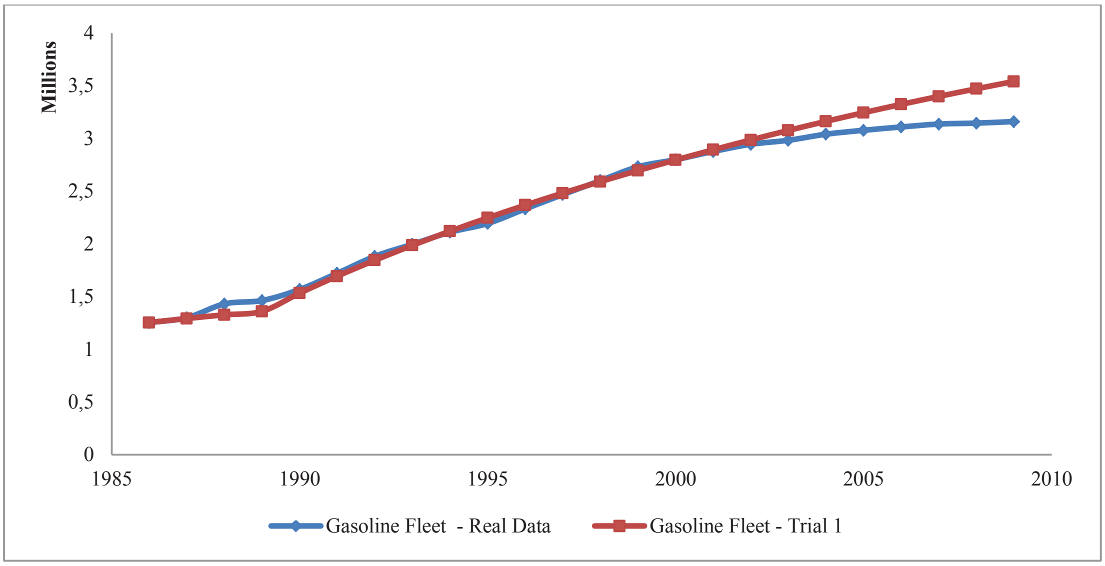


Figure 29: Gasoline fleet evolution- real data vs model results in TRIAL 1

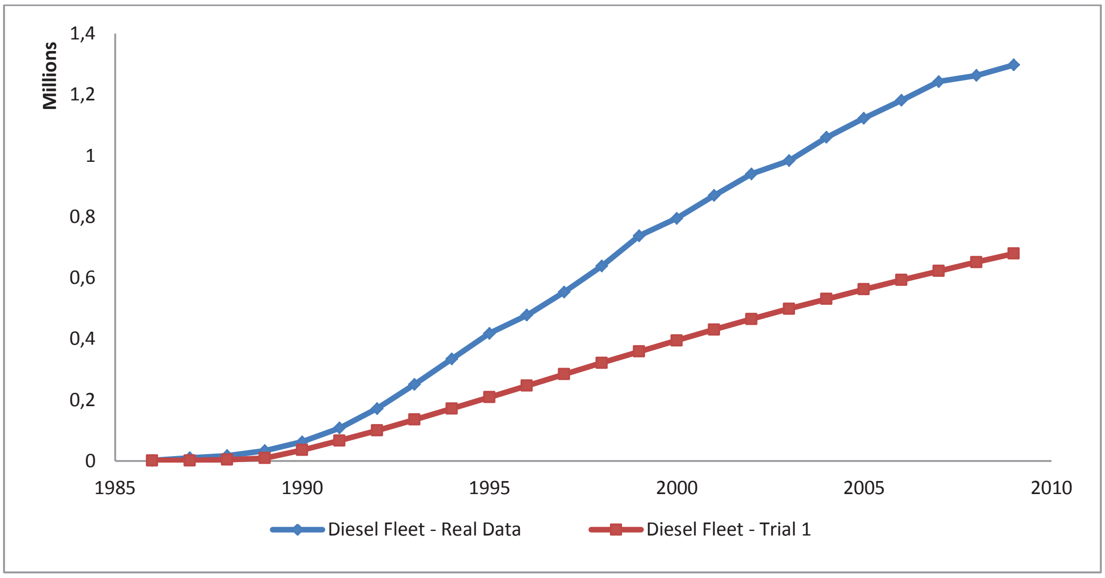


Figure 30: Diesel fleet evolution- real data vs model results in TRIAL 1

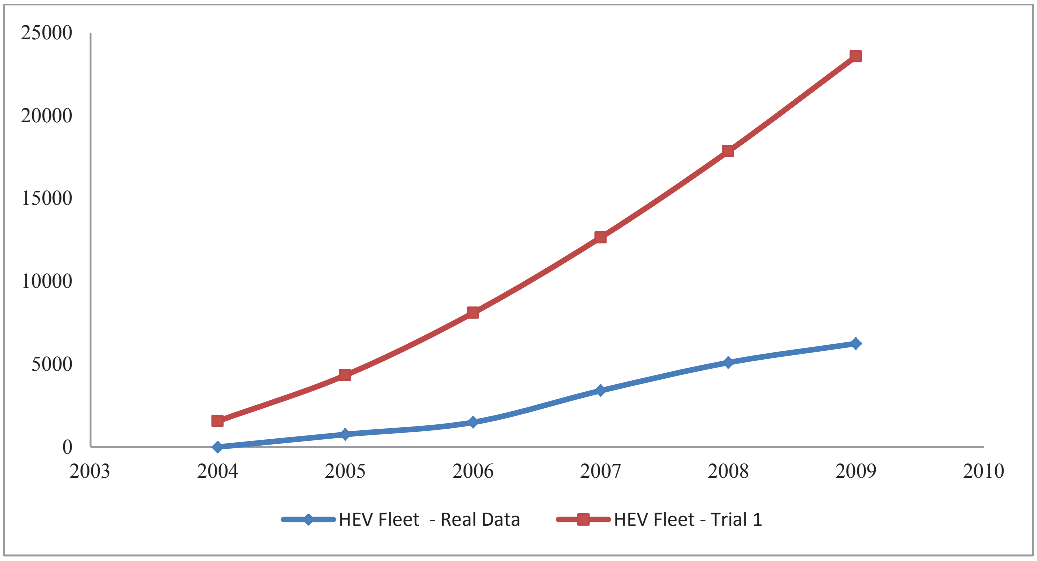


Figure 31: Hybrid fleet evolution- real data vs model results in TRIAL 1

After reviewing the outcome of trail 1 in figures 29 to 31, significant differences between simulated values and real data for diesel and hybrid fleet can be seen. Looking more carefully at the calibration parameters discussed in the early part of section 4.3, the marketing factor seems to be the parameter with the most potential to affect the result of simulation. Therefore it is necessary to study more calibration hypotheses to identify the most proper trend for the marketing factor in terms of simulating the real data more accurately

According to equation 11, the marketing factor is directly affecting the familiarity, which itself affects the perceived utility of each powertrain. The marketing factor therefor seems to be the key calibration factor, and the changes will be focused on it.

b) TRIAL2: Marketing Factor constant over time, different for Diesel and Hybrid

Following the previous discussion, we considered a hypothesis that the marketing factor is constant over time, but it is different for Diesel and Hybrid technologies.

The calibrated values for some parameters in TRIAL 2, are presented in table XXII. It is interesting to note that the absolute values for the coefficients of the fuel station coverage are very low. In fact, the most important parameters for vehicle choice are purchase price, performance and range.

Table XXII: Calibrated factors on TRIAL 2 based on historical data for Portugal

	AVL	α	β				
			Purchase Price	Fuel Cost	Range	Performance	fuel station coverage
TRIAL 2	10.26	0.06	-1.06	-0.19	0.34	0.53	0.01

Focusing on equation 11, which relates the social parameters with the familiarity of individuals with each technology, the calibration step assists us to identify the values of the parameters (Table XXIII).

Table XXIII: Calibrated results for familiarity-related factors in TRIAL 2

	M_{Diesel}	M_{Hybrid}	γ_1	γ_2	γ_3
TRIAL 2	0.09	0.002	0.08	0.002	0.26

Considering the new value found for the marketing factor for diesel, it signifies that at a constant rate, every year around 9% of people got familiar with this technology, during 1986-2009. Moreover, the marketing factor for hybrid vehicles is 0.002, which reflects the very low impact of marketing on the familiarity of individuals with this technology. The value of γ_1= 0.08 shows the impact of vehicle share on familiarity, while γ_2 = 0.002 shows the low impact of word of mouth on familiarity growth. In this hypothesis γ_3= 0.26 meaning that every year 26% of the familiarity is lost due to forgetfulness - a quite significant value.

The comparison between the calibrated results and real data is shown in figures 32 to 34. It is obvious that there is significant improvement comparing to TRIAL 1; However the fact that there was need to consider technology-dependent factors is not totally comfortable, therefore it was decided to investigate another hypothesis, to check the situation where the marketing factor is time-dependent but technology-independent.

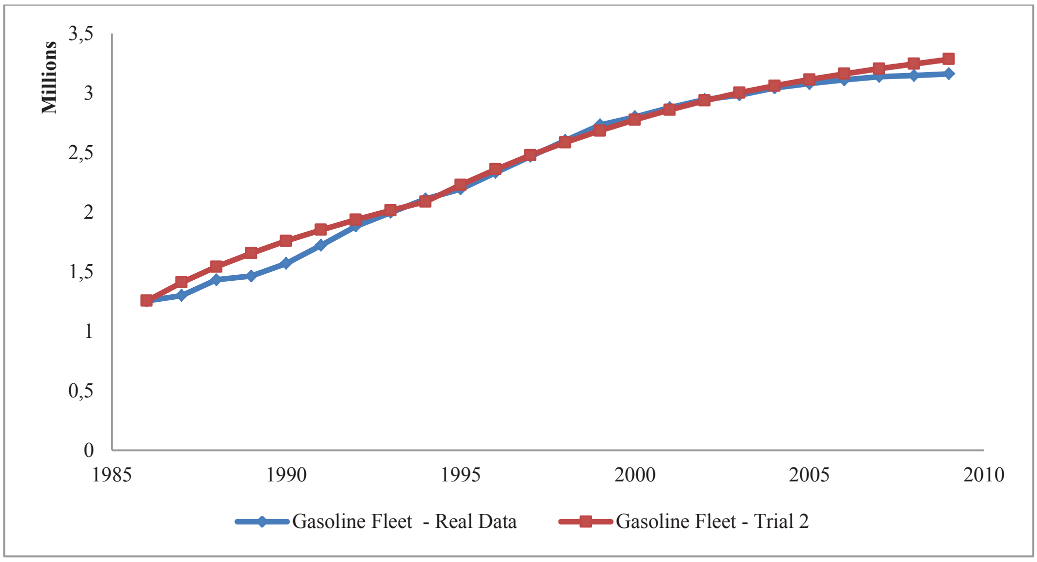


Figure 32: Gasoline fleet evolution- real data vs model results in TRIAL 2

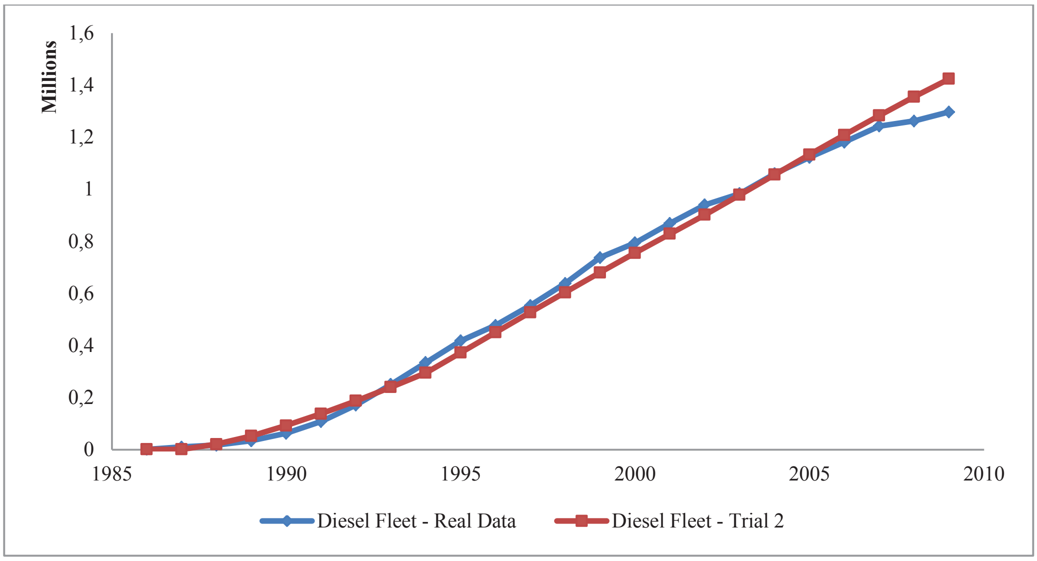


Figure 33: Diesel fleet evolution- real data vs model results in TRIAL 2

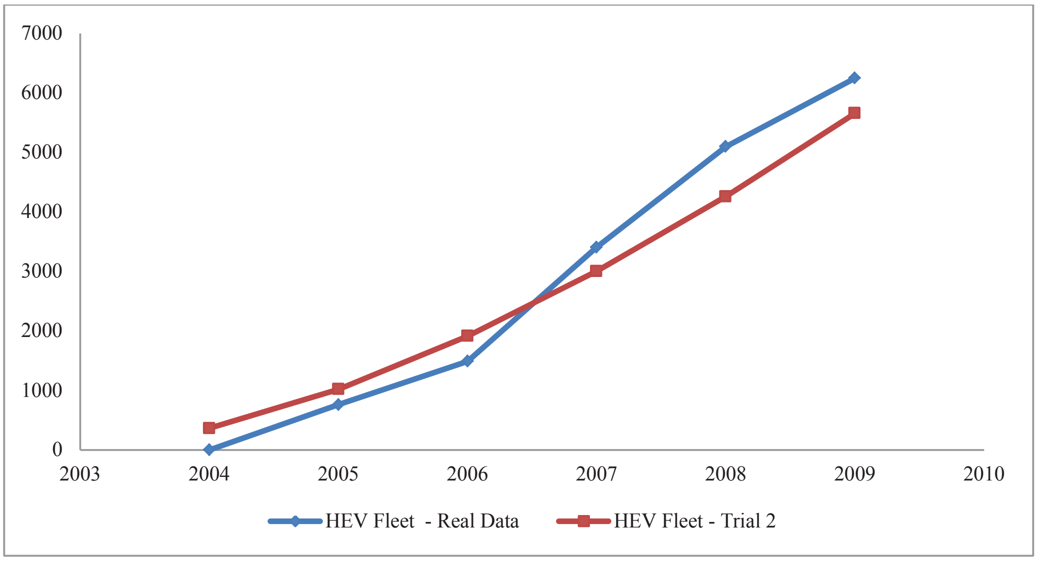


Figure 34: Hybrid fleet evolution- real data vs model results in TRIAL 2

c) Time-dependent Marketing Factor, similar for Diesel and Hybrid

Following the previous arguments, we have considered another assumption, with the marketing factor being time-dependent, but common for both Diesel and Hybrid technologies. The calibrated parameters in TRIAL 3, are presented in table XXIV. Again, we can see that the absolute value for the coefficient of fuel cost and performance is very low. In fact, the most important parameters for vehicle choice are the purchase price and the range.

Table XXIV: Calibrated factors on TRIAL 3 based on historical data for Portugal

	AVL	α	β				
			Purchase Price	Fuel Cost	Range	Performance	fuel station coverage
TRIAL 3	10.00	0.06	-9.00	-0.01	2.57	0.01	0.19

Regarding the parameters that affect the familiarity of individuals with each technology (equation 11), the calibrated values were identified. In order to identify a pattern for changes of the marketing factor over time, we decided to consider a combination of three step functions:

$$M_{diesel} = IDM + \text{step}(M_{diesel1},1990) + \text{step}(M_{diesel2},1995) + \text{step}(M_{diesel3},2000) \quad (26)$$

where:

IDM represents the initial diesel marketing;

$M_{diesel1}$ is the changes in diesel marketing since 1990;

$M_{diesel2}$ is the changes in diesel marketing since 1995;

$M_{diesel3}$ is the changes in diesel marketing since 2000.

Considering the fact that, in this TRIAL, the initial marketing factor for these two technologies was supposed to be the same, the function for the marketing factor of hybrid technology will be:

$$M_{hybrid} = \text{step}(IDM, 2002) \quad (27)$$

Considering the time-dependency of the marketing factor, the results of the calibration for M_{diesel} and M_{hybrid} are shown in figure 35.

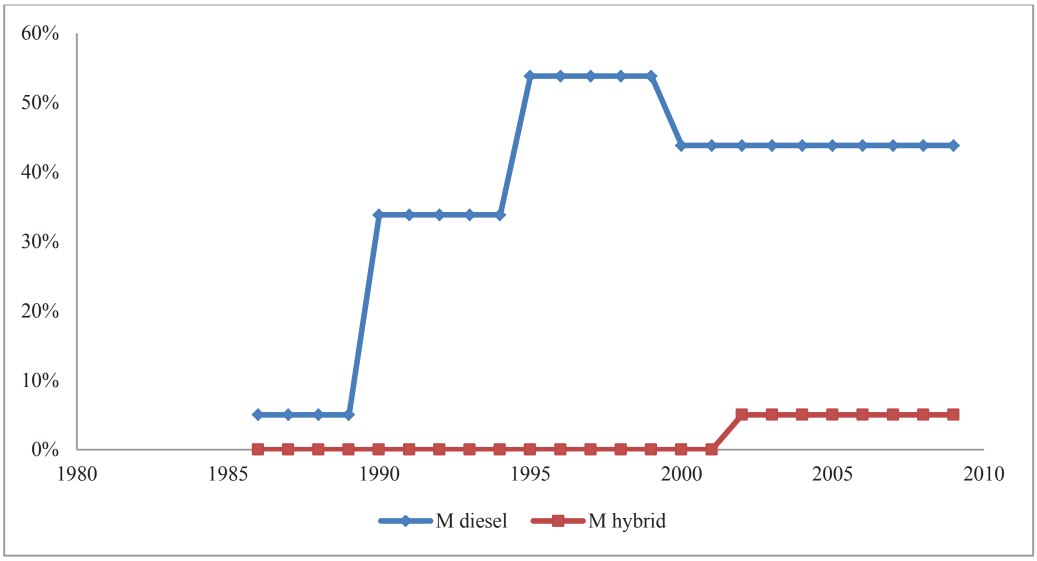


Figure 35: Calibrated values for M_{diesel} and M_{hybrid} in TRIAL 3

As assumed in this hypothesis, the marketing value in the initial period of technology introduction is the same (M_{hybrid} =5%). The trend of changes in marketing for diesel can be described as follow:

- initial low marketing for a new technology;
- gradual growth in marketing from 1990;
- reaching the saturation level during 1995-2000;
- gradual reduction in response to reaching the saturation level of familiarity.

The results of the calibration of other parameters that directly affect the familiarity (equation 11) are presented in table XXV. The value of γ_1=0.1 reflects the impact of vehicle share on familiarity, while γ_2=0.01 shows the low impact of word of mouth on familiarity growth. In this hypothesis γ_3=0.4 which reflects that annually 40% of familiarity is lost due to forgetfulness.

Table XXV: Calibrated results for some of familiarity-related factors in TRIAL 3

	γ_1	γ_2	γ_3
TRIAL 3	0.1	0.01	0.4

Figures 36-38 show the comparison between the calibrated results and real data. It is interesting to note that although the simulated gasoline fleet is very similar to the real data, there are still significant differences between the simulated values and real data for diesel and hybrid fleet. Therefore, we should keep the marketing factor time dependent, but separate it for diesel and Hybrid technologies. This will be done in the following section.

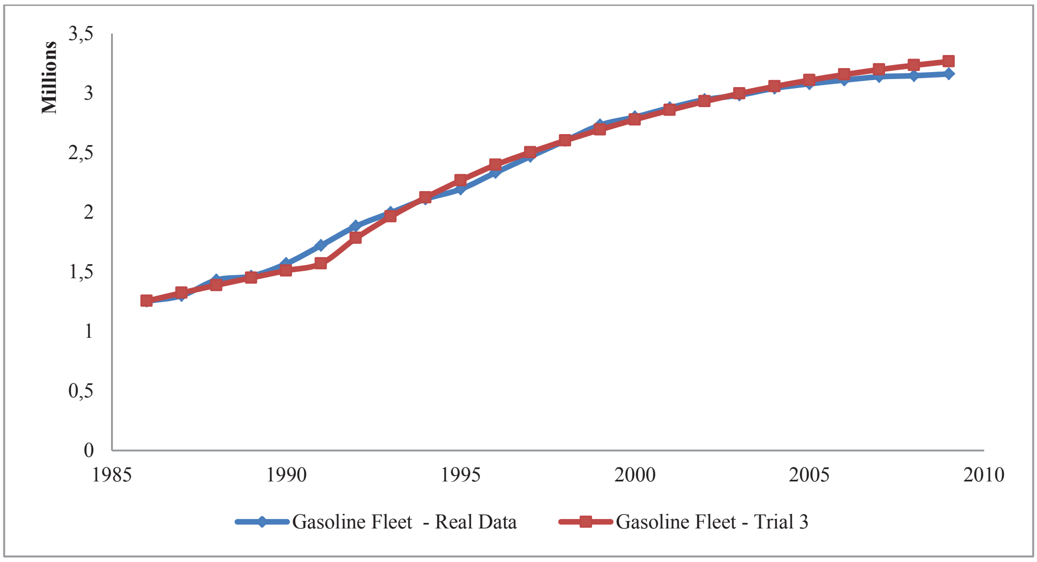


Figure 36: Gasoline fleet evolution- real data vs model results in TRIAL 3

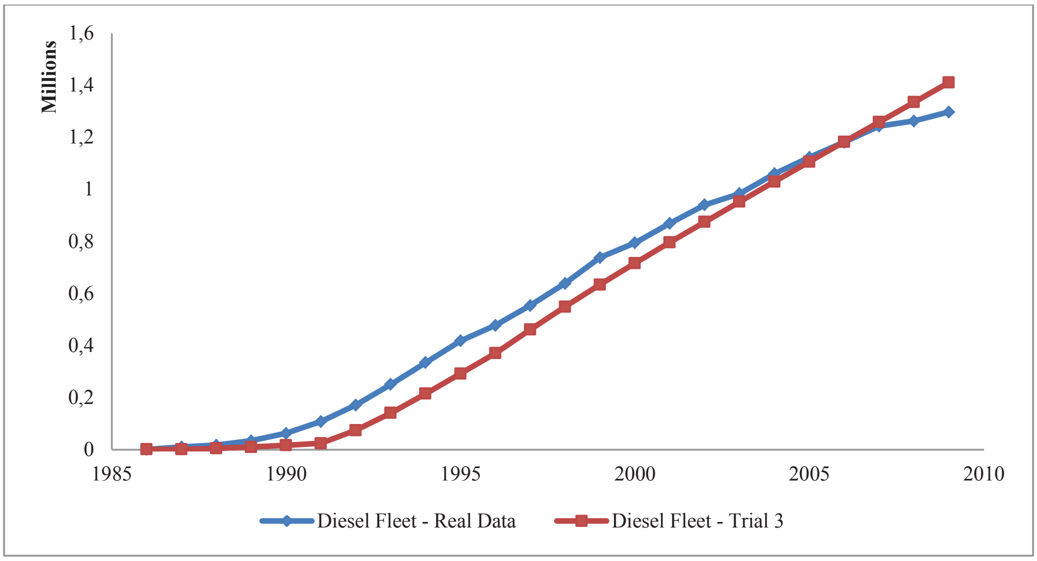


Figure 37: Diesel fleet evolution- real data vs model results in TRIAL 3

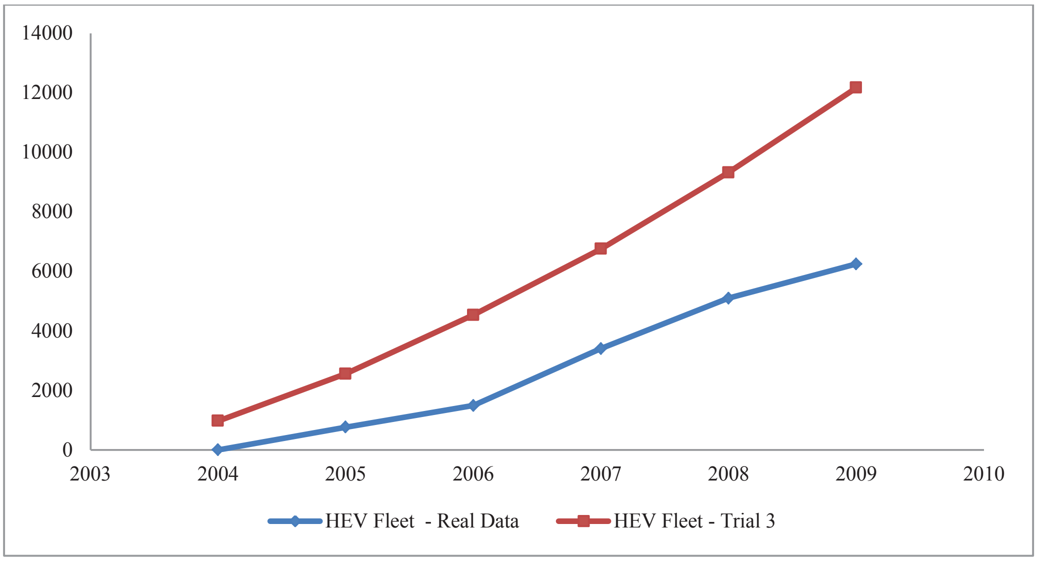


Figure 38: Hybrid fleet evolution- real data vs. model results in TRIAL 3

d) Time-dependent Marketing Factor, different for Diesel and Hybrid

Following the debate of the previous sections, we have considered another assumption, with the marketing factor being time-dependent, and different for Diesel and Hybrid technologies.

Some of the calibrated parameters in TRIAL 4, are presented in table XXVI. Again, it should be noted that the absolute value for the coefficients of performance and fuel station coverage are relatively low. In fact, the most important parameters for vehicle choice are purchase price, range and fuel cost.

Table XXVI: Calibrated factors on TRIAL 3 based on historical data for Portugal

	AVL	α	β				
			Purchase Price	Fuel Cost	Range	Performance	fuel station coverage
TRIAL 4	16.91	0.06	-4.41	-1.05	1.24	0.44	0.40

As presented in the previous trial, in order to identify a pattern for changes of the marketing factor over time, we have decided to consider a combination of two step functions. The same formulation (equation 26) was applied for $\mathrm{M_{diesel}}$, while the formulation for $\mathrm{M_{hybrid}}$ was revised, in order to study different marketing values for the hybrid vehicle:

$$\mathrm{M_{hybrid}}\ \ \mathrm{step}(IHM, 2002) + \mathrm{step}(\mathrm{M_{hybrid1}}, 2005) \tag{28}$$

where:

IHM represents the initial hybrid marketing;

$\mathrm{M_{hybrid1}}$ is the changes in hybrid marketing since 2005.

Considering the time-dependency characteristic of the marketing factor, the results of calibration for $\mathrm{M_{diesel}}$ and $\mathrm{M_{hybrid}}$ are shown in figure 39.

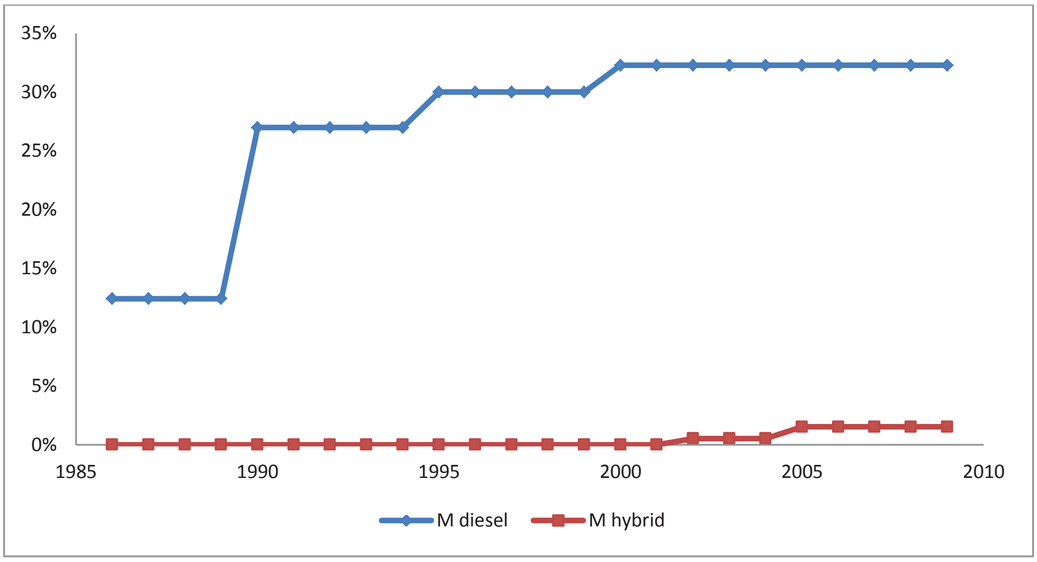


Figure 39: Calibrated values for $\mathrm{M_{diesel}}$ and $\mathrm{M_{hybrid}}$ in TRIAL 4

The trend of changes in marketing for diesel can be described as follows:

- initial low marketing for a new technology;
- gradual growth in marketing from 1990 that continues till 2000;

- reaching the saturation level around 2000.

The trends in the hybrid marketing follow the same trend of gradual growth after the initial low marketing. It is expected that it follows the trend for diesel from now on. The results of calibration of other parameters that directly affect the familiarity (equation 11) are presented in table XXVII.

The value of γ_1=0 shows that the impact of vehicle share on familiarity is insignificant, while γ_2=0.01 reflects the low impact of word of mouth on familiarity growth. In this hypothesis γ_3=0.4 meaning that 40% of familiarity is lost due to forgetfulness annually.

Table XXVII: Calibrated results for some of familiarity-related factors in TRIAL 4

	γ_1	γ_2	γ_3
TRIAL 4	0	0.01	0.4

Figures 40-42 show the comparison between the calibrated results and real data. It seems that this hypothesis stating that the marketing factors are time-dependent, and different for Diesel and Hybrid technologies, is the most suitable one to simulate the real data for the evolution of the gasoline, the diesel and the hybrid fleet.

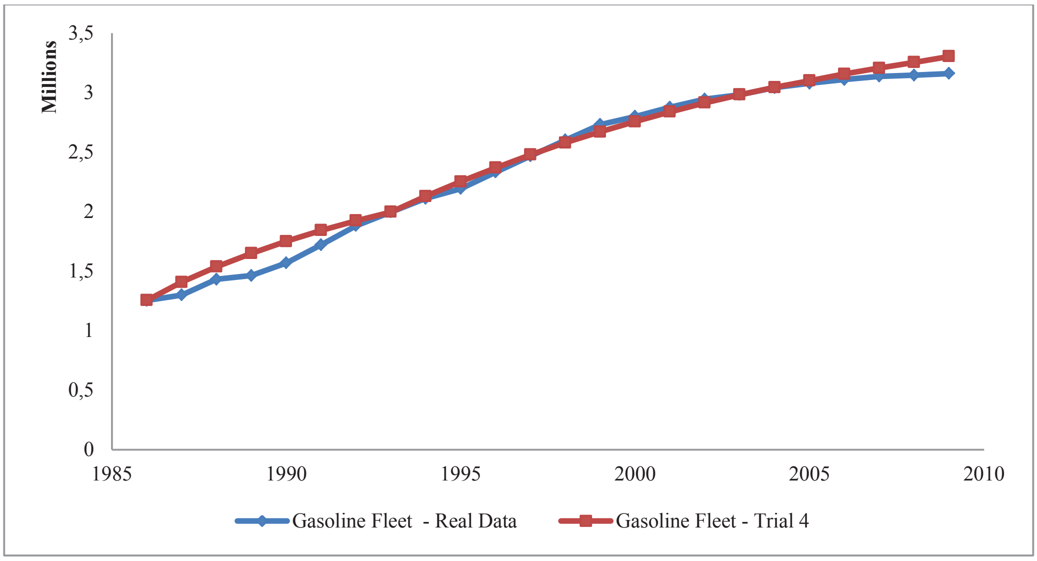


Figure 40: Gasoline fleet evolution- real data vs model results in TRIAL 4

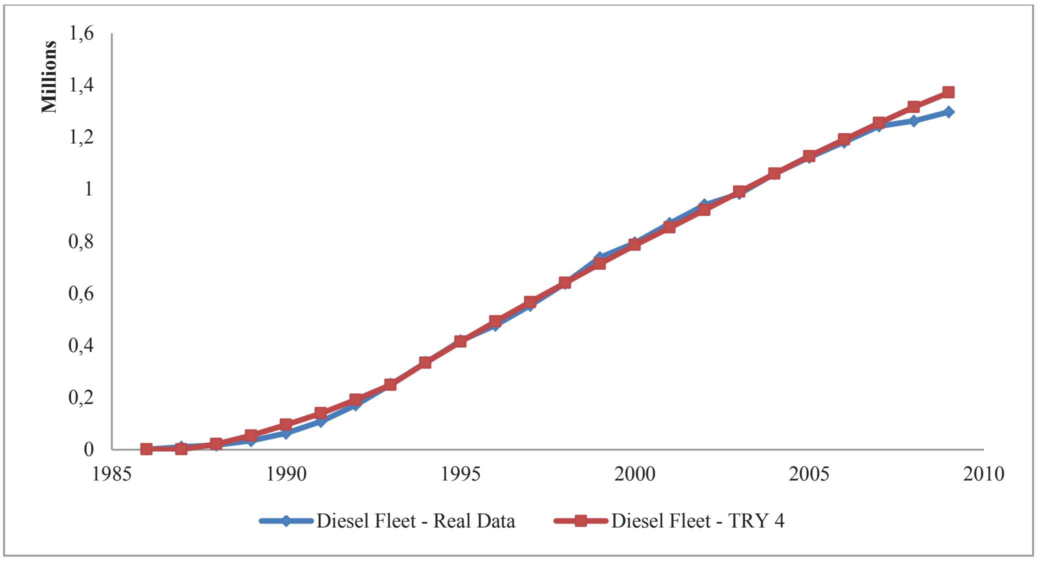


Figure 41: Diesel fleet evolution- real data vs model results in TRIAL 4

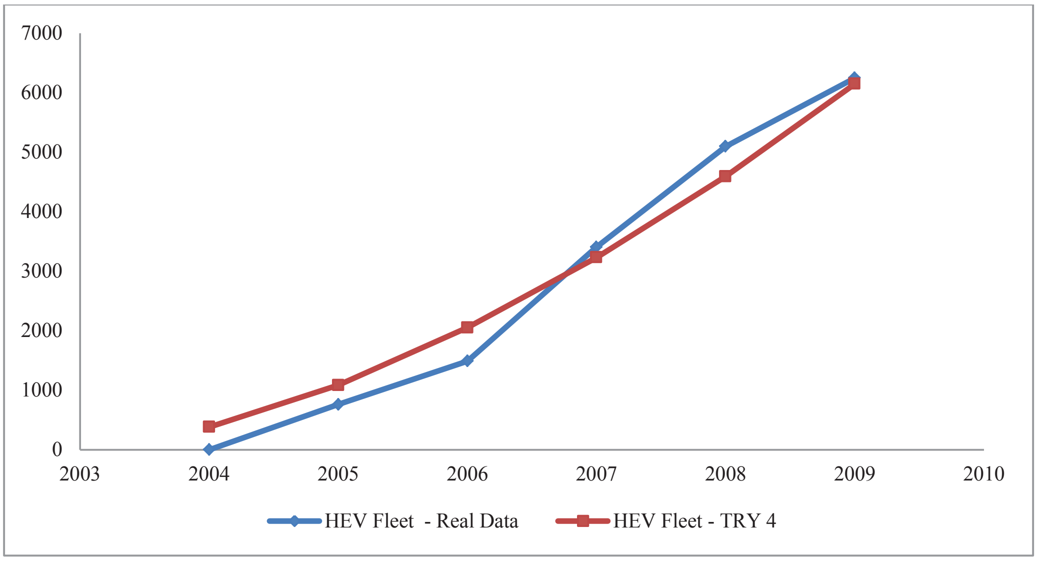


Figure 42: Hybrid fleet evolution- real data vs model results in TRIAL 4

4.3.3. Findings and discussion

After considering four hypotheses regarding the calibration of the system dynamics model, historical data were used to test these hypotheses, in the previous sections. Table XXVIII presents the calibrated values for the vehicle choice model, for all four hypotheses. These can be interpreted as the importance weights that the customer puts on each of these attributes.

Table XXVIII: Calibrated factors based on historical data for Portugal

Coefficient	Calibrated Value			
	TRIAL 1	TRIAL 2	TRIAL 3	TRIAL 4
Purchase Price	-9.00	-1.06	-9.00	-4.41
Fuel Cost	-0.01	-0.19	-0.01	-1.05
Range	2.59	0.34	2.57	1.24
Performance	0.01	0.53	0.01	0.44
Fuel station coverage	0.48	0.01	0.19	0.40

Considering the calibrated values for the sensitivity of customers to the choice factors in almost all cases, it seems that the purchase price followed by the range the fuel cost are the main drivers. Interestingly, it is obviously notable that the performance and the fuel stations coverage are not overly important factors - however this observation may be somehow misleading, considering the fact that the calibration was made essentially using the data for diesel and hybrids, while these technologies do not need new fuel stations, and that is not the case of PHEVs or Hydrogen fuel cells.

As it was mentioned earlier, in this study several hypotheses have been investigated regarding the characteristics of the marketing factor. According to figures 29-42, the results for the fourth hypothesis show the higher resemblance to real data. This proves that the marketing factors are time-dependent. Besides, because of different characteristics of diesel and hybrid technologies, marketing factors should be calibrated separately for each of these technologies.

4.4. Estimation of the transition cost

Several definitions of "transition cost" can be found in the literature. This can be viewed as the cost to the customer including the initial price, fuel price, maintenance cost, or the cost to the decision makers such as the incentives for vehicles, fuels and fuel stations. Therefore, we start by outlining the definition for transition cost that is going to be adopted in this study.

4.4.1. Definition

Here, the transition cost is taken in the perspective of the costs to the society that are paid by the government. It is therefore defined as the sum of all the discounted incentives required for the transition to take place. These incentives can be either for the purchase price of the vehicle, the fuel cost or the fuel stations.

$$TTC = \sum_t (IVPP)_t \ + \sum_f IFP_f + \sum_f IFS_f \qquad (29)$$

where:

TTC is the total transition cost;

$IVPP_t$ represents the incentive for purchase price of technology *t*;

IFP_f captures the incentive for price of fuel *f*;

IFS_f is the incentive for fuel stations of fuel *f;*

t and *f* are the technologies and fuels, respectively.

Considering equation 12 on nominal utility estimation, we see that purchase price, fuel cost and fuel station coverage can directly affect the results of the vehicle choice model. Putting incentives for the purchase price or fuel prices of specific alternative fuel-technology vehicles can result in lowering the expenses to the individuals. The less costly a new technology becomes, the higher the nominal utility of that technology will reach. The share of purchase for each technology, according to equation 10, depends directly on the nominal utility value and therefore the sales share of an AFV can be increased by having incentives in place.

Besides, the incentive for fuel stations can increase their profitability (equation 14), and this could result in more stations for fuel *f* in planning and construction phase (equations 21 and 23). According to equation 16, the increase in the number of available fuel stations can cause the fuel station coverage to increase and improve the annual sales of the vehicles using fuel *f*.

4.4.2. Methodology

An optimization module has been added to the model, so that the lowest transition cost can be estimated. The Objective Function (OF), to be minimized is defined as follows:

$$OF = TTC + M \times GtT \qquad (30)$$

where:

TTC represents the total transition cost;

M is the trade-off factor in terms of euro/share of AFV in the LDV fleet;

GtT represents the gap to target in terms of “share of AFV in the LDV fleet”.

As expected, the value of M as the trade-off factor can be changed according to the decision maker’s preferences. A high M (one billion euro per share of AFV in the LDV fleet) means that for each percent point of the gap to the target (share of AFV in the LDV fleet), the objective function will be penalized by one billion euros. In this situation, the main characteristic of the optimal point is the very low gap to the target. On the other hand, if M has a low value (lower than a thousand euro per share of AFV in the LDV fleet), the optimal point will be far from the target but, at the same time, with a low transition cost.

The constraints adopted for the application case-study are the following:

a) Incentive factor for Purchase Price of Vehicle ≤ 95%
b) Incentive factor for fuel ≤ 95%
c) Incentive factor for fuel stations ≤ 95%
d) Duration of Incentive for Initial Price of Vehicle ≤ 15 (years)
e) Duration of Incentive for fuels ≤ 15 (years)
f) Duration of Incentive for Fuel stations ≤ 15 (years)
g) $\mathrm{Marketing_i} \leq$ Max Annual $\mathrm{Marketing_i} = 0.1$
h) Total Transition Cost ≤ 10 or 20 (billion €)
i) Vehicle lifetime: no limit or ≤ 10 (Years)

The first three conditions (a, b and c) represent the maximum limit of incentives for the initial price of a vehicle, the fuel and the fuel stations respectively. The first two values are the share of purchase price or fuel price of each alternative fuel vehicle that can be received by the customer as incentive, while the third factor is the share of capital investment for fuel stations that will be paid by the government. In practical terms, a value of 0.25 in the first condition means that 1/4 of the purchase price of a vehicle will be compensated by the incentive; while this value for the second condition means that each liter of a fuel will be 25% cheaper than the real price.

The next three constraints (d, e and f) represent the maximum duration of the incentive policy for the initial price of the vehicle, fuel and fuel stations respectively. Condition g defines the maximum level of annual marketing effort that will make the familiarity with the new technology to grow.

In order to consider the situation where transition costs can be limited, constraint h can be added to the optimization module. The last condition (i), corresponds to the case where a vehicle scrappage policy is in place to discard the cars after they reach the age limit.

4.5 Policy Scenarios

We have analyzed several scenarios to investigate the impact of supportive policies such as incentives. The first scenario deals with the "business as usual" trend of fleet evolution. Then, the impact of incentives for vehicles, fuels and fuel stations is studied. Considering the limitation of available budgets for incentives, another scenario was investigated. As the results were far from the target for the AFV fleet, we have introduced a vehicle early retirement, policy, which was at some points in history already implemented in many countries including France, Spain and Portugal ([166]). Therefore, we have studied the impact of these policies. In fact, several studies tried to assess the effectiveness of Scrapping Schemes for Vehicles in terms of their economic, environmental, and safety impacts (IHS Global Insight, [167]). Therefore, in this study the developed method was tested for a set of scenarios to investigate the impact of a vehicle early retirement policy on AFV annual sales. These scenarios can be described as follows.

Scenario A: Business as usual (no optimization)

In this scenario, there will be no incentive supports for vehicle, fuels or fuel stations, and the fleet turn over follows the historical trend.

Scenario B: Incentives on vehicles, fuels and fuel stations (constraints a to g)

The optimization module was applied in order to identify the optimal combination of incentives to reach a predefined target by year 2030.

Scenario C: Limited incentives on vehicles, fuels and fuel stations, with a limit of 10 billion € (constraints a to h)

Constraint h was added to the previous scenario, in order to identify the optimal combination of incentives in the case where total incentives cannot exceed 10 Billion € (in case this proves insufficient to reach the target, the best approximation is considered).

Scenario D: Incentives on vehicles, fuels and fuel stations with the possibility of implementing vehicle retirement policy (constraints a to g and i)

In order to assist the decision makers to make informed decisions, this scenario could potentially investigate the impact of early vehicle retirement in terms of reaching the target and total transition costs.

Scenario E: Limited incentives (20 billion €) on Vehicles, fuels and fuel stations with the possibility of implementing vehicle retirement policy (constraints a to i)

We have investigated the results in the case of limited incentives, while the model can implement a vehicle retirement policy.

Scenario F: Limited incentives (10 billion €) on vehicles, fuels and fuel stations with the possibility of implementing a vehicle retirement policy (constraints a to i)

This scenario is similar to scenario E except for the value for the maximum transition cost. Table XXIX compares the six scenarios.

Table XXIX: Scenario analysis for estimating the transition cost

Scenarios	Description		
	Optimization	Limit on total Incentive	Early Scrappage Policy (up to 10 years)
A (Base)	NO	NO	NO
B	YES	NO	NO
C	YES	10 Billion €	NO
D	YES	NO	YES
E	YES	20 Billion €	YES
F	YES	10 Billion €	YES

Now, it is possible to estimate the transition cost for each screening alternative that resulted from the multi-criteria analysis (Table XIV in chapter 3).

4.6. Results and discussion

In this chapter a system dynamics model has been developed in order to analyze the transition of alternative fuel vehicles considering the co-evolutionary dynamics between infrastructure supply and vehicle demand.. In this sub-chapter the model is used to assess the transition characteristics for six different targets / policy scenarios, with emphasis on determining the effectiveness and requirements in terms of incentives. The shares of technologies in the light duty vehicle fleets that characterize each of the target scenarios come from the application of the "phase one" screening alternatives applied to Portugal (subchapter 3.4) and are:

- Alternative 1: [100% Hybrid Electric Vehicle using Diesel (HEVD)]
- Alternative 2: [50% Hybrid Electric Vehicle using Gasoline (HEVG) and 50% HEVD]
- Alternative 3: [33.3% Biodiesel vehicle (using B20), 33.3% HEVG and 33.3% HEVD]
- Alternative 4: [25% vehicle using E85, 25% Biodiesel, 25% HEVG and 25% HEVD]
- Alternative 5: [25% Biodiesel, 25% HEVG, 25% HEVD, 25% PHEV]
- Alternative 6: [25% Biodiesel, 25% HEVG, 25% HEVD, 25% BEV]

The transition to each of these alternatives will be analyzed under each of the policy scenarios defined in subchapter 4.6 and summarized in table XXIX.

4.6.1. Estimation of the transition cost to reach a [100% HEVD] fleet target

Results of the optimization module under each policy scenario of table XXIX, assuming that the target is the first alternative in the screening set [100% HEV-diesel], are shown in figure 43. It provides a snapshot of the predicted fleet compositions in Portugal, by the year 2030 under each policy scenario.

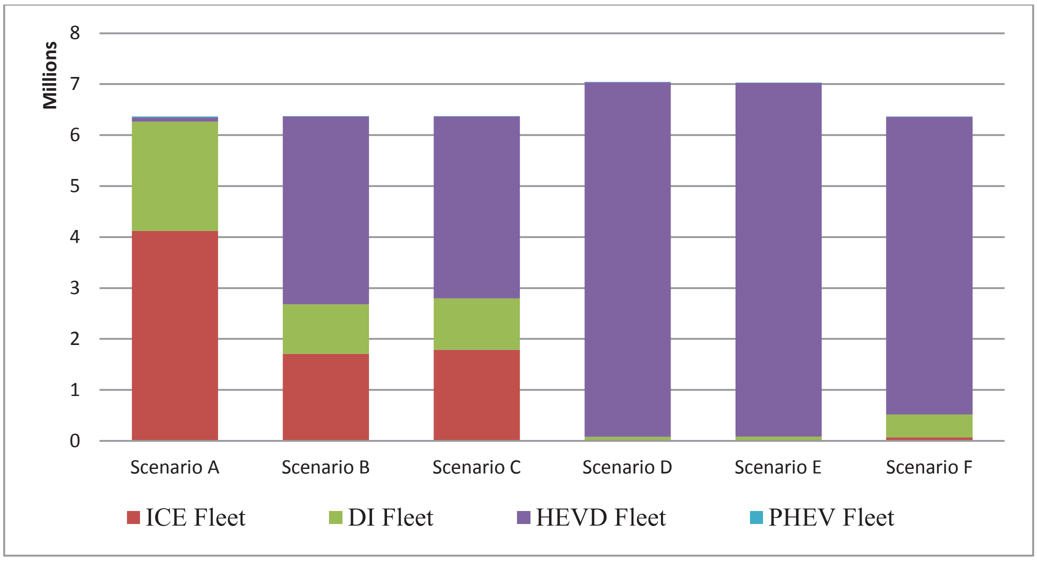


Figure 43: LDV fleet composition in 2030 predicted under each policy scenario, for [100% HEVD] fleet target

In figure 43, the light duty vehicle fleet compositions for the six scenarios are shown. In the base scenario (scenario A), which does not have any support incentives, the results suggest that the new technologies (including the hybrids, ethanol based and plug-in hybrid vehicles) will only be able to reach 3% of the fleet by 2030.

However, the fleet composition could potentially change, in the situation that supportive incentives for HEVD vehicles are in place. In scenarios B and C, there is a significantly higher share of HEV-diesel vehicles in the fleet. Scenarios D and E are the only two scenarios that are able to get very close to the intended target of [100% HEVD] fleet. One key message of these results is that a high penetration of hybrid vehicles can only be achieved if including the implementation of an early retirement policy

The total transition cost estimated for each policy scenario is presented in table XXX. It is important to recall that the value of the incentives includes an incentive for the HEV-diesel purchase price, as there is little support for incentivizing the fossil fuel (in this case diesel). According to the definition of transition cost in this study, these incentives are paid by the government.

Table XXX: Total transition costs for the different scenarios for [100% HEVD] fleet target (in billion €)

in billion €	A	B	C	D	E	F
Vehicle incentive	0	11.8	10	20.9	20	10
Fuel incentive	-----	-----	-----	-----	-----	-----
Station incentives	-----	-----	-----	-----	-----	-----
Total transition cost	0	11.8	10	20.9	20	10

The first insight from table XXX is that there are significant differences in the amount of optimized incentives identified in scenarios B and C when compared with the incentives in scenarios D and E, where an early retirement policy was implemented.

A second interesting feature of the developed model is that it can assist the decision makers with detailed information on the effects of the amount and duration of incentives (Table XXXI). The first finding is that applying the described methodology to estimate the transition cost in section 4.4.2, the incentives for the purchase price of HEVD in most of the scenarios are very close to the maximum limit. This is due to the fact that the model tends to put the maximum allowable incentive in place in order to reach the target of [100% HEVD] fleet.

Another interesting finding is that in the scenarios in which the budget for incentives is limited (scenarios C, E and F), the model tends to distribute it through the maximum allowable years (instead 0f concentrating them in the first years), while it reduces the amount of incentive per vehicle. This can be clearly seen in scenarios E and F, compared with scenario D, in which there is no constraint on the budget for incentives. This can be justified by the fact that a critical factor for social parameters such as familiarity is the time. Therefore, if the incentives are distributed in a long period of time, the familiarity of customers with AFV will be more significant.

Table XXXI: Information on the incentives in different scenarios for a [100% HEVD] fleet target

	A	B	C	D	E	F
Incentive on purchase price of HEVD	0	95%	83%	95%	91%	52%
Duration of incentive in years	0	15.0	15.0	13.9	14.2	14.8

4.6.2. Trade-off analysis of policies for [100% HEVD] fleet target

An interesting method to analyze the effectiveness of the incentives is to plot the trade-offs comparing the gap to the target and the amount of incentives for each scenario (figure 44).

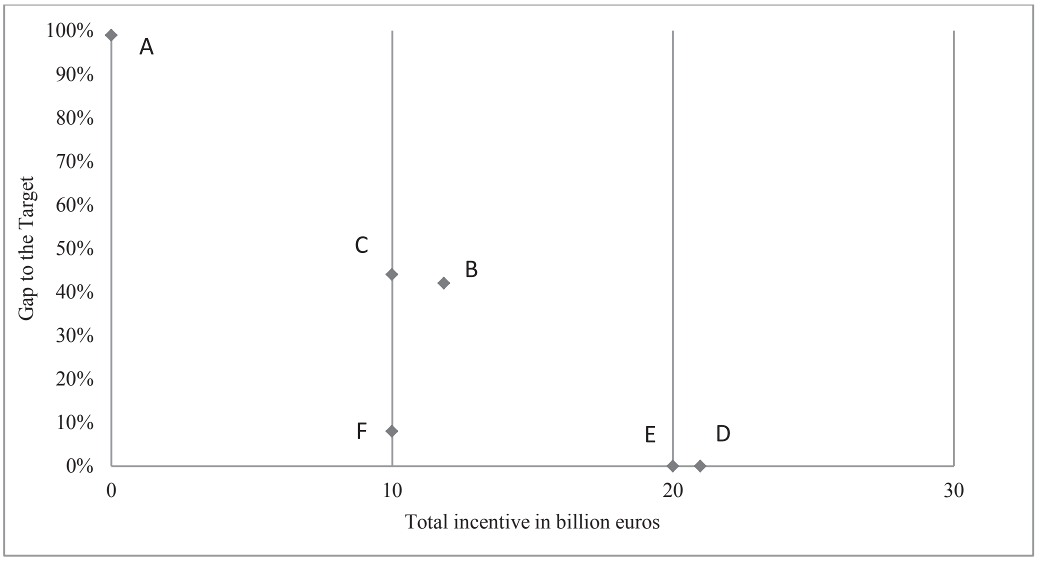


Figure 44: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [100% HEVD] fleet target

From figure 44, it is obvious that Scenario D with around 21 billion euros is the most expensive one; while there is no transition cost associated with Scenario A (Base Scenario).

An important observation is that starting from the base, it is possible to lower the gap by 50% with almost 10 billion euros (scenario C), but in order to actually reach the target (for example in scenarios E or D), the required incentive will be almost the double. Besides, it is also worth mentioning that with the same incentive budget, introducing the early retirement policy can significantly lower the gap to the target. For example, a comparison of scenarios C and F shows that the gap to the target in scenario F is around 35% lower, while the total transition cost is the same.

4.6.3. Estimation of transition Cost for a [50% HEVG, 50% HEVD] fleet target

The developed system dynamics model assists us to analyze the transition of the target which is the second alternative in the screening set [50% HEVG, 50% HEVD]. Figure 45 shows the predicted fleet compositions in Portugal, by the year 2030 under each policy scenario of table XXIX.

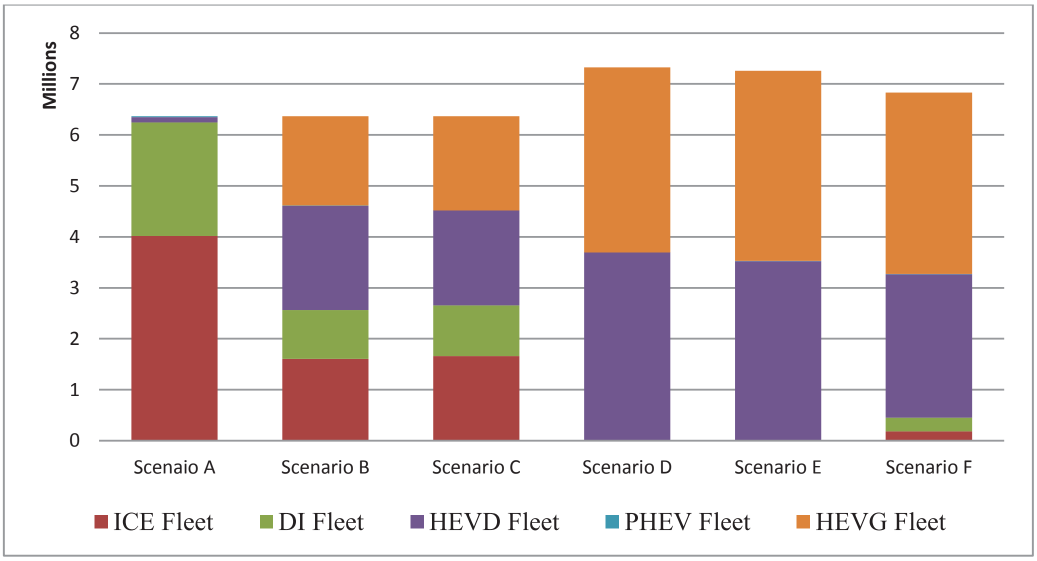


Figure 45: LDV fleet composition in 2030 for each policy scenario for a [50% HEVG, 50% HEVD] fleet target

As expected, in the base scenario, there is no significant progress in the adoption of hybrid-gasoline and hybrid diesel vehicles till 2030. However, the fleet composition could change, in response to the implementation of incentives for AFVs. In scenarios B and C, there is a significantly higher share of HEVG and HEVD in the fleet, but still far from the target.

Figure 45 also shows that scenarios D and E are the only two scenarios able to get very close to the target of [50% HEVG, 50% HEVD] fleet. Like in the case of the previous target, it seems that reaching a high penetration of AFVs can be achieved only after implementing an early retirement policy.

The total transition cost estimated for each policy scenario is presented in table XXXII, we would like to recall that the value of the incentives includes the incentive for HEVG and HEVD purchase price, mainly because there is no interest in incentivizing the fossil fuels.

Table XXXII: Total transition costs for the different scenarios for a [50% HEVG, 50% HEVD] fleet target (in billion €)

in billion €	A	B	C	D	E	F
Vehicle incentive	0	11.9	10	22.9	20	10
Fuel incentive	-----	-----	-----	-----	-----	-----
Station incentives	-----	-----	-----	-----	-----	-----
Total transition cost	0	11.9	10	22.9	20	10

The first insight from table XXXII is that there is a significant difference in the amount of optimized incentives identified in scenarios B and D, in which an early retirement policy was implemented. But it is worth mentioning that considering the result of the AFV fleet evolution (figure 45), it seems that reaching the target of [50% HEVG, 50% HEVD] fleet is a very expensive path.

Another interesting capability of the developed model is that it can assist the decision maker with detailed information on the amount and duration of incentives (Table XXXIII). We can therefore consider that, applying the described methodology to estimate the transition cost in section 4.4.2, the incentives for the purchase price of HEVG and HEVD in most of the scenarios are very close to the maximum limit. This was mainly due to the aim of reducing the gap to the target by using the maximum allowable incentive in place.

Another interesting finding is that in the scenarios where the budget for incentives is limited (such as scenarios C, E and F), the model tends to distribute it in the maximum allowable years, while it reduces the amount of incentive per vehicle. This can be seen in an obvious way in scenarios E and F, when compared with scenario D in which there is no constraint on the budget for incentives.

This can be justified by the fact that a critical factor for social parameters such as familiarity is the time. Therefore, if the incentives are distributed in a longer period of time, the familiarity of customers with AFV will be more significant.

Table XXXIII: Information on the incentive in different scenarios for a [50% HEVG, 50% HEVD] fleet target

	A	B	C	D	E	F
Incentive on purchase price of HEVG	0	95%	79%	91%	79%	42%
Incentive on purchase price of HEVD	0	95%	84%	95%	85%	52%
Duration of incentive in years	0	15.0	15.0	14.5	14.8	14.8

As justified by figure 45, we have analyzed scenarios D, E and F to study the impact of vehicle early retirement policy on filling the gap to the target and total incentives. In these scenarios, the vehicle lifetime is a decision parameter (constraint i). The results show that the model chooses 10 years for all these three scenarios which is the minimum allowable lifetime of a light-duty vehicle in this study. Therefore, in these three scenarios the vehicles that reach their lifetime limit will be discarded.

4.6.4. Trade-off analysis for a [50% HEVG, 50% HEVD] fleet target

An interesting method to analyze the effectiveness of the incentives is to plot the trade-offs comparing the gap to the target and the amount of incentives for each scenario (figure 46).

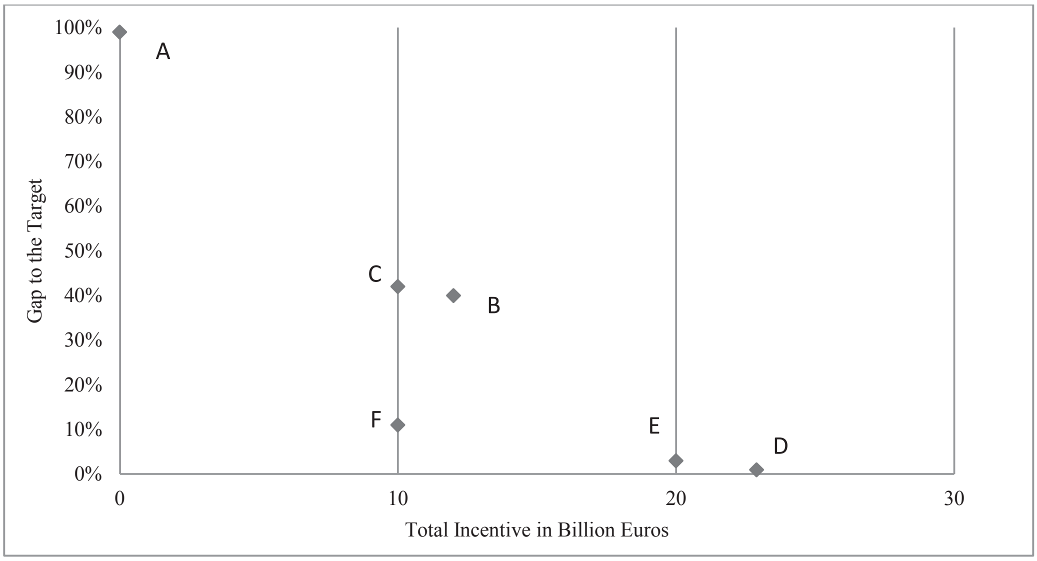


Figure 46: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [50% HEVG, 50% HEVD] fleet target

From figure 46, it is obvious that Scenario D with around 23 billion euros is the most expensive one; while there is no transition cost associated with Scenario A (Base Scenario).

An important observation is that starting from the base point, it is possible to lower the gap by 50% with almost 10 billion euros (scenario C), but in order to reach the target, for example in scenarios E or D, the required incentive should at least be doubled.

Besides, it is also worth mentioning that with the same incentive budget, introducing the early retirement policy can significantly lower the gap to the target. For example, comparing scenarios C and F shows that the gap to the target in scenario F is 30% less, while the total transition cost is the same.

4.6.5. Estimation of transition cost for a [33.3% Biodiesel, 33.3% HEVG, 33.3% HEVD] fleet target

In this section the third alternative in the screening set which is [33.3% Biod, 33.3% HEVG, 33.3% HEVD], will be analyzed. The predicted fleet compositions in Portugal, by the year 2030 under each policy scenario are presented in figure 47.

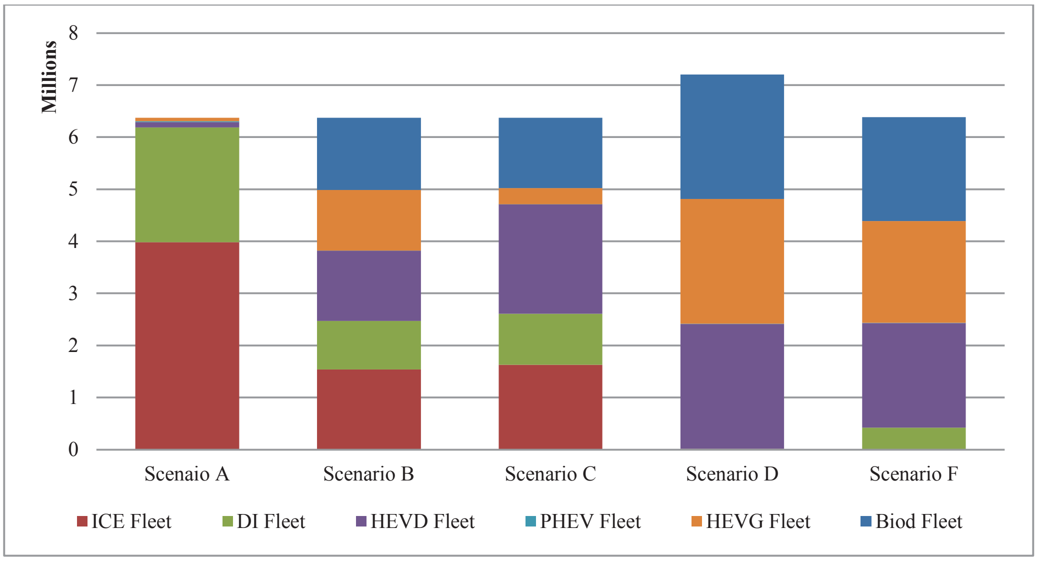


Figure 47: LDV fleet composition at 2030 for each policy scenario for a [33.3% Biod, 33.3% HEVG, 33.3% HEVD] fleet target

Logically, with no incentives in place, the AFV share will not be significant in 2030. On the other hand, the fleet composition could change, in response to the implementation of incentives for AFVs. In scenarios B and C, there is a significantly higher share of Biod, HEVG and HEVD in the fleet, but still far from the target.

As a result, we have investigated the impact of an early vehicle retirement policy in scenario D. Figure 47 also shows that scenarios D and F are the only two scenarios able to get very close to the target of a [33.3% Biod, 33.3% HEVG, 33.3% HEVD] fleet. Like the previous target, it seems that reaching the high penetration of AFVs can be achieved only after implementing an early retirement policy.

As justified by figure 47, we have analyzed scenarios D and F to study the impact of a vehicle early retirement policy. The model chooses 10 years for the lifetime of vehicles in all these three scenarios in order to reduce the gap to the target. It is also worth mentioning that scenario E was removed from the analysis as the total transition cost in scenario D was less than 20 billion euros.

Table XXXIV reveals the total transition cost estimated for each policy scenario that consists of the incentives for vehicle purchase price, fuels and fuel stations.

Table XXXIV: Total transition costs for the different scenarios for a [33.3% Biod, 33.3% HEVG, 33.3% HEVD] fleet target (in billion €)

in billion €	A	B	C	D	F
Vehicle incentive	0	11.7	9.6	14.8	9.36
Fuel incentive	0	0.81	0.4	0.99	0.63
Station incentives	0	0.04	0	0	0
Total transition cost	0	12.55	10	15.79	10

The first insight from table XXXIV is that, differently from the results for previous target, there is no significant difference in the amount of optimized incentives identified in scenarios B and D. Besides, from the result of the AFV fleet evolution in figure 47, it seems that reaching the target of a [33.3% Biod, 33.3% HEVG, 33.3% HEVD] fleet through scenario D, is a very expensive path.

Table XXXV presents detailed information on the amount and duration of incentives on the purchase price, fuel and fuel station for a [33.3% Biod, 33.3% HEVG, 33.3% HEVD] fleet target. The first finding is that the incentives for the purchase price of AFVs in scenario B are very close to the maximum limit, this being due to the fact that the model aimed at putting the maximum allowable incentive in place, in order to reach the target of a [33.3% Biod, 33.3% HEVG, 33.3% HEVD fleet].

As expected, in the scenarios where the budget for incentives is limited (scenarios C, and F), the model tends to reduce the incentive on vehicles as well as their duration. This can be seen, in an obvious way, in scenarios C and F, when compared with scenarios B and D, respectively, where no constraint on the budget for incentives was assumed.

Table XXXV: Information on the incentive in different scenarios for a [33.3% Biod, 33.3% HEVG, 33.3% HEVD] fleet target

	A	B	C	D	F
Incentive on purchase price of biodiesel vehicle	0	95%	83%	66%	58%
Incentive on purchase price of HEVG	0	95%	31%	65%	56%
Incentive on purchase price of HEVD	0	95%	85%	62%	31%
Duration of incentive on vehicle in years	0	15.0	14.6	15.0	7.8

According to table XXXIV, fuel incentives also play a role in changing the trend of AFV adoption. The findings on the amount of incentives on B20 and their duration are presented in table XXXVI. As expected, in the case of limited incentives (scenarios C and F), the model recommends to postpone the placement of incentives on fuel.

Table XXXVI: Incentive for fuels in different scenarios for a [33.3% Biod, 33.3% HEVG, 33.3% HEVD] fleet target

	A	B	C	D	F
Incentive on B20	0	95%	54%	95%	95%
Duration of incentive on fuels in years	0	15.0	12.3	9.0	7.3

The incentives on stations for this target were not significant (Table XXXIV), this being quite unexpected. Yet, this can be explained as follows. Reviewing equation 14, the main driver for the profitability of fuel stations was the demand for alternative fuels. Therefore, in response to incentivized purchase prices for AFVs, the number of AFV sales increases, and this can finally result in fuel demand growth. In other words, the incentives from the government for the vehicle purchase prices and for fuel can cause the investment in fuel stations to become profitable, potentially attracting the private investors to financially support the new fuel stations.

4.6.6. Trade-off analysis for a [33.3% Biod, 33.3% HEVG, 33.3% HEVD] fleet target

As highlighted earlier, trade-offs analysis on the result of analyzing this alternative can provide interesting insights for us, when comparing the gap to the target and the amount of incentives in each scenario (figure 48).

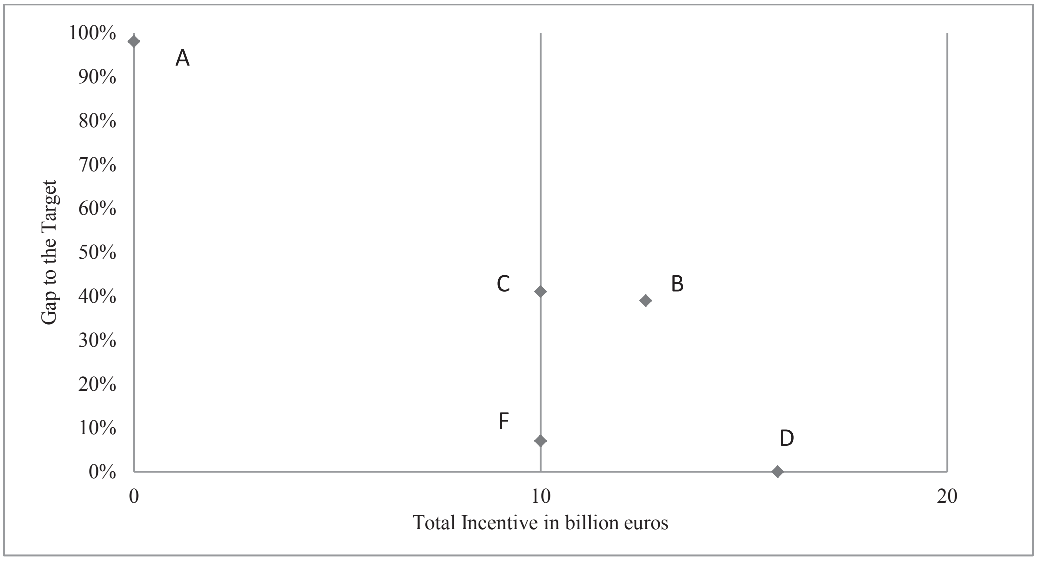


Figure 48: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [33.3% Biod, 33.3% HEVG, 33.3% HEVD] fleet target

From figure 48, it is obvious that Scenario D with around 16 billion euros is the most expensive one; while there is no transition cost associated with Scenario A (Base Scenario). An important observation is that starting from the base point, it is possible to lower the gap by 60% with almost 10 billion euros (scenario C). More interestingly, the implementation of a early vehicle retirement policy can result in lowering the gap to the target to 7% with the same level of transition costs (Scenario F).

4.6.7. Estimation of transition cost for a [25% E85, 25% Biod, 25% HEVG, 25% HEVD] fleet target

Now, the next alternative in the screening set [25% E85, 25% Biod, 25% HEVG, 25% HEVD], is analyzed. Figure 49 shows the predicted fleet compositions in Portugal, by the year 2030 under each policy scenario.

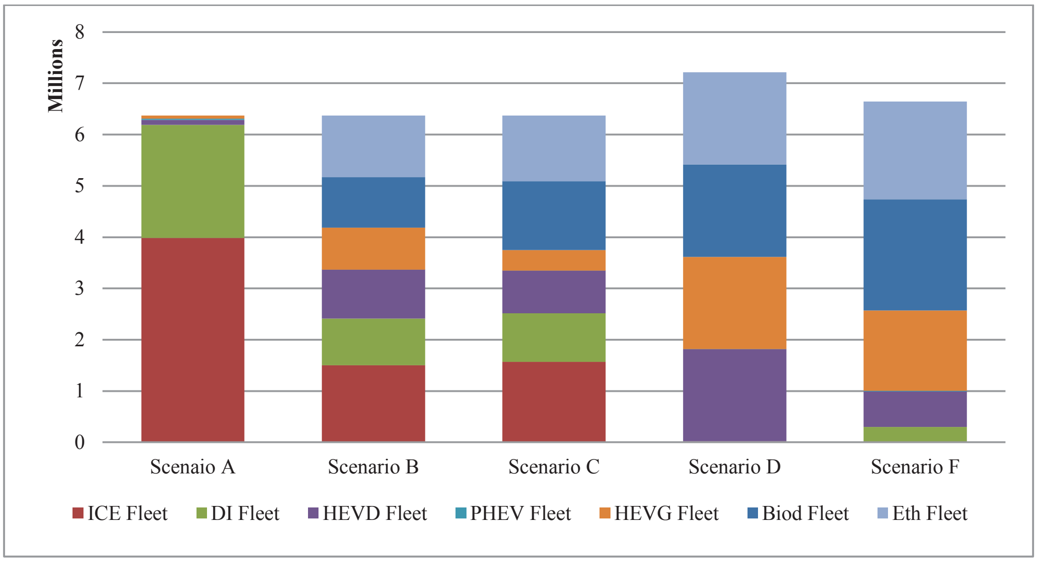


Figure 49: LDV fleet composition at 2030 for each policy scenario for a [25% E85, 25% Biod, 25% HEVG, 25% HEVD] fleet target

Comparing the results of scenario A in the absence of incentives, with results in the scenarios B and C with the presence of incentives, shows the impact of incentives. In fact, in scenarios B and C, the share of AFVs in the fleet becomes significant, but still far from the target. Therefore, we have studied two more scenarios (D and F) to analyze the impact of an early vehicle retirement policy. As a result, the difference in the shares of AFVs in scenarios D and F and the target of a [25% E85, 25% Biod, 25% HEVG, 25% HEVD] fleet becomes insignificant.

The total transition costs that includes incentives for vehicle purchase price, fuels and fuel stations, estimated for each policy scenario is presented in table XXXVII. According to these results, the implementation of an early retirement policy in scenario D can cause the incentives to increase 24% when compared with scenario B.

Table XXXVII: Total transition costs for the different scenarios for a [25% E85, 25% Biod, 25% HEVG, 25% HEVD] fleet target (in billion €)

in billion €	A	B	C	D	F
Vehicle incentive	0	11.59	9.70	14.92	9.76
Fuel incentive	0	0.59	0.3	0.30	0.24
Station incentives	0	0.03	0	0	0
Total transition cost	0	12.21	10	15.12	10

Another interesting capability of the developed model is that it can assist decision makers with the detailed information on the amount and duration of incentives (Table XXXVIII).

The incentives for the purchase price of AFVs in scenario B reach the maximum limit, which is primarily determined by the fact that the model tends to reach the target of a [25% E85, 25% Biod, 25% HEVG, 25% HEVD] fleet.

Another interesting outcome is that in the scenarios where the budget for incentives is limited (scenarios C and F), the model tends to reduce the incentives on the hybrid-gasoline and hybrid-diesel vehicles. This can probably be related with the current adoption of hybrid vehicles. In other words, to reach this target, the model applies incentives more on the totally new technologies rather than semi-new technologies such as hybrid vehicles.

Table XXXVIII: Incentive for vehicles in different scenarios for a [25% E85, 25% Biod, 25% HEVG, 25% HEVD] fleet target

	A	B	C	D	F
Incentive on E85 vehicle	0	95%	95%	49%	52%
Incentive on B20 vehicle	0	95%	95%	69%	92%
Incentive on HEVG	0	95%	47%	59%	32%
Incentive on HEVD	0	95%	67%	86%	0%
Duration of incentive on vehicles in years	0	15.0	15.0	14.6	14.2

According to table XXXVII, the fuel incentive also plays a role in changing the trend of AFV adoption. The incentives on E85 and B20, are presented in table XXXIX. As expected, in the case of limited incentives (scenarios C and F), the model recommends to postpone the introduction of incentives on fuel to the last 4-5 years of the planning horizon.

Table XXXIX: Incentive for fuels in different scenarios for a [25% E85, 25% Biod, 25% HEVG, 25% HEVD] fleet target

	A	B	C	D	F
Incentive on E85	0	95%	95%	82%	53%
Incentive on B20	0	95%	95%	27%	40%
Duration of incentive on fuels in years	0	14.6	3.5	14.7	4.7

The incentives on stations for this target were not significant (Table XXXVII), which is a bit surprising. Yet, this can be explained as follows. Reviewing equation 14, the main driver for the profitability of fuel stations was identified to be the demand for alternative fuels. Therefore, in response to an incentivized purchase price for AFVs, the number of AFV sales increases, which can finally result in fuel demand growth. In other words, the incentives from the government for vehicle purchase price and fuel can cause the investment in fuel stations to become profitable, possibly fascinating the private investors to financially support the new fuel stations.

4.6.8. Trade-off Analysis for a [25% E85, 25% Biod, 25% HEVG, 25% HEVD] fleet target

An interesting approach to analyze the helpfulness of the incentives is to plot the trade-offs comparing the gap to the target and the amount of incentives for each scenario (figure 50).

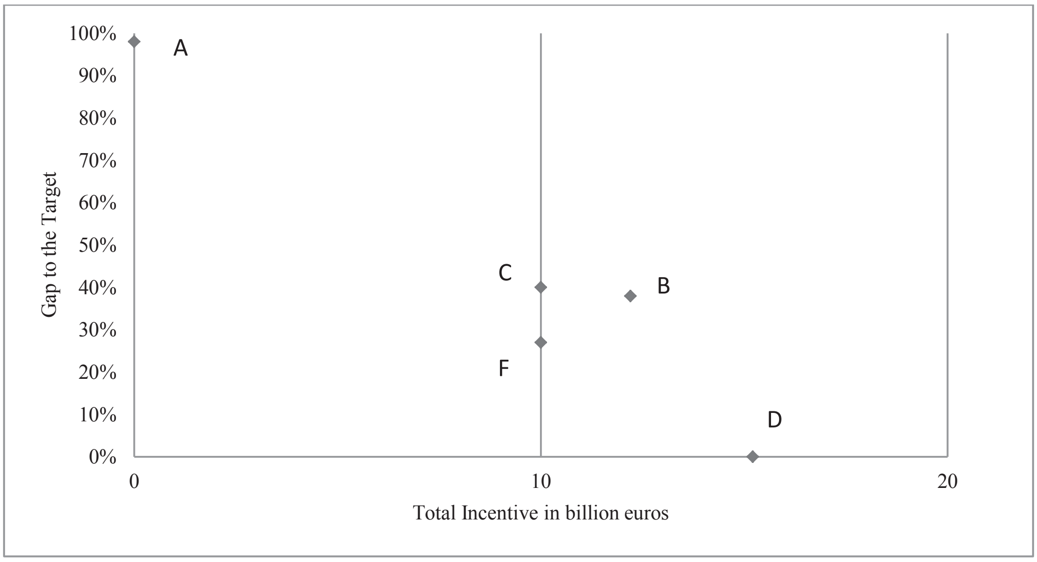


Figure 50: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [25% E85, 25% Biod, 25% HEVG, 25% HEVD] fleet target

The first finding according to figure 50 is that scenario D with around 15 billion euros is the most expensive one. An important observation is that starting from the base point (scenario A), it is possible to lower the gap by 60% with 10 billion euros (scenario C), but in order to reach the target, for example in scenario D, the required incentive should increase by 50%.

Contrary to previous alternatives, it seems that introducing the early retirement policy cannot significantly lower the gap to the target. The gap to the target for scenario F, is only 13% less than scenario C, considering the same incentive budget.

4.6.9. Estimation of transition cost for a [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] fleet target

Results of the optimization module for each scenario assuming that the target is the fifth alternative in the screening set [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] are shown in figure 51. This basically shows the predicted fleet compositions in Portugal, by the year 2030 under each policy scenario.

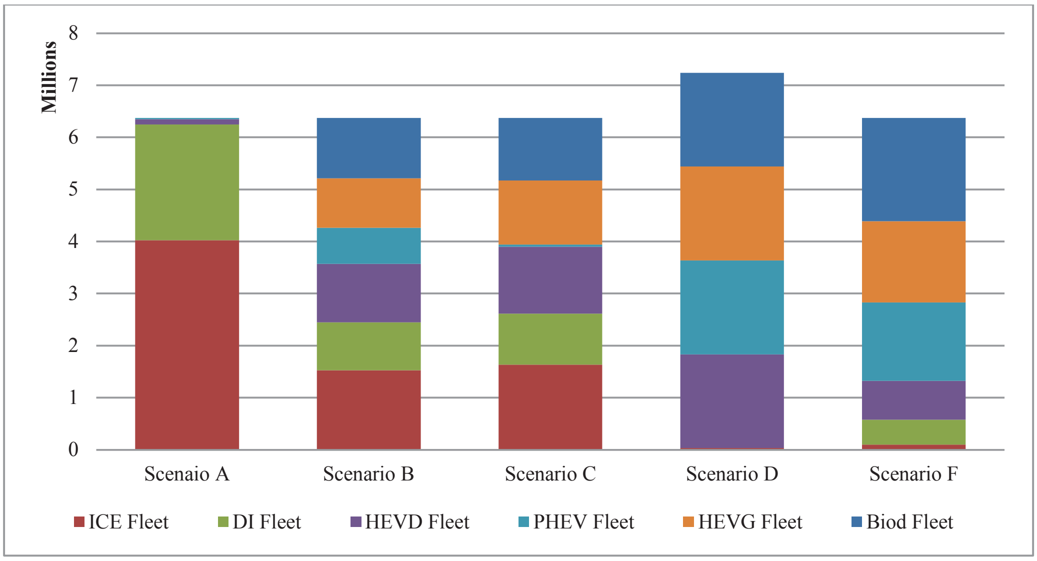


Figure 51: LDV fleet composition at 2030 for each policy scenario for a [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] fleet target

Unsurprisingly, in the base scenario, there is no significant progress in the adoption of AFVs till 2030. However, the fleet composition could change, in response to the implementation of incentives for AFVs. In scenarios B and C, there is a significantly higher share of HEVG, HEVD, Biod and PHEV in the fleet, but still far from the target. As a result, scenario D was considered, to study the impact of early vehicle retirement policies. Figure 51 also illustrates that scenario D is the only scenario that can reach the target of a [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] fleet.

The disaggregated result of transition costs consisting of incentives for AFV purchase price, fuel price and fuel station, is presented in table XL for each policy scenario.

Table XL: Total transition costs for the different scenarios for a [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] fleet target (in billion €)

in billion €	A	B	C	D	F
Vehicle Incentive	0	12.08	9.55	16.30	9.27
Fuel Incentive	0	1.10	0.45	2.04	0.73
Station Incentives	0	0.04	0	0	0
Total transition cost	0	13.22	10	18.34	10

The first insight from table XL is that the most significant share of incentives goes to the vehicle purchase price, in each policy scenario. Scenarios B and D are the most expensive scenarios and the results also highlight the relatively significant difference (4 billion €) in transition cost in scenario D, as the result of implementing the early vehicle retirement plan, when compared with scenario B.

Another interesting feature of the developed model is that it can support decision makers with the detailed information on the amount and duration of incentives (Tables XLI).

As expected, the incentive on vehicles reduces in the scenarios such as C and F when compared with scenarios B and D, in which the total incentive is limited. Reviewing the impact of early vehicle retirement policies can be seen in the results from scenario B and D. The magnitude of incentives for all AFVs has reduced, but due to the early retirement of vehicles, in overall, the transition cost has increased.

Table XLI: Information on the incentive in different scenarios for a [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] fleet target

	A	B	C	D	F
Incentive on biodiesel vehicle	0	95%	95%	67%	74%
Incentive on HEVG	0	95%	76%	73%	88%
Incentive on HEVD	0	95%	74%	69%	21%
Incentive on PHEV	0	95%	5%	85%	95%
Duration of incentive on vehicle in years	0	15.0	15.0	14.5	8.7

According to table XL, the fuel incentive also plays a role in changing the trend of AFV adoption. The incentives on biodiesel and electricity are presented in table XLII. As expected, in the case of limited incentives (scenarios C and F), the model recommends to reduce the duration of incentives on fuel and postpone those incentives to the last 7-8 years of the planning horizon.

Table XLII: Incentive for fuels in different scenarios for a [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] fleet target

	A	B	C	D	F
Incentive on B20	0	95%	95%	95%	49%
Incentive on electricity	0	95%	95%	95%	95%
Duration of incentive on fuels in year	0	14.8	8.0	15	6.9

The incentives on stations for this target were not significant (Table XL), which is a bit surprising. This may partially be explained by reviewing equation 14 which implies that the main driver for the profitability of fuel stations is the demand for alternative fuels. Therefore, in response to an incentivized purchase price for AFVs, the number of AFV sales increases, which can finally result in fuel demand growth. In other words, the incentives from the government for vehicle purchase price and fuel can cause the investment in fuel stations to become profitable, and this could potentially attract the private investors to financially support the new fuel stations. Therefore, there is no need for direct incentives for fuel stations.

4.6.10. Trade-off analysis for a [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] fleet target

Similarly to the previous analysis we have studied the policy scenarios using the trade-offs plot for a [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] target (figure 52).

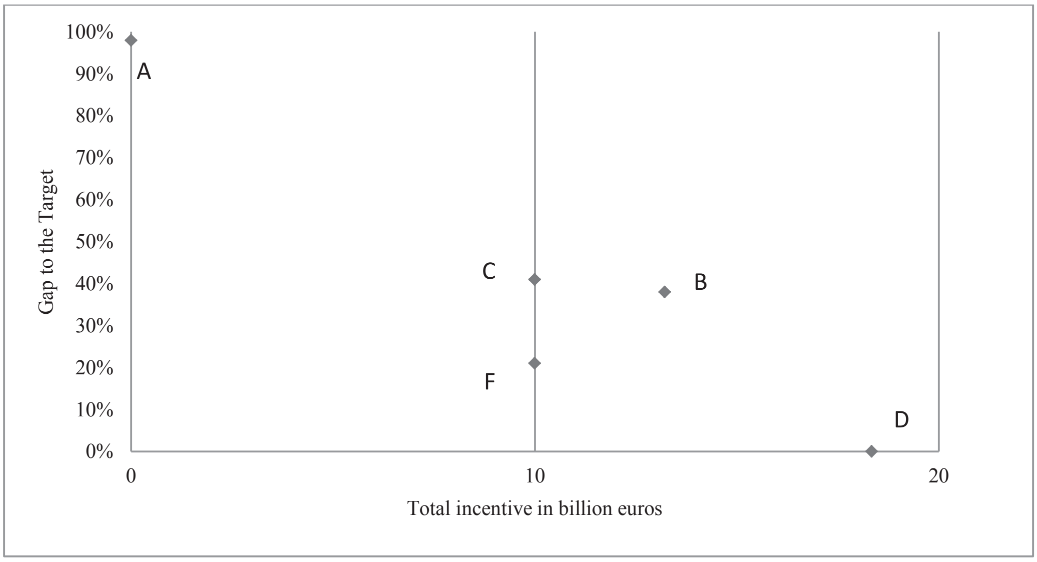


Figure 52: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] fleet target

From figure 52, it is obvious that Scenario D, with around 18 billion euros, is the most expensive one; while there is no transition cost associated to Scenario A (Base Scenario). An important observation is that starting from the base point; it is possible to lower the gap by 60% with almost 10 billion euros (scenario C). Nevertheless, in order to reach the target in scenario D, the required incentive should increase by 80%.

Besides, it is also worth mentioning that with the same incentive budget, introducing the early retirement policy can significantly lower the gap to the target. For this target, the results for scenarios C and F show that the gap to the target in scenario F is 20% less, while the total transition cost is the same.

4.6.11. Estimation of transition cost for a [25% Biod, 25% HEVG, 25% HEVD, 25% BEV] fleet target

The last alternative in the screening set includes a [25% Biod, 25% HEVG, 25% HEVD, 25% BEV] of LDV fleet in 2030. Policy scenarios described in section 4.4.2 should be analyzed for the adoption of this alternative. The results of the predicted fleet compositions in Portugal, by the year 2030, under each policy scenario are shown in figure 53.

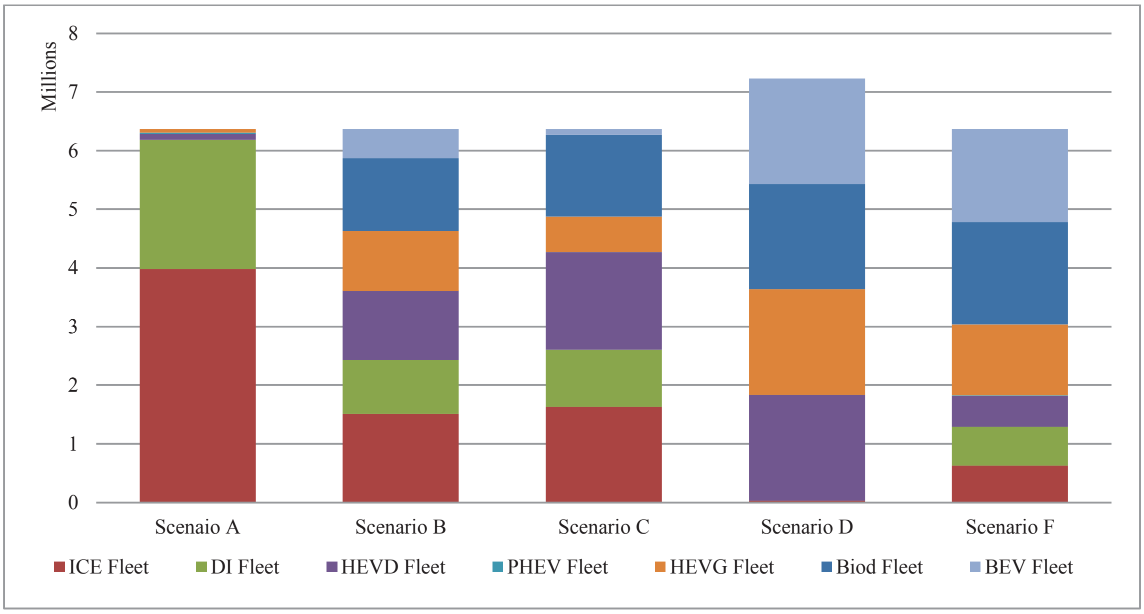


Figure 53: LDV fleet composition at 2030 for each policy scenario for a [25% Biod, 25% HEVG, 25% HEVD, 25% BEV] fleet target

In scenario A, as expected, there is no significant progress in the adoption of AFVs till 2030. However, the incentives on vehicle purchase price, fuel and fuel station can change this trend. In scenarios B and C, there is a significantly higher share of AFVs in the fleet, but still far from the target. As a result two more scenarios (D and F) were considered to study the impact of early vehicle retirement policies.

According to figure 53, scenarios D and E are the only two scenarios that able to get very close to the target of a [25% Biod, 25% HEVG, 25% HEVD, 25% BEV] fleet. Like the previous targets, it seems that reaching the high penetration of AFVs can be achieved only after employing an early retirement policy. The total transition cost estimated for each policy scenario is presented in table XLIII. The transition cost is disaggregated into incentives for vehicle purchase price, fuel and fuel station. As shown in table XLIII, there are significant differences in the amount of optimized incentives identified in policies. The impact of an early retirement policy in scenario D was the increase of around 6 billion euros, when compared with scenario B. Considering the result of AFV fleet evolution in figure 53, it seems that reaching the target of a [25% Biod, 25% HEVG, 25% HEVD, 25% BEV] fleet is a very expensive path.

Table XLIII: Total transition costs for the different scenarios for a [25% Biod, 25% HEVG, 25% HEVD, 25% BEV] fleet target (in billion €)

in billion €	A	B	C	D	F
Vehicle Incentive	-----	12.30	9.59	18.46	10
Fuel Incentive	-----	0.74	0.41	0.30	-----
Station Incentives	-----	0.04	-----	-----	-----
Total transition cost	0	13.08	10	18.76	10

Another useful outcome of the developed model is the comprehensive information on the amount and duration of incentives (Tables XLIV). As expected, comparing scenarios C with B and F with D, shows the gradual reduction in the amount and duration of incentives on vehicles, as a result of assuming the limited budget for governmental incentives in scenarios C and F.

Besides, it is possible to compare the results of scenarios B and D to study the impact of an early vehicle retirement policy. Considering the result of table XLIII, the total transition cost has increased around 50%, while the incentive per AFV has decreased. This is mainly due to the fact that more vehicles are retired early, and therefore, the AFV sales have increased significantly in scenario D, when compared with scenario B.

Table XLIV: Incentive for AFVs in different scenarios for a [25% Biod, 25% HEVG, 25% HEVD, 25% BEV] fleet target

	A	B	C	D	F
Incentive on biodiesel vehicle	0	95%	95%	95%	91%
Incentive on HEVG	0	95%	66%	60%	55%
Incentive on HEVD	0	95%	90%	57%	6%
Incentive on BEV	0	95%	62%	84%	65%
Duration of incentive on vehicle in year	0	15.0	13.9	14.7	13.1

Based on the results of table XLIV, we have studied the amount and duration of incentives on fuels. The incentives on biodiesel and electricity are presented in table XLV. As expected, in the case of limited incentives (scenarios C and F), the model recommends to reduce the duration of incentives on fuel and postpone those incentives to the last 11 and 7 years of the planning period, respectively.

Table XLV: Incentive for fuels in different scenarios for a [25% Biod, 25% HEVG, 25% HEVD, 25% BEV] fleet target

	A	B	C	D	F
Incentive on B20	0	95%	59%	29%	1%
Incentive on electricity	0	95%	19%	65%	5%
Duration of incentive on fuels in year	0	15.0	11.1	15.0	6.7

The incentives on stations for this target were not significant (Table XLIII), this being a somehow unexpected result, that may be partly clarified by equation 14, as the main driver for the profitability of fuel stations is the demand for alternative fuels. Therefore, in response to an incentivized purchase price for AFVs, the number of AFV sales increases, which can finally result in fuel demand growth. In other words, the incentives from the government for vehicle purchase price and fuel can cause the investment in fuel stations to become profitable and this could potentially attract the private investors to financially support the new fuel stations. Thus, the need to incentivize the fuel stations is negligible.

4.6.12. Trade-off analysis for a [25% Biod, 25% HEVG, 25% HEVD, 25% BEV] fleet target

Again, the plot of trade-offs can assist us to get more insight on the effectiveness of the incentives for each scenario in reducing the gap to the target (Figure 54).

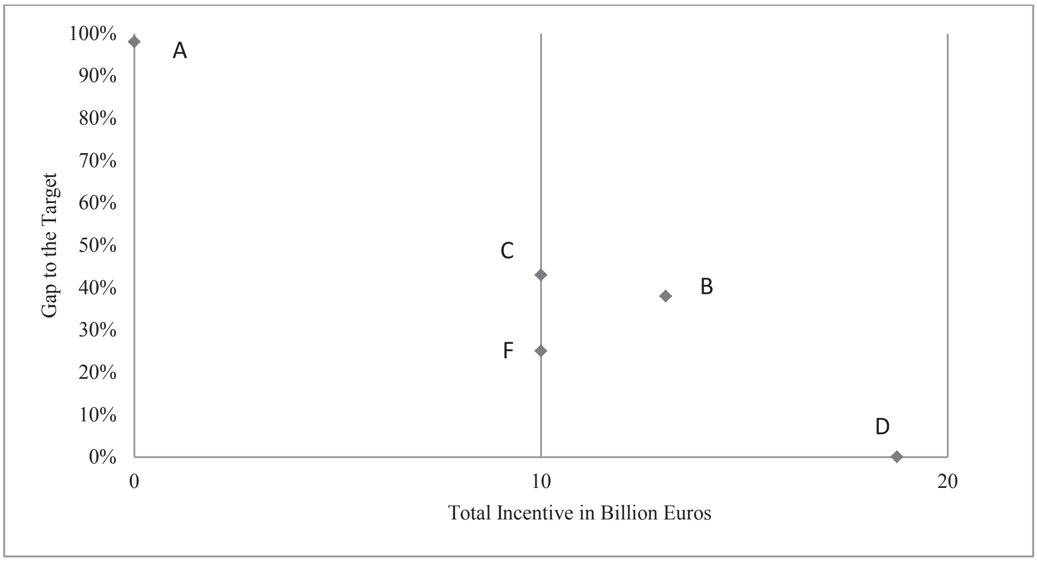


Figure 54: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [25% Biod, 25% HEVG, 25% HEVD, 25% BEV] fleet target

According to figure 54, in order to remove the gap to the target, the policy scenario D should be adopted with around 19 billion euros for incentive support. We can see that moving from the base point (scenario A), it is possible to lower the gap by 57%, with almost 10 Billion euros (scenario C).

Besides, it is also worth mentioning that with the same incentive budget, applying the early retirement policy can significantly lower the gap to the target. For this target, comparing scenarios C and F shows that the gap to the target in scenario F is 18% less, while the total transition cost is the same.

4.6.13. Comparison of transition costs after the system dynamics model with the initial ones

As it was mentioned in chapter 3 (section 3.1.1), the initial multi-criteria analysis included an initial estimation for the transition costs for alternative fuel vehicles. Figure 55 provides a comparison of transition costs between the initial estimation versus the estimation after the system dynamics model, for each of the alternatives 1-6 described in the beginning of section 4.6.

It's worth mentioning that as scenario D is the only policy scenario that shows a zero (or nearly zero) gap to the target, we have considered the outcome of that policy scenario as the estimated transition cost for each screening alternative.

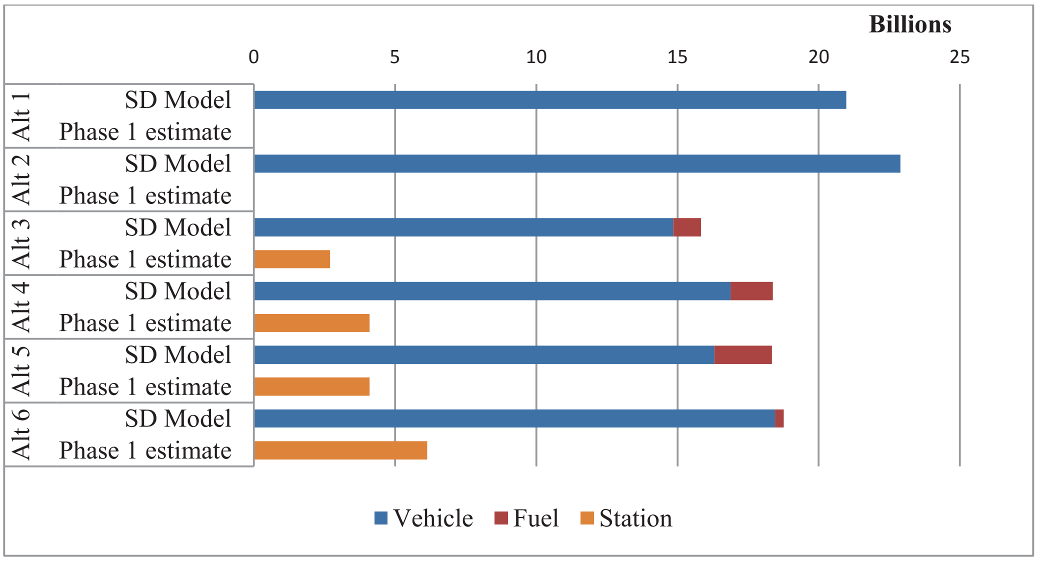


Figure 55: Comparison of transition cost: initial estimation versus results from the system dynamics model

The most important message from figure 55 is that the transition cost estimated from the system dynamics model is much higher than the initial estimation. Besides, contrary to the initial estimation, the share of transition cost for the fuel stations is not significant, and the focus of the supportive policies should be more on the initial price of vehicles and fuels. This can be justified as follows.

From equation 14, we can see that the main driver for the profitability of fuel stations is the demand for alternative fuels. Therefore, in response to an incentivized purchase price for AFVs, the number of AFV sales increases, which can finally result in fuel demand growth. In other words, the incentives from the government for vehicle purchase price and fuel can cause the investment in fuel station to become profitable, and this could potentially attract the private investors to financially support the new fuel stations.

4.6.14. Impact assessment of high oil price on transition cost

After having developed a method to estimate the transition cost for alternative fuel vehicles, we now investigate the sensitivity of the results to critical factors. Fuel price seems to be a decisive factor and it would therefore be interesting to review the impact of a high fuel price on the results of a policy scenario. Following the discussion in chapter 3 (section 3.3.2), it was assumed that by 2030, the price of gasoline and diesel, in a high oil price scenario, could reach 2.1 €/liter (instead of 1.6 in the base case) and 1.7 €/liter (instead of 1.3 in the base case), respectively.

We have then studied the first alternative in the screening set (100% HEVD fleet). As shown in figure 43, scenario D is the only plan where the share of HEVD reaches the target. Therefore, the same policy scenario was studied under the conditions of a high oil price. The impact of high oil price on the fleet composition is presented in table XLVI.

As expected, the higher oil price will increase the fuel cost for Internal Combustion gasoline Engines (ICE) and ICE Diesel (DI) vehicles. In relative terms, the fuel cost for HEVD and PHEV decreases, causing the nominal utility of this technology to increase according to equation 12. The overall impact is the reduction in conventional vehicle fleet and the increase in the AFV fleet.

Table XLVI: Portuguese fleet composition in the base scenario and with a high oil price

	Scenario D	**Scenario D + High oil price**
ICE Gasoline Fleet	0	23449
ICE Diesel Fleet	81352	0
HEVD Fleet	6956992	7288885
PHEV Fleet	3190	3701

It was also found out that the estimated transition cost for high oil has increased by 1% when compared to the 21 billion euros for scenario D. This can be justified by the number of HEVD fleet which shows a 5% increase. Therefore, in overall, the spent incentive for HEVD decreases from 3000 to 2900 (€/vehicle).

4.7. Highlights

Planning the transition period for the adoption of alternative fuel-technology powertrains is a challenging task. In this study, a system dynamics approach was applied to analyze the interaction between the development of fuel stations and vehicle sales. This model was calibrated for Portugal with historical data for the sales of light duty vehicles between 1986 and 2009. The calibrated model was then used to estimate the transition costs to reach a predefined target of AFV fleet. These targets are the alternatives in the screening set that resulted from the multi-criteria framework described in chapter 3.

We have analyzed six scenarios to investigate the impact of incentive policies. The first scenario deals with the "*business as usual*" trend of fleet evolution. Then, the impact of incentives for vehicles, fuels and fuel stations has been studied. Considering the limitation of available budget for incentives, another scenario was investigated. As the obtained results were quite far from the target for AFV fleet, we have introduced vehicle early retirement policies. We have then tested a set of scenarios to investigate the impact of these policies on the AFV annual sales.

The analysis resulted in some major findings. System dynamics enabled us to take into account the interaction between the AFV demand and the fuel station, by using feedback loops. It was a useful approach in estimating the transition cost for the adoption of AFVs.

The results on the transition cost estimation for a [100% HEVD] fleet target are presented in Tables XXX and XXXI. A preliminary insight from table XXX is that there is a significant difference in the amount of optimized incentives identified in the different scenarios. Another interesting feature of the developed model is that it can assist the decision maker with detailed information, on the amount and duration of incentives. According to table XXXI, the incentives for purchase price of HEVD, in most of the scenarios, are very close to the maximum limit, as the model tends to put the maximum allowable incentive in place in order to reach the target of a [100% HEVD] fleet.

An additional interesting finding is that in the scenarios where the budget for incentives is limited (scenarios C, E and F), the model tends to distribute it in the maximum allowable years, while reducing the amount of incentive per vehicle. This is obvious in scenarios E and F, when compared to scenario D in which there is no constraint on the budget for incentives.

This can be justified by considering the fact that a critical factor for social parameters such as familiarity is the time. Therefore, if the incentives are distributed in longer periods of time, the familiarity of customers with AFV will be more significant.

The model also helps us to understand that almost all the targets are only reachable in 2030, if a vehicle early retirement policy is in place. For the [100% HEVD] fleet target, it is also worth mentioning that with the same incentive budget, introducing the early retirement policy can significantly lower the gap to the target. A comparison of results for scenarios C and F shows that the gap to the target in scenario F is around 35% lower, while the total transition cost is equal to 10 billion euro in both scenarios.

Figure 55 compares the transition cost of the system dynamics model with the initial estimation, showing that the transition cost estimated by the SD model is much higher than the initial estimation of the transition cost. Contrary to the initial estimation, the share of transition cost for the fuel stations is not significant, and the focus of the supportive policies should be more on the initial price of vehicles and fuels. In fact, the main driver for the profitability of fuel stations was identified to be the demand for alternative fuels. Therefore, in response to an incentivized purchase price for AFVs, the number of AFV sales increases, and this will eventually result in a fuel demand increase. I.e., the incentives from the government for the purchase price and fuel of AFVs can cause the investment in fuel stations to become profitable, potentially attracting the private investors to financially support the new fuel stations.

Chapter 5 - Phase 3: Integrated Analysis

In this chapter the suggested procedure for integrating the results of a multi criteria comparison (proposed in chapter 3) and the system dynamics model (introduced in chapter 4) will be presented. As it was thoroughly explained in section 3.1.3, an initial transition cost data was considered for the MCDA model ("phase1"), collected from several sources ([68], [85] and [89]). Later, in chapter 4, a system dynamics model was developed, which results in updated values (and understanding) for the transition cost of AFV fleets. This raises the need to integrate the two stages, ensuring that the updated cost estimated is fed-back to the MCDA model. That is achieved through the proposed integrated analysis in this chapter, which will hopefully allow us to enhance the transition cost estimation for the multi criteria analysis using the results of system dynamics model, and therefore improve the results of the multi-criteria comparison.

5.1. Integrated approach

Figure 55 in chapter 4, showed the comparison between the initial estimation for the transition cost for AFV adoption and the result of the system dynamics analysis. This comparison highlighted:

- the importance of analyzing the market transition of AFV;
- the need for updating the inputs of multi-criteria comparison framework.

In this work, we propose an integrated approach for a multi-criteria analysis of alternative fuel-technology vehicles, as presented by the flowchart in figure 56. After the first collection of data, the Multi-Criteria Decision Aid (MCDA) tool was applied to identify the characteristics of each alternative in each attribute. Then a sequential screening was adopted to identify the screening set of alternatives. As it was described in chapter 4, a system dynamics model was developed in order to analyze the transition for the adoption of alternative fuel vehicles. As discussed thoroughly in section 4.4.2, six policy scenarios were considered to estimate the transition cost to achieve each alternative.

As presented in section 4.5, the results the policy scenarios can be usually represented in trade-off figures, allowing us to examine the effectiveness of incentives on filling the gap to the target for each screening alternative. We have included all these fleet compositions and their related transition costs in the MCDA process. Therefore, the developed multi-criteria comparison framework will be re-applied for comparing not only all the previous alternatives combining up to four technologies, but also the alternatives identified through the policy scenario analysis, used to identify an updated screening set of alternatives. The new alternatives in the screening set are defined as the new targets for the system dynamics model, and the relevant transition costs are calculated. This iterative analysis will continue until there is no new alternative in the screening set at the end of the MDCA analysis compared to the previous iteration.

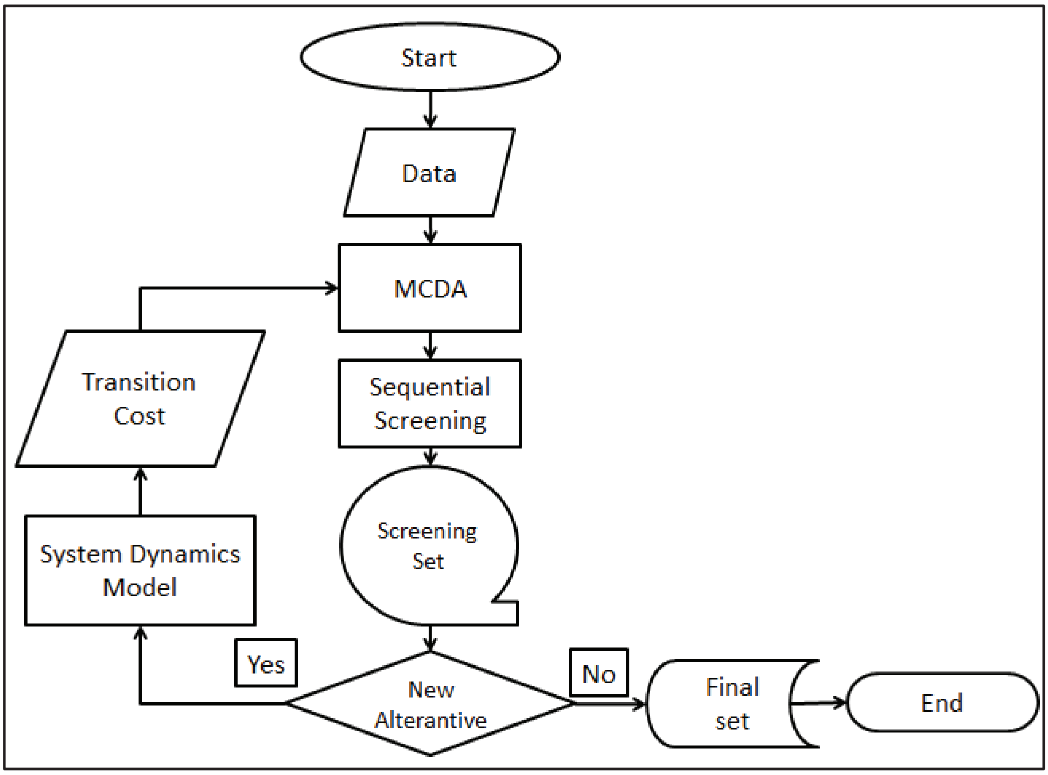


Figure 56: Flowchart for the integrated multi-criteria analysis of alternative fuel-technology vehicles

5.2. Findings and discussion

In order to test the applicability and performance of this approach, designed to integrate the multi-criteria comparison framework like the system dynamics model, we have used Portugal as a case study, in line with the work presented in the previous chapters.

5.2.1. Result of the iterative analysis

Iteration 0

The procedure starts with inputting data to the multi criteria comparison framework (see figure 56). As expressed thoroughly in chapter 3, a sequential screening approach was adopted to identify the screening set of alternatives. The data for Portugal was used to demonstrate the methodology, and the result of applying the “phase 1” sequence was the first screening set of alternatives, which was presented in section 3.3. These alternatives are structured as shares of alternative fuel-technology vehicles in the light-duty vehicle fleet in 2030.

Then, the developed system dynamics model was applied to obtain a more realistic estimate of the transition cost for the screening alternatives that had resulted from phase 1. As mentioned in chapter 4, the transition cost for the first screening set of alternatives was calculated for all the policy scenarios described in section 4.4 (see the outcomes in tables XXX, XXXII, XXXIV, XXXVII, XLI and XLIII).

The transition costs for all the alternatives of the first screening set, taken from policy scenario D, are presented in table XLVII. This transition cost consists of three components of incentives: vehicles, fuels and stations.

Table XLVII: Estimated transition cost for the first screening set of alternatives according to the SD model of chapter 4 and initial estimation

	Vehicle Incentives (From SD model)	Fuel Incentive (From SD model)	Station Incentives (From SD model)	Total Incentives (From SD model)	Total Incentives (initial estimation)
Alternative 1	21.0 B €	--------	--------	21.0 B €	0
Alternative 2	22.9 B €	--------	--------	22.9 B €	0
Alternative 3	14.8 B €	0.99 B €	--------	15.8 B €	2.7 B €
Alternative 4	16.9 B €	1.49 B €	--------	18.4 B €	4.1 B €
Alternative 5	16.3 B €	2.04 B €	--------	18.3 B €	4.1 B €
Alternative 6	18.5 B €	0.3 B €	--------	18.8 B €	6.1 B €

The estimated transition costs for the first screening alternatives for all six policy scenarios have been reviewed. As scenario D is the only policy scenario that shows a zero (or nearly zero) gap to the target, we have updated the estimated transition cost for each screening alternative with the outcome of that policy scenario. At this point, we added the alternatives that had resulted from other policy scenarios for all 6 screening alternatives to the set of initial alternatives. The results of transition costs estimations for all of these additional alternatives were calculated as presented in section 4.4 (tables XXX, XXXII, XXXIV, XXXVII, XL and XLIII).

Iteration 1

Following the proposed approach, the identified alternatives with their updated transition costs were added to the list of initial alternatives, and the later should have their values updated. The only attribute that is affected as a result of the system dynamics analysis is the transition cost (see section 3.1.3) and therefore these costs are revised for the screening alternatives. Thus, the inclusion of the alternatives with updated information can potentially affect the results of the MCDA and the new screening set of alternatives needs to be identified.

The new alternatives that constitute the second screening set, resulting from running again the procedures of phase 1 and which emerge as the potentially best, are listed in table XLVIII.

Table XLVIII: Screening set of alternatives (Iteration 1)

	DISI-Gasoline	DISI-Ethanol	DICI-Biodiesel	HEV-Gasoline	HEV-Diesel	PHEV	BEV
Alternative 1			50%		50%		
Alternative 2	33%			33%	33%		
Alternative 3				33%	33%	33%	
Alternative 4	25%		25%		25%	25%	
Alternative 5	25%			25%	25%	25%	

Comparing with the first screening alternatives presented in table XIV (in section 3.3), it is found that all of the screening alternatives resulting from iteration 1 are new. Therefore, the iterative process needs to continue. Each of these alternatives is therefore analyzed using the developed system dynamics model, under the policy scenarios described in section 4.4.2. The results of the trade-off analysis for the second screening set of alternatives are presented in figures 57-60.

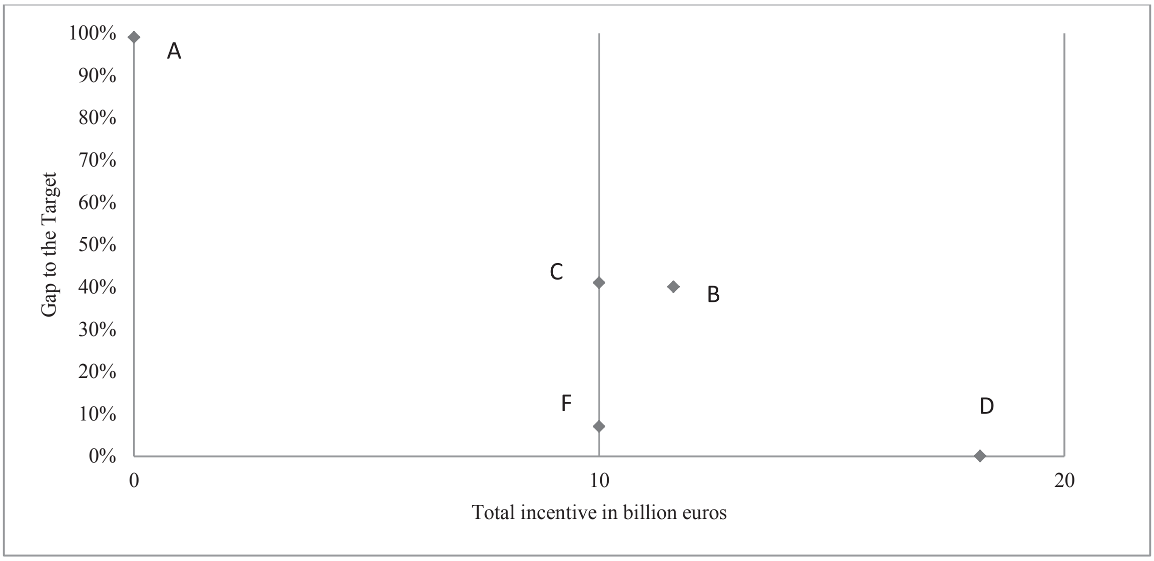


Figure 57: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [50% Biod, 50% HEVD] fleet target

From figure 57, we can see that, in order to completely fill the gap to the target, the total incentive should be as high as 18 billion euros, while 60% of the gap can be achieved by almost 10 billion euros following scenario C. It should be noted that implementing the early vehicle retirement policy can cause the gap to the target to be as low as 7% in scenario F, while the total incentive is 10 billion euros.

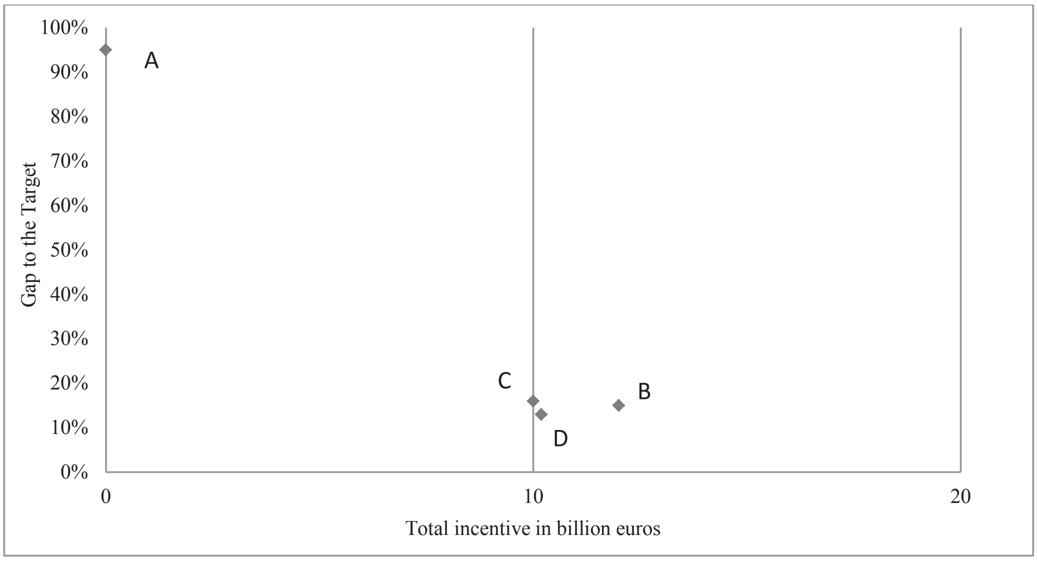


Figure 58: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [33% ICE, 33% HEVG, 33% HEVD] fleet target

The first insight from figure 58 is that the gap to the target of a [33% ICE, 33% HEVG, 33% HEVD] fleet cannot be avoided completely. The main contributor is the share of gasoline cars that is not going to stay around 33%, mainly because of the shift towards diesel cars. Note that contrary to the previous target, these results do not show major differences after employing the early vehicle retirement policy.

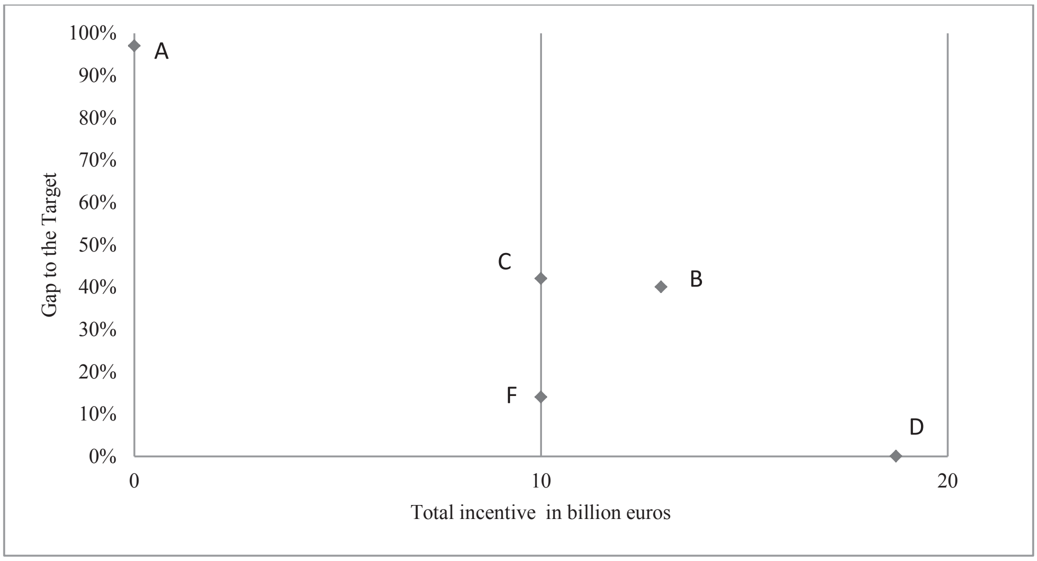


Figure 59: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [33% HEVG, 33% HEVD, 33% PHEV] fleet target

The first insight from figure 59 is that the less costly scenarios such as scenarios B and C, were able to reduce the gap to the target by 60%. This motivates the implementation of early vehicle retirement policies.

Therefore, scenarios D and F were studied. It is important to highlight that filling the gap to the target of a [33% HEVG, 33% HEVD, 33% PHEV] fleet is very expensive (scenario D with 18.7 billion euros). Putting the 10 billion euros limit in total incentives, the gap to the target has increased to 14%.

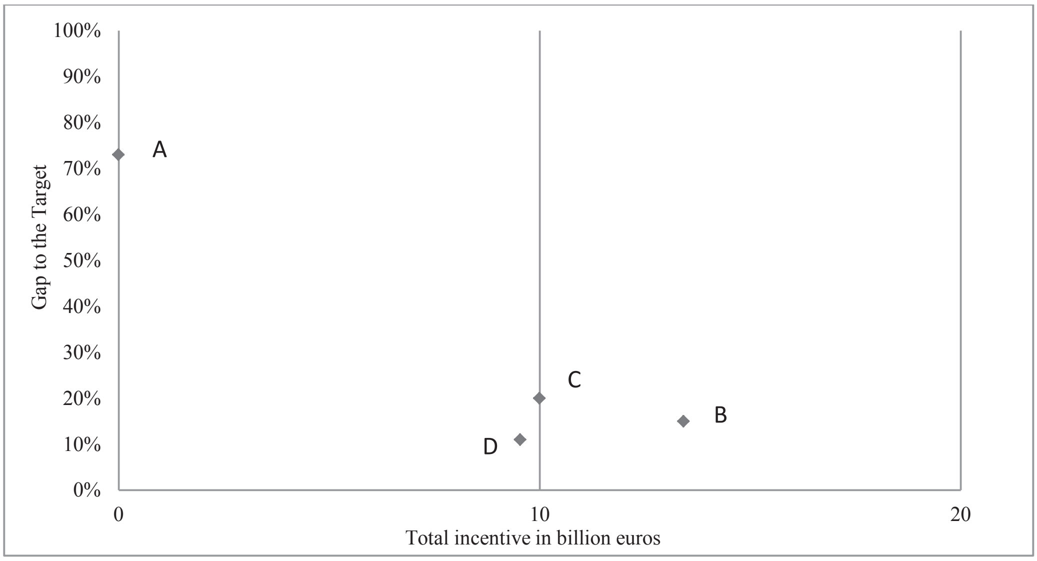


Figure 60: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [25% ICE, 25% Biod, 25% HEVD, 25% PHEV] fleet target

The results presented in figure 60 illustrates that there is a problem in reaching the target of a [25% ICE, 25% Biod, 25% HEVD, 25% PHEV] fleet, due to the fact that it was decided not to affect the sales of gasoline and diesel with external interventions such as incentives. In scenario B, the gap to the target reaches 15% while the total transition cost is around 13.4 billion euros. After considering the implementation of early vehicle retirement, the transition cost has dropped to 9.5 billion euros in scenario D, while the gap to the target has also reduced to 11%.

The outcome of the trade-off analysis for the next screening alternative [25% ICE, 25% HEVG, 25% HEV, 25% PHEV] is presented in figure 61.

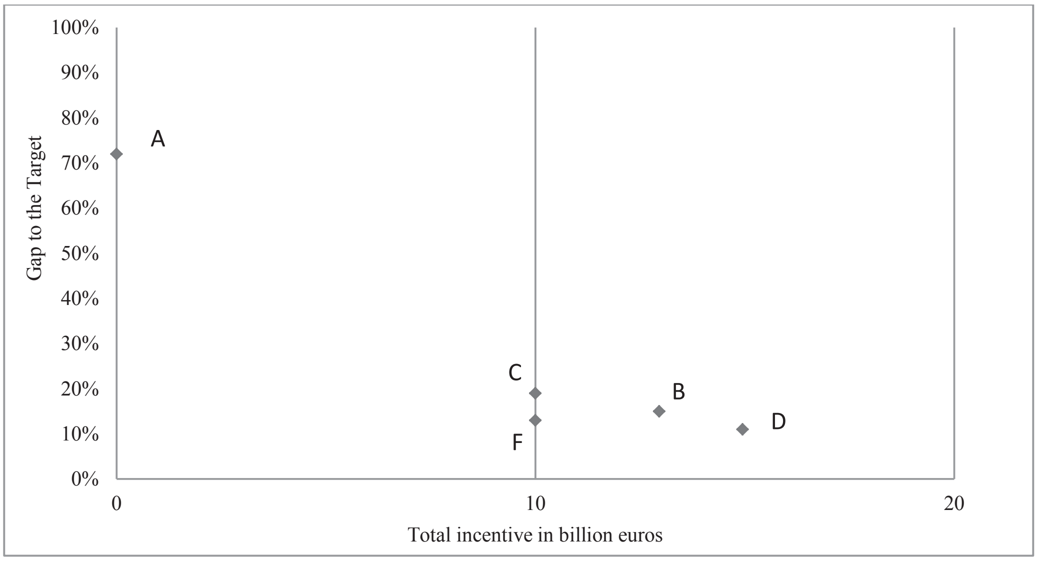


Figure 61: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [25% ICE, 25% HEVG, 25% HEV, 25% PHEV] fleet target

Figure 61 shows the effectiveness of incentives on filling the gap to the target of a [25% ICE, 25% HEVG, 25% HEV, 25% PHEV] fleet in five policy scenarios. The transition cost in scenario B is around 12.9 billion euros, while the gap to the target is 15%. This gap can be reduced by implementing a vehicle early retirement policy, in scenario D, to 11%. Having the limit budget of 10 billion euros for total transition cost, scenarios C and F were able to reduce the gap to 19% and 13%. This clearly shows the impact of adopting an early vehicle retirement policy. Details of total incentives for the alternatives of second screening set in scenario D are presented in table XLIX. This table also shows the gap to the target in this policy scenario.

Table XLIX: Findings on transition cost and gap to the target for the second screening set of alternatives

	Vehicle Incentives	Fuel Incentive	Station Incentives	Total Incentives	Gap to the Target
Alternative 1	18.2 B €	--------	0.04 M €	18.2 B €	0%
Alternative 2	10.2 B €	--------	--------	10.2 B €	13%
Alternative 3	17.4 B €	1.35 B €	1.25 M €	18.7 B €	0%
Alternative 4	8.24 B €	1.30 B €	0.07 M €	9.54 B €	11%
Alternative 5	14.1 B €	895 M €	1.24 M €	15.0 B €	11%

Similar to iteration 0, and after reviewing the estimated transition cost for the first screening alternatives for all policy scenarios, the transition costs were updated for the screening alternatives with the outcome of policy scenario D. Then, we added the alternatives resulting from other policy scenarios for all 5 screening alternatives to the set of initial alternatives.

Iteration 2

The second iteration starts with inputting the updated estimated transition costs (from table XLIX) to the MCDA and adding the alternatives that were analyzed under suggested policy scenarios, to the list of alternatives. Running the process described in iteration 0 again, we get the third screening set of alternatives, presented in table L.

Table L: Third screening set of alternatives (Iteration 2)

	DISI-Gasoline	DICI-Diesel	DICI-Biodiesel	HEV-Gasoline	HEV-Diesel	PHEV	BEV
Alternative 1	50%				50%		
Alternative 2			33%		33%	33%	
Alternative 3				33%	33%		33%
Alternative 4		25%		25%	25%	25%	
Alternative 5		7%	50%		43%		

The first four alternatives are new, when compared with the list of alternatives in the previous screening sets, but alternative 5 is associated with the outcome of estimating the transition cost for the first alternative from iteration 1, in scenario F. The transition cost for this alternative, according to figure 57, is 10 billion euros and the gap to the target is 7%. As there are four new alternatives in the screening set, the iterative procedure must continue (see figure 56).

The results of the trade-off analysis for the third screening set of alternatives are presented in figures 62-65.

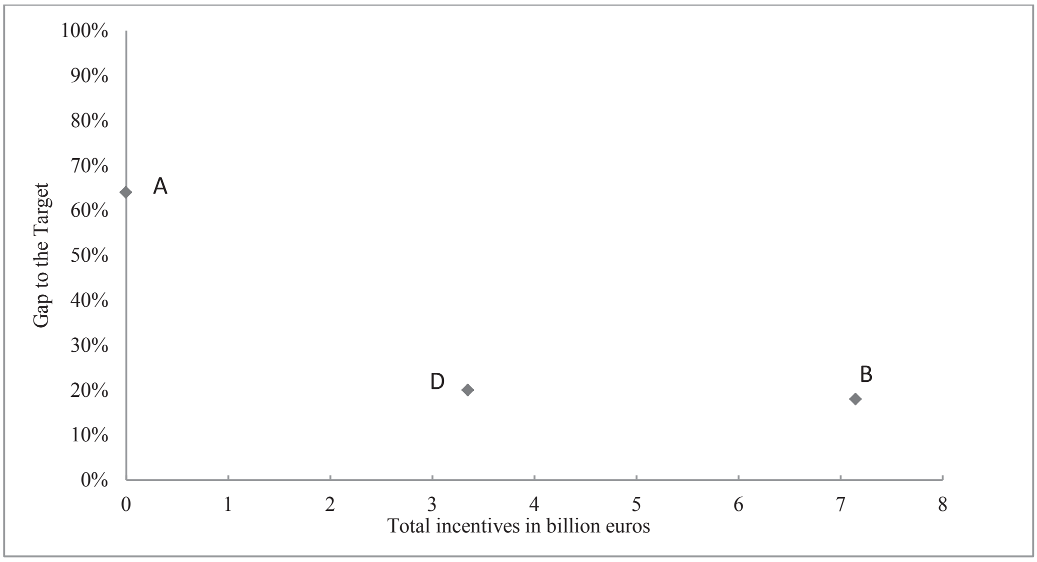


Figure 62: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [50% ICE, 50% HEVD] fleet target

The first insight from figure 62 is that the gap to the target of a [50% ICE, 50% HEVD] fleet cannot be avoided completely. The main contributor is the share of gasoline car, which is not going to be around 50% mainly because of the shift towards diesel cars. Figure 62 shows that, in order to lower the gap to the target to 18% in scenario B, the total incentive should be around 7.1 billion euros, while the implementation of early vehicle retirement policies can reduce the transition cost to 3.6 billion euros.

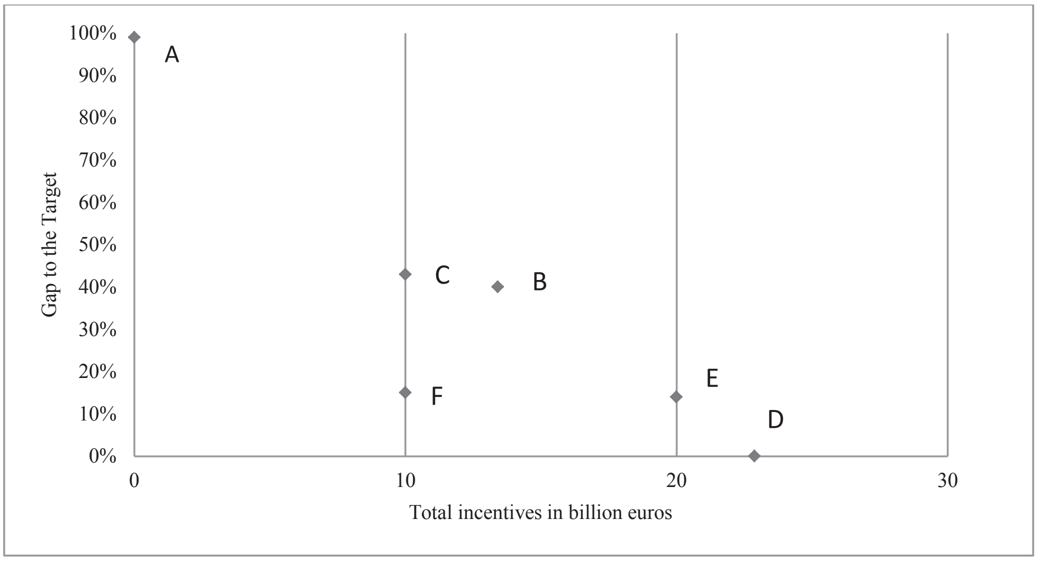


Figure 63: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [33% biod, 33% HEVG, 33% HEVD] fleet target

The first insight from figure 63, is the diversity of policy scenarios in terms of transition cost estimation and gap to the target. It also shows that in the absence of an early vehicle retirement policy, scenarios B and C show the path towards reducing the gap to 40%. This gap can be further reduced after considering the early vehicle retirement plan in scenarios D, E and F.

It is interesting to compare the gap to the target in scenarios C and F, when the transition cost has a similar limit of 10 billion euros. The early vehicle retirement policy enables the faster turnover of vehicle towards adopting more AFVs and the gap in scenario F is 15% when compared to 43% in scenario C.

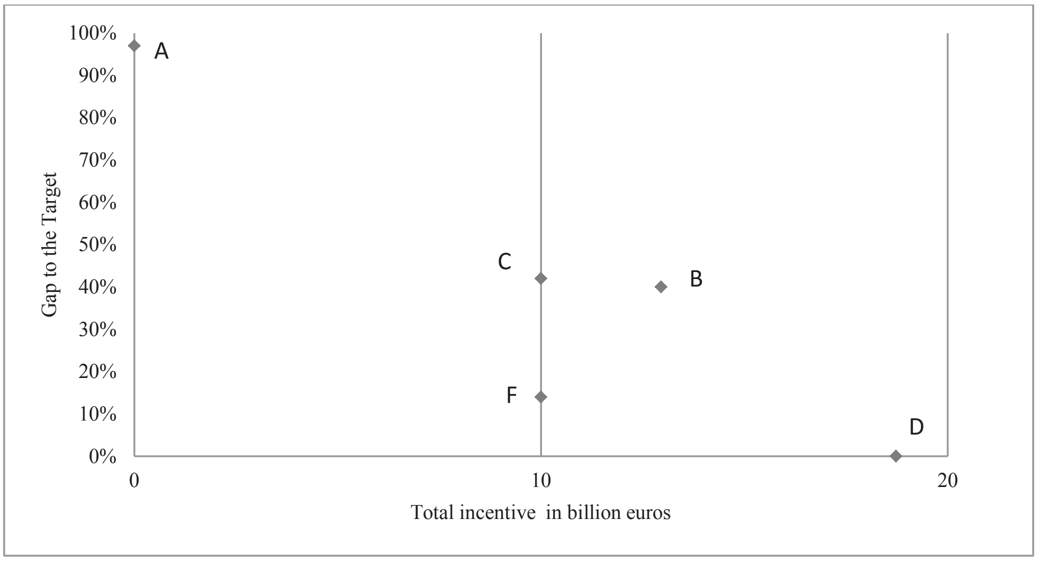


Figure 64: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [33% HEVG, 33% HEVD, 33% BEV] fleet target

The first insight from figure 64 is that the less costly scenarios, such as scenarios B and C, were able to reduce the gap to the target by 60%. This explains the inspiration for the employment of an early vehicle retirement policy. Therefore, scenarios D and F were studied. Note that filling the gap to the target of a [33% HEVG, 33% HEVD, 33% BEV] fleet is very expensive (scenario D with 18.9 billion euros). Putting the 10 billion euros limit in total incentives, the gap to the target has increased to 10% compared with scenario D.

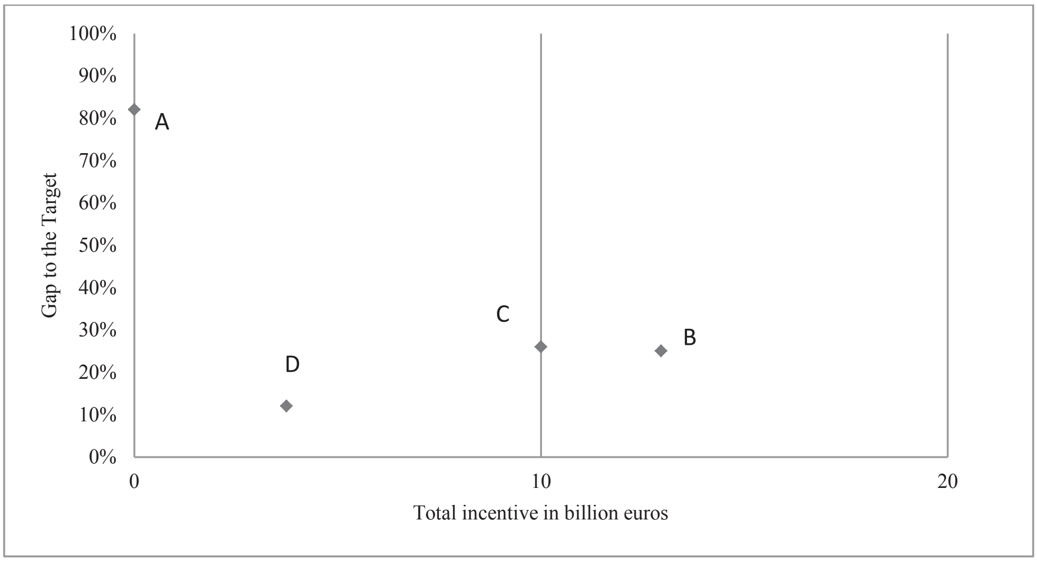


Figure 65: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [25% DI, 25% HEVG, 25% HEVD, 25% PHEV] fleet target

The results presented in figure 65 demonstrates that there is a problem reaching the target of a [25% DI, 25% HEVG, 25% HEVD, 25% PHEV] fleet, as it was decided not to affect the sales of gasoline and diesel, with external intervention such as incentives. In scenario B, the gap to the target reaches 25% while the total transition cost is around 12.9 billion euros. After considering the implementation of an early vehicle retirement, the transition cost has dropped to 3.7 billion euros in scenario D, while the gap to the target has also reduced to 12%.

The associated transition cost and the gap to the target for each alternative in the third screening set was calculated using the system dynamics model (see table LI).

Table LI: Findings on transition cost and gap to the target for the third screening set of alternatives

	Vehicle Incentives	Fuel Incentive	Station Incentives	Total Incentives	Gap to the Target
Alternative 1	3.35 B €			3.35 B €	20%
Alternative 2	20.4 B €	2.49 B €	11.3 M €	22.9 B €	0%
Alternative 3	18.9 B €			18.9 B €	0%
Alternative 4	3.89 B €	32 M €	0.49 M €	3.92 B €	12%

Similar to iteration 0, and after reviewing the estimated transition cost for first screening alternatives for all policy scenarios, we have updated the estimated transition costs for screening alternatives, with the outcome of policy scenario D. Then, we added the alternatives resulting from other policy scenarios, for all 4 screening alternatives, to the set of initial alternatives.

Iteration 3

The procedure continues with the updated data for the transition costs to the MCDA and adding the alternatives that were analyzed under the suggested policy scenarios, to the list of alternatives. The sequential screening technique was adopted to identify the third screening set of alternatives (Table LII).

Table LII: Fourth screening set of alternatives (Iteration 3)

	DISI-Gasoline	DICI-Diesel	DICI-Biodiesel	HEV-Gasoline	HEV-Diesel	PHEV	BEV
Alternative 1				100%			
Alternative 2		33%		33%	33%		
Alternative 3			33%		33%		33%
Alternative 4	30%	20%			50%		
Alternative 5	12%	13%		25%	25%	25%	

The first three alternatives are new, when compared with the list of alternatives in previous screening sets.

Alternative 4 is the outcome of the system dynamics analysis for the first alternative of the third screening set (table L) in policy scenario D. Alternative 5 is associated with the results of the transition analysis of the forth alternative of the third screening set (table L) in policy scenario D. The transition costs for alternatives 4 and 5, are 3.35 and 3.75 billion euros, respectively. As there are three new alternatives in the screening set, the procedure continues.

The results of the trade-off analysis for the fourth screening set of alternatives are presented in figures 66-69.

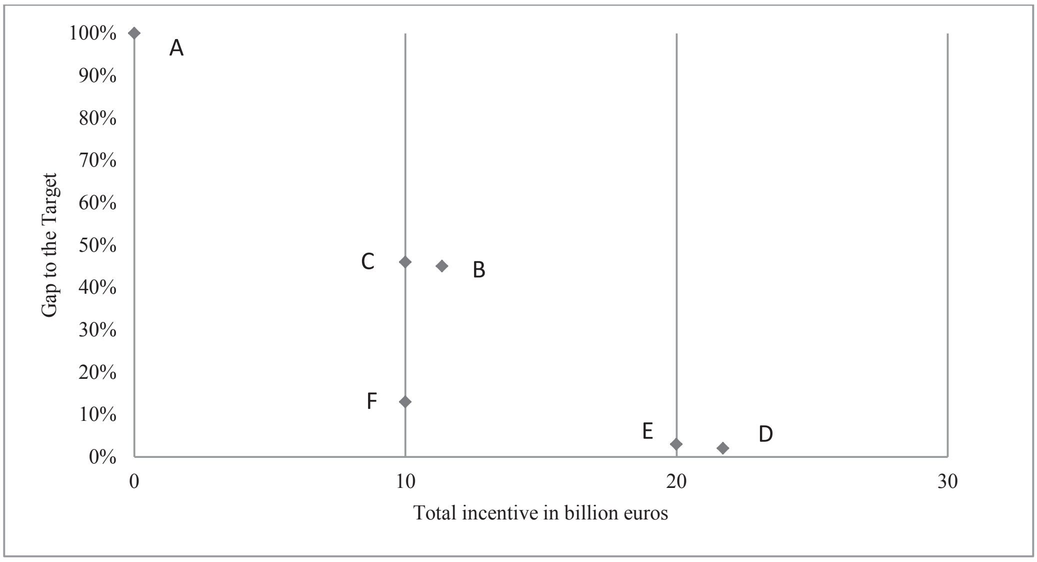


Figure 66: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [100% HEVG] fleet target

From figure 66 we can see that there are significant differences in the transition cost estimation for policy scenarios. Note that, in order to lower the gap to the target to 45% in scenario B, the total incentive should be around 11.3 billion euros. On the other hand, the implementation of an early vehicle retirement policy can significantly reduce the gap to the target. For example, in expensive scenarios such as D and E, the gap to the target has reduced to 2-3%, respectively.

Again, the comparison of results in scenarios C and F shows that the early vehicle retirement policy can reduce the gap to the target from 46% in scenario C to 13% in scenario F, while the total incentives in both scenarios are equal to 10 billion euros.

The results of comparing the effectiveness of incentives in different policy scenarios for the target of a [33% DI, 33% HEVG, 33% HEVD] target are shown in figure 67.

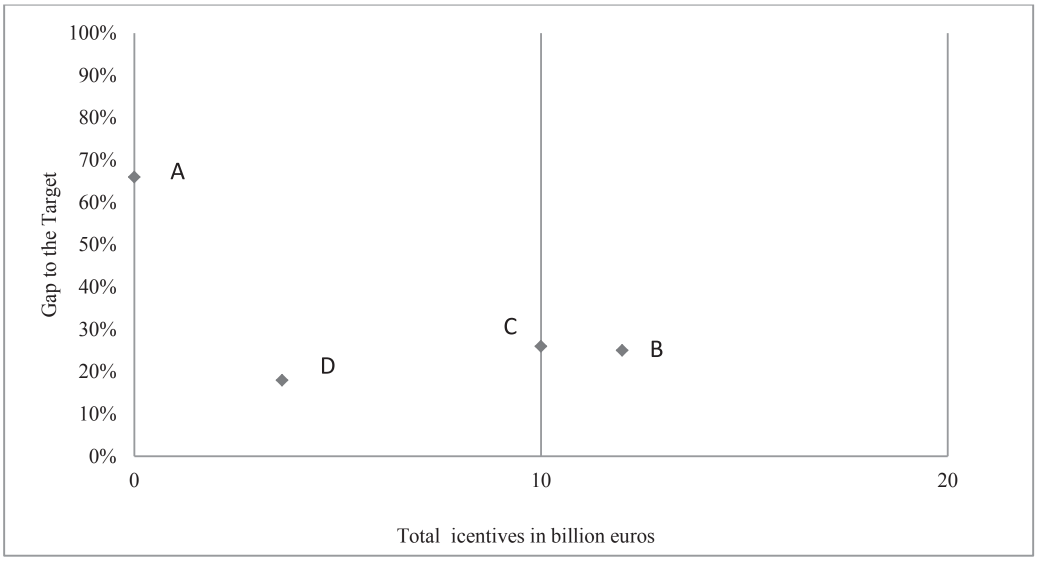


Figure 67: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [33% DI, 33% HEVG, 33% HEVD] fleet target

The first insight from figure 67 is that the gap to the target of a [33% DI, 33% HEVG, 33% HEVD] fleet cannot be avoided completely. The main contribution is the share of ICE-gasoline vehicles in the market. Scenarios B and C show that it would be possible to lower the gap even without implementing an early vehicle retirement policy, while the total incentives will be significantly higher. In fact, the transition costs in scenarios B and C are 229% and 174% more than the incentives in scenario D. This is mainly due to the fact that in scenario D, vehicle will be replaced by AFV vehicles when they reach their lifetime of 10 years. This will result in a faster diffusion of AFVs than in scenarios B and C, and in a reduction in the need for incentives.

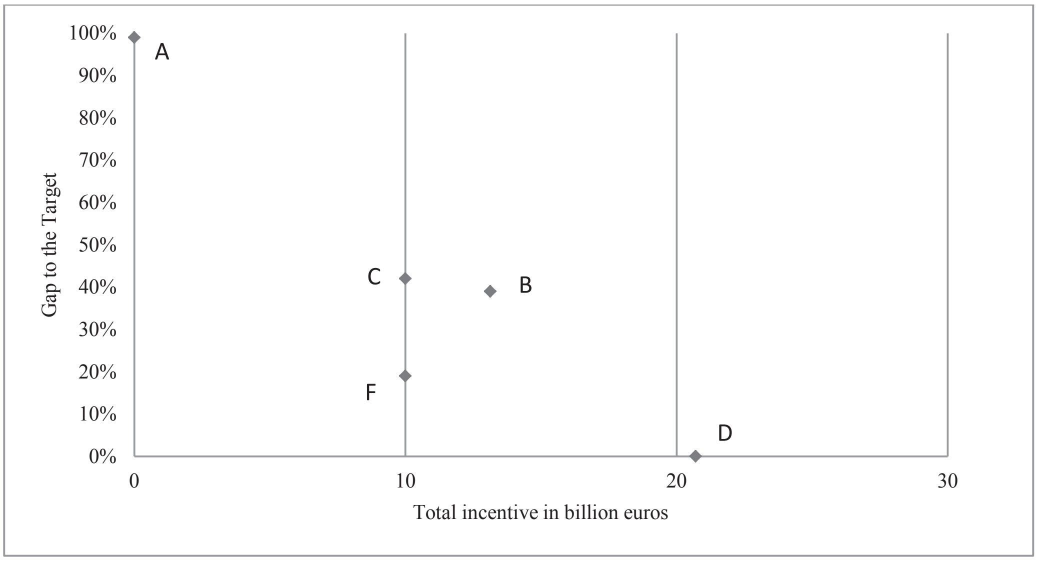


Figure 68: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [33% Biod, 33% HEVD, 33% BEV] fleet target

Figure 68 shows that in scenarios B and C, the gap to the target can only be reduced to 39%-42%, while the transition cost is 13.1 and 10 billion euros, respectively. However, studying the impact of an early vehicle retirement policy in scenarios D and F shows that the gap to the target can be reduced even more. Considering the 10 billion euros limit on total incentives, the gap to the target is 19% which is significantly better than in scenario C.

As the first three alternatives are new, we follow the described procedure and identify the related transition cost and gap to the target for each of those alternatives (Table LIII).

Table LIII: Findings on transition cost and gap to the target for the fourth screening set of alternatives

	Vehicle Incentives	**Fuel Incentive**	**Station Incentives**	**Total Incentives**	**Gap to the Target**
Alternative 1	21.7 B €			21.7 B €	2%
Alternative 2	2.43 B €			2.43 B €	18%
Alternative 3	19.3 B €	14.3 B €	7.61 M €	20.7 B €	0%

After reviewing the estimated transition costs for the fourth screening alternatives for all policy scenarios, and considering the fact that the only scenario that shows zero or near near-zero gap to the target in scenario D, we have updated the estimated transition cost for screening alternative with the outcomes of that policy scenario. Then, the alternatives resulted from other policy scenarios for all 3 screening alternatives were added to the set of initial alternatives.

Iteration 4

Next, we update the data of transition costs for multi-Criteria comparison, including the alternatives that resulted from policy scenarios of the three new alternatives from iteration 3. The next screening set was identified after applying the sequential screening technique (Table LIV).

Table LIV: Screening set of alternatives (Iteration 4)

	DISI-Gasoline	**DICI-Diesel**	**DICI-Biodiesel**	**HEV-Gasoline**	**HEV-Diesel**	**PHEV**	**BEV**
Alternative 1		50%			50%		
Alternative 2	25%	25%		25%	25%		
Alternative 3	25%			25%	25%		25%
Alternative 4	12%	13%		25%	25%	25%	
Alternative 5	17%	16%		33%	33%		

The first three alternatives are new when compared with the list of alternatives in previous screening sets. Alternative 4 is the last alternative in the previous screening set (table LII) and alternative 5 is associated with the results of the transition analysis of the second alternative of the fourth screening set (table LII) in policy scenario D. The transition costs for alternatives 4 and 5, are 3.92 and 2.43 billion euros, respectively. As there are three new alternatives in the screening set, procedure must go on.

The results of the trade-off analysis for the fifth screening set of alternatives are presented in figures 69-72.

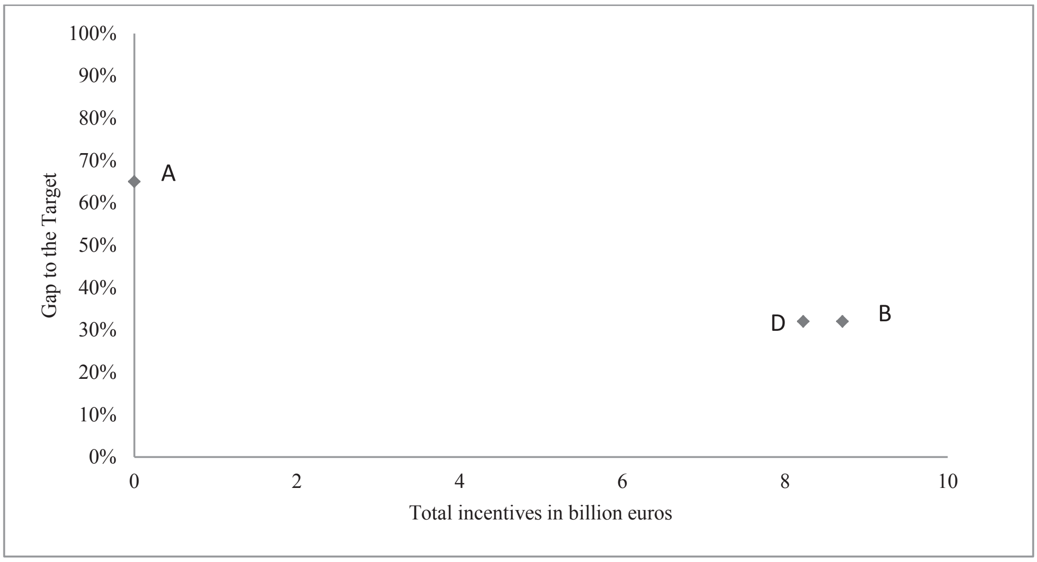


Figure 69: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [50% DI, 50% HEVD] fleet target

We can see, in figure 69, that the amount of incentives in scenarios B and D are lower than 10 billion euros, relatively lower than previous targets. This is due to the significant share of diesel vehicles in the target fleet combination. The gap to the target in both of these scenarios is 32%, but scenario D is 6% cheaper. In scenario D, the model replaces vehicles more frequently with AFVs as a result of the early vehicle retirement policy which could reduce the required incentives when compared with scenario B.

The results of comparing the effectiveness of incentives in different policy scenarios for a [25% ICE- 25% DI, 25% HEVG, 25% HEVD] target is shown in figure 70.

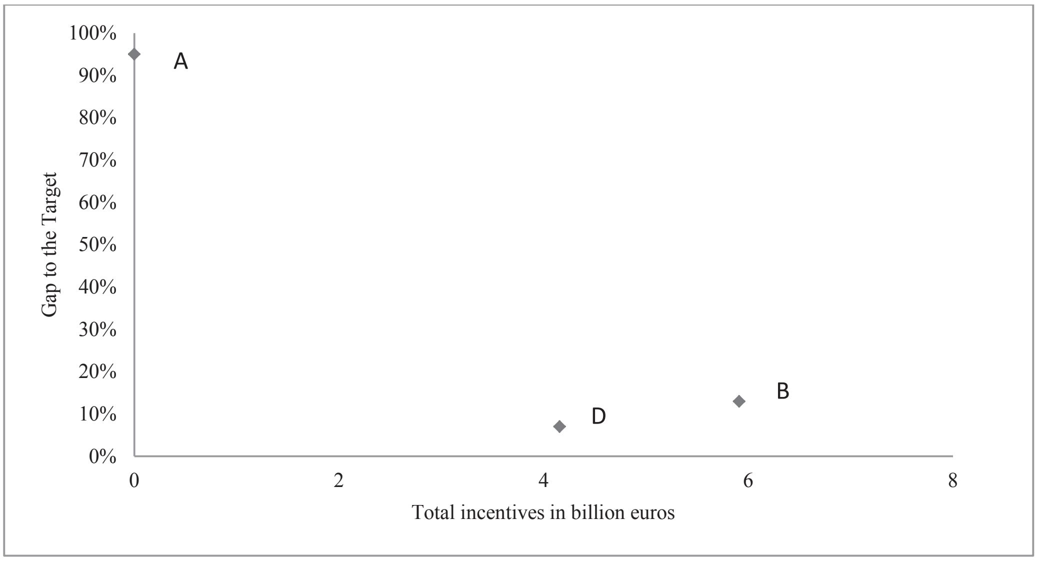


Figure 70: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [25% ICE- 25% DI, 25% HEVG, 25% HEVD] fleet target

From figure 70 we can see that both scenarios D and B were able to reduce the gap to the target significantly with a reasonable amount of incentives. This finding seems reasonable, considering the share of AFVs (25% HEVG and 25% HEVD) and conventional vehicles (25% ICE- 25% DI) in the target alternative.

Besides, it should be noted that the total incentives in scenario D are 42% lower than the total incentives in scenario B. This is mainly due to the fact that in scenario D, the model considers the implementation of an early vehicle retirement policy and the vehicles will be replaced by the AFV vehicles when they reach their lifetime of 10 years. This will result in lower required incentives for scenario D, when compared with scenario B.

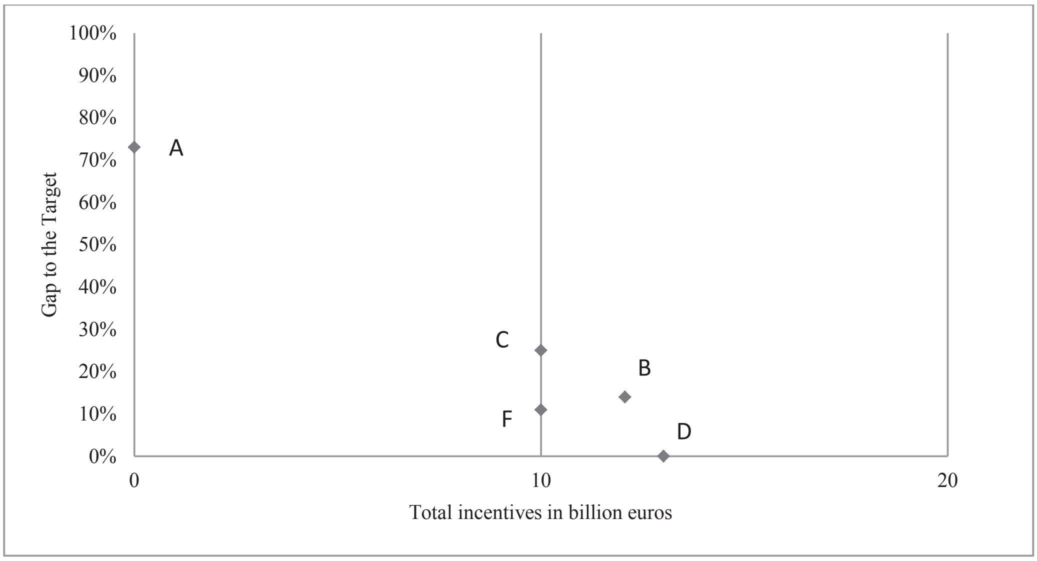


Figure 71: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [25% ICE, 25% HEVG, 25% HEVD, 25% BEV] fleet target

Figure 71 shows that in scenarios B and C, the gap to the target can only be reduced to 14%-25%, while the transition cost is 12.1 and 10 billion euros, respectively. However, studying the impact of an early vehicle retirement policy in scenarios D and F, the gap to the target can be reduced even more. Considering the 10 billion euros limit on total incentives, the gap to the target is 11% which is significantly better when compared to scenario C.

As discussed earlier, the first three alternatives are different than the previous alternatives, thus, we need to identify the transition cost for each of them, using the system dynamics model. After reviewing the estimated transition cost for the fifth screening set of alternatives for every policy scenarios, and as scenario D has the least gap to the target, we have updated the estimated transition cost for the screening alternatives, with the outcome of policy scenario D. Table LV shows the transition cost for these three new screening alternatives and the gap to the target.

Table LV: Estimated Transition cost for the fifth screening set of alternatives

	Vehicle Incentives	Fuel Incentive	Station Incentives	Total Incentives	Gap to the Target
Alternative 1	8.23 B €	--------	--------	8.23 B €	32%
Alternative 2	4.16 B €	--------	--------	4.16 B €	7%
Alternative 3	13.0 B €	--------	1.29 M €	13.0 B €	0%

Besides, it was decided to add the alternatives resulting from other policy scenarios, for all 3 screening alternatives to the set of initial alternatives.

Iteration 5

Next, we update the data of the transition costs for the multi-criteria comparison, including the alternatives resulting from policy scenarios of the three new alternatives in iteration 4. Through the suggested sequential screening technique, the sixth screening set was generated (Table LVI).

Table LVI: Sixth screening set of alternatives (Iteration 5)

	DISI-Gasoline	DICI-Diesel	HEV-Gasoline	HEV-Diesel	PHEV
Alternative 1	50%		50%		
Alternative 2	33%	33%	33%		
Alternative 3	12%	13%	25%	25%	25%
Alternative 4	17%	16%	33%	33%	

The first two alternatives are new when compared with the list of alternatives in previous screening sets. Alternatives 3 and 4 however were alternatives 4 and 5 in the previous screening set of alternatives (table LIV). Given that there are two new alternatives in the screening set, the procedure must pursue.

The results of the trade-off analysis for the fifth screening set of alternatives are presented in figures 72-73.

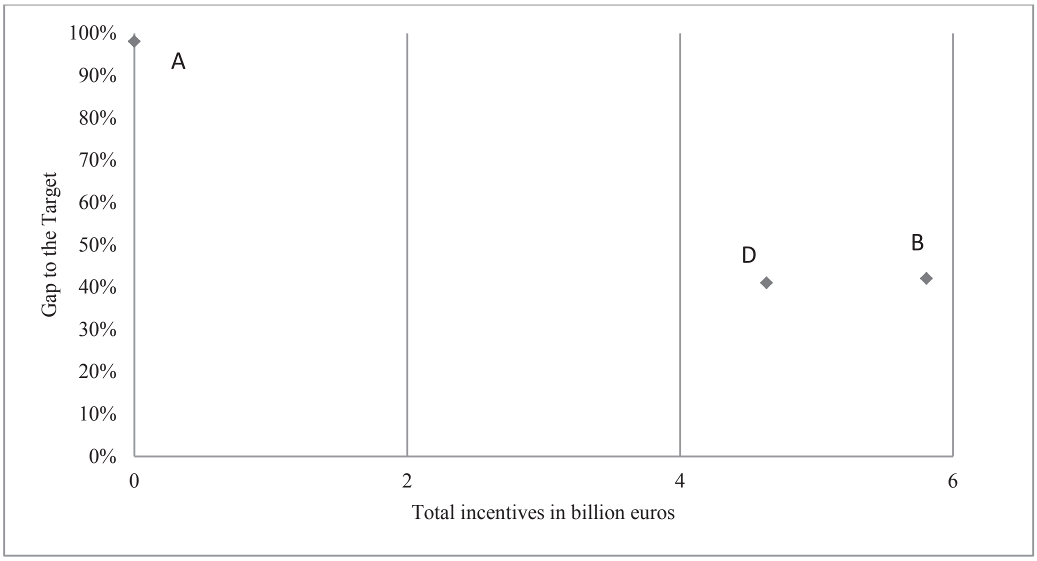


Figure 72: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [50% ICE, 50% HEVG] fleet target

In figure 72 we see a significant gap to the target in scenarios B and D. As explained before, the main contributor is the share of gasoline cars, which is not going to be around 50% mainly because of the shift towards diesel cars. The implementation of an early vehicle retirement policy in scenario D affects the result in a sense of reducing the required incentives (25%), while the gap to the target is almost unchanged.

The results of comparing the effectiveness of incentives in different policy scenarios for the target of a [33% ICE, 33% DI, 33% HEVG] target is shown in figure 73.

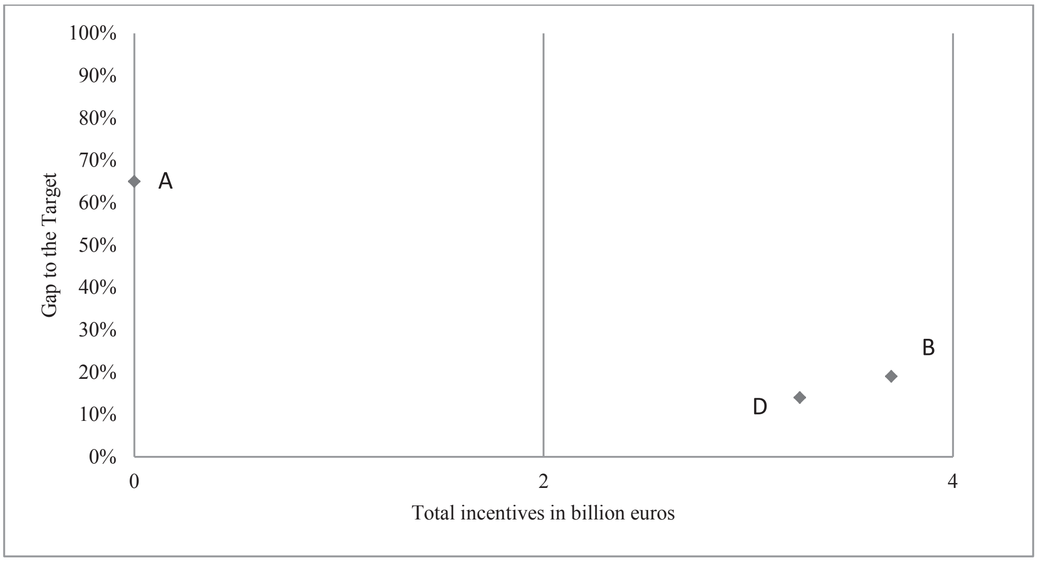


Figure 73: Trade-offs between the gap to the target and total incentives for the policy scenarios analyzed when trying to reach the [33% ICE, 33% DI, 33% HEVG] fleet target

From figure 73, it's noticeable that both policy scenarios B and D were able to reduce the gap to the target significantly, with a reasonable amount of incentives. The total transition costs in scenarios B and D are 3.7 and 3.25 billion euros respectively, while the gap to the target is 19% and 14%. This finding seems reasonable, considering the share of AFVs (33% HEVG) and the share of conventional vehicles (33% ICE and 33% DI) in the target alternative.

Besides, note that the total incentives in scenario D are 14% lower than the total incentives in scenario B. This is mainly due to the fact that in scenario D, the model considers the implementation of an early vehicle retirement policy and the vehicles will be replaced by the AFV vehicles when they reach their lifetime of 10 years. This will result in lower required incentives in scenario D, when compared with scenario B.

As discussed earlier, the first two alternatives are different from previous alternatives; thus, we have identified the transition costs for each of alternatives, using the system dynamics model.

After reviewing the estimated transition cost for the sixth screening set of alternatives for all policy scenarios, and given that scenario D has the lowest gap to the target we have updated the estimated transition costs for screening alternatives with the outcome of that scenario. Table LVII shows the transition cost for these two new screening alternatives and their gap to the target.

Table LVII: Estimated Transition cost for the sixth screening set of alternatives

	Vehicle Incentives	Fuel Incentive	Station Incentives	Total Incentives	Gap to the Target
Alternative 1	8.88 B €	--------	--------	8.88 B €	41%
Alternative 2	3.25 B €	--------	--------	3.25 B €	14%

Iteration 6

In the 6th iteration, we have updated the data of the transition costs for multi-criteria comparison, and have included the alternatives resulting from policy scenarios of the two new alternatives in iteration 5. The next screening set was identified after applying the sequential screening technique (Table LVIII).

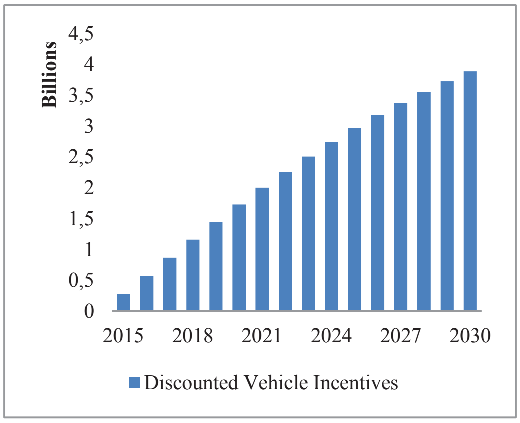
Table LVIII: Screening set of alternatives (Iteration 6)

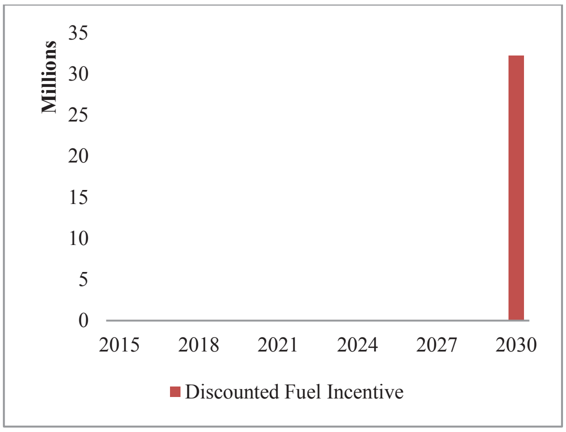
	PISI-Gasoline	DICI-Ethanol	DICI-Diesel	DICI-Biodiesel	HEV-Gasoline	HEV-Diesel	PHEV	BEV
Alternative 1	12%	----	13%	----	25%	25%	25%	----
Alternative 2	17%	----	16%	----	33%	33%	----	----

Now, it is found that there are no new alternatives, since alternatives 1 and 2 already showed up previously as alternative 4 and 5 in the sixth screening set of alternatives (table LVI). This means that the iterative analysis has converged and the above two alternatives are the members of the final screening set.

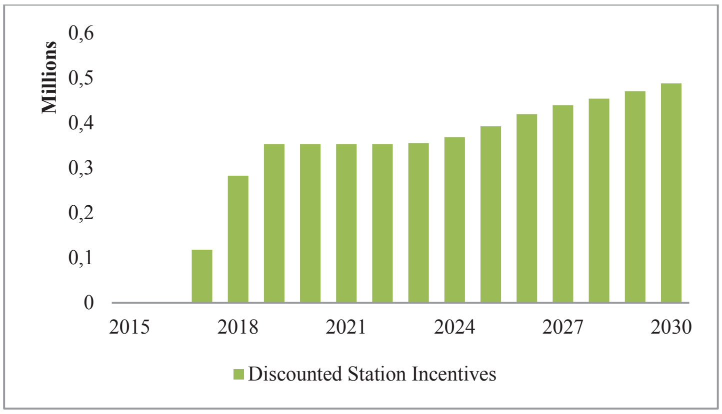
5.2.2. Final Screening set

As presented in the previous section, the final screening set was identified after 6 iterations. There are two alternatives in the final screening set. When compared to the initial screening set, these two alternatives require much less investment, while the shares of new alternative fuel vehicles such as PHEVs, BEVs and biofuel based engines are significantly lower. Considering the policy scenarios presented in section 4.4.2., the transition cost is 3.92 billion euros for alternative 1, and 2.43 billion euros for alternative 2. This estimation was based in assumptions associated with scenario D. In fact, for both alternatives, the Early Scrappage Policy (ESP) suggests that the vehicles need to be discarded after 10 years. The accumulated incentives overt time for vehicle, fuel and fuel stations for each of these two alternatives under policy scenario D are presented in figures 74 and 75.





a b



c

Figure 74: Accumulated incentives over time on vehicles (a), fuel (b) and stations (c) for alternative 1

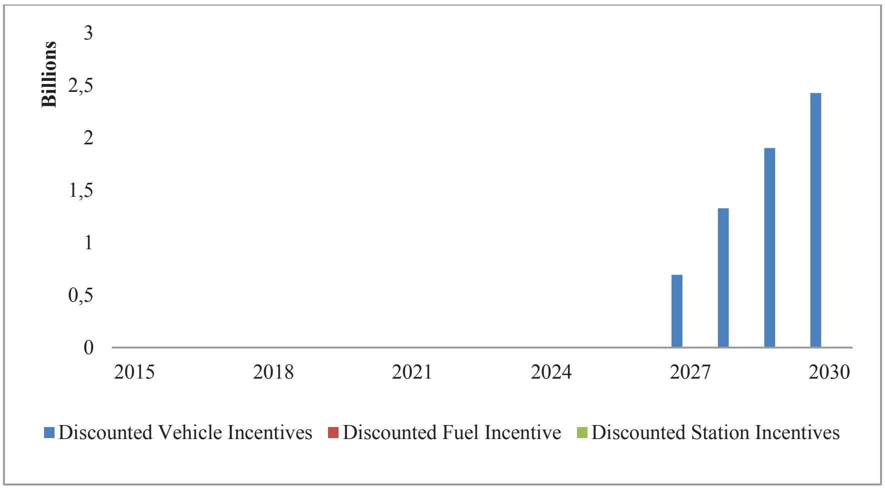


Figure 75: Accumulated incentives over time on vehicles for alternative 2

Another potentially important factor for the decision maker is the duration of the incentives. This study can provide valuable information and insights regarding the duration of incentives for vehicles, fuels and stations (table LIX).

Table LIX: Duration of incentives in years

	Vehicle Incentive	Fuel Incentive	Station Incentive
Alternative 1	15	0.4	14.5
Alternative 2	2.8	----	----

Considering both figures 74, 75, and table LIX, we concluded that the major share of incentives should be spent on vehicles. This actually is in line with the findings through the calibration of the model with Portuguese historical data: as presented in section 4.3.3, the most important factor in the user's choice model was the initial price of vehicles. According to figure 74-b, the incentives spent on fuel should be very limited. In fact, this outcome is consistent with the low fuel coefficient in the vehicle choice model, identified as a result of calibrating the model with Portuguese historical data.

Table LIX also highlights that the incentives on stations need to start earlier. One of the main outcomes of an early start of incentivizing the stations is the fast growth in station coverage which is an important factor in the user's choice function. Besides, it can also be seen that changes in social related factors (such as familiarity) take time. I.e., if the policy maker is eager to improve the familiarity of people with a technology, the social motivators need to be in place as early as possible, to enforce favorable impacts.

Considering the multi-criteria characteristic of this decision making framework, let us now review the assessment of the two final alternatives with respect to the decision making attributes (figure 76).

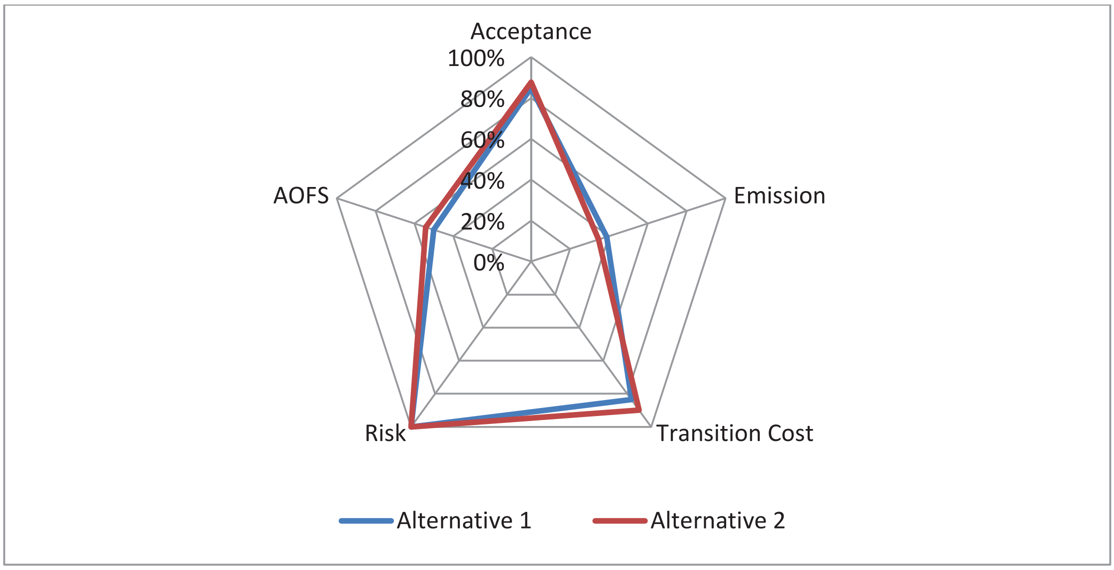


Figure 76: Comparison of final two alternatives with respect to the impacts in the decision making attributes

First of all, it is obvious that almost all the characteristics of both alternatives very much look alike. However, the first alternative is staying superior in term of the “emissions” attribute, mainly because of the impact of PHEV. On the other hand, the second alternative seems to be cheaper and superior in terms of availability of fuel supply. This is understandable, because of the assumption that there are more geographically diverse sources of fossil fuels than electricity for the case of Portugal.

As mentioned before, both of these alternatives were identified in the policy scenario in which an early scrappage policy was in place. Therefore, we have investigated the case where there is an associated cost to motivate people to discard their cars at a predefined time (10 years in this case). According to the European Automobile Manufacturers' Association report ([166]), the amount of incentives to be paid to the owner of a car (older than 10 years) in previous campaigns was 1000 Euros per discarded vehicle. The impact of including this cost (ESP incentive) on the total incentive is presented in figure 77.

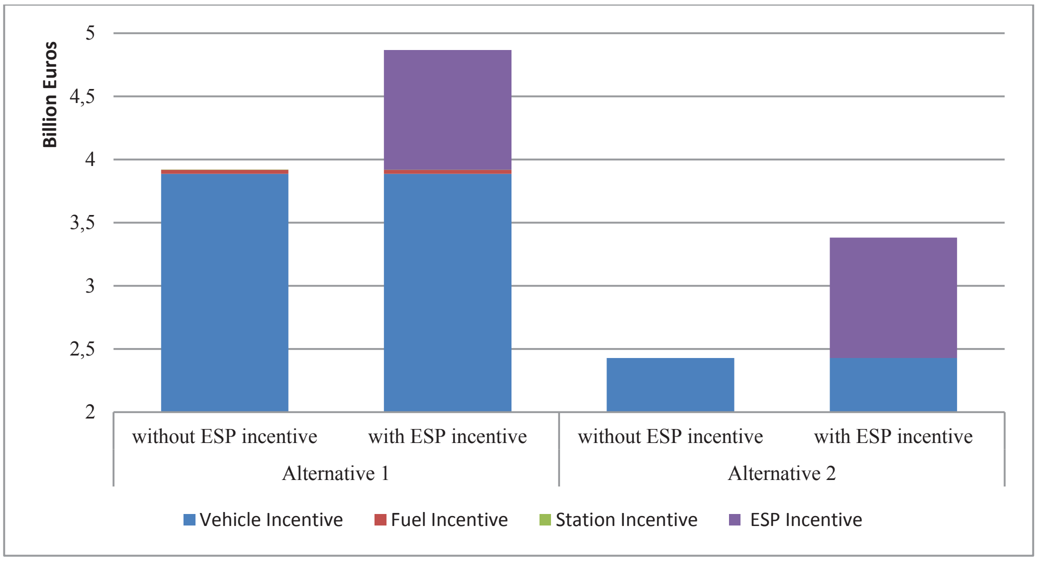


Figure 77: Comparative assessment of total incentives - without and with incentive for Early Scrappage Policy (ESP)

As expected, the total transition cost will increase considerably in the case of including the incentive for an early scrappage policy. Note that the gap to the target in both cases (without and with ESP incentive), for both alternatives, was similar. Besides, the findings highlight the potential of the method developed to cope with including expenses that were not anticipated in the earlier stage of the modeling process.

5.2.3. Impact of a high oil price on transition costs of the final screening set

As a critical step of this analysis, we have investigated the sensitivity of the transition cost estimation for the final screening set. Thus, the impact of the “high oil price” situation on the proposed supportive policy was evaluated. As explained before, (section 3.3.2), it was assumed that by 2030, the price of gasoline and diesel in a high oil price scenario raises from 1.6 to 2.1 € / liter for the gasoline, and from 1.3 to 1.7 € / liter for the diesel.

Figure 78 shows the total incentives and the share of incentives for vehicles, fuels and stations. As expected, the total transition cost in the "high oil price" scenario shows a slight decrease.

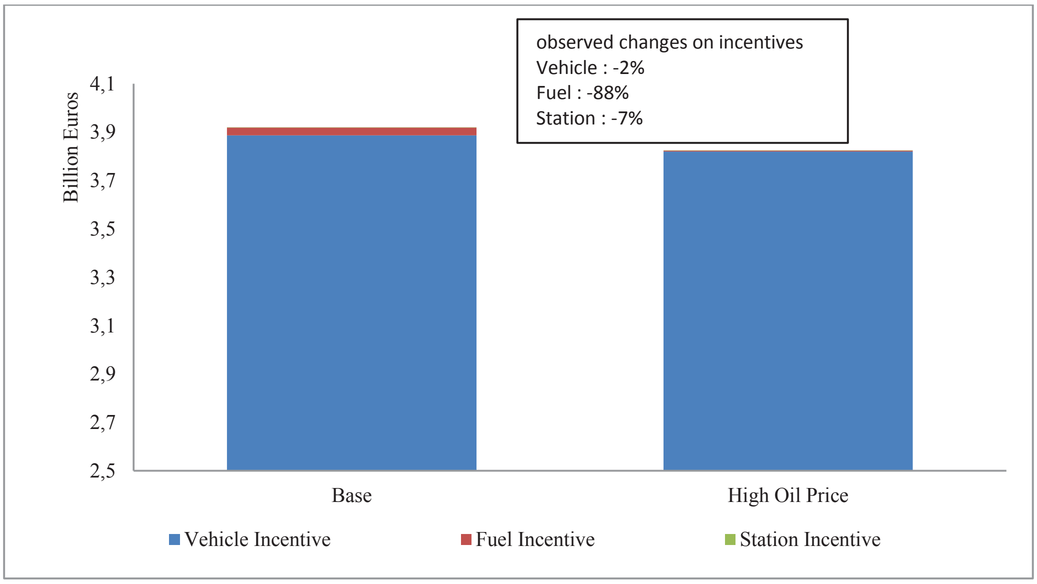


Figure 78: Comparison of total transition cost for alternative 1 - base and high oil price

It can be observed from figure 78 that every segment of incentives has decreased in the high oil price situation. In fact, the changes in incentives on vehicle, fuel and fuel stations are -2%, -88% and -7%, respectively. Therefore, the highest incentive reduction was on fuels, which is somehow expected, as the main difference in the base and high oil price situation is the change in the fuel cost of AFVs.

Elaborating further on the results produced in the high price scenario for the fuel incentives, figure 79 compares the results needed to promote the transition to alternative 1 in terms of the amount and duration needed. It is important to recall that since incentivizing the fossil fuels is not considered, the incentives in fact refer only to electricity.

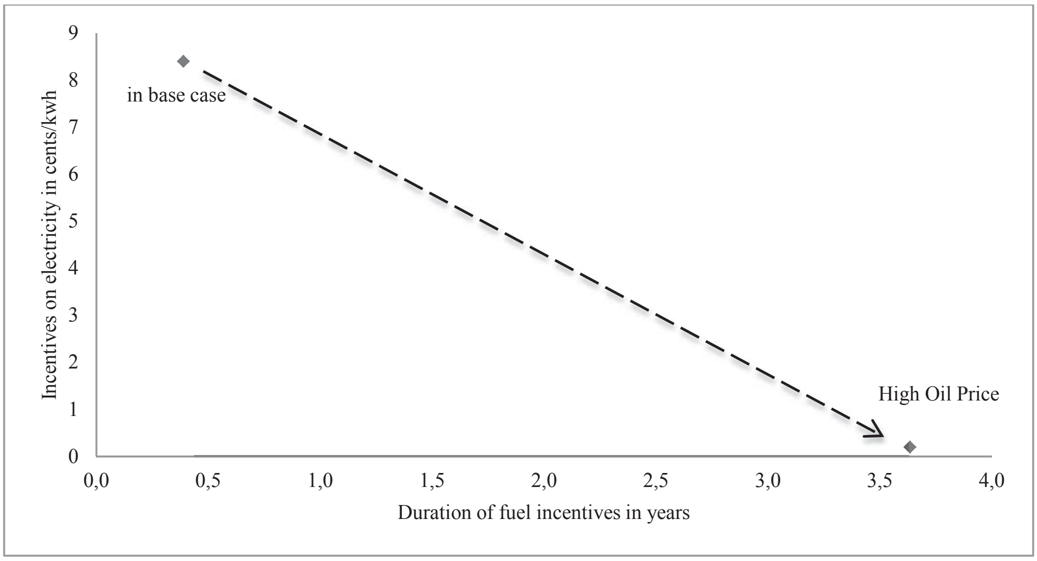


Figure 79: Impact of high oil price on the amount and duration of the incentive on electricity need for the transition to alternative 1.

As shown in figure 79, the amount of incentive on electricity drops significantly, while on the other hand the duration of the fuel incentive has increased to more than three years. This can be justified by the following argument: As explained in chapter 4, social awareness (represented in this study by familiarity factor) plays a crucial role in the early adoption of AFVs. In the high oil price situation, the duration of incentives on fuels has increased significantly, when compared with the base scenario. This could result in an improvement in the utility of PHEV and increase the familiarity of individuals sooner than in the base scenario.

This analysis was repeated for the second alternative. As expected the total transition cost has decreased significantly (more than 20%). Besides, figure 80 illustrates the total incentives and the 21% reduction in total incentives as a result of a high oil price situation.

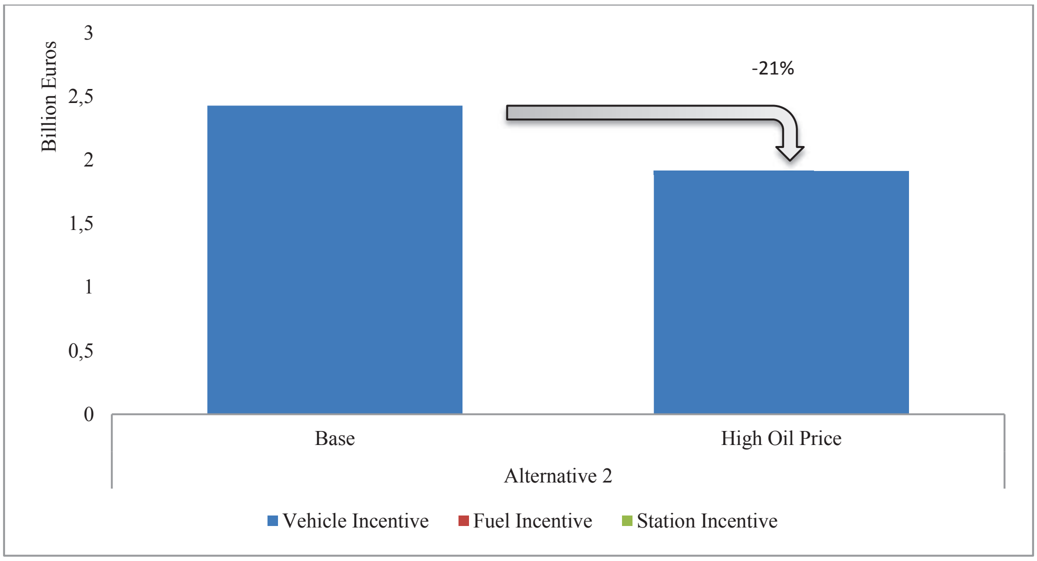


Figure 80: Comparison of total transition cost for alternative 2 - base and high oil price

According to our discussion in section 4.6.1, the only incentive that matters for hybrid vehicles (either gasoline-hybrid or diesel-hybrid) is the incentive on the purchase price of these AFVs. Therefore, figure 81 compares the two incentive values for the purchase price of these two technologies (left Y-axis) and the duration of incentive on these two technologies (right Y-axis) in the base scenario and in the high oil price situations.

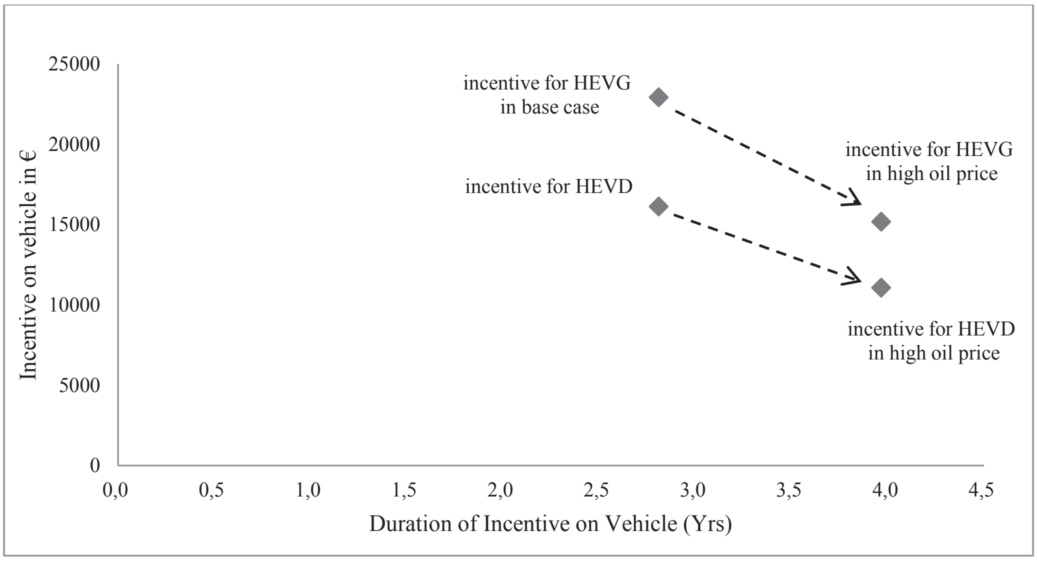


Figure 81: Impact of high oil price on the incentives for vehicles and its duration, for hybrid-gasoline and hybrid-diesel vehicles

Finally, from figure 81, we can see that, although the duration of vehicle incentives has increased, the amount of incentives for vehicles has obviously dropped, resulting in a total reduction of 21% in the total incentive in the high oil situations. As explained before, this increase in the duration of incentives is associated with the improvement in the familiarity of individuals with the AFV.

5.3. General findings

The applicability and value of the whole iterative MCDA/SD methodology was verified with Portugal as a case study. Initially, the screening set resulting from the MCDA had 6 alternatives: ([100% HEVD], [50% HEVG, 50% HEVD], [33.3% Biod, 33.3% HEVG, 33.3% HEVD], [25% E85, 25% Biod, 25% HEVG, 25% HEVD], [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] and [25% Biod, 25% HEVG, 25% HEVD, 25% BEV]).

After the first iteration, there were still 5 alternatives, but they were now different: ([50% Biod, 50% HEVD], [33.3% ICGE, 33.3% HEVG, 33.3% HEVD], [33.3% HEVG, 33.3% HEVD, 33.3% PHEV], [25% ICGE, 25% Biod, 25% HEVD, 25% PHEV], [25% ICGE, 25% HEVG, 25% HEVD, 25% PHEV]).

There were necessary 6 iterations until the solutions converged, until no new alternatives appeared in the screening set. In the final screening set there were only two alternatives: ([12% ICGE, 13% DI, 25% HEVG, 25% HEVD, 25% PHEV], [17% ICGE, 16% DI. 33.3% HEVG, 33.3% HEVD]).

An interesting and very important observation was that the estimated cost of alternatives changed considerably through the convergence process. For instance, the estimated cost of alternative ([25% Biodiesel, 25% HEVG, 25% HEVD, 25% BEV]) was 6.1 billion euros before the application of the SD models and became 18.8 billion euros after it; The cost of the lowest cost screening alternative ([25% ICGE, 25% Biod, 25% HEVD, 25% PHEV]) was 9.54 billion euros at the end of iteration 1, but had decreased to 2.4 billion euros at the end of the convergence process. This demonstrates that the model can be useful not only on achieving more accurate estimates but also in searching for more cost-efficient alternatives to meet the policy goals.

In what regards the policy scenarios, it was found that the intended shares of technologies could only be reached if the policy pack includes Early Scrappage Policy (ESP) schemes. An analysis on the ESP age suggests that the intended results can be achieved if vehicles are discarded after 10 years. If no ESP is adopted, the models suggest that even with significant volumes of incentives to alternative vehicles and fuel stations, it will not be possible to achieve a significant penetration of AVs by 2033.

As mentioned, both of the alternatives in the final screening set were identified in the policy scenario in which an early scrappage policy was in place. Therefore, we have investigated the case where there is an associated cost to motivate people to discard their cars at a predefined time (10 years in this case). Considering the value of 1000 Euros per discarded vehicle, the total transition cost will increase considerably in the case of including the incentive for an early scrappage policy. Note that the gap to the target in both cases (without and with ESP incentive), for both alternatives, was similar. Besides, the findings highlight the potential of the method developed to identify expenses that were not anticipated in the earlier stage of the modeling process.

As a critical step of this analysis, we have investigated the sensitivity of the transition cost estimation for the final screening set as a result of oil price increase. As explained before, (section 3.3.2), it was assumed that by 2030, the price of gasoline and diesel in a high oil price scenario raise from 1.6 to 2.1 € / liter for the gasoline, and from 1.3 to 1.7 € / liter for the diesel.

It can be observed from figure 78 that every segment of incentives has decreased in the high oil price situation. As expected, the highest incentive reduction was on fuels, as the main difference in the base and high oil price situation is the change in the fuel cost of AFVs. Therefore, we have focused on the changes of incentives on fuels (in this case electricity).

Results in figure 79, show that the amount of incentive needed for electricity has dropped significantly. On the other hand the duration of the fuel incentive has increased to almost four years. This can be justified by the following argument: As explained in chapter 4, social awareness (represented in this study by familiarity factor) plays a crucial role in the early adoption of AFVs. In the high oil price situation, the duration of incentives on fuels has increased significantly, when compared with the base scenario. This could result in an improvement in the utility of PHEV and increase the familiarity of individuals sooner than in the base scenario.

Chapter 6 - Conclusions

The research project described in this dissertation aimed at developing a multi-criteria decision framework for supporting the design of long term policies for personal passenger transportation vehicles, including alternative fuel-technology vehicles. One of the most challenging and innovative features was to include in the model an analysis of the transition phase in AFV adoption.

This final chapter summarizes the findings of this research, presented and discussed in detail throughout the dissertation. Section 6.1 highlights the main research achievements, and section 6.2 presents some suggestions of topics for future research.

6.1 Main achievements

This work started with a comprehensive review of the literature focusing on the assessment of Alternative Fuel-Technology Vehicles. We first did a review on the Life Cycle Analysis method, followed by two similar approaches: Total Life Cycle Cost (TLCC) analysis and Societal Life Cycle Cost approach. This review enabled us to identify the main factors that can potentially affect the comparison of different pathways (alternatives). These factors include the vehicle drivetrain type, feedstock of the fuels, vehicle lifecycle, GHG emissions and air pollution, region of the study, and security of fuel supply. These factors can generally be associated either to the policy makers or to the users. As the focus of this research is to develop a tool that can be used by a policy maker who is concerned with the interests of the final users, we have designed a list of attributes in a holistic manner, considering the interests of both policy makers and users. The list adopted is constituted by: user acceptance; emissions to atmosphere; transition cost; risk of technology development; and availability of fuel supply.

As one of the initial goals of this research was to develop a multi-criteria decision aid (MCDA) tool, a review on MCDA methods was done. Based on the results of this survey and taking into account the specific requirements of our research, a Multi-Attribute Utility Theory (MAUT) approach was selected, mainly because it could enable the decision maker to clearly express preferences over tradeoffs. This approach facilitates rational choices, in the sense that the course of action with the highest expected utility would also be the most preferred alternative consistent with the axioms of decision theory.

For the basic MCDA problem of choosing the best alternative, it is useful for a decision maker to start by eliminating those alternatives that do not seem to be interesting. This procedure is often called “screening”. After reviewing the available screening techniques, in this work a multi-stage screening process was applied: starting with a Pareto optimality approach, followed by a Data Envelopment Analysis (DEA) based screening and a Trade-off Weights (TW) screening procedure.

To illustrate the proficiency of the MCDA method, Portugal was chosen as a case study. The first screening set was identified and a preliminary conclusion was that Hybrid-Diesel is the prevailing technology among the most interesting alternatives, followed by Hybrid-Gasoline and biodiesel. However, a screening set is a list of alternatives that deserve to be presented to the decision maker. To make the final choice, we then need to collect more information about the decision maker’s attitude and interests.

Even if the MCDA analysis of chapter 3 alone would already provide some insight to the decision-making process, it was acknowledged that some of the model inputs – especially that of transition cost – could be significantly changed by a detailed consideration of the transition phase. A system dynamics model was thus developed (chapter 4) to analyze the co-evolution of refueling infrastructure and AFV sales.

The main difficulty in the development of the system dynamics model was its calibration. As one of the major purposes of this model is to learn from the adoption of new technologies (in this case diesel cars), we needed to investigate some hypotheses regarding the characteristics of the marketing factor. Through the case-study of Portugal, it was found that the fourth hypothesis (time-dependent and technology dependent marketing factor) leads to the higher resemblance of the model results to real data.

The model application to Portugal showed that the estimated transition costs after the system dynamics model were considerably different from those estimated initially. For example, the initial estimated transition costs for a screening alternative [25% Biodiesel, 25% HEVG, 25% HEVD, 25% BEV] was 6.1 billion euros initially, while after applying the system dynamics model, the updated estimated transition costs became 18.8 billion euros.

The fact that the consideration of the system dynamics model changes considerably the transition costs confirms the value – if not even the need – of having an iterative procedure between the processes described in chapter 3 (MCDA analysis) and in chapter 4 (System dynamics analysis).

This iterative framework was developed in chapter 5, ensuring that the developed multi-criteria comparison framework will be re-applied for comparing all the alternatives, in order to identify an updated screening set of alternatives. The new alternatives in the screening set are defined as the new targets for the system dynamics model, and the relevant transition cost will be calculated. This iterative analysis will continue until there is no new alternative in the screening set.

The applicability and value of the whole method was verified with the Portugal as a case study. It was found that there were necessary 6 iterations until the solutions converged. The initial screening set had 6 alternatives: ([100% HEVD], [50% HEVG, 50% HEVD], [33.3% Biod, 33.3% HEVG, 33.3% HEVD], [25% E85, 25% Biod, 25% HEVG, 25% HEVD], [25% Biod, 25% HEVG, 25% HEVD, 25% PHEV] and [25% Biod, 25% HEVG, 25% HEVD, 25% BEV]). After the first iteration, there were 5 alternatives: ([50% Biod, 50% HEVD], [33.3% ICGE, 33.3% HEVG, 33.3% HEVD], [33.3% HEVG, 33.3% HEVD, 33.3% PHEV], [25% ICE, 25% Biod, 25% HEVD, 25% PHEV], [25% ICGE, 25% HEVG, 25% HEVD, 25% PHEV]). At the end, there were only two alternatives in the final screening set: ([12% ICGE, 13% DI, 25% HEVG, 25% HEVD, 25% PHEV], [17% ICGE, 16% DI. 33.3% HEVG, 33.3% HEVD]).

An interesting and very important observation was that the estimated cost of alternatives changed considerably through the convergence process. For instance, the estimated cost of alternative ([25% Biodiesel, 25% HEVG, 25% HEVD, 25% BEV]) was 6.1 billion euros before the application of the SD models and became 18.8 billion euros after it. The cost of the lowest cost screening alternative ([25% ICGE, 25% Biod, 25% HEVD, 25% PHEV]) was 9.54 billion euros at the end of iteration 1, but had decreased to 2.4 billion euros at the end of the convergence process. This demonstrates that the model can be useful not only on achieving more accurate estimates but also in searching for more cost-efficient alternatives to meet the policy goals.

In what regards the policy scenarios, it was found that the intended shares of technologies could only be reached if the policy pack includes the Early Scrappage Policy (ESP) schemes. If no ESP is adopted, the models suggest that even with significant volumes of incentives to alternative vehicles and fuel stations, it will not be possible to achieve a significant penetration of AFVs by 2030.

Concerning the fittest technologies to the Portuguese context, it was found that the combination of gasoline, diesel, hybrid-gasoline, hybrid-diesel and PHEV in light-duty passenger vehicle fleet provide promising outcomes from a multi-criteria comparison perspective.

It may be surprising that pure-electric vehicles did not appear in the final screening alternatives. Considering the result in figure 19, the low value of electric based alternatives in terms of acceptance, transition costs, and availability of fuel supply seems to be the major obstacles for the adoption of these alternatives. However in the situation in which the share of renewable electricity increases from 55% to 70%, the share of PHEVs and BEVs in the screening set is clearly increased when compared to the first screening alternatives in the base scenario (Table XV).

Considering the potential uncertainty in several factors (model inputs), we have analyzed the sensitivity of the decision process to the most critical parameters, including the share of renewable electricity, the GHG externality cost, and oil price. We investigated a high GHG damage cost scenario (50 instead of 20 €/tonne-

CO_2 Eq) and a high oil price scenario (gasoline: 2.1 from 1.6 € / liter, diesel: 1.7 from 1.3 € / liter).

As expected, in the high GHG damage cost case, the alternatives in the screening set tend to shift s to less GHG emitting technologies. Table XVI shows the share of biofuels (Ethanol and biodiesel) in almost all screening alternatives has increased, e.g., in one alternative, the share of ethanol and biodiesel has increased from 25% to 50%in the LDV fleet. Reviewing the screening set of alternatives in table XVII, it seems that, within the range analyzed, the impact of higher oil price is insignificant. This can be justified by the fact that it will affect only the performance of alternatives on fuel price and related user's acceptance, which is only a small part of the whole Multi Criteria decision aid framework. The results clearly show that the most sensitive parameters are the share of renewables in electricity and the GHG externality cost.

6.2 Future Developments

Even if the goal of developing an MCDA framework that accounts for the transition phase has been successfully achieved, there are a number of issues requiring further developments and research. The main ones identified in this work are the following.

- Introduce the effects of more sociotechnical factors in the vehicle choice models. For example, waiting time for refueling/charging the car in the fuel stations can be a very important factor for many individuals. People with different attitudes towards environment can assign different weights on the importance of vehicle's emissions as a decision factor. Moreover, individuals put a different value for a different visual design of vehicles with the same technology. These are a few examples of attributes that have the potential to be added to the vehicle choice model and affect the outcome.
- Improve the data collection about preferences of individuals on vehicle choice factors using tools such as surveys. The focus of these surveys should be on identifying the interests of car owners specifically on the vehicle purchase price, and vehicle performance. Considering the dependency of the individuals' preferences on vehicle choice factors with time, it would be interesting to collect the data, periodically.
- Present the results to an actual decision maker (e.g., a member of the government), and obtain his/her specific thresholds for some of the attributes, in order to better adapt the findings to his/her preferences. For example, in order to reach an actual choice of an alternative, it would be necessary to ask about how much are they willing to support vehicles with lower emissions. Also, trying to find an answer to the importance of domestic fuel production when compared with the situation of importing fuels.
- Apply the methodology to other countries and situations, if possible with different energy contexts, in order to make a comparative analysis of the outcomes (this would enable finding more general conclusions and possibly confirming the importance of the energy context).

- Introduce the issue of flexibility over time. This is an area in which the technology is evolving very quickly and new data could change the preferred alternatives. It would therefore be important to introduce at some point the issue of “low regret” options even if with the loss of some efficiency. It could also be interesting to delay some decisions until some technology characteristics become defined - again assuming the possibility of some loss of efficiency.

This list of topics somehow reflects the fact that this research was performed in a relatively new area in terms of problem structuring and methodological approaches. Therefore, while having provided a valuable contribution, there is considerable space for complementary research in order to enable informed and technically sound policy-making in the area.

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Appendix 1: Projected initial price of alternative fuel-technology powertrains

Table LX: Projected Initial Price of alternative fuel-technology powertrains in 2030 (€)

Alternative fuel-technology Powertrains	Initial Price in €		
	Low	Likely	High
PISI-Gasoline	19600	20000	25100
PISI-Ethanol	20000	22000	22000
PISI-Methanol	20500	22000	22000
PISI-CNG	21200	22000	26000
PISI-LPG	20350	22000	28000
PISI-H2	21500	23500	24350
DISI-Gasoline	19600	20000	25100
DISI-Ethanol	20000	22000	22000
DICI-Diesel	21000	23500	24000
DICI-Biodiesel	24000	22000	24000
FCNR-H2	23600	27000	31200
FCWR-Gasoline	24500	35000	27500
FCWR-Methanol	24500	35000	27500
HEV-PISI-Gasoline	21100	24000	29800
HEV-DICI-Diesel	27000	24000	27800
PHEV	23000	25000	28000
BEV	28000	34000	43000

Appendix 2: Collected data on the projected emissions from alternative fuel-technology powertrains in 2030

Table LXI: Projected CO_2 Emission from WTW and Material in 2030 (g-CO_2/km)

Alternative Fuel Technology Vehicles	WTW			Material, Manufacturing and disposal
	Low	Likely	High	
PISI-Gasoline	128,0	160,0	165,2	31,0
PISI-Ethanol	37,0	75,4	80,9	19,6
PISI-Methanol	217,0	217,1	217,0	19,9
PISI-CNG	122,4	137,6	186,0	20,5
PISI-LPG	180,0	183,1	186,0	19,9
PISI-H2	148,2	147,8	148,2	22,2
DISI-Gasoline	92,0	160,0	198,0	30,0
DISI-Ethanol	39,0	60,0	80,9	30,0
DICI-Diesel	104,0	140,0	187,0	32,0
DICI-Biodiesel	52,7	75,0	98,6	32,0
FCNR-H2	100,0	100,0	100,0	48,0
FCWR-Gasoline	98,0	141,0	210,0	50,0
FCWR-Methanol	149,1	149,0	149,1	50,0
HEV-PISI-Gasoline	87,0	140,0	173,9	33,0
HEV-DICI-Diesel	119,0	122,0	124,0	33,0
PHEV	39,0	96,0	121,0	43,0
BEV	26,0	52,0	57,0	48,0

Table LXII: Projected Air Pollution resulting from WTW and Material in 2030 (g/km)

Alternative Fuel Technology Vehicles	Air Pollutions				
	Nox	VOC	SO2	CO	PM10
PISI-Gasoline	0,25	0,25	0,15	1,28	0,11
PISI-Ethanol	0,47	0,29	0,12	1,42	0,15
PISI-Methanol	0,83	0,32	0,12	3,30	0,07
PISI-CNG	0,21	0,05	0,11	0,90	0,07
PISI-LPG	0,21	0,14	0,08	1,11	0,08
PISI-H2	0,20	0,13	0,17	0,65	0,08
DISI-Gasoline	0,55	0,45	0,15	3,20	0,14
DISI-Ethanol	0,47	0,29	0,12	1,42	0,15
DICI-Diesel	0,46	0,12	0,13	0,46	0,10
DICI-Biodiesel	0,46	0,12	0,13	0,46	0,10
FCNR-H2	0,14	0,01	0,19	0,02	0,06
FCWR-Gasoline	0,17	0,14	0,08	0,16	0,04
FCWR-Methanol	0,30	0,11	0,10	0,13	0,04
HEV-PISI-Gasoline	0,18	0,18	0,11	0,89	0,09
HEV-DICI-Diesel	0,30	0,10	0,11	0,36	0,07
PHEV	0,01	0,01	0,00	0,11	0,15
BEV	0,09	0,00	0,30	0,01	0,07

Appendix 3: Initial estimation for transition cost of Alternative fuel technology vehicles

Table LXIII: Initial transition cost estimation obtained from literature review

Alternative Fuel Technology Vehicles	Qualitative estimation	Normalized utility
PISI-Gasoline	No cost	100%
PISI-Ethanol	Low cost	67%
PISI-Methanol	Low cost	67%
PISI-CNG	Low cost	67%
PISI-LPG	No cost	100%
PISI-H2	High cost	0%
DISI-Gasoline	No cost	100%
DISI-Ethanol	Low cost	67%
DICI-Diesel	No cost	100%
DICI-Biodiesel	Low cost	67%
FCNR-H2	High cost	0%
FCWR-Gasoline	No cost	100%
FCWR-Methanol	Low cost	67%
HEV-PISI-Gasoline	No cost	100%
HEV-DICI-Diesel	No cost	100%
PHEV	Low cost	67%
BEV	Medium cost	33%

Appendix 4: Combinations of Inputs-Outputs considered for the DEA based screening

	Inputs	Outputs
Combination 1	Risk, Transition Cost and Emissions	Acceptance and AOFC
Combination 2	Transition Cost and Emissions	Acceptance, AOFC and Risk
Combination 3	Risk and Emissions	Acceptance, AOFC, Transition Cost

Appendix 5: Boundaries for calibration of the parameters.

$$0 \leq \mathrm{M_i} \leq 0.2$$

$$-10 \leq \beta_n \leq 10$$

$$AVL \leq 20 \text{ (Years)}$$

$$0 \leq \alpha \leq 0.1$$

$$0 \leq \mathrm{IDM} \leq 0.2$$

$$0 \leq \mathrm{IHM} \leq 0.2$$