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A New Approach to Design Policies for the Adoption of Alternative Fuel-Technology Powertrains

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Abstract**—**Planning the transition period for the adoption of alternative fuel-technology powertrains is a challenging task that requires sophisticated analysis tools. In this study, a system dynamic approach was applied to analyze the bi-directional interaction between the development of the refueling station network and vehicle sales. Besides, the developed model was used to estimate the transition cost to reach a predefined target (share of alternative fuel vehicles) in different scenarios. Several scenarios have been analyzed to investigate the effectiveness and cost of incentives on the initial price of vehicles, and on the evolution of fuel and refueling stations. Obtained results show that a combined set of incentives will be more effective than just a single specific type of incentives.

Keywords**—**adoption of Alternative Fuel Vehicles,System Dynamic Analysis, Plug-in Hybrid Vehicles

I. Introduction

THE transitioning process of fuels for 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 and 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 fuel would need to be produced and distributed to a network of refueling 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. The greatest challenge of this transition process is to get all the critical elements spatially and temporally aligned [1]. 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.

In recent years, significant attention has been given to the adoption of alternative fuel technology vehicles.

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Unfortunately, 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 [2], goal of 10% by the year 2000 and also of 30% displacement by the year 2010 [3].

A strong tendency in such failed attempts has been to justify failure by individual causes, such as higher vehicle purchase cost or operating costs, poor vehicle performance, low refueling (or recharging) station coverage, or inadequate government incentives. However, such simplistic justifications fail to consider the entire system and do not fully consider the complexity of overcoming a highly entrenched technology such as the gasoline ICE (internal combustion engine). Additionally, solutions that encourage the adoption of alternative-fueled-vehicle often only consider the end states, such as target number of vehicles or the fuel production costs, at high volume or large-scale “optimized” solutions to fuel distribution, with little consideration given to the transitional dynamics that would lead to realizing these end states. Recognizing the importance of transitional issues, and in order to obtain a better understanding of the challenges for displacing petroleum-derived fuels, a systems approach is required.

II. Background

To maximize the likelihood of a successful transition for an alternative fuel technology vehicle, it is vital to have a better 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 more often referred in the literature are [1]:

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

Some of the methodologies that address the important elements of a dynamic transition of alternative fuel vehicles will be briefly reviewed and discussed next.

HyTRANS (short for Hydrogen Transition) is a model being developed by Oak Ridge National Laboratory (ORNL) that addresses various elements of the hydrogen transition [4].

It evolved from the TAFV (Transitional Alternative Fuels and Vehicles) model [5]. 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 use of alternative fuels and vehicles, considering possible barriers related to infrastructural needs and production scale. It accounts for dynamic linkages between investments and vehicle and fuel production capacity, tracks vehicle stock evolution, and represents the effects of increasing scale and expanding retail fuel availability on the effective costs to consumers. The choices and prices for fuels and vehicles are endogenous. As a dynamic transitional model, it can help to assess what may be necessary to achieve mature, large scale, alternative fuel and vehicle markets, and how much this transition may cost. Various policy cases were considered including fleet vehicle purchase mandates, fuel subsidies, and tax incentives for low greenhouse gas emitting fuels [6]. The use of these models showed that transitional impediments are very important to the transportation sector and may overwhelm scenarios based on theoretically attainable production costs and market penetrations. Limited retail fuel availability and vehicle production scale-economies are critical factors. The Complex Adaptive System (CAS) model analyzes the evolution of a hydrogen infrastructure in its initial stages of implementation, and was developed by RCF Consulting in collaboration with the Argonne National Laboratory (ANL) and various industry and academic partners [7]. This model uses agent-based modeling techniques to improve understanding of how the transition to a hydrogen infrastructure might occur. This dynamic model addresses transitional issues, and intends to link the hydrogen infrastructure with vehicle demand [8]. 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 [9]. Heterogeneous agents 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 illustrated 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.

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 [10]. This tool has been developed to explore the co-evolutionary dynamics between infrastructure supply and vehicle demand. In his paper, he explores in-depth the dynamics resulting from local demand-supply interactions with strategically locating fuel-station entrants. The dynamics of vehicle and fuel infrastructures was examined under heterogeneous socio-economic/demographic conditions. The research reveals the formation of urban adoption clusters as an important mechanism for early market formation. However, while locally speeding diffusion, these micro-mechanisms can hinder the emergence of a large, self-sustaining market. Other feedbacks that significantly influence the system dynamics, such as an endogenous topping-off behavior, are discussed. 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 [11], tried to analyze the Swedish market using the system dynamics approach. They suggest that the government should set policies that are directly related to objectives, rather than directly selecting the technology. The support for biofuels through different subsidies and regulative measures has also been scrutinized and is not favored by many environmentalists.

III. System Dynamics Model

In this study, the methodology developed by Struben[10], was adopted with some modifications. These modifications 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.

Considering the dynamic characteristics of the evolution of light duty vehicle fleet, 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.

A. Main positive feedbacks

Fig.1 illustrates the two key reinforcing (positive) feedbacks of the model.

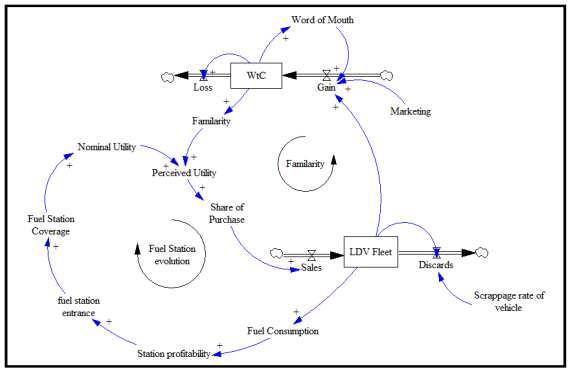

Fig. 1 Main positive feedbacks

Reinforcing feedback 1: "Fuel Station Evolution"

The first reinforcing feedback is the heart of the dynamic interdependence between refueling 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 Fueling Stations will improve the coverage of the fuel stations. 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 fueling stations. The balance will be reached through the parameter Station Profitability: the lower the Station Profitability, the lower is the likelihood that other station owners will enter the market, this resulting in a no additional Fueling Stations.

Reinforcing feedback 2: "Familiarity"

The second key reinforcing feedback illustrated in Fig.1 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.

B. 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 saturated 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.

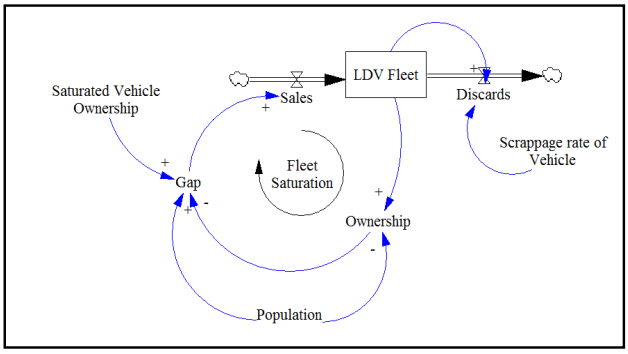

Fig. 2 Balancing feedback "Fleet Saturation"

This concept will potentially affect the annual sales of vehicles, in a way that there would be lower sales when there is a lower gap between the real vehicle ownership and the saturated level of vehicle ownership. This "Gap" can be estimated as follows:

Gap=Population×(Saturated Vehicle Ownership-Ownership) (1)

Balancing feedback 2: "Station Saturation"

Another balancing feedback arises from the fact that the profitability of investment on fuel/charging stations will decrease as the number of stations in the market increases (fig.3).

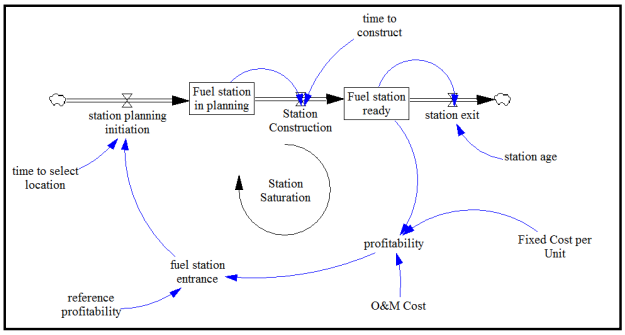

Fig. 3 Balancing feedback "Station Saturation"

While an increase in the number of Fueling Stations helps to increase the utility of the alternative fuel vehicle, it also has a counter-balancing effect that is seen through the Saturation of Stations in this loop. The saturation of fuel stations will happen when there are too many stations which will indeed lower the profitability of investments on fuel/charging stations. This will lead to a reduction of the number of Fueling Stations, thus resulting in a balancing feedback.

After identifying the key feedback loops that drive the whole system, it is now important to present the key model

inputs. Although a detailed listing and formulation of the variables included in the system dynamics model is beyond the scope of this article, some of the more significant model inputs are listed in fig.4.

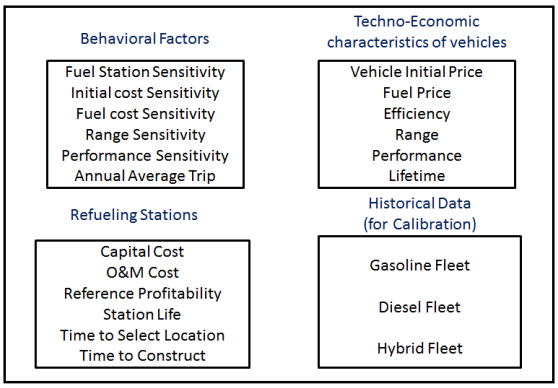

Fig. 4 Major model inputs

Being consistent with the cross-disciplinary nature of System Dynamics, this model includes economic, technological, and behavioral inputs for both the supply side (i.e., refueling stations) and the demand side (i.e., vehicle and fuel purchases).

As the purpose of this study is to analyze a set of alternative fuel-technology options, it is crucial to collect data for current and projected values for the following technologies:

- Hybrid Vehicle (HEV);
- Ethanol based engine (E85);
- Plug-in Hybrid Vehicle (PHEV).

As this research investigates 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. This will also reduce the error of assuming a similar station coverage in the whole are of the case study (thus avoiding the "flaw of averages"). For our case study, we decided to include 5 main sub-regions. We have also assumed that the fuel station coverage in each region will impact the annual sale of AFV in that region alone and not in the others.

Regarding the users' preferences on different technologies, a "logit" model has been adopted in order to estimate the nominal utility of each powertrain as follows:

$$U_{i,r} = \sum_n \beta_n \times u_{i,r,n} \quad (2)$$

where β_n is the coefficient representing the sensitivity of the customer for n choice factors. $u_{i,r,n}$ is the characteristic of each alternative fuel-technology option i, in region r, and for variant choice factor n. $U_{i,r}$ represents the nominal utility of each technology. Considering that one of the decision factors is the availability of fuel stations in each region, the nominal utility will depend on the region r as well as on the characteristics of each technology i.

It was assumed that the customers will make their choice according to the perceived utility of associated technology, this being modeled as follows:

$$Share\ of\ Purchases_{i,r} = \frac{F_i \times U_{i,r}}{\sum_i \sum_r F_i \times U_{i,r}} \quad (3)$$

Where F_i is the familiarity of the customer with each technology i.r is an index for the region and i represents different powertrain options.

The following step was to use historical data to calibrate the model and identify the values for the choice model coefficients.

C. Calibration

Calibration of a model can be partially done by comparing the model behavior with time series data collected in the "real world". When a model is structurally complete and simulates properly, calibration of the model can be done. In our case, calibration involves finding the values of the model parameters that make the model generate behavior curves that best fit the real data.

In order to calibrate the model, real data is essential. For this purpose we have chosen Portugal as the case study, and the historical data for the evolution of gasoline, diesel and hybrid vehicles for the Portuguese fleet has been used [12]. Data regarding the fuel price was obtained from statistics provided by DGEG organization [13].

In Vensim [14], an optimization module is available that can be used to calibrate and estimate the parameters. In order to use it, one needs to define the "payoff" concept. The payoff is the measure, reported at the end of the simulation, numerically stating how good the simulation was. In the calibration phase, the payoff is the accumulated difference between model estimate and real data.

Using the optimization module in the Vensim model, we tried to calibrate the model with the real data and to identify the values for the coefficient of the choice model.

TABLE I
CALIBRATED FACTORS BASED ON HISTORICAL DATA FOR PORTUGAL

Variable	Calibrated Value
Initial Cost coefficient	-4.41
Fuel Cost coefficient	-1.05
Range coefficient	1.24
Performance coefficient	0.44
Refuel station coefficient	0.40

Considering the calibrated values for the sensitivity of customers to the choice factors, it seems that the Initial Cost, the Fuel Cost as well as the Range are the main drivers. Interestingly, it is obviously notable that the Performance and the Density of Fuel Stations are not very important factors - although this observation might be somehow misleading, considering that the calibration was made essentially using the period of introduction of diesel and hybrids, and these technologies do not need new refueling stations, and that is the case of PHEVs or Hydrogen fuel cells.

In figures 5 to 7, the result of the calibration and the differences between the real data and the simulated data using

the system dynamics model are shown. It is clear that the simulated data from model shows a considerable resemblance to real data.

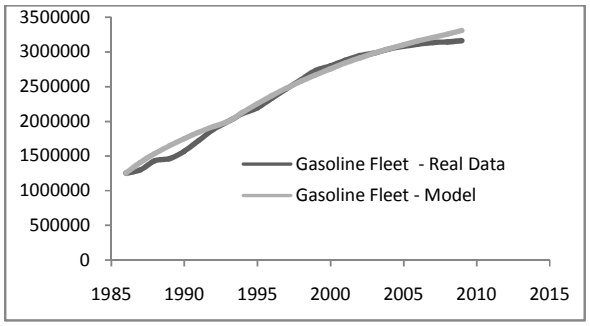

Fig. 5 Gasoline fleet evolution- model vs real data

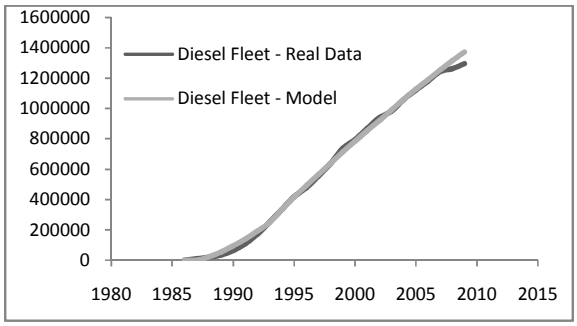

Fig. 6 Diesel fleet evolution- model vs real data

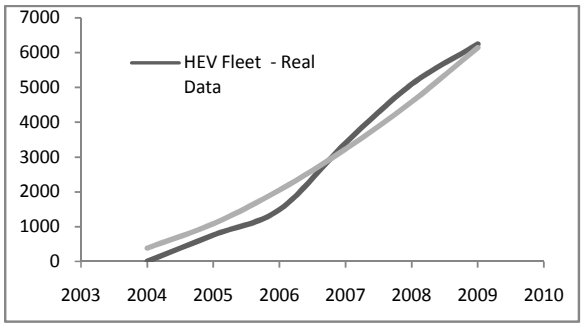

Fig. 7 Hybrid fleet evolution- model vs real data

D.Scenario Analysis

After calibrating the model, we can project the evolution until 2030 following the scenario inputs. The main scenario inputs are presented in tables II to IV. All costs and prices are estimated at present value ([15]-[20]).

TABLE II
INITIAL VEHICLE PRICES

Vehicle's initial Price	current	2030
Hybrid Vehicle (€)	28000	24000
Ethanol Vehicle (€)	25000	22000
Plug-in Hybrid Vehicle (€)	31500	26000

TABLE III
FUEL PRICES

Fuel Price	current	2030
Gasoline (€/liter)	1.46	1.6
Diesel (€/liter)	1.26	1.3
Ethanol (€/liter)	1.2	1.2
Electricity (€/KWh)	0.178	0.178

TABLE IV
REFUELING STATIONS - CAPITAL COST AND NON-FUEL O&M COST

	Fixed Capital Cost (€)	Non-fuel O&M Cost (€)
Ethanol Station	50000	5000
Battere Charging Station	6000	500

Using the assumptions regarding the initial price of vehicles, the fuel price and the fuel station capital costs as an input to the system dynamics model, it is possible to investigate the scenario in which there is no incentive plans or external interference. This scenario will be called "base scenario". In fig.8, the light duty vehicle fleet composition in the base scenario is shown. In 2000, almost 20% of the fleet used diesel, and currently this percentage is over 30%. In the base scenario, 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.

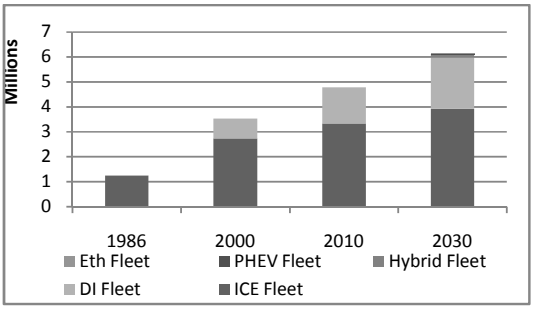

Fig. 8 Evolution of the Light-Duty Vehicle feet in base scenario: historical until 2010 and model projections for 2030

After analyzing the base scenario with no incentive plan, the next step is to analyze the transition cost for the adoption of alternative fuel vehicles. The goal is to try to identify a package of incentives that allows reaching a predefined target, or getting as close as possible to it. For that purpose it is essential to clarify the definition of transition cost.

E. Transition costs

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, the fuel cost or the refueling stations. Therefore we have:

Transition Cost =

$$\sum_{t}(Incentives\ on\ Vehicle's\ \ initial\ Price)_t + \sum_{f}(Incentives\ for\ Fuel\ Price)_f$$

$$+\sum_{f}(Incentives\ on\ Refueling\ Stations)_{f} \quad (3)$$

where t and f are the technologies and alternative fuels, respectively.

IV. Case Study

As it was mentioned before, in this study we decided to investigate the transition cost for a predefined target. This target is defined in terms of the shares of each specific alternative fuel vehicle in the total fleet intended for 2030.

TABLE V
TARGET FOR SHARE OF TECHNOLOGY IN THE TOTAL FLEET AT 2030, CONSIDERED FOR DETERMINING THE NECESSARY INCENTIVES

Fuel/technology Drivetrain	Share in LDV Fleet at 2030
Hybrid Vehicle (HEV)	20%
Ethanol based engine (E85)	10%
Plug-in Hybrid Vehicle (PHEV)	10%

An optimization module has been added to the model, so that the lowest transition cost can be estimated. The objective function to be minimized, is defined as follows:

Objective Function =
Total Transition Cost + M × Gap to Target (4)

Here M is the trade-off factor that can be changed according to the decision maker's preferences. In fact, a higher M (bigger than a billion) will result in an optimal point with a lower gap towards the target, but a higher transition cost. On the other hand, if M has lower value (lower than a thousand), the state of the optimal point will be more difference with the target but with low transition cost.

The constraints of the optimization function are the following:

a) Incentive factor for Initial Price of Vehicle ≤ 95%
b) Incentive factor for fuel ≤ 95%
c) Incentive for Refueling ≤ Maximum Incentive$_f$
d) Duration of Incentive for Initial Price of Vehicle ≤ 15 (years)
e) Duration of Incentive for fuels ≤ 15 (years)
f) Duration of Incentive for Refueling Stations ≤ 15 (years)
g) Marketing ≤ Max AnnualMarketing$_f$Marketing$_f$ = 0.1

The first three expressions (a, b and c) represent the maximum limit of incentives for the initial price of vehicle, the fuel and the refueling stations respectively. The first two values are the share of initial price or fuel price of each alternative fuel vehicle that can be received by the customer as incentive. In practical terms, a value of 0.25 in the first condition means that 1/4 of the initial 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.

In fact, f indicates different fuel options. 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 refueling stations respectively. The last condition (g) defines the maximum level of annual marketing effort that will cause the familiarity of the society with the new technology to grow (fig.1).

We have decided to analyze the several scenarios of incentives, organized in the following way:

Scenario A: Incentives on the initial price of vehicles (constraints a, d and g)

Scenario B: Incentives on fuels (constraints b, e and g)

Scenario C: Incentives on refueling stations (constraints c, f and g)

Scenario D: Incentives on fuel and refueling stations (constraints b, c, e, f and g)

Scenario E: Incentives on the initial price of vehicles, fuel and refueling stations (all the constraints)

The results of the optimization for each scenario are shown in fig.9, providing a snapshot of the possible fleet compositions, by the year 2030 in Portugal.

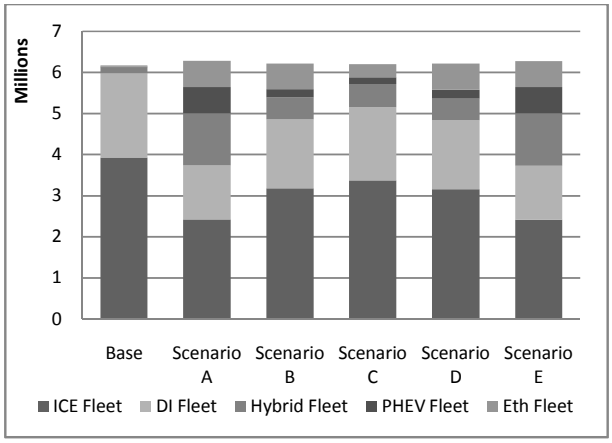

Fig. 9 LDV fleet composition at 2030 for each scenario

Fig.9 shows that scenarios A and E were able to reach the targets for the share of AFVs in the market (defined in table V), while there is a significant gap with the share of hybrid vehicles in the other scenarios (B, C and D). The main message of these results is that a high penetration of hybrid vehicles requires significant incentives for the initial price of the vehicles. Total transition costs related for scenarios are presented in table VI.

TABLE VI
TOTAL TRANSITION COSTS FOR THE DIFFERENT SCENARIOS (IN €)

in €	A	B	C	D	E
Vehicle Incentive	4.94 Billion				5.17 Billion
Fuel Incentive		690 Million		695 Million	2.94 Million
Station Incentives			40.8 Million	3.6 Million	2.85 Million

The first insight from table VI, is that there are huge, significant differences in the amount of optimized incentives identified for each scenario. The main reason is that, considering the number of vehicles and the amount of incentives on the vehicles, the maximum for total vehicle incentive is much higher than incentives for fuel or stations. Therefore, focusing just on the comparison of incentive values might be misleading and some other impacts such as the effectiveness of these incentive plans need to be evaluated. One method is to plot the trade-offs comparing the gap with the target and the amount of incentives for each scenario (Fig.10).

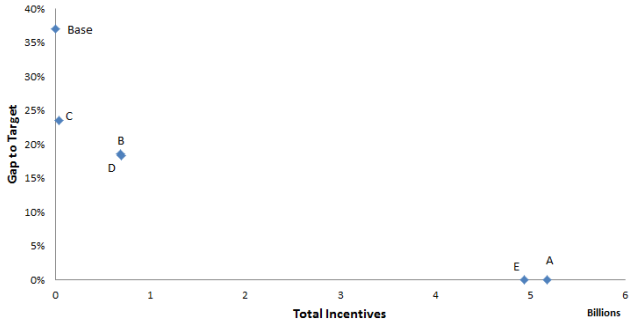

Fig. 10 Trade-offs for scenarios

From fig.10, it is obvious that Scenario A with 4.94 billion euros is the most expensive one, while Scenario C, with 40.8 million euros, seems to be relatively inexpensive.

An important observation is that starting from base point, it is possible to lower the gap by 50% with only 690 Million euros (scenario B), but in order to reach the target, for example in scenario A or E, the required incentive will be extremely higher (around 5.2 Billion Euros).

Besides, it is also obvious that the combined incentive plan (Scenario E) was able to reach the target at the lower cost (4.8% lower than scenario A).

V. Conclusion

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 refueling stations and vehicle sales. This model was calibrated for Portugal with historical sales of light duty vehicles between 1985 and 2009. The calibrated model was then used to estimate the transition costs to reach a predefined target of AFV penetration at different scenarios of incentives. Several scenarios have been analyzed to identify the effectiveness of incentives on the initial price of vehicles, on the fuel price or on the refueling stations. The results show that reaching the target is almost 7 times more expensive than reaching half of it. In any case, a combined set of incentives will be the most efficient policy measure rather than using just one type of incentive.

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