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Long term diffusion dynamics of alternative fuel vehicles in Brazil

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ABSTRACT

Alternative fuel vehicles (AFV) are a promising alternative to reduce greenhouse gas emissions in the transportation sector and ultimately, to contribute to a more sustainable society. Within the current commitments of the Brazilian Government to international agreements, in terms of emissions reductions by 2030, some new policies have been implemented, in order to incentivize the diffusion of AFV in the country. Yet, how will these policies contribute to the goal of increasing its fleet in the long-term, how long will it take and what are the differences (if any) among the policies, in terms of their effectiveness, are questions that remain unanswered. In this sense, the main aim of this paper is to investigate the impact of public policies in the long-term diffusion dynamics of AFV in Brazil. In order to do so, a system dynamics model is developed, based on the Generalized Bass Diffusion model, the Cobb-Douglas function and the learning curve theory. The model is used to test four different policies and some uncertainties related to: (i) the exemption of the import duty; (ii) the reduction of the motor vehicle property tax; (iii) the exemption of the tax on manufacturing goods; and (iv) a banning regulation for internal combustion engine vehicles in the long-term. The results highlight the importance of the current incentive policies but at the same time call for reinforcing efforts in order to increase the AFV fleet to significant values by 2030. Conversely, the banning regulation obtains a higher diffusion rate, but only achieves significant values by 2060. The paper concludes by showing the main contributions and policy implications of the effectiveness of the four policies studied as well as some suggestions for future work.

1. Introduction

The rise of environmental awareness has been growing in the last decades as a result of the increasing number of reports and studies pointing out to the anthropogenic nature of climate change. As a result, previous studies have shown that global greenhouse gas emissions are the main cause of climate change, which in turn, backfire, affecting the human beings' quality of life (Meadows and Meadows, 2007). Thus, many of the most important agreements worldwide have as main goal to reduce greenhouse gas emissions, such as the Sustainable Development Goals (SDG), in order to move towards a more sustainable developed world. Within the SDG, technologies have taken an important role in addressing greenhouse gas emissions and climate change. More specifically, renewable energy technologies have been suggested as the most promising ones.

In terms of the current set of renewable energy technologies, they are mainly deployed in the power sector (wind, solar PV and others) and the transportation sector (alternative fuel vehicles or AFV, such as plug-in electric vehicles and hybrid electric vehicles). In developing countries, renewables may offer off-grid electricity access to rural communities, lower costs of energy for industry and cleaner means of transportation, reducing greenhouse gas emissions.

Despite the current policy mechanisms aiming at increasing the diffusion of renewables, such diffusion and deployment has been rather slow, especially in developing countries, due to market failures, system failures and also, the fact that renewable energy technologies are embedded in complex socio-technical systems (Negro et al., 2012), which are difficult to steer through policy.

Abbreviations: AFV, Alternative Fuel Vehicle; BM, Bass Diffusion Model; ANFAVEA, Brazilian National Association of Motor Vehicle Manufacturers; IBGE, Brazilian Institute of Geography and Statistics; CC, Conventional Cars; EVs, Electric Vehicles; EMA, Exploratory Modeling Analysis; FTA, Future-oriented Technology Analysis; GBM, Generalized Bass Diffusion Model; HFCV, Hydrogen Fuel Cell Vehicle; ID, Import Duty; MVPT, Motor Vehicle Property Tax; SDG, Sustainable Development Goals; SD, System Dynamics; TMG, Tax on Manufacturing Goods.

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At the Conference of the Parties to the United Nations Convention (COP21), Brazil's government committed to reduce greenhouse gas emissions by 43% by 2030 (reference year: 2005). In addition, about 37% of CO_2 emissions were produced by the energy sector, whereby the transportation subsector represents 42.1% (Ministry of Science and Technology, 2014). This means, AFV will be key to minimize the environmental impact related to the transportation sector in the country. However, the current AFV fleet is insignificant, representing 0.0078% of the total fleet in 2015 (Anfavea, 2017).

In Brazil, Bravo et al. (2014) investigated the advantages of a more sustainable fleet, showing that policy incentives and more reasonable taxes are essential for AFV diffusion (Vaz et al., 2015). analyze policies from different countries and conducted a preliminary evaluation of its enforcement in Brazil. As far as policies are concerned, there are two fiscal incentives recently implemented, aiming at addressing (i) the import duty (ID) and (ii) the motor vehicle property tax (MVPT). In addition, a third fiscal incentive related to the tax on manufacturing goods (TMG) awaits approval. However, little is known about how will these policies impact the diffusion of AFV in the long-term.

Moreover, some developed countries have, recently, proposed regulations banning the sales of internal combustion engine vehicles (conventional cars or CC) in the next decades as well as their full withdrawal (such as a regulation proposed by Germany's Bundesrat). Thus, how will these policies contribute to increasing the fleet of AFV in Brazil – in the long term- and moreover, what would happen if banning regulations are also implemented in the country? In this sense, the main aim of this paper is to investigate the impact of public policies in the long-term diffusion dynamics of AFV in Brazil.

In order to do so, we develop a diffusion model under the system dynamics tradition. System Dynamics (SD) has been broadly used in long-term diffusion studies due to the fact that they can incorporate the complexity and uncertainties of such analyses, by describing non-linear and non-stationary processes, reinforcing and balancing feedback, and long time delays (Baran and Legey, 2013).

The model is based on the Bass Diffusion theory, which highlights the social nature of technology diffusion processes, specially of radical technologies, such as AFV; and the legitimacy building mechanism due to advertising and promoting policies aimed at increasing the social exposure of the radical technology (Bass, 1969). In our study, we use a special type of the Bass Diffusion model, which accounts for the inclusion of other decision variables such as the AFV price, known as the Generalized Bass Diffusion Model (Bass et al., 1994). Moreover, we assume the AFV price decreases due to the effect of a learning curve (Argote and Epple, 1990). Also, we consider a growing potential market, in accordance with the Cobb-Douglas function (Bass, 1969), as price decreases over time.

The model is calibrated using parameters estimated for the Brazilian market in the period 1980–2010. We then, use the model to test the effectiveness of four policies on the diffusion of AFV, related with: (i) ID; (ii) MVPT; (iii) TMG; and the (iv) ban of CC sales from 2030 and its circulation by 2050. Next, we briefly describe the state of art on AFV diffusion literature, the current state of emissions reduction policies in Brazil and the research outline of this study.

1.1. Analysis of the state of the art on AFV diffusion literature

Previous literature has pointed out a number of barriers to the widespread market penetration and diffusion of AFV. Wiedmann et al. (2011) examined risk-related adoption barriers and their impact upon innovation resistance to sustainable solutions in the automotive sector. Their risk evaluation are classified as financial, performance (technological and infrastructural), physical (security), time consuming (learning how to use and refueling availability), social and psychological risk. Browne et al. (2012) presented a framework to identify and qualitatively evaluate AFV barriers. The authors used a classification of seven categories: financial, technical, institutional, public acceptability, regulatory, policy failures and physical barriers.

These important factors influencing the AFV diffusion process has been a matter of specific studies. Park et al. (2011) examined the influences of the price level and number of fueling station on the market saturation of hydrogen fuel cell vehicle (HFCV). Lee et al. (2013) considered the feedback effect of three technical attributes (fuel efficiency, vehicle price and infrastructure) on different green cars (hybrid and electric vehicles and HFCV) market share. Neumann et al. (2014) analyzed the market share and timing of electric vehicles (EVs) diffusion based on individual consumers' preferences (recharging technique). Kieckhäfer et al. (2017) examined the car manufacturers own internal policies, indicating this as having an essential role in overcoming AFV barriers, as they could take actions to expand the market on their own with expedient portfolio decisions.

With respect to policies and instrument to encourage the adoption of AFV, Ardila and Franco (2013) summarized four categories: fiscal (e.g. taxes, subsidies), physics (e.g. infrastructure), soft (e.g. advertising, marketing) and knowledge (e.g. research and development in clean technologies). Some studies have focused on quantifying the effectiveness of different policies. Studies indicate that in countries such as Colombia (Ardila and Franco, 2013), Turkey (Kieckhäfer et al., 2017) and England (Shepherd et al., 2012), policies that invest in communication and marketing strategies for the diffusion of electric cars result in more significant impacts than subsidy policies.

The uncertainty of the future economic market is another factor that needs consideration. Ardila and Franco (2013) show how changes in the market (from external factors) can significantly alter the spread of electric cars in Germany. A 25% increase in conventional fuel prices may result in an increase of electric car numbers by up to two times by 2020. Ultimately, they discuss on how policy measures should be flexible and adaptable to the economic scenario changes and external factors. Shepherd (2014) provided a full topic about modeling the uptake of AFV on his review of SD models applied in transportation. The author states that typically the quantitative papers include a diffusion process, a fleet aging chain and a choice model for purchasing decision. In terms of impact of policies, the review shows that most studies find that the diffusion is not affected greatly by subsidies but more by regulation and infrastructure.

Wolf et al. (2015) present an empirically grounded agent-based modeling approach to simulate the effects of policy interventions (tax exemption, purchase subsidy and the introduction of an exclusive zone for EVs) and social influence on German consumers' transport mode preferences. Zhang et al. (2016) explored different types of policies to explain the quick rise of EVs across 88 cities in China. The authors highlight the higher importance of consumer-oriented policy (e.g. lowering parking rates, operation subsidy, low electricity charging expense, subsidy to firms building charging stations) over producer-oriented (e.g. R&D support, government procurement, purchase subsidies), to effectively promote EVs. Kangur et al. (2017) developed an agent-based social simulation model to explore how policies interact with Netherlands consumer behavior over a long time period. The authors used a cross-section survey data to calibrate their model, and their results indicate that effective policy requires a long-lasting implementation combining monetary, structural and informational measures.

In Brazil, a few studies dealing with the diffusion of electric and hybrid cars has been conducted previously. Baran and Legey (2013) measured the impact of EVs on Brazilian market energy consumption, demonstrating how electricity could act as a complement for ethanol and gasoline. Bravo et al. (2014) evaluated the advantages of a more sustainable fleet and possible causes of the AFV scarcity in Brazil. The authors point out that policy incentives and more reasonable taxes are essential factors for its diffusion. Vaz et al. (2015) analyze policies from different countries and conducted a preliminary evaluation of its enforcement in Brazil. Baran and Legey (2013) showed that 81% of a survey respondent believe price to be the main factor hindering the diffusion of electric cars in Brazil and 89% of them are convinced that they will occur, but very slowly. However, none of them has developed quantitative forecast analysis of the impact of policy and regulations.

As shown previously, there is, still, much to be investigated about AFV in Brazil. Among them, quantitative forecasts of the long-term impact of policy have not been conducted so far and our paper aims to fill this gap.

1.2. Current state of ‘emissions reduction’ policies in the Brazilian Transportation Sector

Government policies play a great role in collaborating to promote an up take of a product and possible cost reduction to make them more accessible to society. In Brazil, the price of these electric and hybrid cars is still in the category of premium cars, far from the purchasing power for the majority of people. In Browne et al. (2012), vehicle price was identified as relevant and a quite significant barrier for AFV. Vaz et al. (2015) showed that 70% of the survey respondents believe that the insufficiency of subsidies and tax incentives adversely affect the diffusion of electric cars in the country.

Vaz et al. (2015) brings an analysis of different policies practice in many countries and ends with several suggestions of policies practice elsewhere that Brazilian government could also consider applying in the country. Amongst all policies suggested by the author (e.g. target efficiency, financing, incentive to R&D, monetary incentives, distributed generation), from the authors viewpoint, monetary incentive is the policy that provides the greatest impact on tax collection and have median complexity on implementation.

At the same time, according to Mazzucato (2013), the conventional economic theory justifies State intervention when the social return of the investment is higher than financial private return, as if to correct market failures. Most of the radical and revolutionary innovations that have fueled the dynamics of capitalism, points to the State, the origin of the bravest “entrepreneurs” investments.

To accelerate adoption, some countries’ government provides credit subsidies for electric, hybrid and other alternate fuel vehicles according to some criteria, e.g. emissions and battery efficiency. For example, in France, up to US$ 7,718[1], in UK, 25% of car price (with a maximum value of US$ 8,000, approximately), in USA, up to US$ 7500 and in Japan, up to US$ 8,000, approximately (Martins, 2015; Vaz et al., 2015).

Another policy example, but more strict, is likely to take place in Germany. The country is well known to promote the use of renewable energy and has a bold target of cutting greenhouse gas emissions by up to 95% in 2050. Recently, Germany’s Bundesrat (the legislative body that represents the federal states at the national level) announced a regulation to ban the sales of internal combustion engines by 2030 in the country, which can also affect all of the European Union. According to the regulation, only zero-emission vehicles would be allowed on the market after that time, and only its fleet circulation from 2050. This regulation has yet to be approved by Germany’s Bundestag if it is to turn into a law. At the moment it is still under discussion (Bundesrat, 2016).

In Brazil, there is no such policy offering direct credit subsidies or regulation to ban internal combustion engines vehicles. However, there are two fiscal incentives the government has recently implemented related to (i) ID and (ii) MVPT. In addition, there is a third fiscal incentive related to (iii) TMG, the Senate Project-law nº 174/2014 (Brazil, 2014) that is currently awaiting for the Economic Affairs Committee approval. Each policy is described as follows:

1.2.1. Policy 1 — Import Duty (ID)

The import tax has a fundamental role on electric and hybrid cars in Brazil, since all of the vehicles in the current market are imported. Currently, the standard fee is 35% over the car price, but since October 2015, this tax has been reduced to zero for EVs and fuel cell cars. This regulation also includes hybrids cars with engine displacement smaller than 3000 cm^3, but for these the tax varies from 0% to 7% according to efficiency. The purpose of this decision is to promote new propulsion technologies and attract investments for national manufacturing (Brazil, 2015). However, it is worth mentioning that it is not clear how long this regulation will take place, remaining an uncertain aspect. This policy will certainly economically benefit car dealers, considering the lower taxes involved. It will, however, affect the government taxes income, but we could assume that this conduct will help lower vehicle prices for consumers.

1.2.2. Policy 2 — Motor vehicle property tax (MVPT)

The MVPT is the automotive ownership annual tax. Its value can change depending on the region where the owner lives. As a reference, in São Paulo State, the most populous state in Brazil with 44.7 million people in 2016 (Ibge, 2016), this tax is 3% to vehicle powered exclusively by alcohol, natural gas or electricity and combinations between themselves. The tax to others passenger cars is 4% over the vehicle market price (Secretaria da Fazenda - Sao Paulo, 2017).

According to Abve (2016) — the Brazilian Association of Electric Vehicles — there are seven states giving tax discounts or exemption. The states that give tax exemption are Ceará, Maranhão, Pernambuco, Piauí, Rio Grande do Norte, Rio Grande do Sul and Sergipe, while Mato Grosso do Sul, Rio de Janeiro and São Paulo give 50% discounts in this tax, in which the benefit is limited to vehicles costing equal or less than R$ 150,000.00.

There are similar consequences of this policy compared with the previous one. Fewer government taxes income and a potential positive effect for the consumer due to this cost incentive. It does not affect car dealers directly, but it just might indirectly, if they are able to attract more consumers to their product.

1.2.3. Policy 3 — Tax on manufacturing goods (TMG)

The tax on manufacturing goods in Brazil is classified according to its engine displacement. Vaz et al. (2015) suggests this aliquot should be classified according to efficiency or emissions. Another suggestion would be creating a new category for electric and hybrid vehicles. Today, they are in the “others” category with the highest tax of 25%, while combustion engine cars pay from 7% to 25%.

Currently, the Senate Project-law nº 174/2014 (Brazil, 2014) awaits for an approval from the Economic Affairs Committee and if approved, will result in the exemption of the TMG from this category of vehicles for a period of 10 years. It also includes tax exemption from parts imported to assembly in Brazil, including its import duties, in case there is no national production. This policy would most likely encourage national production of electric and hybrid cars, which has not been present at the moment.

[1] Exchange rate used: US$ 1.00 = 0.90697 Euro.

In Brazil, the electric and hybrid vehicle market is still very limited. There is only one option of electric, the BMW i3 (costing[2] about US$ 67,249 and US$ 70,596). The hybrid options are Toyota Prius (US$ 35,378), Lexus CT200h (US$ 150,845), Ford Fusion Hybrid (US$ 44,566), Mitsubishi Outlander PHEV (US$ 62,658) and BMW i8 (US$ 25,591). The price data was taken from Fipe (2016) – Foundation Institute of Economic Research of Sao Paulo University – which is an estimate based on market sales and it is the official reference used in Brazil. All these models are imported, hence the relevance of government incentive policies.

1.3. Research outline

The remainder of the paper is organized as follows: In Section 2 we introduce the theoretical and methodological framework, including the Bass Diffusion theory, learning curves, SD and the research design. In Section 3 we present the model and explain how it has been developed, as well as the validation and sensitivity analysis procedures. In Section 4 we present the results, divided in three sub-sections: set of policies to be tested, policy testing and scenarios, and a long-run view of the AFV market in 2060. The paper ends with the conclusions and main implications of this research in Section 5.

2. Theoretical and methodological framework

2.1. Bass Diffusion model

The BM postulates the diffusion curve of a product or technology and is based on a pre-determined potential market. The basic premise of the BM is that the adoption probability of a product (or technology) would depend on two forces or mechanisms, which are assumed to be independent from each other. The first one comes from external influences such as advertising, it is dependent of the potential market (a fraction of it) and independently of the number of adopters and it is known as the 'adoption by innovation' mechanism.

As the number of adopters rises, the potential market diminishes (all other things being equal) and consequently, the 'adoption by innovation' mechanism loses strength (as it is directly proportional to the potential market). The second force or mechanism is dependent on the number of previous adopters and, therefore, its contribution rises with the increase of adopters, forming a positive feedback, also known as 'adoption by imitation' mechanism (Bass, 1969).

Each mechanism, previously described, depends on one specific coefficient, the innovation coefficient (p) for 'adoption by innovation' and the imitation coefficient (q) for 'adoption by imitation' (Mahajan et al., 1991). Thus, if $F(t)$ is the cumulative function and $f(t) = \frac{\partial F(t)}{\partial t}$ is the density function of adoption at time "t", and "m" the potential market, the adoption probability of a product at a given time expressed by the original Bass model is given by Equation (1):

$$\frac{f(t)}{m - F(t)} = p + \frac{q}{m}F(t) \tag{1}$$

The GBM is an enhanced version of the BM, which includes decision variables such as price or/and advertising (Bass et al., 1994).

The GBM includes a mapping function $X(t)$, named "current marketing effort". The idea is to reflect the current effect of dynamic marketing variables on the conditional probability of adoption at time t, Equation (2) (Bass et al., 1994):

$$\frac{f(t)}{m - F(t)} = \left(p + \frac{q}{m}F(t)\right)X(t) \tag{2}$$

The mapping function serves to shift the BM upward or downward, i.e. anticipate or delay adoptions. Without decision variables, i.e. if $X(t) = 1$ or constant, the GBM reduces to BM. Thus, it reflects the effects of lags in the variable decision. Considering the price $P(t)$ as a decision variable extension and β the effectiveness of price over the time-based diffusion, the mapping function is given by Equation (3) (Mahajan et al., 1991):

$$X(t) = 1 + \beta\,\frac{P(t) - P(t-1)}{P(t-1)} \tag{3}$$

This function will then be implemented in Equation (2). It is possible to include additional decision variables to the mapping function (such as advertisement, infrastructure among others), for further details, see Bass et al. (1994).

The BM is one of the most popular models for new product growth and it is widely used in marketing, strategy, management of technology, and other fields (Sterman, 2000). In the energy sector, the BM and GBM have been used to forecast adoption patterns of technologies such as solar photovoltaic systems (Guidolin and Mortarino, 2010), nuclear energy (Dalla Valle and Furlan, 2014) and green cars (Lee et al., 2013) such as HFCVs (Park et al., 2011).

2.2. Learning curves

The benefits of innovation often increase over time as research and product development lead to improvements in features, functionality, quality, and other attributes of product attractiveness. Similarly, the price of new technologies often falls significantly over time through learning curves, scale economies, and other feedbacks (Sterman, 2000).

The first record on organizational learning curves was published by Wright (1936), who reported that unit labor in air-frame costs declined with cumulative output. Since then, learning curves have been studied in different industries. The phenomenon of the learning curve is also known as progress curve and/or experience curve and it is the outcome of learning by doing and learning by using (Rosenberg, 1982). Rosenberg (1982) describes "learning by doing" as the effect of the producers of a new technology learning over time – or over amount produced – to make the technology cheaper or improve quality. While "learning by using" is described as the effect of users of a given technology increasing their productivity over time as they learn how to better use this new technology.

The rates at which organizations learn may vary significantly. Argote and Epple (1990) identified some main reasons why organizations learning rate may vary. These reasons include organization "forgetting", employee turnover, transfer of knowledge from other products and organizations, and economies of scale.

Learning curves can be related with process experience such as productivity, quality, or cost. Regarding cost reduction, it captures the way in which producers, distributors, and others learn to produce at lower costs as they gain experience. The learning curve arises as workers and firms learn from experience, working faster and reducing errors. Then, unit cost falls enabling lower prices, increasing both market share and industrial demand, boosting sales even more. With greater sales, firms invest in R&D leading to process innovations (such as automation and training), reducing errors, boosting productivity and, again, lowering cost (Rosenberg, 1982).

[2] Exchange rate used: US$ 1.00 = R$ 3.17 (Brazilian Real).

To incorporate a learning curve into a diffusion model, we assume that any cost reductions are fully passed into price. The price will be in function of its initial value and the effect of learning on price (Equations (4) and (5)):

$$P(t) = P(0)^{*}\textit{Effect of Learning on Price} \tag{4}$$

$$\textit{Effect of Learning Price} = \left(\frac{F(t)}{F(0)}\right)^{c} \tag{5}$$

The $P(t)$ is the function of price and $F(t)$ is the cumulative experience at a given time. $P(0)$ and $F(0)$ are the initial price and cumulative experience, respectively. The exponent c determines the strength of the learning curve and should be negative (costs fall as cumulative experience grows).

Typically, unit costs fall by a fixed percentage *fp* with every doubling of experience (Equation (6)):

$$\left(1 - f_p\right)P(0) = P(0)\left(\frac{2F(0)}{F(0)}\right)^{c} \tag{6}$$

or

$$c = \log_2\left(1 - f_p\right) \tag{7}$$

Then, combining Equations (4), (5) and (7), the price $P(t)$ obeys Equation (8):

$$P(t) = P(0)\left(\frac{F(t)}{F(o)}\right)^{\log_2\left(1-f_p\right)} \tag{8}$$

2.3. System dynamics for long-term policy analysis

System dynamics (SD) modeling has been extensively applied in the management domain, led by Jay Forrester in the 1950s (Forrester, 1958), but has over the past few decades began to be applied to other areas, including government policy, healthcare and the automobile industry (Sterman, 2000). The SD approach combines nonlinear dynamics, computational models and feedback loops, through the use of stocks and flows, which are simulated over time (Sterman, 2000).

Within the field of sustainability, SD has as well a long tradition. Beginning with the famous ‘limits to growth’ study, published in Forrester (1971) and later in Meadows et al. (1972), system dynamics scholars applied the notion of stocks and flows to model the complex dynamics of economic growth and its impact on the environment, population and food in a global scale and in a long-term policy analysis of a 100-year horizon (Meadows et al., 1972). Even though this study generated ample critics (see for instance, Cole et al., 1973), none of the following studies contradicted the ‘limits to growth’ findings, which were related to the notion that no human economic system can grow forever (Meadows and Meadows, 2007).

In terms of technology diffusion studies, such as ours, a large share of SD models in the literature has relied on the BM, see for instance Milling (2002). Some of main reasons, for the seamless integration of BM within SD models, are: (i) the behavioral nature of SD models, which tend to incorporate social phenomena, such as word-of-mouth, which is a key assumption in the BM; (ii) BM equations are commonly presented as differential equations, which is the same mathematical language used in SD, facilitating the adaptation to the stock and flow notation and (iii) the time horizon, which in both, SD modeling and BM, tend to forecast mid-term to long-term dynamics.

Within the field of renewable energy technologies, applications of SD models are more recent and many have been inspired by the BM as well. Toka et al. (2014) develop a SD model, based on BM, describing the diffusion of biomass in the Greek residential sector for the 2015–2030 time period. Radomes Jr and Arango (2015) develop a SD model for the solar PV sector in the city of Medellin, Colombia whereby the BM serves to model the diffusion under subsidies and feed-in tariff policy for the period 2015–2035. Jimenez et al. (2016), based on BM, develop a SD model to analyze the diffusion of residential solar PV with and without storage systems for the 2014–2027 time period.

Moreover, applications of SD modeling in the broad renewable energy domain can also be found in the literature. Cardenas et al. (2016) investigate the effects of incentive policies for renewable energies in Colombia under supply-demand forces, for the 2013–2035 time period. Jeon et al. (2015) develop a method for optimizing financial subsidies and public R&D investments for solar PV by means of SD and analyze the case of South Korea for the 2015–2035 time period. Ahmad et al. (2015) analyze the effectiveness of feed-in tariff policies in Malaysia and for the 2012–2050 time period. Jeon and Shin (2014) propose a technology valuation method for renewable energy technologies, combining SD and Monte Carlo simulation under a two-factor learning curve and applying it to the solar PV case in South Korea for the 2012–2027 time period. Aslani et al. (2014) investigate the role of renewable energy diffusion in diversifying the energy grid in Finland and the effects on dependency and security of energy supply by means of a SD model for the 2011–2020 time period. Robalino-López et al. (2014) study the role of renewable energy technologies on CO_2 emissions reductions in Ecuador and in contrast with gross domestic product (GDP) growth for the 2010–2020 time period. Aslani and Wong (2014) analyze the effectiveness of renewable energy policies in the United States by simulating the costs of renewable energy operation and promotion for the 2010–2030 time period. And Musango et al. (2012) develop a SD model to assess the effects of policies on biodiesel in South Africa and on sustainability and local, national and regional levels for the 2005–2095 time period.

As far as SD in the AFV domain is concerned, Shepherd (2014) argues SD offers a good fit to evaluate the diffusion of AFV. In his review, the author explains that this is driven by the policy interest but is also an area which is well suited to the SD approach, as it makes use of existing structures such as the BM, which has been applied to adoption of new technologies in other areas. Furthermore, “strategic policy issues at regional or national level involving delays and feedbacks between different systems such as land use and transport have also been developed as an area where SD has something to offer” (Shepherd, 2014). For example, Struben and Sterman (2008) develop a dynamic model describing the diffusion of and competition among AFV focusing on the generation of consumer awareness through feedback from consumers’ experience, word of mouth and marketing. Shepherd et al. (2012) adapt Struben and Sterman (2008)’s model to study factors affecting diffusion of EVs in UK, the impact on emissions of CO_2 and the cost to the government for the period of 2010–2050. Kieckhäfer et al. (2017) combine agent-based simulation with SD to depict the automotive market and analyze the impact of manufacturers’ own portifolio decisions.

As it can be observed, SD applications within the renewable energy domain in general, and within AFV in particular, have been implemented for long-term policy analysis. Although deep uncertainties arise in the long-term future (Lempert et al., 2003), which means the resulting models will not be reliable images of the real world system (Bankes, 1993), specialized literature on long-term policy analysis argues such models might provide insights about the future behavior of the real world system, if the several assumptions and guesses were correct (Bankes, 1993). Moreover, as Lempert et al. (2003) points out, the overall aim of a SD model is to offer an enhanced learning about the system in study, whereby the model helps in changing – or at least in testing – the current mental model (i.e. beliefs, assumptions and expectations) of how the real world system will behave and respond to policy interventions.

Anyhow, two major alternatives are envisioned, in terms on how to cope with the deep uncertainties involved in long-term policy analysis. The first, known as exploratory modeling analysis (EMA), offers a systematized procedure to develop a large number of computational experiments (Kwakkel and Pruyt, 2013) in order to explore the impacts of the set of uncertain parameters in the model by means of techniques such as Monte Carlo sampling, factorial analysis and so on.

The second, the field broadly known as future-oriented technology analysis (FTA), which could be defined as the set of analytical tools that allows finding suitable ways to develop explanations about the future (Ciarli et al., 2015) including qualitative tools (such as Delphi and technology roadmapping) as well as quantitative ones (such as bibliometrics, social network analysis, agent-based modeling and SD) (Ciarli et al., 2015). The compromise of FTA exercises is to offer a better understanding of the forces shaping the long-term future, which should be taken into account when formulating policy analyses and interventions, rather than on offering traditional forecasts and accurate predictions of future events.

Our study fits within this second category, that of FTA. Some exemplary studies using SD in the sense of an FTA exercise are the works by Auvinen et al. (2014) whereby technology roadmapping and SD are used in order to develop long-term policy analysis for the transportation sector in Finland. Another study of this kind is the work by Dyner and Larsen (2001) whereby SD is suggested as adequate when the future is highly uncertain and when high risks are associated with the system at hand, in their case, the electricity market in Colombia. Moreover, scenarios offer the possibility to investigate a 'range of futures' in environments of deep uncertainty (Courtney, 2003) and they can be developed qualitatively (e.g. through Delphi or other participative techniques) or quantitatively (e.g. through simulation modeling) or even, combining both (Zurek and Henrichs, 2007).

Specifically, SD falls within the quantitative scenario planning of FTAs and can capture the influence of changes in quantitative indicators, as well as policy and management interventions of qualitative nature. These models can incorporate the complexity and uncertainties of long-term policy analyses, within the sustainability domain, and include "… non-linear and non-stationary processes, multiscale effects, and transformational change …" (Bryan et al., 2016). On the other hand, as far as EMA is concerned, its applicability in our subject of study is promising, but we leave it for future work. We propose, in this sense, the use of SD as a forward-looking tool – in the FTA sense – whereby a range of futures is observed and analyzed, with the aim to understand the complex long-term dynamics that might unfold in the AFV market in Brazil for the next 5 decades.

2.4. Research design

In this study, we use the BM for the CC historical fit licensing from 1980 to 2014 period. The BM can describe the S-shape diffusion curve of a product based on pre-determined potential market. We used the historical data of car licensing from the Brazilian National Association of Motor Vehicle Manufacturers (ANFAVEA, abbreviation in Portuguese). Moreover, information on population

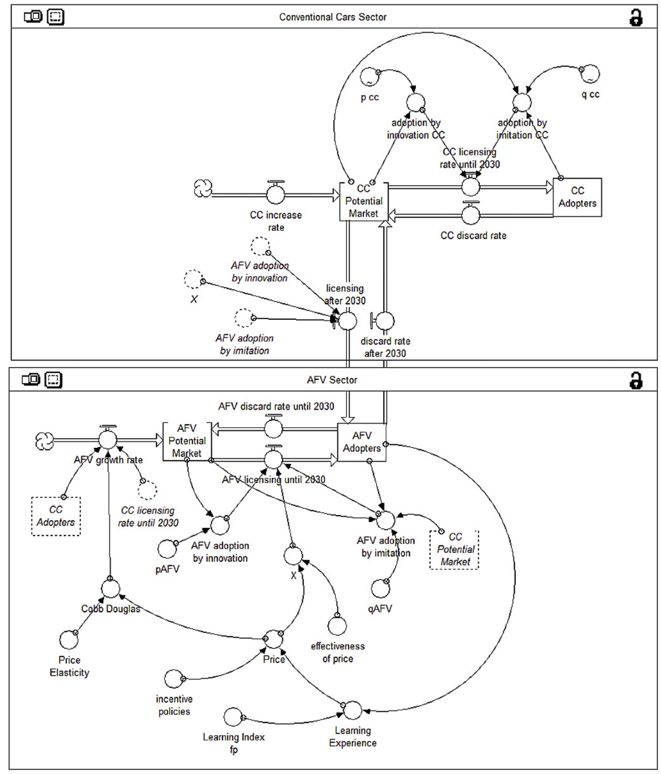


Fig. 1. Simplified SD model for the Brazilian market of CC and AFV.

data was taken from Brazilian Institute of Geography and Statistics (IBGE, abbreviation in Portuguese) database, which is used for the historical potential market estimation.

As previously described, the BM is influenced by two adoption forces, namely, the external and internal influence represented by an innovation and imitation coefficient, respectively. Thus, with the information of CC licensing and the potential market estimation, it is possible to fit the innovation and imitation coefficients with historical data (1980–2010). The licensing behavior is then forecasted for the next decades.

Then, it is possible to link the CC adopters with the AFV potential market and, therefore, forecast the diffusion of electric and hybrid cars in Brazil, from 2010 to 2030 (at first). We use the generalized GBM to assess the diffusion and the effectiveness of three government policies that recently came into force in Brazil, with one particularly still on hold for its final approval. The GBM is a developed version of the BM and it includes decision variables such as price and infrastructure.

Both the effectiveness of price (from GBM) and the effect of learning on price (from the learning curve) requires additional parameters (e.g. effectiveness of price, fixed percentage) to drive the price influence over the diffusion process. These parameters were selected from the literature, presented hereafter. In this paper, we assess the influence these policies may have on the AFV average price and, ultimately, on the adopters rate. We also consider a learning curve influence on the diffusion process, which relates to the way producers, distributors and others learn to produce at lower costs as they gain experience. We therefore consider a few uncertainties, testing different levels of cost reductions that may potentially arise from those government policies and passed them into price. The AFV average price will be in function of its initial value, the policy in study and the effect of learning on price.

Finally, from 2030 to 2060, we simulate the incorporation of another policy in Brazil, the one proposed by the Germany's

Table 1
Model parameters and assumptions – Conventional cars sector.

Model Parameter	Estimated Value	Source
CC Discard rate	6%/year	National Survey by Household Samples (*Pesquisa Nacional por Amostra de Domicílios*, PNAD)
Discard rate after 2030	6%/year	We assume the same value as above
p^{cc}	Varies from (0.009 in 1980) to (0.002 in 2014) and follows a linear trend until 2030. After 2030 its value is 0.	Historical fit based on Fleet Size (1980–2014) and on the BM parameter estimation (Ibge, 2016).
q^{cc}	Varies from (0.004 in 1980) to (0.125 in 2014) and follows a linear trend until 2030. After 2030 its value is 0.	Historical fit based on Fleet Size (1980–2014) and on the BM parameter estimation
f^{cc}	22 million cars in 2009	Based on data from (Ministry of Environment, 2011)
m^{cc}	97.5 million cars in 2014	Based on the average population growth from 1980 to 2014 of adults over 20 years old.

Model Assumptions with respect to conventional cars

We assume the market for conventional cars will obey natural demand and supply forces until 2030 (simulated by the BM). After 2030, the licensing rate (i.e. sale of new CC) for CC will be zero, that is, after 2030, it will not be possible, anymore, to buy a new conventional car.

With respect to the market growth for new cars, we assume it depends on the population growth of adults over 20 years old.

Bundesrat. In summary, we conduct an investigation of four policies over the diffusion of AFV in Brazil, related with: (i) ID, (ii) MVPT, (iii) TMG and the (iv) ban of CC sales from 2030 and its circulation by 2050. The first two national policies (related with ID and MVPT) are currently active. However, there are some uncertainties related to them with respect to the time period and the potential impact on cost reduction. The third policy (related with TMG) is currently waiting for a final approval, and if it is, uncertainties regarding cost reduction impact could be investigated as well. The last policy in this study attempts to simulate a similar incentive than the one proposed by Germany's Bundesrat. This policy has yet to be approved by Germany's Bundestag to be valid in the country, still, here we simulate if a similar policy is implemented in Brazil.

Some extensions for both models (BM and GBM) have been included and will be presented in the next section. The combined use of well-established literature mathematical models (e.g. BM and GBM, learning curve, Cobb-Douglas functions) was further facilitated by the use a SD approach for the modeling process and analysis of policies and feedbacks. With this, we are able to conduct policy testing and analyze the evolution of key variables of interest (e.g. potential market, number of adopters). The SD model is developed in Stella® Software from Isee Systems and data analysis and plotting in Microsoft Excel®.

3. Model development and validation

Fig. 1 shows the SD model comprising two sectors (or submodels): the CC sector and the AFV sector. The model proposed here integrates the dynamic and structural complexities of the car market in Brazil. Next, in each sector the logic behind the model is explained, as well as their parameters and assumptions.

3.1. Conventional cars sector

The conventional cars sector uses a BM structure with two stocks: CC potential market (m^{cc}) and CC fleet (f^{cc}). CC potential market (m^{cc}) is the stock of new cars that have not been sold yet and represent the potential market for conventional cars. CC fleet (f^{cc}) is the stock of conventional cars' fleet in the country.

We assume m^{cc} increases as the population size of the country increases at a "CC increase rate". For simplification purposes, we specifically take into account the population size of adults over 20 years old (i.e. we assume a potential buyer or owner of a new car to have at least 20 years old). Furthermore, the stock m^{cc} also increases as car owners discard their vehicles and re-enter the market as potential adopters/buyers looking for a new car. It is worth to mention that the used car market is aggregated within the CC fleet stock (f^{cc}), since used cars are still part of the car fleet in the country.

There are two influx of cars into m^{cc} due to discard rates (i.e. owners or buyers discarding their old cars and looking to buy a new one) depending on the time period, before 2030 and after 2030 (we assume a ban on the sale of new CC will be put into place in 2030 and, therefore, it will only be possible to buy AFV after 2030). Thus, the first influx of cars is due to the 'CC discard rate until 2030' and the second influx of cars is due to the 'discard rate after 2030', which refers to its discard rate back to the potential market (from 2030 aggregated into a general one, the mcc). For simplification purposes, we assume a constant discard rate of 6% of the fleet being renewed each year, an average value obtained from National Survey by Household Samples (*Pesquisa Nacional por Amostra de Domicílios*, PNAD).[3]

In this sense, the two licensing rates outflowing m^{cc} (i.e. new CC selling) are influenced by the 2030 ban we have explained above: 'CC licensing rate until 2030' simulates the annual sales of new conventional cars until 2030 and 'licensing after 2030' determines an annual migration of potential owners/buyers in the m^{cc} market towards AFV.

Both outflowing rates are determined by the "adoption by innovation CC" and "adoption by imitation CC" mechanisms of a classical BM. Two parameters are needed for the computation of 'adoption by innovation CC' and 'adoption by imitation CC': (i) an innovation coefficient (p^{cc}) and (ii) an imitation coefficient (q^{cc}). We used historical data from 1980 to 2014 and estimated the values of p^{cc} and q^{cc}. It is worth mentioning that both coefficients change over time as the size of the market, technology and other factors change. The key parameters and assumptions for the conventional cars sector model, are shown in Table 1.

3.2. Alternative fuel vehicle sector

Similar to the conventional cars sector, the alternative fuel vehicle (AFV) sector comprises a structure with two stocks: AFV potential market (m^{AFV}) and AFV fleet (f^{AFV}). Until 2030, we assume the AFV potential market (m^{AFV}) is proportional to the annual CC adopters and it follows the Cobb-Douglas function (potential market rises as AFV prices decrease). After 2030, due to the ban of CC sales, the AFV potential market includes the total CC potential market (which includes the increase of the market from population growth of adults over 20 years old as well as all CC fleet). On the

[3] MCT. Brazilian Ministry of Science and Technology (2006) (*Ministério da Ciência e Tecnologia*). Available at: <www.mct.gov.br/upd_blob/0008/8848.pdf>. Accessed in: July 2016.

Table 2
Model parameters and assumptions – AFV sector.

Model Parameter	Estimated Value	Source
AFV Discard rate	6%/year	National Survey by Household Samples (*Pesquisa Nacional por Amostra de Domicílios*, PNAD)
Discard rate after 2030	6%/year	We assume the same value as above
p^{AFV}	0.0000585	Authors own estimates in order for the adopters curve fit historical data
q^{AFV}	0.2422	Based on Massiani and Gohs (2015) for the Toyota Prius
F^{AFV}	56 cars in 2010	Anfavea (2017)
m^{AFV}	4.4 million cars in 2010	Based on the average population growth from 1980 to 2014 of adults over 20 years old (Ibge, 2016)
f_p	6%/year	Based on Weiss et al. (2012) for hybrid-electric vehicles
β	−1.1521	Based on Park et al. (2011) for hybrid-electric vehicles sold in Japan
Price-elasticity	0.8	Authors own estimates in order for the price curve to fit historical data

Model Assumptions with respect to AFV

The licensing of AFV depends on adoption by innovation, adoption by imitation and on the effect of price on consumer behavior, denoted by the variable "X".

With respect to the potential market growth, we assume that, between 2010 and 2030, it depends on the annual CC adopters and follows the Cobb Douglas function. Later, from 2030 to 2060, it depends on the population growth of adults over 20 years old (and at this moment all CC adopters become part of the AFV potential market).

Even though several parameters might be influenced by exogenous factors such as new fuel alternatives, fossil fuel prices, political conditions and so on, we assume the values based on literature and other trustable sources. Anyhow, scenario-based modeling is helpful when the future is highly uncertain (Dyner and Larsen, 2001), besides, the model has the capability to be tested against conditions in which several parameters assume extreme values in order to visualize the effects on important outcomes, such as the fleet of AFV and CC over time. In the sensitivity analysis section, we will better discuss these issues.

The policies being tested in the model influence the AFV price. Each policy has specific attributes, which in turn, influence the licensing of new AFV (i.e. the diffusion of AFV technology) in different ways.

other hand, AFV fleet (f^{AFV}) is the stock of AFV cars in the country. There are two discard rates, which are assumed to be of 6% of total fleet (as in the CC sector) and there are two AFV licensing rates, one before 2030 and the other after 2030. The difference between these two is simply the assumption of full AFV potential market after 2030.

The AFV sector uses a GBM in order to simulate AFV technology diffusion, with 'price' as the decision variable in the mapping function $X(t)$, besides the usual 'AFV adoption by innovation' and 'AFV adoption by imitation' mechanisms of BM. The mapping function $X(t)$ is represented by variable "X" in Fig. 1, and depends on the effectiveness of price, on the current price of AFV for each time step and on the exogenous parameter β (Park et al., 2011).

At the same time, the current AFV price is endogenous and is reduced by the industry learning curve, named as "learning experience" in the model, which in turn, depends on an exogenous parameter, the "learning index" (f_P) (Weiss et al., 2012). The learning curve creates a positive loop favoring the diffusion process (Ministry of Environment, 2011). As the number of adopters rises, the learning curve will reduce the price (by accelerating the cost reduction), which will influence the mapping function computation and ultimately, increase the AFV licensing rate.

The AFV price will also affect the Cobb Douglas function, which is a key input for the growth of the AFV potential market (m^{AFV}). In our model, the Cobb Douglas production function is dependent of the AFV price and of price elasticity. In turn, price-elasticity was estimated at 0.8 and when the AFV price reaches the average regular car price in Brazil (around USD 9.200[4]), its potential market (m^{AFV}) becomes the full potential market. The initial AFV car price is the average price of electric and hybrid cars in 2010 (approximately USD 79.000)[5] in the Brazilian market (Fipe, 2016).

With respect to data about the AFV market in Brazil, since it is still on an early stage, it is very difficult to statistically estimate parameters such as the innovation and imitation coefficients, or even the potential market. Hence, it is a common practice to use estimates from previous literature or from car manufacturers themselves (Massiani and Gohs, 2015). In our case, we use historical data from 2010 to 2016, in terms of AFV fleet and the AFV licensing rate. We then use the GBM to generate future licensing behavior, based on the three key model parameters, mentioned above: p^{AFV}, q^{AFV} and f_p. Even though only a small share of the AFV sector model horizon can be tested against historical data, GBM has been previously used in similar studies, where technology diffusion is at early stages, offering a certain degree of reasonability and confidence on the model's results (see for instance Lavasani et al. (2016)). Table 2 shows the main parameters and assumptions for the AFV sector model.

3.3. Model validation and sensitivity analysis

For the validation of the forecasting electric and hybrid cars model in Brazil, the historical fit of CC was done using BM. For this, we used data such as the licensing historical of CC from 1980 to 2014 (Anfavea, 2017) and their estimated fleet (Ministry of Environment, 2011). Fig. 2 shows the comparison between the simulated licensing rates obtained from the model with the historic data. Fig. 3 presents the fleet comparison from both simulated model and literature estimative.

With the CC model parameters adjusted, it was possible to extrapolate them and connect it with the forecasting AFV model, based on the GBM, as they are connected. As mentioned before, the connection from both models resides in the conventional adoption stock with the AFV potential market. We assume that in the first couple of decades (until 2030), the AFV potential market is linked with the growth of the country's conventional fleet and dependently with the car prices. The potential market follows the Cobb Douglas function, widely used in economic studies. In other words, we assume that the AFV potential market would not exceed the number of car fleet in the country. From 2030 onward, this behavior would change, as it will be presented hereafter.

Fig. 4 presents the cumulative electric and hybrid cars adopters of the historical data and simulated model. As we can see, the AFV in Brazil is still in its early stages. Therefore, the imitator coefficient was taken from literature, and the innovator coefficient (which mostly influence the beginning of a diffusion process) was adjusted to fit our historical data of 3627 cars by the end of 2016. The result was an innovator coefficient $p = 0.0000585$.

The use of the GBM brings an assessment of one or more external variable in the diffusion process. In this study, we evaluate the external factor price. If we vary the price-learning index, one would expect a change in the response of the price experience curve. Fig. 5 shows a sensitive analysis of the fixed percentage (fp)

[4] Exchange rate: 1 USD = 3.17 Brazilian Reais (BRL).

[5] The most expensive AFV, such as the BMWi8 were excluded from the computation of average price.

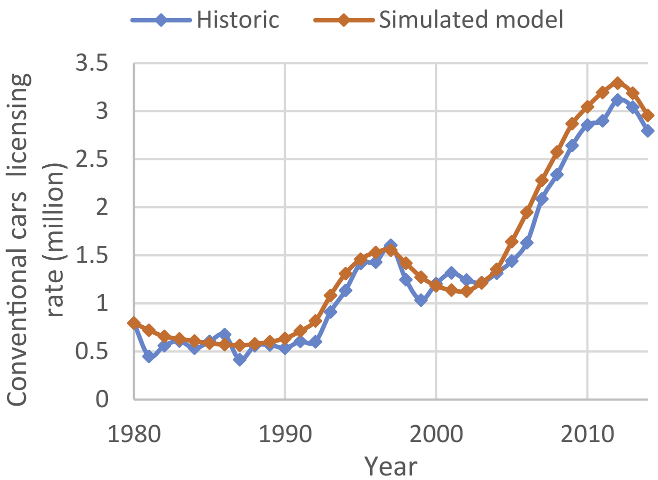


Fig. 2. Conventional cars licensing rate per year simulation with historical rate (Anfavea, 2017).

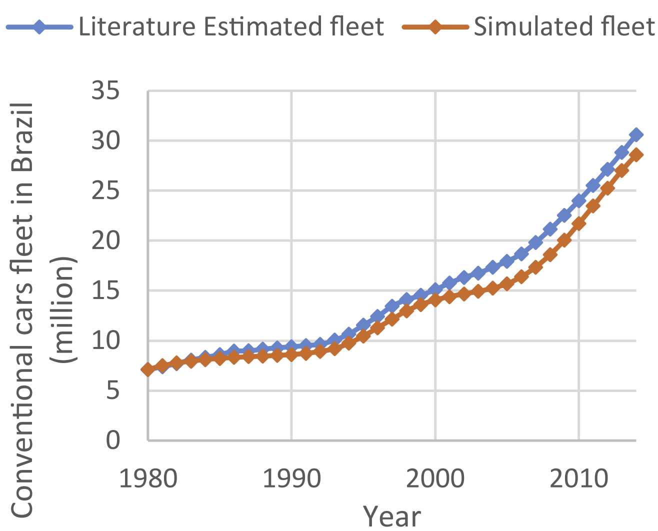


Fig. 3. Conventional cars fleet simulation and Ministry of Environment (2011) estimative.

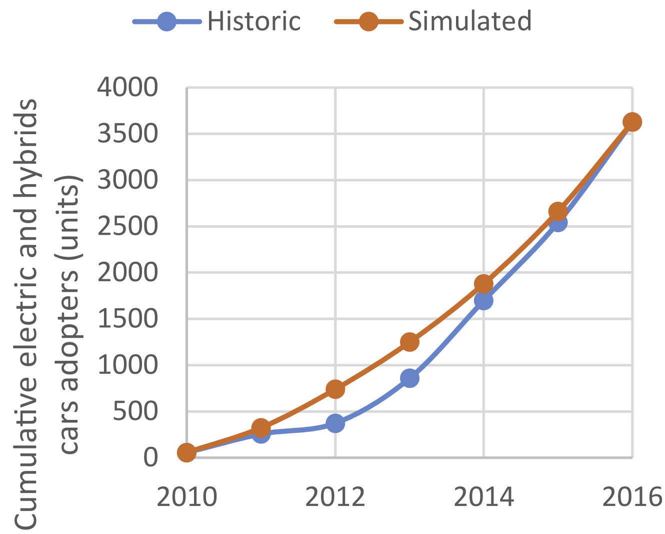


Fig. 4. Cumulative AFV adopters simulated and historical (Anfavea, 2017) of Brazil.

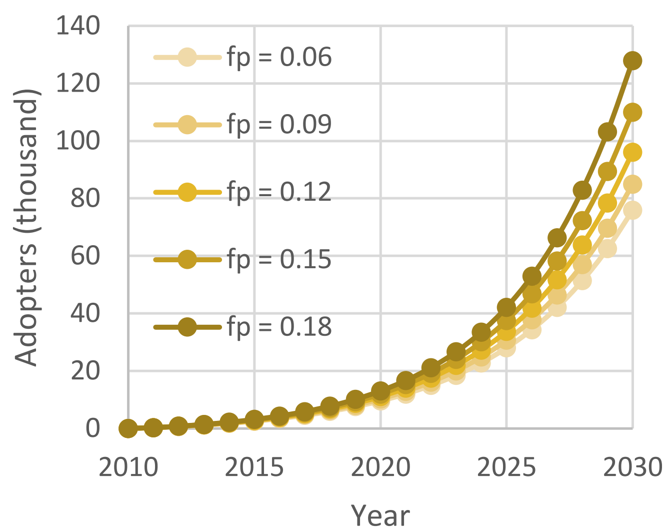


Fig. 5. Number of AFV adopters by learning index (fp).

on the number of adopters. A higher learning rate leads to a higher calculation value from the mapping function (Equation (3)) and, ultimately, enhances the promotion of the adoption rate.

Fig. 6 shows a sensitivity analysis of the imitator (a) and innovator (b) coefficients. As both factors assume higher values, there is an increase in the number of adopters.

4. Results and discussion

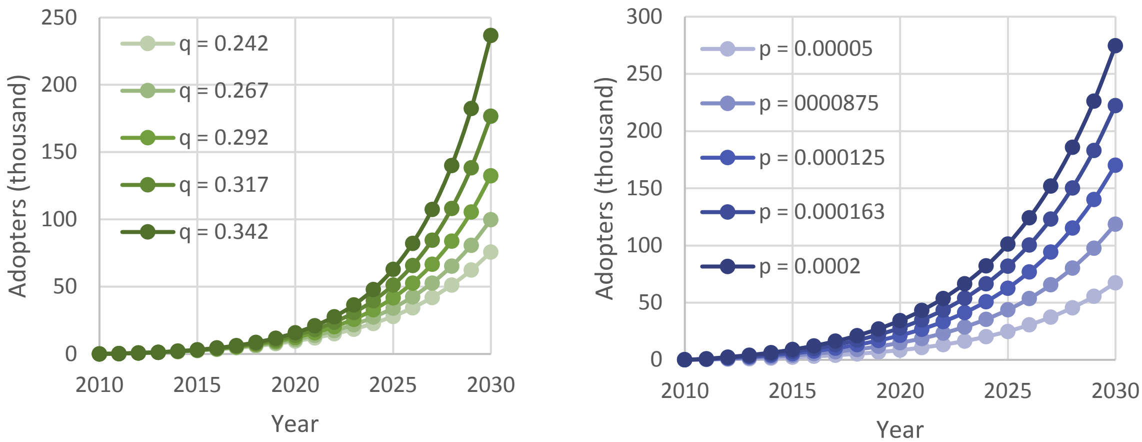
4.1. Set of policies to be tested

We first assess the tax exemption of the ID for electric and hybrid cars, then the tax reduction of MVPT and finally the exemption of the federal TMG. For each policy, we considered three possibilities (Table 3).

For tax incentive related to P1, we assume different length period, as the government has not specified its duration. For P2, we assume it is valid through the whole country to simulate different tax incentive rates. For P3, we consider that by 2018 the car manufacturers will start producing these cars locally. It is worth mentioning that until this date, the Senate Project-Law nº 174/2014 (Brazil, 2014) has not come into regime, it is waiting for the approval of the Economic Affairs Committee to establish TMG exemptions for the manufacture of electric cars or hybrids to ethanol. Thus, we assume different possibilities of price reduction resulted from P3.

Fig. 7 shows the results from all simulated case including the Base Case, in black, where diffusion process occurs without the application of any incentive policy. It is possible to identify a superior effect on the number of adopters through the scenarios related to P3. From 2024, the case scenarios from P3 begin to grow faster than the other policies. The 10 years period of tax exemption from the TMG, as this project-law proposes, considerably reflect in the total number of adopters at the end of 20 years of forecast. For example, the P3C case reaches approximately 140 thousand adopters against approximately 80 thousand in Base Case (Fig. 7).

Depending on the policy in practice, the rise in adopters in comparison with Base Case may be low, median or high (Fig. 8). The case when only P1 is applied generates an average of 18% increase



(a) (b)

Fig. 6. Adopters by (a) imitator 'q' and (b) innovator 'p' factors.

Table 3
Policies classification by type of fiscal incentive and nomenclature used for each case.

Policy 1 (P1): ID exemption starting 2016 (duration)		Policy 2 (P2): MVPT reduction until 2030		Policy 3 (P3): TMG exemption for 10 years starting 2018	
P1A	2 years	P2A	1.5% limit car under R$150k	P3A	20%
P1B	3 years	P2B	3% limit to car under R$150k	P3B	22.5%
P1C	4 years	P2C	3% for any car price	P3C	25%

in the number of adopters, from 11% difference in P1A to a 25% in P1C case. If the incentives come only through P2, there is an 8% average increase of adopters compared with Base Case, the lowest average increase obtained from all cases simulated. The most expressive incentive involves Policy 3, with a 62% average increase in the number of adopters, varying from 54% for the P3A case to 71% increase by the end of 2030 for the P3C case.

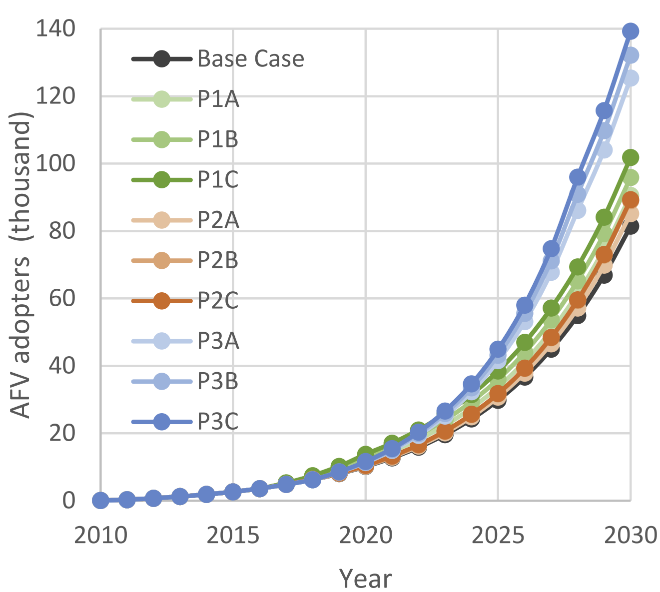


Fig. 7. Cumulative adopters for Base Case and the other case scenarios.

Fig. 8 shows how the exemption of TMG policy (P3) has a greater potential for enhancing the diffusion process. On the other hand, although MVPT (P2) aims to encourage potential buys directly, for the long run, it does not bring expressive increase rate in promoting these cars.

Finally, we conduct the assessment of policy (P4), to test the recent new regulation proposed by Germany's Bundesrat. The proposed regulation bans the sales of internal combustion engine vehicles by 2030 and their full retirement by 2050 and it has yet to be approved by Germany's Bundestag if it is to be made a national law.

4.2. Policy Testing and Scenarios

We test here P1, P2 and P3 and leave P4 for next section (since P4 tests the diffusion behavior by 2060). There are several uncertainties regarding the government incentives. For instance, it is not known how long will P1 be in practice in the country. The same goes for P2. As for P3 (which has not been yet approved) although the length period is known, there is an uncertainty on how much will this tax exemption impact AFV's price. Therefore, we assumed

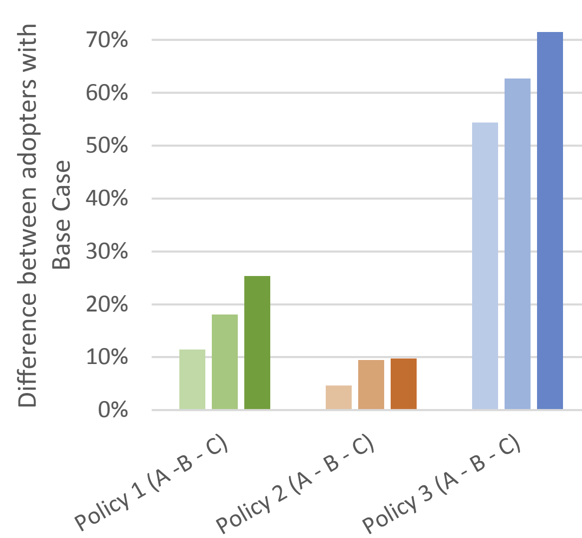


Fig. 8. Difference between cumulative adopters in each case scenario with Base Case in 2030.

a few combinations to investigate different scenarios:

(i) Reference: P1A + P2A + P3A
(ii) Moderate: P1B + P2B + P3B
(iii) Aggressive: P1C + P2C + P3C

The Reference scenario assumes the government will end P1 in 2017 (total of 2-year period) considering P3 will take place the following year, opening a broader access to national manufacturing. We also assume that the manufacturers will be able to cut prices at the rate of 20% (from a total of 25% established in the law), for a 10-year period starting in 2018. As for P2, although the MVPT reduction rate is different amongst Brazilian states, we assume the specific 1.5% rate for all the country.

The Moderate scenario is a bit more optimistic, with a 3-year period ID exemption and the maximum discount of MVPT tax, 3% rate for a limit of car price of R$150 thousand, and the assumption that manufacturers will provide a 22.5% TMG discount on the car prices, also starting in 2018.

The Aggressive scenario considers a 4-year period of P1, the maximum discount of MVPT tax (P2) without limiting the car price and assuming car manufacturers will be able to provide the maximum of 25% TMG discount (P3) on their car prices, also starting in 2018.

In order to assess our results, the following indicators were analyzed:

1. Cumulative adopters
2. Market share for each scenario
3. Difference between adopters with Base Case in the years: 2020, 2025 and 2030

Fig. 9 shows the sales volume for each proposed scenario in comparison with the Base Case scenario. The policies start causing a more visible effect in 2020, when the number of adopters between the Base Case and all other scenarios take different course. After that, around 2025, the three scenarios begin to have their own increase rate. In the Base Case, where no policy is applied, the prediction is a total of 81 thousand adopters by 2030. For the other scenarios, the prediction reaches a total of 152, 166 and 181 thousand adopters for Reference, Moderate and Aggressive case, respectively.

Fig. 10 shows the evolution of the increase of adopters obtained from the application of these policies combined with Base Case. We can observe the difference between adopters with the Base Case through time. In the 2020, the policies have already made certain progress with an average of 44% (39–50%) increase. By 2025, the Reference scenario achieves a 69% increase, the Moderate scenario 80% and Aggressive reaches 94% increase compared with the Base case. Finally, in 2030 we can see the highest resulted from the Aggressive scenario with a 122% increase, and the Reference and Moderate case, 87 and 104%, respectively.

By the year 2030, results indicate an average of 105% increase compared with Base Case. If we take only the Reference scenario, which is the most likely to occur, there might be an 87% increase in AFV diffusion, after implemented the policies in study.

It is not in the scope of this study to discuss how the Brazilian government (or any other) can achieve such diffusion rate, in terms of the many other aspects involved and necessary, such as infrastructure, discard procedure, technology enhancement, among others. However, it is partially the scope of this study to evaluate how incentive policies can affect the economy of scale, considering technology enhancing by the learning curve should influence the price on these cars and further promote their adoption. Fig. 11 shows the decline in price through the years, starting from the average price of 178 thousand (BRL) or[6] approximately 54 thousand (USD) in 2015. By 2030, the AFV Base Case price reaches approximately 130 thousand (BRL) or approximately 40 thousand (USD) (Fig. 11).

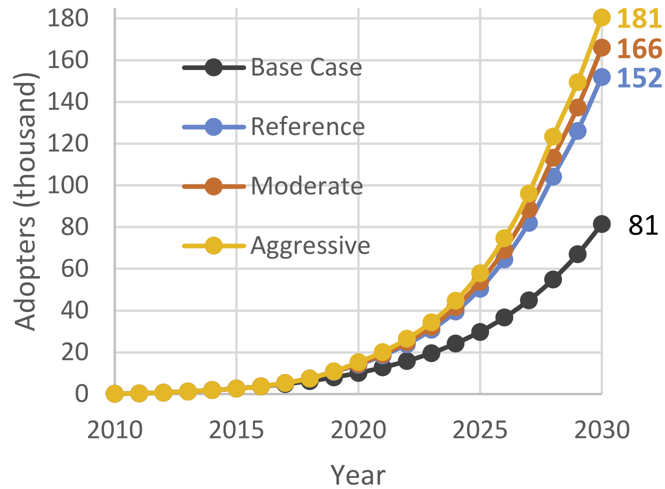


Fig. 9. Cumulative adopters for each scenario.

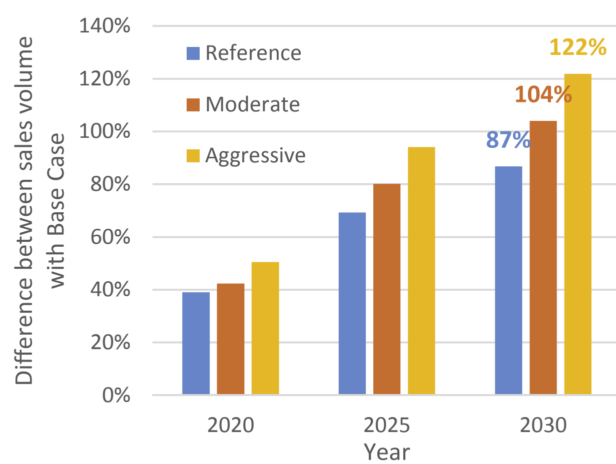


Fig. 10. Difference between sales volume with Base Case in the years: 2020, 2025 and 2030.

The decline in the average price is aggressive. Fig. 12 shows the price percentage difference with Base Case for each scenario in 2030. For the Reference scenario, there is a 5.45% price reduction. For both, the Moderate and Aggressive scenarios, the percentage did not differ significantly, with 6.20 and 6.9% reduction from Base Case, respectively.

Even though the price percentage difference did not differ so much among themselves (scenarios) and from Base Case, it is important to remember that the number of adopters were significantly influenced. Figs. 9 and 10 showed the effectiveness of the policies as they boost the car price reduction (Fig. 11) in number of adopters and in percentage increase. Therefore, even a modest amount of price decline from government incentives and policies can further contribute on the diffusion process.

[6] Exchange rate used: US$ 1.00 = R$ 3.32 (Brazilian Real).

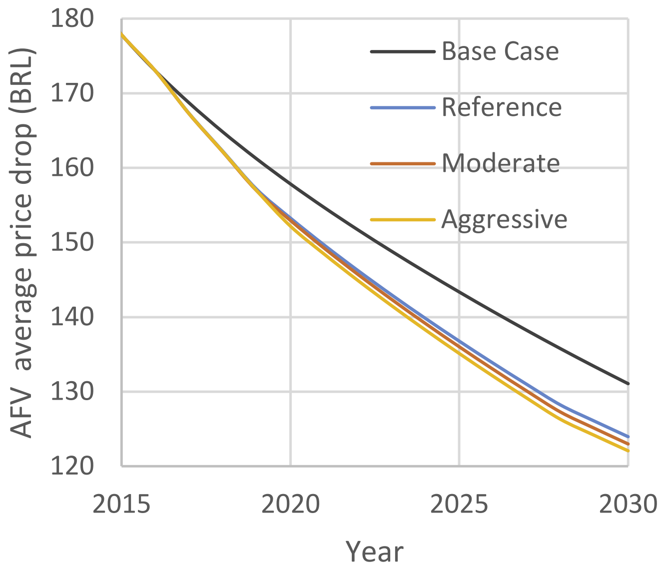


Fig. 11. Learning curve impact on AFV average price.

4.3. A long-run view of the AFV market in Brazil: 2060

Here we assess the behavior of AFV diffusion over a longer period of time until 2060, to specifically test the effectiveness of a long-term policy aiming at banning the circulation of internal combustion engine cars in the country. Our goal here is to offer a look at the AFV market in Brazil if a similar ban – than the one recently proposed in Germany – is implemented in the forthcoming years, i.e. a ban of internal combustion engine vehicles sales from 2030 and its circulation on the road by 2050.

Even though there are deep uncertainties with regard to how the Brazilian market will behave in such a long period of time (our time horizon is 2060, so we can assess any changes after the ban is set in 2050), simulation modeling tools and SD in particular, have been suggested as adequate when dealing with problems of deep uncertainty due to the long term horizon (Courtney, 2003) in order

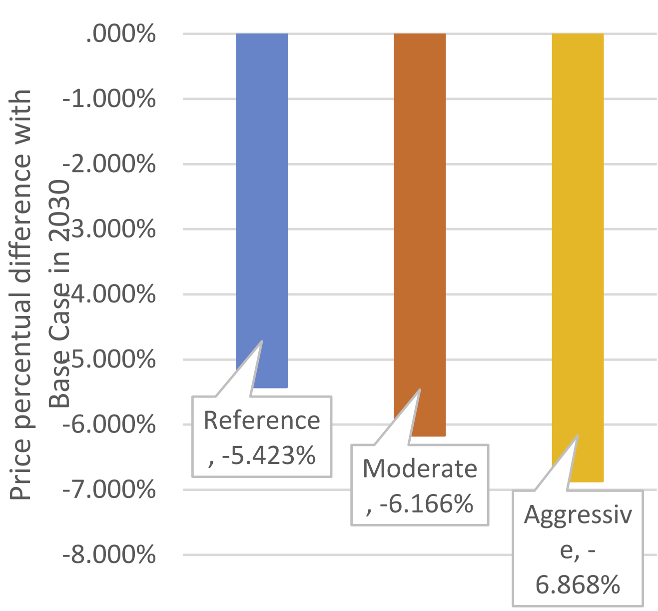


Fig. 12. Price percentage difference with Base Case in 2030.

to develop scenarios in a range of possible futures (Bryan et al., 2016). Figs. 13 and 14 shows the AFV and CC market behavior as denoted by: the AFV and the CC potential market and the AFV and the CC fleet, respectively.

Accordingly, CC fleet rises steeply until 2030, and then declines as no new CC sales are permitted after that year. Its potential market also declines after 2030, as consumers are forced to buy AFV only. Furthermore, the sharp decrease of the CC fleet by 2050, when the ban prohibits CC circulation from that year on, accelerates the growth of the AFV fleet, which, by 2060 reaches 15.8 million cars (Base Case) to 32.2 million (Aggressive case) (Fig. 14).

Fig. 15 shows the difference between sales volume with Base Case for each scenario, Reference, Moderate and Aggressive. It is important to mention that from 2030 to 2060, there is no application of the first three policies assessed (P1, P2 and P3). The results obtained here are derived from the remaining effect from previous years (results from Section 4.2). It is interesting to notice that from 2050 the difference in sales with Base Case start diminishing compared with previous years. This may be due to the fact that from this year on, consumers are forced to buy AFV only, providing a higher adoption rate phase for Base Case, as it had previously not been able to (due to less incentives).

5. Conclusions

In this study, we investigate the impact of government policies on the long-term diffusion of AFV in Brazil. In order to do so, we developed a SD model, based on the GBM with price as external variable. We conduct several simulation experiments by testing four policies: tax exemption of the ID for electric and hybrid cars (Policy 1); tax reduction of MVPT (Policy 2); ten-year Federal Tax exemption on TMG (Policy 3). Lastly, we analyze a banning regulation (such as the one recently proposed in Germany) (Policy 4).

We first ran several scenarios considering policies 1, 2 and 3 (three scenarios each). Based on our results, it is clear that policy incentives are required in the country, in order to obtain a higher diffusion rate. When compared against the *Base Case* (where no policy incentive is applied), all three policies (irrespective of the differences between specific scenario runs) turn out with higher diffusion rates. More specifically, Policy 3 obtains a 50%–70% increase with respect to the *Base Case*, the highest of all three policies. Still, even the least successful policy in our analysis (Policy 1) obtains a 10%–25% increase, when compared to the *Base Case*. Although Policy 3 has a lower tax reduction when compared to Policy 1, its length period (10 years) is very promising. Local car manufactures can certainly benefit from it, not only considering sales for the local market, but also considering the potential of exports operations.

In terms of absolute numbers, on the other hand, the AFV installed base by the year 2030 is near 140 thousand vehicles for the most successful scenario and approximately 81 thousand for the Base Case, which means that even the most successful scenario obtains a relatively low number of AFV, if compared with the internal combustion engine vehicles installed based. From a policy-making perspective, this result is also relevant, since it shows that even the most successful policy instruments will need to be improved, if a larger market share of AFV is desired by 2030.

In addition, our results show the lagged response of the diffusion rate to incentive policies. All nine scenarios show little difference to each other in the short to mid-term (until 2020 approximately) and only begin to show differences from 2020 onwards. In other words, nearsighted policymaking may actually hinder the AFV diffusion in the long term if implementation delays are not taken into account.

Afterwards, we developed three composite scenarios by

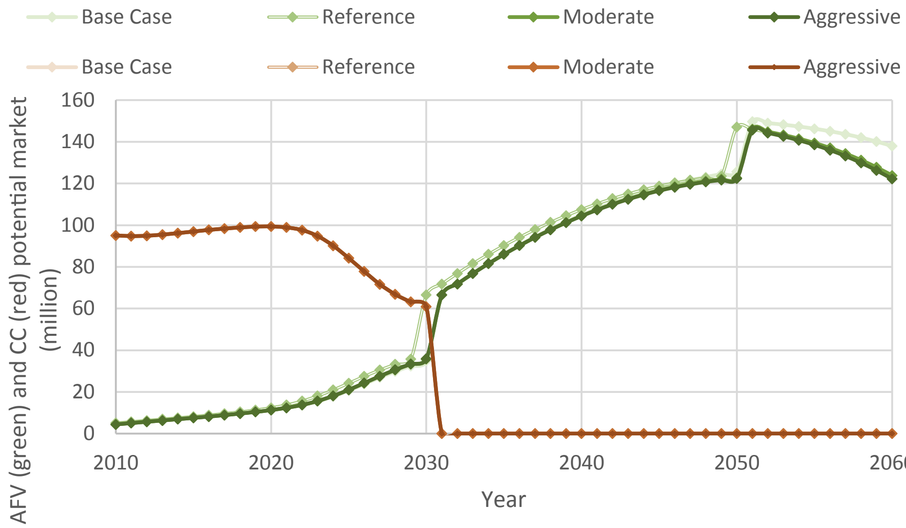


Fig. 13. AFV (green) and CC (red) potential market for the Ban Policy P4 (2010–2060).

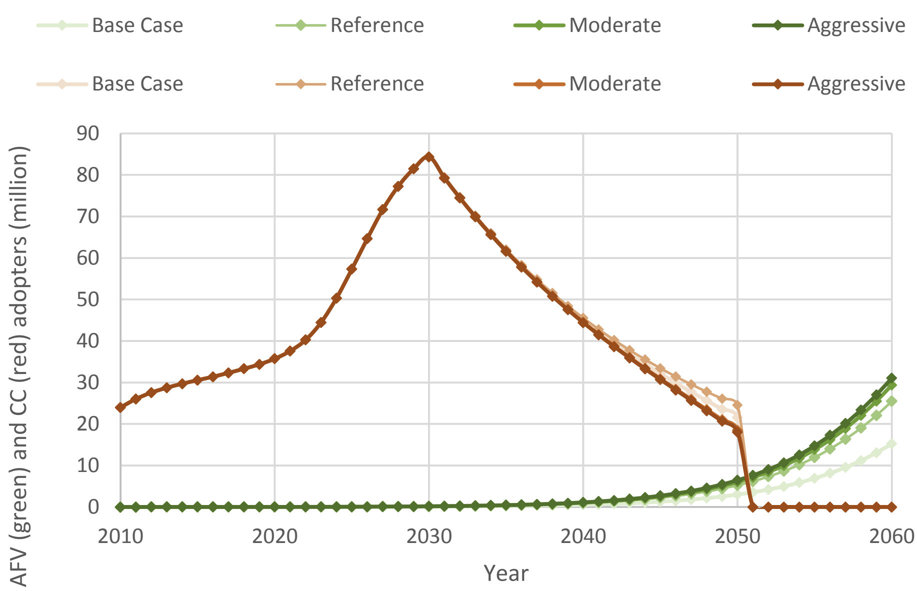


Fig. 14. AFV (green) and CC (red) fleet for the Ban Policy P4 (2010–2060).

combining Policy 1, 2 and 3, namely: (i) Reference scenario; (ii) Moderate scenario; and (iii) Aggressive scenario. The rationale behind these scenarios is that usually more than one policy is active at the same time as it is the current case in Brazil. Our results suggested even higher diffusion rates than when the policies were implemented in separate. Even the least optimistic scenario, namely "reference scenario", achieved an 87% increase with respect to *Base Case* and higher than the most successful policy in the first set of experiments (Policy 3 alone) and a total of 152 thousand AFV vehicles by 2030.

It is worth noting these second set of experiments allows to measure and assess the compounded effect of simultaneous policies – with different life spans – on the diffusion rate and therefore, offer a more realistic set of scenarios in order to forecast the growth of the AFV fleet. First, the life span for Policy 1 is of a few years and varies slightly between the reference, moderate and aggressive scenarios, yet, its impact on AFV diffusion by 2030 is considerable. Second, the discount of the MVPT (Policy 2), also varies slightly and contributes considerably and the same for the tax manufacturing exemptions (Policy 3).

From a policymaking perspective, the composite policy set investigated herein offers novel insights on the effects of policy timing and on how such policy may be sequenced, in order to obtain the best possible outcomes in the long-term. For instance, for other renewable energies, such as wind, policies regulate energy supply for long timeframes of up to 20 years, known as long-term contracts. Similarly, the activation and deactivation of the aforementioned policies could be sequenced for longer timeframes, increasing trust and confidence of end customers but also of other market agents, in order to reduce investors' risks.

Moreover, we conduct one additional experiment, which aims at offering a long-term vision of the AFV market, where a highly aggressive policy takes place. The rationale behind our fourth experiment is that the most effective means to accelerate the diffusion of AFV is by implementing a banning regulation for internal combustion engine vehicles (or conventional cars). Naturally,

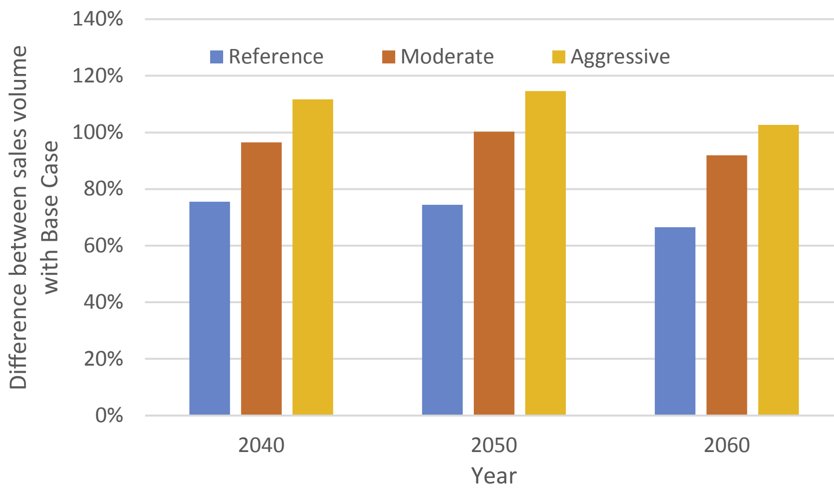


Fig. 15. Difference between sales volume with Base Case in the years: 2040, 2050 and 2060.

such ban would imply a radical change in energy, technology and road infrastructure, besides the change in the habits of end customers. Therefore, we assume this policy would take a long time to implement (and in accordance with Germany's forecasts which is trying to implement a similar policy) and, thus, suitable for the applicability of SD models.

Our fourth policy highlights a market growth of approximately 30 million AFV by 2060, for the aggressive scenario (the most optimistic one) and of approximately 15 million AFV for the *Base Case*. This result, is as well highly enlightening, since it indicates that even a highly aggressive policy such as this one, would take a very long time to produce a relatively large AFV installed base. Certainly, several economic, social and technological conditions are unknown in such a long period of time and, therefore, this exercise should be taken with caution. Rather than offering a precise forecast of the AFV fleet, its spirit is to offer a perspective – within the FTA tradition – of the need to reinforce policies in the forthcoming years and decades if we are willing to actually reduce significantly, greenhouse gas emissions and to increase, significantly, the 'green cars' fleet.

Even though our model offers a comprehensive perspective of AFV diffusion in Brazil, there are many avenues for future research. First, infrastructure (such as charging stations) has not been taken into account and it may prove as a limiting factor or inducing factor, depending on how policies will promote their development and coevolution with AFV market growth. Second, current historical national data on AFV licensing, provided by ANFAVEA does not disaggregate AFV types (battery electric and hybrid electric cars are accounted together), making it unfeasible to properly investigate their diffusion growth individually. Third, the increase in power demand, due to the growth of the AFV market, is also an important issue that needs to be further investigated, as the growth of AFV must be in line with the country's power generation capacity expansion.

Also, **s**everal assumptions were made in order to build the SD model. However, it is important to highlight they can be modified and updated as more data becomes available. One issue that may as well be explored in future work – and that it has not been done here – is the sensitivity of the AFV market to deep uncertainties in the long-term future. Approaches such as the EMA might help in shedding more light on how the AFV market will grow in the presence of highly uncertain model parameters. We find its applicability promising, but leave it, as well, for future work.

Finally, our study proves useful to test the effectiveness (and performance) of policies and, in a sense, offers insights to inform policy-making about the expected outcomes of specific policy interventions – from a complex systems perspective, in line with current debates and challenges within environmental and energy policy making.

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