Adoption of alternative fuel vehicles in the Netherlands

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Abstract: Today, several Western European nations are considering to reform their tax systems in order to reach a sustainable and just society. This process takes a lot of time and is subject to many complexities and uncertainties. Well-designed systemic policies may accelerate this process substantially. In this paper we investigate the effectiveness of alternative policies to accelerate the adoption of alternative fuel vehicles in the Netherlands. Recent insights in the Dutch vehicle market suggest the need for a better understanding of the environmental and financial effects of different policy alternatives across all sorts of uncertain developments in vehicle and infrastructure technology, alternative fuel availability and choice behavior. In this paper, we assess the robustness of alternative policies across parametric uncertainties, but also across structural and model uncertainties. In order to do so, we construct two system dynamics choice models to include assumptions of utility maximization as well as regret minimization – which, according to the literature, could result in very different levels of adoption. We then use these methods to test the current alternative fuel vehicles policy, a recently proposed alternative, and a closed-loop alternative.

Key words: Alternative Fuel Vehicles, System Dynamics, Dynamic Choice Modeling, Regret Minimization, Fiscal Policy Analysis

1. Introduction

The Dutch government and all private partners recognize the vital contribution of mobility to society. All parties in the Dutch system also recognize that the current automotive system has very negative effects on the economy, people and the environment (Ministry of Infrastructure and the Environment, 2014; Bakker, Maat, & van Wee, 2014). That is why these parties are in favor of a transition towards sustainable mobility. For several years, the Dutch government has been trying to reduce the negative external effects of automotive mobility by providing tax benefits for low- or zero-emission cars. However, past and current fiscal measures to stimulate Alternative Fuel Vehicle (AFV) diffusion in order to reduce the external effects have resulted in rather mixed outcomes.

Dutch subsidies to stimulate the adoption of Electric Vehicles (EV) and Plug-in Hybrid Electric Vehicles (PHEV) have on the one hand resulted in a considerable adoption of these vehicles on the Dutch car market. Today, there are approximately 7.000 EVs and 40.000 PHEVs on a total of approximately 8 million passenger vehicles (Dutch Environmental Agency, 2014; Rijksdienst voor Ondernemend Nederland, 2015).

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However, the fiscal policy has resulted in unforeseen adverse, even perverse, effects. For instance, due to a plethora of incentives, sales of the Mitsubishi Outlander PHEV have boomed (Dutch Environmental Agency, 2014), but are likely to bust with minor changes in the tax system. Although the Outlander is an expensive SUV, cumulating all tax measures makes that this high-quality car is practically for free. However, Outlanders contribute only marginally to the reduction of environmental externalities. Worse, they only do so in comparison to equivalent Internal Combustion Engine (ICE) vehicles. The Dutch tax system has nevertheless resulted in 15.275 Outlanders in the Netherlands (Rijksdienst voor Ondernemend Nederland, 2015). In fact, the tax system alone has made the Outlander the most popular AFV on Dutch roads. Ironically, it may even have seduced many Dutch to opt for an Outlander instead of a smaller, less polluting, car. Moreover, the costs of the tax policy have, due to the fact that these SUVs are expensive and are practically paid for by the tax payer, exploded (Dutch Environmental Agency, 2014). These and other unanticipated 'side-effects' of the Dutch tax policy suggest that a much better understanding of the role of the government and tax system related to the adoption of AFVs is needed (Wiebes, 2014).

Partly in response to these effects, the system has recently been modified – although marginally, by enough to change overall choice behavior. Again. However, within a few months' time, the Dutch tax system, including tax regulations related to passenger vehicle purchases, ownership and leasing (Wiebes, 2014), will be drastically reformed. This reform has been announced by the government to be a major tax shift in favor of labor and against pollution. This green reform is likely to have a very significant effect on the individual choice behavior related to AFVs and therefore of society as a whole (Chorus, Koetse, & Hoen, 2013). In view of influencing the governmental policy process, societal groups have recently suggested vehicle tax policies.

However, societal adoption of AFVs is not dependent on the tax system alone. According to the Ministry of Infrastructure and the Environment, the transition towards AFVs mostly depends on the evolution of EV technology and the availability of renewable fuels such as bio fuels and hydrogen (Ministry of Infrastructure and the Environment, 2014, p. 17). The literature also suggests that social interaction strongly influences technological adaption (Struben & Sterman, 2008; Keith, 2012; Struben J. , 2006). The interplay of these endogenous effects makes the transition to AFVs dynamically complex. Most of these effects are also highly uncertain. Before opting for one alternative tax policy or another, their environmental effectiveness and financial efficiency should therefore be tested thoroughly. An integrative approach that allows for exploring the effects of alternative policies across many possible effects and plausible futures is therefore needed. This is what the System Dynamics method is used for.

The focus of this research

In this paper, we investigate the robustness and sustainability of alternative tax policies to supporting the adoption of AFVs across many uncertain technology, fuels and choice behavior evolutions. We consider the two kinds of robustness discussed by Tetlow (2007): robust performance and robust stability. Robust performance is all about effectiveness across an ensemble of scenarios or a range of models. Robust stability captures whether a policy produces stable (economic) behaviour across an ensemble of scenarios or a range of models.

Figure 1 provides an overview of policies that could be analyzed. The time horizon investigated here covers the period 2015-2040. This time horizon is chosen because of the long term feedback loops that are active in both the automobile industry and the transition to new technologies in general, but also because of the short time horizon considered by Dutch policymakers (KiM, 2015). The key performance indicators considered here relate to the environmental contribution as well as the financial sustainability. The first goal of this research is thus to provide the Dutch government with a better understanding of the system to allow them to make better choices. The second goal of this research is to develop models that will be used by one of the Dutch planning bureaus and Dutch ministries to compare alternative policies.

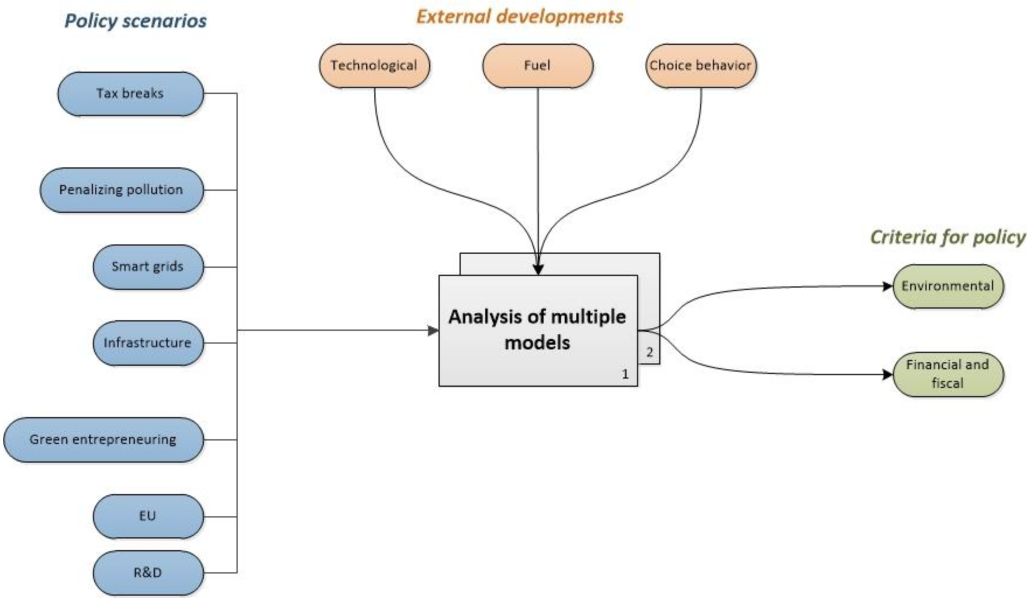

Figure 1 Overview of model analyses and policy testing for robustness (Bastiani, 2015)

The third goal of this research on the other hand is methodological, namely to compare different choice models. Usually in discrete choice behavior modeling with a multinomial logit function the parameter Beta, which mimics the preference for a specific alternative, remains a constant (Ben-Akiva, et al., 1999; De Dios Ortúzar & Willumsen, 2011; Chorus, 2010). In previous System Dynamics studies on the adoption of AFVs this parameter is assumed to remain constant as well (Struben & Sterman, 2008; Keith, 2012). They nevertheless model socialization effects to account for the change in people's perception after being confronted with a new technology. System Dynamics is a method to investigate and analyze such dynamically complex issues (Forrester, 1961; Pruyt, 2013). In this paper, using a System Dynamics model, we show to what extent the results of static choice models are affected by alternative assumptions and changing technology performance.

Therefore, we compare two paradigms – Random Utility Maximization (RUM) and Random Regret Minimization (RRM) – assuming alternative mathematical choice functions. Chorus, Koetse & Hoen (2013) have compared RUM and RRM for the adoption of AFVs in the Netherlands. They have estimated static choice models, so an interesting addition to their analysis is to explore what the effects are of a dynamic choice function for both RUM and RRM assumption based on their initial models. Previous research shows that RUM and RRM lead to different conclusions for the same choice experiments (Chorus, 2010; Beck, Chorus, Rose, & Hensher, 2013).

By definition, models are always wrong (Sterman, 2002; Pruyt, 2013). That is one reason why policies tested with models may not perform well when implemented in the real world. Severe or deep uncertainty may be a more important cause of divergence. Excellent alternatives for many scenarios may actually perform poorly in some scenarios and in different models. That is why we prefer to test for policy robustness under deep uncertainty, to come to designing adaptive robust policies (Hamarat, Kwakkel, & Pruyt, 2012). Adaptive means that the policy can be adapted according to the circumstances, for example to the market phase of the AFV technology. In order to do so, we use the Robust Decision Making methodology (Lempert, Popper, & Bankes, 2003; Lempert, Groves, Popper, & Bankes, 2006). Interestingly, this adaptive policy making approach is in line with the vision of the Dutch government and AFV-related sectors (Ministry of Infrastructure and the Environment, 2014).

Before studying the effects of alternative vehicle tax systems, we describe our model-based exploration. In section 2.1 the SD models are described to capture the difference between utility and regret choice functions. In section 2.2, four financial policies will be simulated. Finally, results will be discussed in section 3 with an outline for research after this paper will be given.

2. Modeling the dynamics of choice behavior and technological developments

In this section, the conceptual outline of the developed System Dynamics models is presented. Therefore a causal loop diagram is presented in Figure 2, which captures only the major variables of the models and the difference between utility maximization and regret minimization. For the full model descriptions, we refer to the attached model files and to the master thesis of Bastiani (2015).

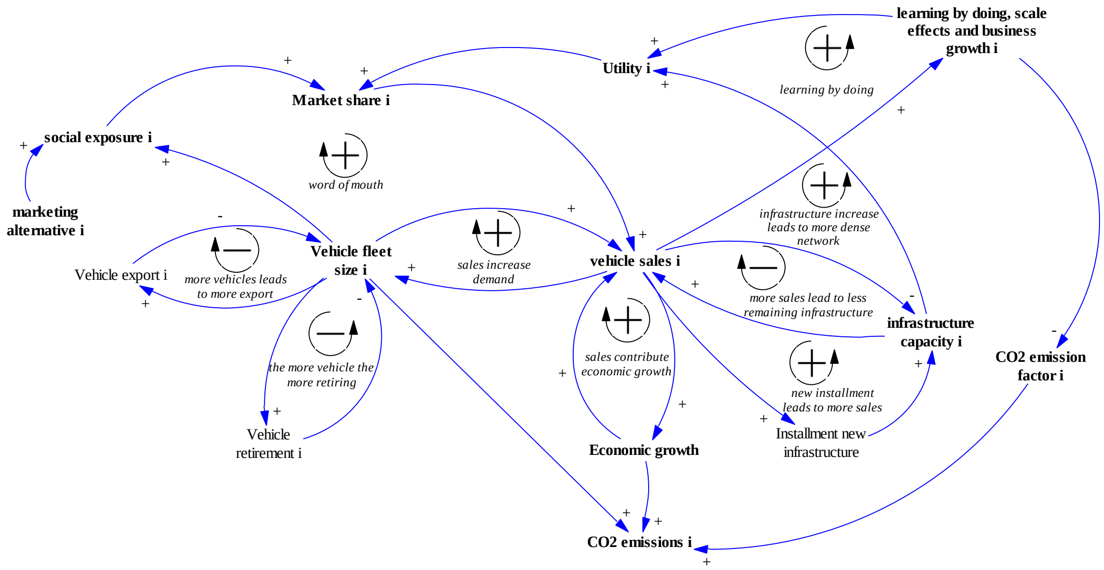

Figure 2 Causal loop diagram of specified SD model without policy (Bastiani, 2015)

Firstly, the vehicle fleet dynamics in the models are described. Secondly, it is showed how society's choice for a vehicle technology is modeled (with both utility maximization and regret minization) and how that contributes to the further development of that technology's market in the model. Thirdly, the feedback loops that largely explain the simulation model's behavior will be discussed. Finally, multiple tax policies will be tested under parameter uncertainty to obtain robustness.

2.1. The Simulation Models

Vehicle fleet dynamics

Changes in vehicle fleet sizes in the models occur due to new vehicle sales, export and retiring. In these models, no second hand vehicle sales are modeled. The aging of vehicles (from age 0 to 5 year to age 5 to 15 year) is internally modeled to represent different buying behavior of people always driving new vehicles and people driving second hand cars. It is assumed that after fifteen years vehicles retire on average.

Market shares, utility and regret

The actual choice for a vehicle technology is modeled by the market share auxiliaries. These market shares are calculated by dividing the exponent of the utility of an alternative by the sum of all the utilities of all alternatives (Ben-Akiva, et al., 1999). But first the utility U_i needs to be specified. This is the sum of empirically estimated parameters β_m, which are specific for each attribute variable, times the actual performance of the alternative on that attribute X_{im}. Additionally, but not mentioned in the formulae, is the addition of an alternative specific constant, or a systematic aversion people appear to have in the survey against a technology. This is represented by the following formula.

$$U_i = \sum_{\mathrm{m}=1}^{\mathrm{M}} \beta_m \times X_{im}$$

Using a multinomial logit (MNL) formula means that if a relative utility V_i of one alternative a increases, the market share P_j of another alternative j decreases. This is specified by the following function.

$$P_i = \frac{exp(U_i)}{\sum_{j=1}^{J} exp\,(U_j)}$$

In a second model, the regret minimization formula is used to calculate the systematic regret people might experience compared to another alternatives. In Figure 3 it is accentuated with yellow lines where the SD model changes when regret is assumed instead of utility. Regret R_i is then mathematically represented as follows (Chorus, Koetse, & Hoen, 2013).

$$R_i = \sum_{\mathrm{j} \neq \mathrm{i}} \sum_{m=1}^{M} ln\left(1 + exp\left[\beta_m \times \left(X_{jm} - X_{im}\right)\right]\right)$$

And the choice probability or market share is then only slightly different from the original RUM MNL formula.

$$P_i = \frac{exp(-R_i)}{\sum_{j=1}^{J} exp\,(-R_j)}$$

For all individuals there are many more possible attributes that determine one's choice. It is found in (Chorus, Koetse, & Hoen, 2013, p. 905) that seven attribute variables are statistically significant for the Dutch private car market.

For all individuals there are many more possible attributes that determine one's choice. It is found in (Chorus, Koetse, & Hoen, 2013, p. 905) that seven attributes are statistically significant for the Dutch private car market. These are purchase price, tax percentage charge for company lease (or Bijtelling in Dutch), own contribution for drivers using company leasing, driving range, detour time to refuel of recharge, recharge or refuel time and the number of available car models of a technologies. Additionally, two policy alternatives (free parking and the use of dedicated bus lanes for a technology) and their coefficients are estimated by Chorus et al. and they are also included in the model for future use.

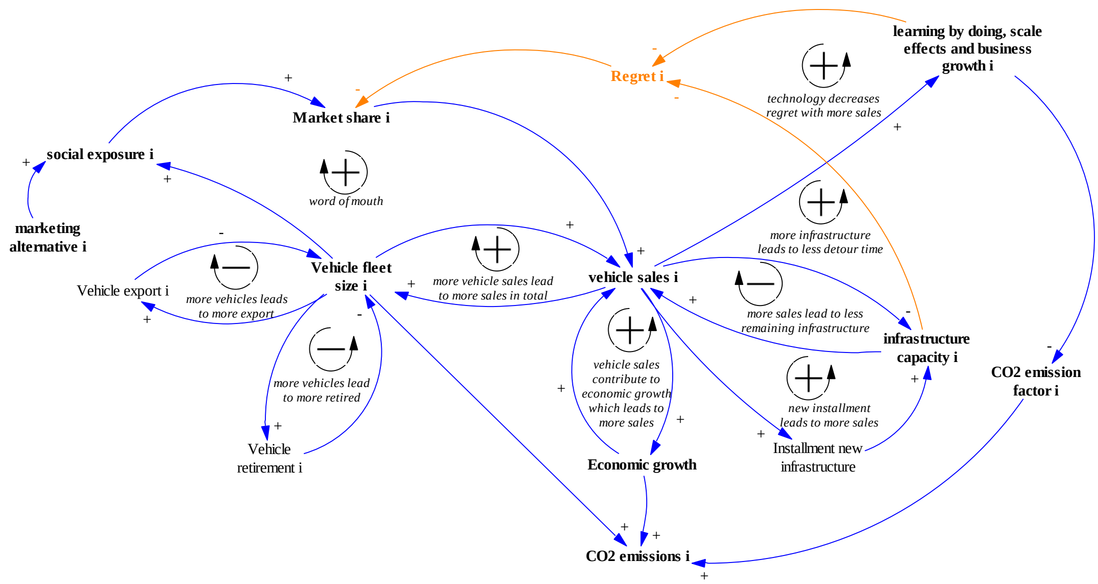

Figure 3 Causal loop diagram of model assuming regret minimization (Bastiani, 2015)

The actual demand for vehicles of a technology is modeled by multiplying the market share from the choice function times the total demand for cars for the entire car fleet and a socialization multiplier (see next section). This drives the actual adoption or discarding of the technology in the model, which is dependent of the actual supply of the technology (Keith, 2012) and the capacity of the infrastructure (Eising, van Onna, & Alkemade, 2014).

Socialization

When the size of the fleet of technology i increases, social exposure to that technology increases (Keith, 2012; Struben & Sterman, 2008). This can be modeled in many different ways. Keith and

Struben & Sterman model it with a complex co-flow structure to keep track of people's perceptions when they use a technology i, and how they perceive technology j and other technologies. In the specification of this paper's model, it was found that this complex construct can just as well be replaced by a much simpler function and get identical results for this analysis.

In order to stay close to the empirical foundation of the previously described choice models, socialization is modeled by specifying a multiplier for the demand of a technology i. This keeps the calculation of market shares mathematically intact as the sum of all shares remains equal to one. This multiplier is always the value 1 for gasoline, as that is the technology that everyone is familiar with already. It is assumed that in the scope of this study, no technology can compete with gasoline to make people forget about the technology.

This configuration allows for a simple, but unfounded, way to model the social effects on the adoption of a technology. First impressions show similar results to Keith's (2012) of modeling the effects, albeit far more simple and therefore preferable. Future analyses should show if this model assumption produces stable results with exploratory modeling.

Learning curves and R&D

Feedback occurs from the adoption of a technology towards the knowledge and expertise of car manufacturers, the maintenance industry and other supporting industries (Sterman, 2000). This effect is captured by a learning curve function that is found in (Keith, 2012; Struben & Sterman, 2008) and is used to improve the quality of a technology proportionally to the extent to which it is adopted.

When an attribute variable like the purchase price of a vehicle is supposed to decline due to learning effects and scale effects in the manufacturing process, the attribute variable is divided by the learning effect. If the attribute is driving range of electric vehicles, the initial driving range is multiplied by the learning effect.

No spillovers of knowledge have been taken into account so far. It is reasonable to assume that if for instance electric cars use lightweight materials to be more efficient, gasoline cars will take advantage of that knowledge. This is likely because the majority of developers of electric cars are the same as gasoline cars (if we ignore Tesla and other niche market developers). Also, it is prudent to note that the knowledge level of a technology at a specific point in time is assumed to be equal to amount of vehicles that are adopted at the point in time. It is very likely that the relation is nonlinear, as current gas vehicle manufacturers have a major advantage to new technology developers when it comes to R&D and knowledge.

Infrastructures

It is found in literature that the electricity grid could prove to create a barrier to growth of EVs (Eising, van Onna, & Alkemade, 2014). Therefore it is modeled how the capacity of the energy infrastructure behaves over time. Eising et al. state that Liander (a major Dutch energy supplier) can harbor approximately an additional 1.7 million EVs at this point in time. Liander services approximately 37% of Dutch households, so a rough estimation of the total additional capacity of EVs can be made, assuming that Liander is just as spatially dispersed in The Netherlands as the other suppliers. Then 1.7/37*100=4.6 million (PH)EVs can be serviced in the Netherlands at this point in time. However, this estimation of Liander assumes a 4kVA charging station. Because of desire of consumers for fast charging 12kVA stations might be expected to be installed in the future. In that case the actual capacity is far lower. Also in urban areas, the network load is much more problematic than on an national level (Eising, van Onna, & Alkemade, 2014). So an actual effective additional capacity of 50% of the estimated capacity is chosen, just to be safe, and assumed finally to be 2.3 million battery electric or plugin hybrid electric vehicles.

For new installment, a forecast over future energy demand for EVs and PHEVs is used to predict new installments to be made in time by the electric network providers. This installment could be slower than the growth of electricity based vehicles requires, leading to a dampened growth of the technologies. A potential policy could then be investing in new infrastructure or even in the use of smart grid technologies.

The effects of the infrastructure dynamics comes back to the choice function through the attribute variables of recharging and refueling time and the additional detour that has to be made to reach the infrastructure. For the detour time this is assumed to be a linear relation between the amount of gasoline stations that are present in 2015, having a 0 minute addition detour, against a 30 minute additional detour when there is hardly any infrastructure in 2015. A lookup function needs to be specified to model this effect on the detour variables. The charging time will be modeled as partly dependent of the learning curves of the technology and partly dependent of the available infrastructures.

Economy

Economic growth is found to influence the amount of vehicle sales in the Netherlands (Bastiani, 2015). Therefore, the rate at which new cars are sold is partially dependent of the economic growth and a stochastic component. Economic growth is then again increased when vehicle sales grow autonomously, albeit with a very marginal effect. The majority of economic growth is modeled by a smoothed stochastic component as well, uniformly distributed between a range of -3 and +4 percent growth of GPD per year.

Transport performance and emissions

Derived from the economic growth is the change in individual transport performance (vehiclekilometer per year). This change heavily influences the model's performance on CO_2 emissions, which is also dependent the total amount of cars of a given technology and the corresponding emission factor of that technology.

Finances

Not visualized in the causal loop diagram is the financial component of the models. The tax revenues for the Dutch government are investigated in order to account for the financial robustness of the policies. Tax revenues are represented in this model by car sales tax (an additional CO_2 dependent penalty) and tax percentage charges for company leasing. General road taxes (taxes everyone with a car has to pay) are excluded from the analysis because of the indirect presence of that tax component in the individual contribution of the choice models. It was also not possible to derive those tax revenues from Dutch statistics.

2.2. Analysis

Results of tax policies

In this section five policy scenarios will be discussed. Firstly, policy scenario 1 depicts the current policy settings as it is in 2015. The second policy scenario constitutes a proposal by the Dutch State Secretary of Finances. The third policy comes from a major alliance of private car owner federations to make the Dutch car tax system more simple and enable more market efficiency. The fourth policy explores the potential effects and behavior of the model when all electric cars are taxed at 0% and conventional fuels are taxed at an increasing tax rate. These result cannot be taken to be predictive because the models require additional testing. The results do show different adoption behavior in the model while remaining financial stability of tax revenues. This could indicate leverage points that would qualify for both financially and environmentally robust policy.

Policy #	Policy name
1	Base scenario
2	Proposed policy new tax system by State Secretary
3	Equal market opportunities for all technologies
4	Full government commitment to EV, paid by penalizing emissions
5	Full government commitment to EV and fuel cell, paid by penalizing emissions

Table 1 Overview of policy scenarios

First, the results of the base scenario for both RUM and RRM will be compared to give an understanding of the difference in outcomes. Figure 4 shows the different outcomes of a latin hypercube sensitivity simulation of both RUM (red) and RRM (green) for the actual market share of PHEVs. The sampling is done across an uncertainty ensemble of multiple parameters regarding the learning curve, socialization, infrastructure and economic growth. Apparently, the choice models already force a high dislike for conventional technologies, as the other technologies show similar graphs of adoption. RRM shows an even higher dislike for conventional gasoline, which is retraceable to the choice model.

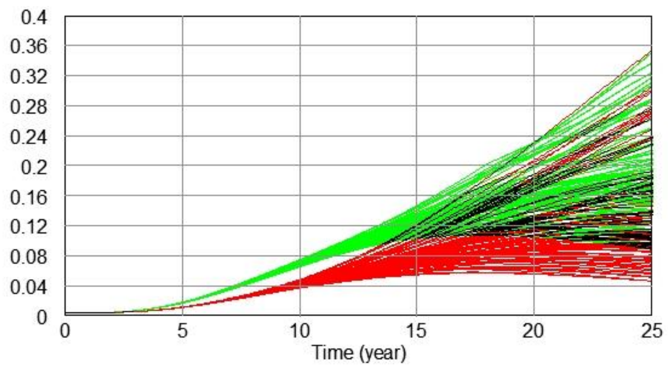

Figure 4 Comparison of utility maximization (red) and regret minimization (green) of Policy 1 Base scenario for the market shares of PHEVs

The single model runs are presented (Figure 5) to easily present the results of the different policies on CO2 emissions. Albeit somewhat unrepresentative of real emissions, already because of the unrealistic emission factors published by car dealers, the different performances of the policies can be derived from the graph. Under the earlier mentioned uncertainty ensemble, the models produce similar results so far. These results are shown for RUM, and the order of policies does not change with RRM except for the absolute values.

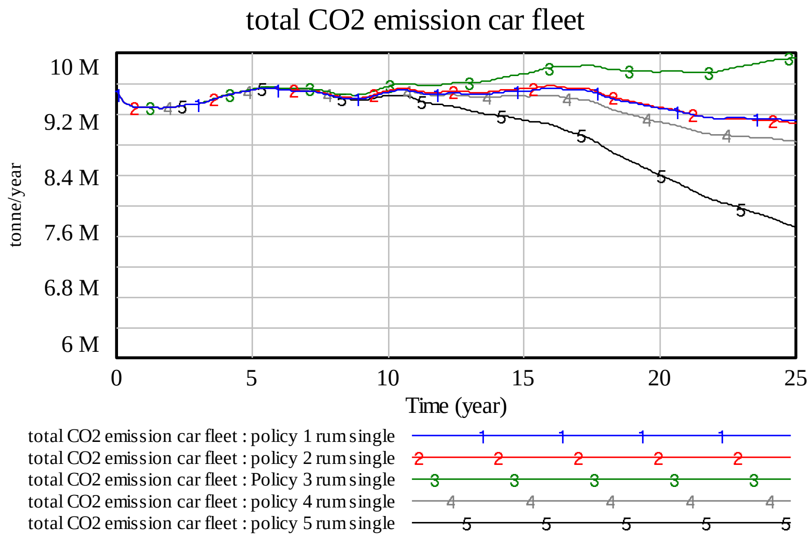

Figure 5 Overview of single model run results

Such a difference in absolute numbers of the most environmentally favorable policy 5 is presented in Figure 6. The market shares of fuel cell technology shows more growth under RUM than under RRM, where it shows relatively more goal seeking behavior.

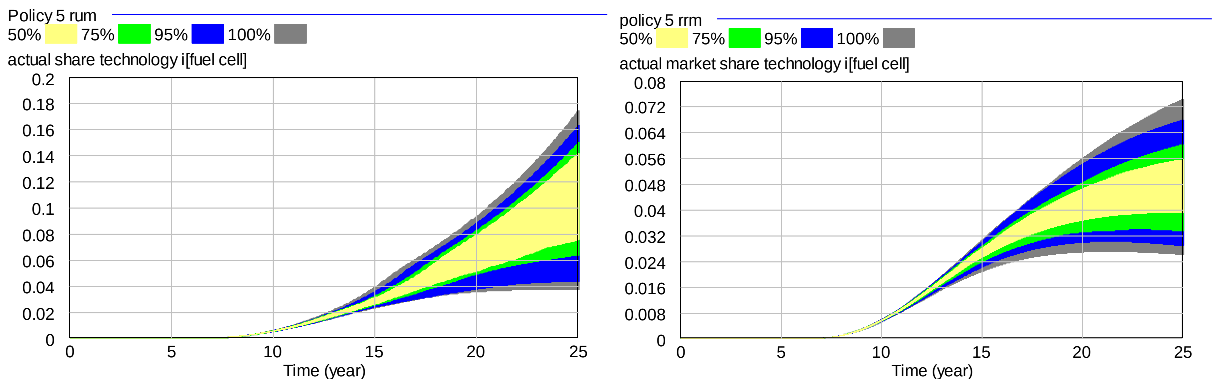

Figure 6 Comparison of market shares of fuel cell vehicles under the uncertainty ensemble in both RUM (left) and RRM (right)

3. Discussion and concluding remarks

In this paper we have seen a first attempt of fulfilling the research goals of identifying Dutch tax policies alternatives that both sustainable and robust. The different System Dynamics models assuming utility maximization and regret minimization allow for a first glance into the effect of policy scenarios with financial incentives under deep uncertainty. Less discussed but also captured by those models is feedback from the adoption development on prices and endogenous choice behaviour changes through social interaction. This is much in line with other SD studies for this topic (Struben & Sterman, 2008; Keith, 2012; Ford, 1995).

A first conclusion from the model experiment that is shown in this paper that the structure of a tax incentive policy for different fuel technologies matters for the outcome of policies regarding adopting AFVs. From this it can be concluded that shifting the tax system to increasingly taxing the gasoline technologies whilst keeping the electric and hydrogen based technologies tax free results into different behavior of the model. The fleet shares of the green alternatives appear to grow faster than with the current policy or the currently suggested policies. Although much testing needs to be done before this claim can be supported, one can also note that these policies are not adaptive. In future research it will be attempted to model an earlier shift to a different tax policy, so the tax revenues can remain even more equal to the base scenario results. An alternative use of the additional tax revenues could lie in investing that tax revenue in new infrastructures

As alternative fuel vehicle technologies improve over time, the gasoline alternative becomes a more extreme alternative in people's perceptions. RRM literature suggests that people prefer compromise alternatives over extreme alternatives (Chorus, 2010). This difference in assumption is therefore concluded to be of major importance for future predictions of technology adoption. For conclusive insights in the actual effects of tax policies and other policies, these two assumptions are not enough to reach policy robustness. Therefore it is recommended to develop even more model in parallel to these models, and simulate and analyze them under deep uncertainty with the exploratory modeling and analysis workbench of TU Delft (Hamarat, Kwakkel, & Pruyt, 2012; Kwakkel & Pruyt, 2013; Hamarat C. , Kwakkel, Pruyt, & Loonen, 2014).

Finally it is concluded that in this model study, the alternative of increasingly penalizing conventional fuel technologies with giving zero emission technologies a full tax break (full electric and fuel cell) is most environmentally robust. For financial robustness, the currently proposed alternative by the State Secretary of Finances is most recommendable. The analysis also shows a high increase in tax revenues in the gasoline penalty. This additional money could be reinvested in many ways to accommodate more AFV adoption, but future research needs to capture this effect. Also, future research using exploratory modeling and analysis is needed to explore true deep uncertainty.

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