Energy Use and Emissions Impacts from Car Technologies Market Scenarios: A Multi-Country System Dynamics Model

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ABSTRACT

In the context of high energy use and greenhouse gas emissions from road passenger transport, the prospects of market diffusion of new car technologies is at present time uncertain. For instance, the impact of current oil prices on the market uptake of electric vehicles is yet to be seen. Systems thinking and scenario analysis are useful to explore possible future outcomes. This paper focuses on car technologies scenarios for the Chinese, German and US markets until 2030. The technologies investigated are: gasoline, diesel, flexi-fuel, liquefied petroleum gas, natural gas, hybrid, plug-in hybrid, battery electric and fuel cell vehicles. Based on the System Dynamics approach, a model integrating discrete choice and accounting frameworks is developed. The developed System Dynamics model is applied to examine alternative policies and to estimate energy use and emissions in each of the markets under various scenarios. The model results illustrate the importance of taking indirect emissions into account. In conclusion, simulated policies sensibly alter car technology uptake and have an impact on the environment. Finally, the ideas of feedback process and expansion of model boundaries are considered to be crucial in modeling such a complex and uncertain system.

Keywords: *electric vehicles, System Dynamics, market scenarios, environmental impacts*

1. INTRODUCTION

Problem Context

According to the fifth assessment report by the Intergovernmental Panel on Climate Change (IPCC), transport generated directly 7.0 gigatons of CO_{2eq} in 2010 (IPCC, 2015). This results from transport activities that involve fuel combustion. Transport-related energy use and emissions are expected to increase if current projections of global vehicle stock growth (Gomez et al., 2013) materialize. Goals have been set by national governments to reduce energy use and greenhouse gas (GHG) emissions from the transport sector (EVI, 2013). With regard to passenger travel by car, technological progress is expected to contribute toward these goals. In particular, technological improvements in internal combustion engine vehicles (ICEVs) and technology substitution of conventional for advanced technologies such as electric vehicles (EVs) are being internationally promoted. In 2014, there were over 665,000 EVs worldwide (EVI, 2015). Despite these plans, the successful market penetration of these technologies is highly uncertain to date. Sustained relatively low oil prices[1] do not favor the market penetration of new, cleaner car technologies. Policy analysis is required to better understand the implications of differing development pathways for alternative car technologies.

Objectives, Scope and Structure

The main objective of this paper is to explore possible future energy and emissions impacts corresponding to different configurations of the car stock[2] in a specific market. For this, estimation of levels of car ownership and investigations of policies that may affect car technology choices are required. With this goal in mind, we generate market scenarios by means of a System Dynamics (SD) model that incorporates feedback processes. The purpose of the model is to enable the model user (ideally, policy-makers) to experiment with the consequences of policy measures implemented in the model.

The following 9 car technologies[3] are included in the model: Gasoline (G), Diesel (D), Flexi-Fuel or Biofuel (FF), Liquefied Petroleum Gas (LPG), Natural Gas (NG)[4], Hybrid (HEV), Plug-in Hybrid (PHEV), Battery Electric Vehicles (BEV) and Fuel Cell or Hydrogen (FC). The model simulates from the year 2000 until 2030. A calibration period from 2000 until approximately 2010, depending on data availability, is considered. In its current version, the model represents (using subscripts) the following 3 key car markets: China, Germany and the US. These countries share the common

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[1] At the time of writing (2 March 2015), crude oil prices are at \$62.58 per barrel of Brent and \$49.76 for the West Texas Intermediate (Oil-price.net, 2015).
[2] We use the term 'car stock' throughout to refer to the number of cars operating in a given country in a particular year. Other terms are often used: see e.g. footnote 1 on (Struben and Sterman, 2008).
[3] Throughout this paper, the term "technology" refers to car powertrain technology.
[4] Represented by Compressed Natural Gas (CNG) cars.

criteria of having a high level of car stock and having declared interest in the market uptake of EVs.

The remainder of the paper is structured as follows: section 2 contains an overview of the literature and introduces the research approach. In section 3, the model is described. Section 4 presents the model results. In Section 5, conclusions are drawn and further research needs are sketched.

2. SURVEY OF STUDIES AND RESEARCH APPROACH

Survey of Studies

Due to the wealth of available studies on the subject, this survey is selective and we restrict ourselves to research questions involving: (i) car ownership forecasting, (ii) choice of the type (e.g. technology) of car, and (iii) estimation of energy and emissions impacts.

Given the topic of this paper, two main bodies of literature were identified: global simulation models and national SD models. The former group of models includes three large-scale models that provide relevant scenarios or roadmaps: IEA Mobility Model (MoMo), ICCT Energy Roadmap and UNECE ForFITS. Table 1 shows their main features.

Table 1 – Overview of global simulation models

Model	Editor	Country	Time Horizon	Vehicle Technologies	Key Model Ouput
Mobility Model (MoMo)	IEA	Global (29 world regions)	2050	G / D / LPG / CNG / HEV / PHEV / BEV / FC	- Market shares - Energy use - Emissions
Energy Roadmap	ICCT	7 world regions & 9 individual countries	2050	G / D / FF / LPG / CNG / HEV / PHEV / BEV / FC	- Energy use - Emissions (GHG & local pollutants)
ForFITS	UNECE	Global	2040	31 powertrains	- Transport activity - Energy use CO_2 emissions

Source: own representation based on (IEA, 2009), (ICCT, 2012) and (UNECE, 2015)

Strictly speaking, none of these models can qualify as an SD model *if* feedback processes[5] are not explicitly incorporated, which seems to be the case at present time. In our view, ForFITS has the potential to become a truly SD model in a future version, as it has already been implemented in the Vensim® platform.

The second group contains models that are more consistent with the SD philosophy. For the choice of technology, most of the available studies make use of some logit framework. Discrete choice modeling is a common method to estimate the market penetration of new vehicle technologies (Al-Alawi and Bradley, 2013). We distinguish between "estimation" and "application" studies. By "estimation" studies we mean those that are the result of designing and conducting a survey[6] and statistically estimating discrete choice model parameters. The resulting output of primary interest is a set of (utility) coefficients. Within this group, we highlight the papers listed in Table 2.

Table 2: Selected "estimation" studies

Author(s)	Country	Vehicle Technologies	Model Type*** [# Attributes]
(Bunch et al., 1993)	US (CA*)	Gasoline / Alternative** / Electric	NMNL [5]
(Brownstone and Train, 1998)	US (CA)	Gasoline / CNG / Methanol / Electric	Mixed MNL [10-12]
(McFadden and Train, 2000)	US (CA)	Gasoline / CNG / Methanol / Electric	Mixed MNL [10]
(Brownstone et al., 2000)	US (CA)	Gasoline / CNG / Methanol / Electric	MNL / Mixed logit [>10]
(Achtnicht, 2011)	Germany	Gasoline / Diesel / Hybrid / LPG/CNG / Biofuel / Hydrogen / Electric	Standard / Mixed logit [6]
(Ziegler, 2012)	Germany	Gasoline / Diesel / Hybrid / Gas / Biofuel / Hydrogen / Electric	MNP [5]
(Hackbarth and Madlener, 2013)	Germany	Gasoline / Diesel / CNG / LPG / HEV / PHEV / BEV / Biofuel / Hydrogen	MNL / Mixed logit [8]

*CA = State of California. **Methanol, ethanol, CNG (see page 6). ***MNL = Multinomial Logit / NMNL = Nested-MNL / MNP = Multinomial Probit.

Source: own representation based on the original references

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[5] Feedback loops can be seen as the result of "the endogenous point of view" (Richardson, 2011).
[6] Usually based on stated preferences (SP). Fortunately, revealed preference (RP) data is becoming increasingly available (cf. e.g. (Schühle, 2014)). See (Brownstone et al., 2000) for some critical issues related to SP-RP data.

By "application" studies we mean here those that develop a discrete choice modeling framework capable of deriving market shares based on selected information from "estimation" studies. In our view, "application" studies represent a pragmatic application of the results derived from "estimation" studies. A selection[7] of "application" studies based on SD modeling is shown in Table 3.

Table 3 –Selected "application" studies

Author	Main Purpose*	Country	Time Horizon	Vehicle Technologies	Applied Logit Values
(Ford, 1995) (BenDor and Ford, 2006)	PP	US (CA)	2020	G / AL** / CNG / HEV / BEV	(Bunch et al., 1993)
(Schade, 2005)	PP	EU	2050	G / D / FF / LPG / CNG / HEV / BEV / FC	-
(Meyer, 2009)	AI	Japan / Germany	2035	G / D / HEV / BEV / FC	(BenDor and Ford, 2006)
(Walther et al., 2010)	AI / PP	US (CA)	2021	G / D / HEV / PHEV / BEV	(Brownstone and Train, 1998)
(Weikl, 2010)	AI	Germany	2030	G / D / LPG / CNG / HEV / EV	-
(Wansart, 2012)	AI / PP	US (CA)	2030	ICE / HEV-G / HEV-D / PHEV / BEV / FC	(Brownstone and Train, 1998)
(Keith, 2012)	AI / PP	US	2050	G / HEV / PHEV / BEV	(Brownstone et al., 2000)

*Main purpose: Public Policy (PP) and/or Automotive Industry (AI). **AL = Alcohol.
Source: own representation based on the original references

The application of a logit framework to derive market shares for each vehicle technology allows the calculation of sales by type of technology. Relying only on this method, disregarding the importance of feedback loops and path dependency (Sterman, 2000), is however a severe limitation (Gomez et al., 2014).

Invariably, the studies mentioned in Table 3 need to make assumptions concerning car ownership levels and the resulting total number of cars operating in the area of analysis. In mature markets, the assumption of a constant car stock is usually adopted.

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[7] Other models of interest are (Keles et al., 2008), (Struben and Sterman, 2008), (Krail, 2009), (Armenia et al., 2010), (Park et al., 2011), (Kühn and Glöser, 2012), (Shepherd et al., 2012) and (Kieckhäfer, 2013).

Research Method

In dealing with complex social systems, Meadows identified four common research methods: optimization, input-output, System Dynamics and econometrics (Meadows in (Randers, 1980)).

In order to successfully deal with the uncertainties of an inherently complex system, an adequately holistic perspective is required. The benefits of systems thinking have been highlighted by, among others, (Senge, 2006) and (Meadows and Wright, 2008). In cases of policy-making in a context of high uncertainty, the scenarios method is suitable for exploring alternative options (Grunwald in (Möst et al., 2009)) (Dieckhoff et al., 2011) (Dieckhoff et al., 2014).

Furthermore, the use of computer-based numerical simulation models can contribute to an increase in understanding on the quantitative impacts of different policy options, thereby improving the effectiveness through which they act.

Consistent with the ideas of systems thinking, scenarios analysis, and feedback thought and policy analysis, we choose to develop an SD model in an attempt to meet the research objective stated in section 1. Note that some of the studies listed on Table 3 have a main focus on the automotive industry and some on public policy. This can be understood as a reflection of the fact that SD, although initially conceptualized for industrial and corporate problems, later found successful applications in a wide range of areas dealing with public policy. In any case, our main interest is in studying problems relevant for public policy. In addition to the models we have mentioned in this section, the SD approach has been applied to many other transport problems[8].

Pioneered by (Forrester, 1958) (Forrester, 1961) (Forrester, 1968), SD stands today as "a computer-aided approach to policy analysis and design", applicable to dynamic problems that require feedback thinking (SDS, 2014). (Richardson, 1991) traces the origins of SD to the thread of "engineering - servomechanism" research in the social sciences.

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[8] A special issue was devoted to transport on the SD Review (Shepherd and Emberger, 2010) and a more recent review of SD applications on transport is given by (Shepherd, 2014).

3. THE DEVELOPED MODEL

Following (Bossel, 2007), the modularization approach is adopted and the model is conveniently split into 9 views[9], each of them representing a particular module. The linkages among the different model modules are represented schematically in Figure 1.
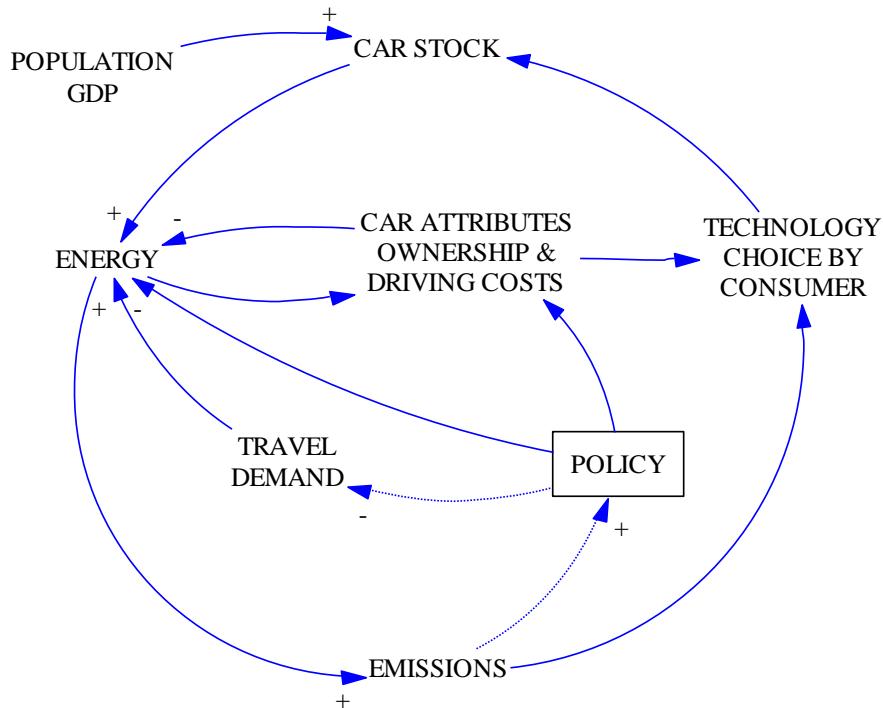

Figure 1 – Representation of the module linkages
Source: own work using Vensim®

Since Figure 1 represents modules and not individual variables, no link polarity is shown for some of the arrows connecting modules, as these in fact entail various linkages (from which an ambiguous relationship between modules arises). For those arrows with a single polarity, the sign of the polarity is shown. It has to be acknowledged that representing the sign of the feedback loop in this type of graph is not straightforward. Further details about the specific relationships and feedback loops (including polarity sign when relevant) are shown for each of the model modules in the following sections. The description of each of the modules below is rather concise: the documentation of the values of assumptions and equations can be found at the end of the paper (see Appendix).

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[9]Figure 1 shows 8 modules, because the "Car Attributes" and the "Ownership and Driving Costs" modules are merged in that figure. In the model, the "Car Attributes" module also contains an "Infrastructure" component. The dotted arrows indicate feedback assumptions that are implicit in the current version of the model.

Population – GDP Module

Key socio-economic assumptions drive the model. These include population and gross domestic product (GDP). Concerning population, although the model can be exogenously fed by available data (UN, 2012), it was deemed more insightful to use that data to approximately determine the reference values of the fractional birth rate. In this way, the model user can still easily vary the population assumptions. A more elaborate population model using cohorts, although feasible to implement, is not developed in this version of the model. With regard to GDP, growth is assumed in all the countries, partially based on (WB, 2014). In the case of China, the rate of growth decreases as the year 2030 is approached.
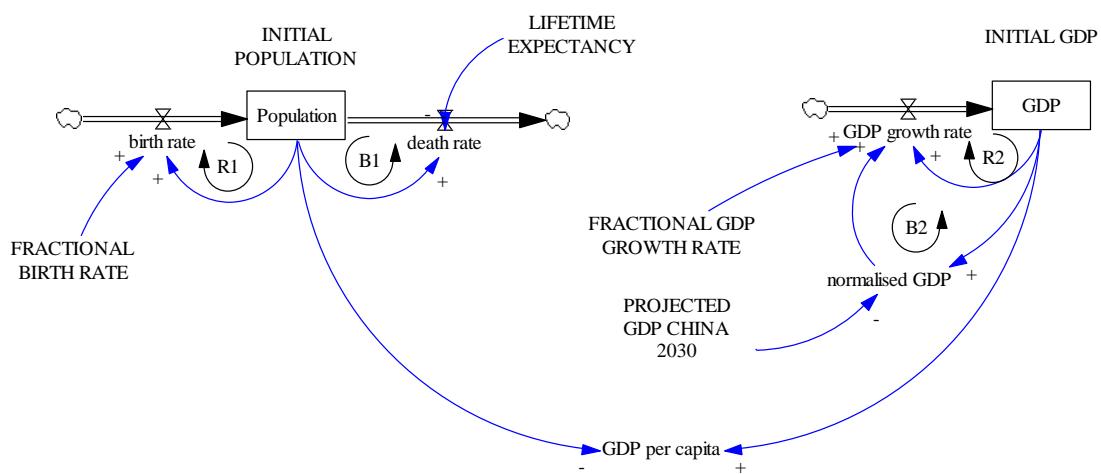

Figure 2 – Structure of the module "Population - GDP"
Source: own work using Vensim®

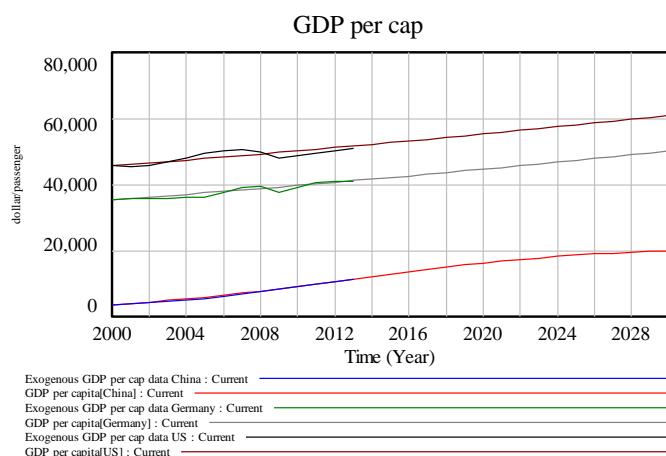The output of this module is "GDP per capita", which enters the "Car Stock" model as an input.

Figure 3 – Behavior of "GDP per capita": historical and simulated
Source: own work using Vensim®

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Travel Demand by Car Module

The main assumption in this module[10] is average annual car mileage. For simplicity and scenario comparability issues, we assume a constant "annual VKT by car" (vehicle-km traveled) of 13,000 km for all the countries. Although satisfactory data for these variables is available for Germany and the US, in the case of China no access to reliable data could be gained.

The key outputs of this module are: (i) VKT, used as an input by the "Energy" module; and (ii) "PKM by car" (passenger-km), which is affected by VKT and can be influenced by policies targeted at average car occupancy rates.

There is a potential of making this module more sophisticated and realistic by linking travel demand by car to income (e.g. using elasticity values).

Car Stock Module

This module contains two sub-sections: the projection of the aggregate car stock and the simulation of the car stock disaggregated by technology. The latter contains a set of subscripts with 9 car technologies.

With regard to the projection of the aggregate car stock, a nonlinear growth model formulation has been chosen. Although different functional forms are available in the literature, we adopt a Gompertz function following (Dargay et al., 2007) and fit coefficients using the calibration optimization tool provided by Vensim®. Key parameters affecting the car ownership ratio[11] are GDP per capita and the level of car saturation.

(Sterman, 2000) warns against over relying on curve fitting exercises. In the second sub-section, we create a stock-and-flow formulation with two levels representing the stock of new cars (≤1 year) and the stock of older cars (>1 year), disaggregated into 9 possible car technologies. The sales rate is the result of "the demand for replacement" and "the demand for first purchase", a distinction recognized long time ago by (Wolff, 1938). It is initially assumed that 50% of the scrappaged cars turn into replacement sales for the *same* technology, creating a reinforcing feedback loop. For this, a constant[12] named "share of technology switching" has been created. Concerning "the demand for first purchase", the simulated choice of technology is determined by the output of a discrete choice modeling framework (see the "Technology Choice" module).

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[10] Since this basic module does not contain feedback processes, its structure is not shown here. Refer to the Appendix for further details.

[11] Other common terms are "car ownership rate" or, more generally, "motorization rate" (usually measured as the number of cars per thousand people). In order to avoid the use of the word "rate", which is in this module reserved for the inflows and outflows from the car stock, we choose to use "ratio" instead.

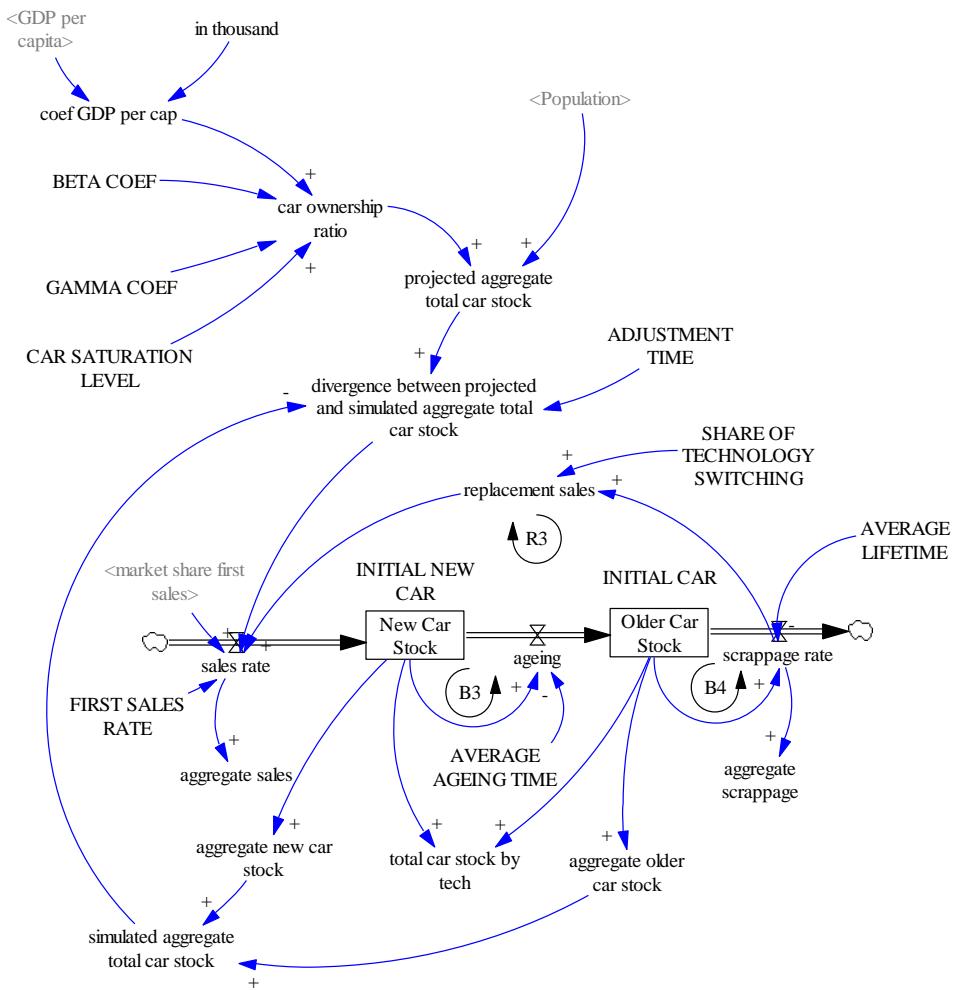[12] In the model, constants are written using capital letters.

Figure 4 – Structure of the module "Car Stock"
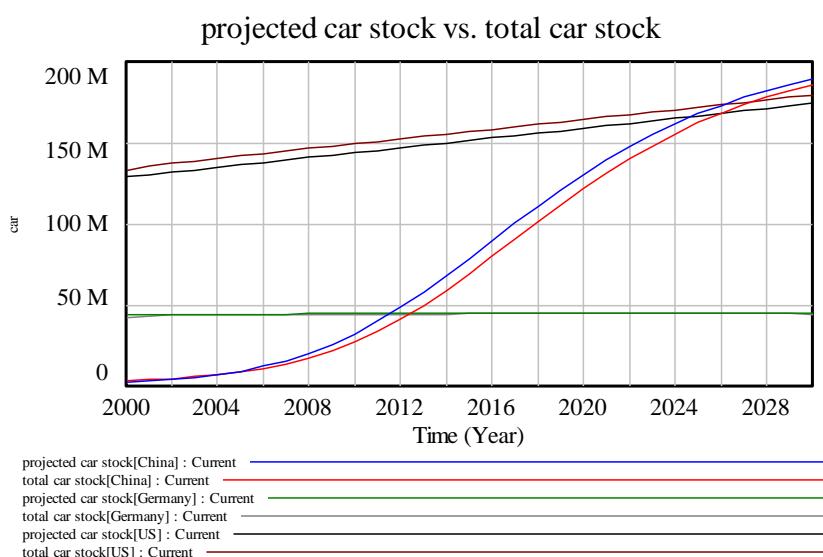Source: own work using Vensim®

Figure 5 –Behavior of "aggregate car stock": projected and simulated
Source: own work using Vensim®

The link between both sub-sections is provided by the dummy variable "divergence between projected and simulated aggregate total car stock". The resulting simulation behavior is a rough approximation of the projection trend, as can be seen in Figure 5.

Car Attributes and Infrastructure Module

This module is divided into two sub-sections: car technical attributes and infrastructure availability. The former contains the representation of car fuel efficiency improvements. The latter shows the assumptions concerning the deployment of fuelling/charging infrastructure. Both sections can be heavily influenced by policy inputs. In the case of car fuel efficiency, emission standards define the rate of technological improvement for ICEVs. Approved policy is already incorporated by default into the model (e.g. EU emission standards for gasoline and diesel cars until 2021). Thus the model user can, in this example, set new emission standards for the period 2022-2030.
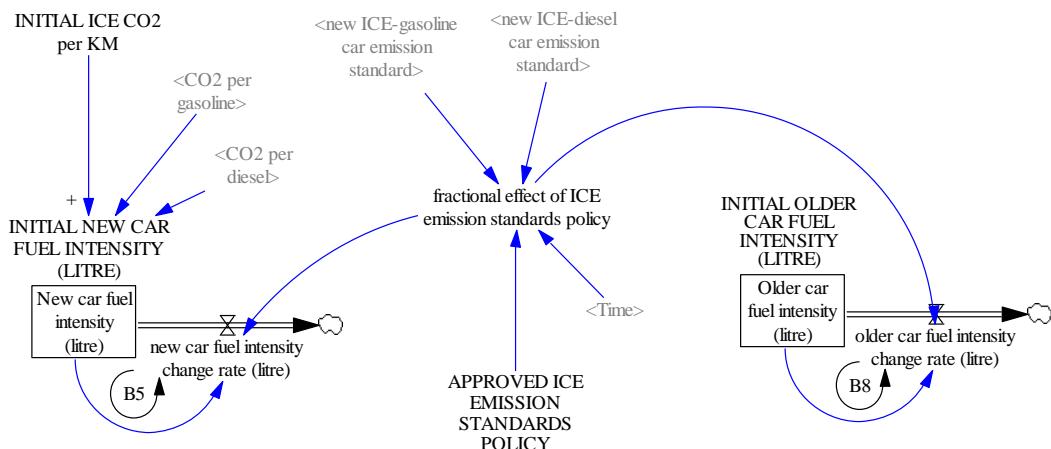

Figure 6 – Partial view of the module "Car Attributes and Infrastructure"
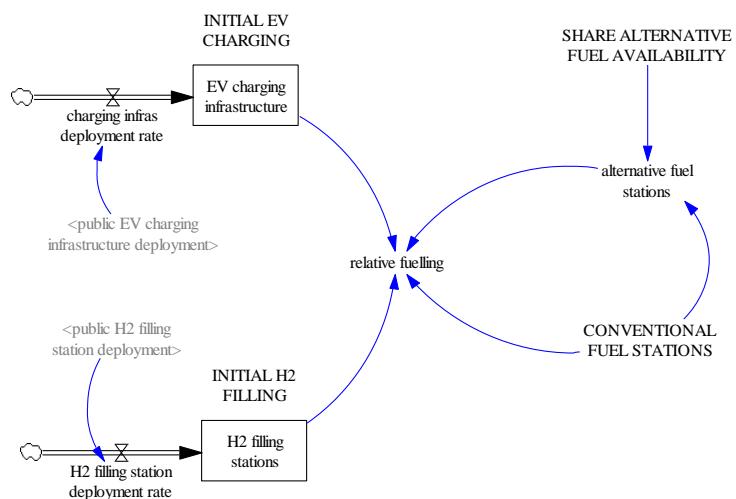Source: own work using Vensim®

Figure 7 – Partial view of the module "Car Attributes and Infrastructure"
Source: own work using Vensim®

The key outputs of this module, namely car fuel intensities, relative range and relative fuelling, are used as inputs to the "Technology Choice" and "Energy" modules.

Ownership and Driving Costs Module

This module is divided into two sub-sections: "ownership costs" and "driving[13] costs". For the initial assumptions, the information shown on Table 4 has, to a large extent, been followed.

Table 4 – Real-world information by selected car technology

Make (*version*)	Technology	Battery capacity [kWh] (range [km])	Consumption (per 100 km)	Car price (US dollar)***
Toyota Auris (*Comfort*)	Gasoline	0	5.4 l	21,761
	Diesel	0	4.2 l	24,000
	HEV (gas.)	-	3.6 l	25,741
Nis. Leaf (*Visia*)	BEV	24 (199)	15.0 kWh	32,337
VW Golf (*Comfort-line*)	Gasoline	0	5.0 l	26,058
	Diesel	0	4.5 l	28,535
	CNG (gas.)	0	3.5 kg	27,664
	BEV	24,2 (130-190)	12.7 kWh	38,010
Ford Focus (*Trend*)	Gasoline	0	5.0 l	22,349
	Diesel	0	4.5 l	24,199
	FF	0	8.3 l	23,981
	LPG	0	7.6 l	25,125
	BEV	23 (162)	15.4 kWh	43,558
Opel Ampera	EREV**	16 (40-80)	1.2 l / 16.9 kWh	42,066
Toyota Prius (*Comfort*)*	HEV (gas.)	-	4.0 l	30,448
	PHEV (gas.)	4.4 (23)	2.1 l (combined)	39,881
Toyota Mirai*	FC	NA	NA	57,500

* Segment D (the rest of the cars belong to segment C). ** EREV = Extended Range EV (gas.). *** Original prices in Euros (conversion at 1 EUR = 1.088583 US dollars)

Source: own work using information on the carmaker's European website

The assumption concerning battery costs is taken exogenously from (EVI, 2013). For gasoline, diesel and EVs, the final purchase price can be affected by national taxation and subsidization.

The structure of this module can be seen in Figure 8. The module outputs are purchase cost and driving cost (dollar per km) by car technology. These are primarily used as inputs to the "Technology Choice" module.

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[13] This is a proxy of total operating costs (insurance, maintenance, etc.) perceived by the car owner.
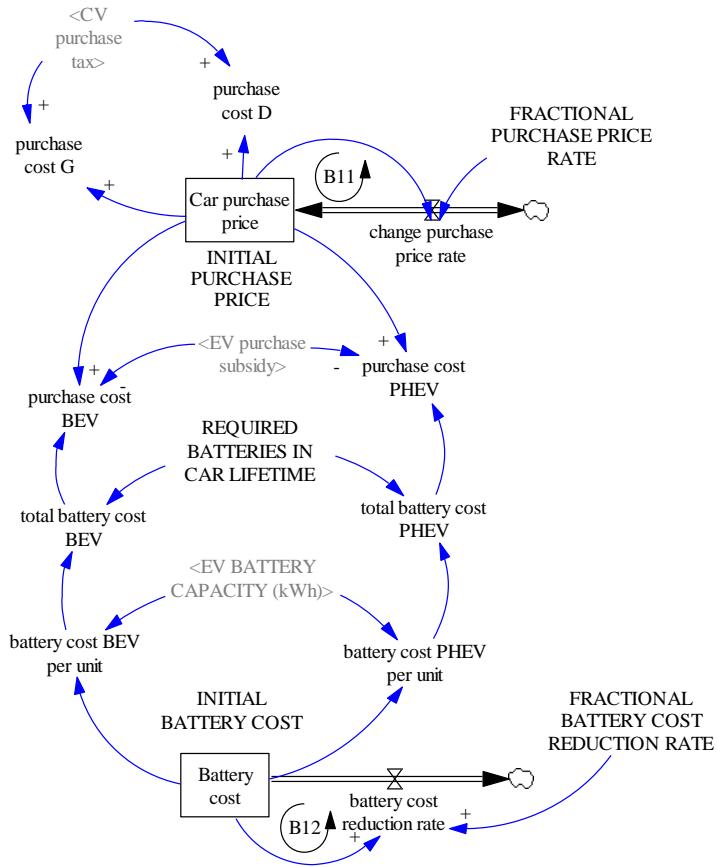
Figure 8 – Partial view of the module "Ownership and Driving Costs"
Source: own work using Vensim®

Technology Choice Module

This module is crucial to elicit new car sales by type of technology. We limit the choice to the full set of technologies available in the market at the time the decision is made. For this, a "commercialization year" variable is created. For instance, FCs become available in 2015 (Germany and US) (Toyota, 2015) and 2016 (China).

As shown in section 2, discrete choice is a common modeling framework for this purpose. There are many types of models and studies that have been applied. In this paper, we use for five attributes (purchase cost, driving cost, emissions, range and fuelling) the utility coefficients by (Hackbarth and Madlener, 2013) for each of the countries. The aggregation process to estimate the market shares is based on (Ben-Akiva et al., 1985). Figure 9 shows the structure of this module.

The key output of this module is "market share first sales" by car technology. As expected, the sum of market shares equals one. Given the annual aggregate sales rate and the predicted market shares by technology, the total number of cars (stock) by

technology can be derived. Thus the outcomes of this module are fed back to the "Car Stock" module.
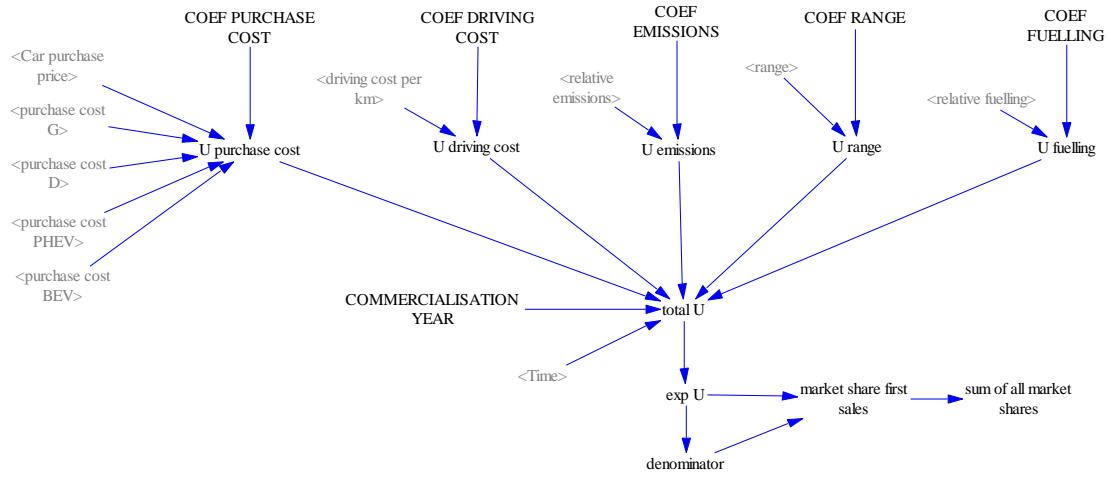

Figure 9 – Structure of the module "Technology Choice"
Source: own work using Vensim®

Energy Module

There are 7 types of energy sources represented in the model. The mapping[14] of fuels to the different car technologies is illustrated by Figure 10.

Given the difficulties of predicting oil prices, as exemplified by past forecasting studies (cf. (Dahl, 2004)) and by the recent stark decrease in oil prices, we simply opt to assume throughout this exercise that the oil price follows a long-term upward trend until reaching 164 dollars per oil barrel (bbl) in 2030. The final (at the pump) price for gasoline and diesel can also be influenced by taxation. The price of the rest of the fuels (ethanol 85 (E85)[15], autogas, CNG, electricity and hydrogen (H_2)) are assumed to remain constant during the simulations.

Figure 10 – Conceptual linkages between car technologies and fuels
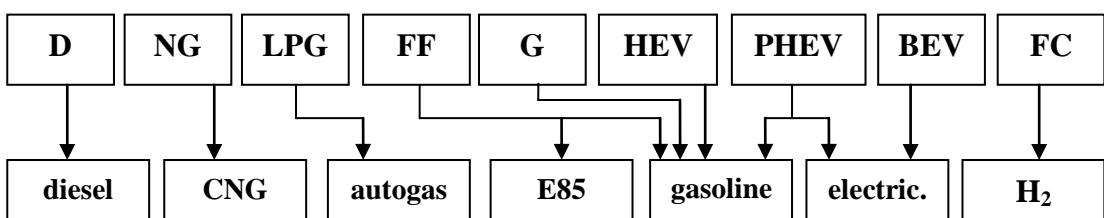
Source: own work

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[14] This is admittedly a model simplification, since physical processes already today enable additional linkages between some fuels and technologies.
[15] Blend of 85% bioethanol and 15% gasoline.

The key results of this module are: aggregate gasoline use and electricity use resulting from the different configurations of the car stock by technology ("car-mix").

Emissions Module

The model covers three main long-lived GHG emissions: CO_2, N_2O and CH_4. The key emission output, using Global Warming Potential (GWP)-100 year values based on (IPCC, 2006), is expressed in grams of CO_{2eq}.

The emissions-related accounting method[16] employed, based on (IPCC, 2006) emission factors, includes:

- Calculation of CO_2/km for new cars by technology. This values are used as an input in the "Technology Choice" module;
- Well-to-tank (WTT)[17] GHG emissions;
- Tank-to-wheel (TTW)[18] GHG emissions;
- Well-to-wheel (WTW) GHG emissions (which equals WTT plus TTW);
- Manufacturing and Scrappage (M&S) emissions;
- Lifecycle[19] GHG emissions (which results from adding WTW and M&S).

In terms of total GHG emissions generated by the total car stock, we deliberately choose to show the module output for two types of analysis: TTW and lifecycle.

Policy Module

In practice, the model view named "Policy-maker's Lab" can be regarded as the "Policy" module. It allows the model user to explore the consequences of varying testing assumptions. (S)He can "shock" the modeled system with policy inputs. Several policy variables specifically target conventional vehicles (CV): gasoline and diesel cars. Furthermore, this module shows key intermediate and final model output and provides access to more detailed country-specific charts.

The listing of the policy measures available in the current version of the model, illustrated by three exemplary scenarios, is shown in the "Scenarios and Policy Analysis" section.

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[16] This module is basically an accounting module based on an adaptation of the A-S-I-F framework (Schipper et al., 2000). Since it contains no feedback loops, the structure of this module is not shown here. See the Appendix for further details.

[17] Also known as 'upstream' or 'indirect' emissions.

[18] Also known as 'on-road' or 'direct' emissions.

[19] It is necessary to remark that no complete lifecycle analysis (LCA) has been undertaken as part of this study.

Model Validation

Given the fact that all models are wrong (Sterman, 2002), it follows that models cannot be verified (Sterman, 2000). System Dynamicists propose validity tests: (Barlas, 1996) indicates three major stages of model validation: *structural tests*, *structure-oriented behavior tests* and *behavior pattern tests*. (Bossel, 2007) recommends that model validity be demonstrated according to *structure*, *behavior*, *empirical validity* and *application*.

The proposed model is, to a large extent, validated through coherent model purpose and output, careful investigation of causal structures, collection and observation of relevant data and general matching of behavior patterns over the relevant time horizon. In addition, the model is fully formulated and the dimensional analysis indicates that all the units of the equations are consistent.

Scenarios and Policy Analysis

The model is run[20] for three slightly different scenarios. The scenarios considered in this modeling exercise can be briefly described as:

- Scenario 1 (S1) "Reference": Implementation of approved policies (e.g. EU emission standards until 2021). No additional policies to promote a certain technology.
- Scenario 2 (S2) "Fossil focus": Policies mainly targeting at ICE efficiency improvements are introduced. No strong attempt is made at improving the carbon intensity of the electricity grid.
- Scenario 3 (S3) "EV breakthrough": Additional policies aiming at facilitating EV market update are promoted. The measures include EV subsidies and investment plans for the deployment of public charging infrastructure.

Each of the three scenarios is applied to the three countries examined in this study. An overview of the set of policies considered is given in Table 5.

Table 5 – Policy inputs under different scenarios

Policy Measures [units]		S1			S2			S3		
		C*	G	U	C	G	U	C	G	U
Regula-tory	New gasoline car emission standard [1/year]	0%			3%	1%	2%	3%	1%	2%
	New diesel car emission standard [1/year]	0%			3%	1%	2%	3%	1%	2%
	Target carbon intensity electric grid [1/year]	0%			0.5%			3%		

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[20] Vensim® supports Euler and Runge-Kutta integration for mathematically solving the equations. Although Runge-Kutta (fourth order) is "probably the most reliable workhorse of numerical integration" (Bossel, 2007) (p. 81), Euler is adequate for our purpose (Sterman, 2000) (Bossel, 2007) and hence it is the one we use.

	Car occupancy rate [passenger]	1.2			1.2			1.2		
Econo-mic	CV purchase tax [dollar]	1,000			1,000			3,000		
	EV purchase subsidy [dollar]	0			0			2,000		
	Gasoline tax [dollar/liter]	0.2	0.6	0.2	0.2	0.6	0.2	0.5	0.7	0.5
	Diesel tax [dollar/liter]	0.3	0.6	0.2	0.3	0.6	0.2	0.5	0.7	0.5
	Target electricity price [dollar/kWh]	0.2			0.2			0.2		
Invest-ment	Public EV charging infrastructure deployment [station/year]	10	10	10	10	10	10	800		
	Public H_2 filling station deployment [station/year]	1	1	1	1	1	1	50		

* C = China / G = Germany / U = US. Note that the policies for EV subsidy and infrastructure investment have a temporary validity and are written as step functions.

Source: own illustration of possible scenarios.

4. DISCUSSION OF RESULTS
Key Results

An important intermediate result is provided by the simulated variable "total car stock by tech", which includes new and older cars disaggregated by technology. An illustrative example for the US is shown in Figure 11.
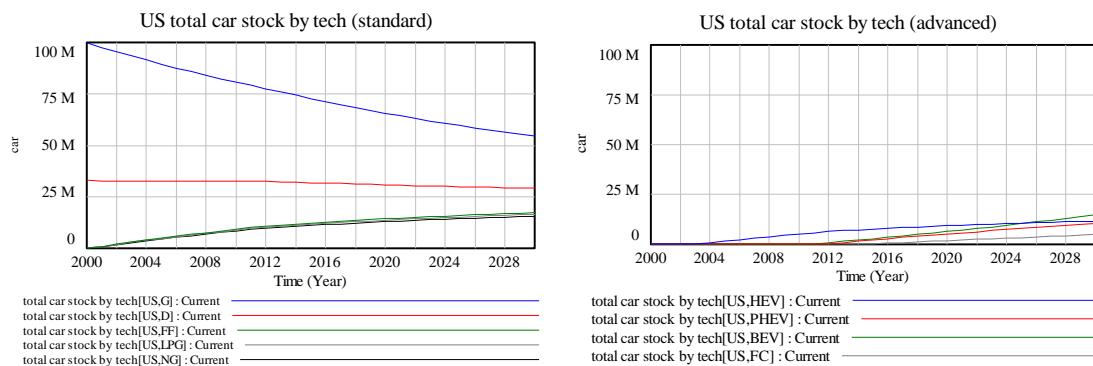

Figure 11 – Behavior of "total car stock by technology"
Source: own work using Vensim®

In addition, the two main results of interest shown in this section are: aggregate gasoline use and GHG emissions. Whereas the former is shown in Figure 12 for each country under the three constructed scenarios; Figure 13 illustrates, using the results of Scenario 1, two different ways of representing corresponding GHG impacts.

As can be seen, although additional policies supporting alternative car technologies contribute to reducing gasoline use, the differences between S2 and S3 are rather small.

The decrease in the demand for oil-based fuels results in an increase in the demand for electricity. Suitable models need to be developed to assess the practical consequences of massive EV charging for the local grid.

Concerning GHG emissions, as the example of S1 illustrates, accounting for TTW emissions only (neglecting WTT and car manufacturing & scrappage emissions) distorts the overall picture about the environmental impacts of car travel. With regard to lifecycle emissions, the potential to dramatically reduce GHGs from car travel remain, for the three markets and under the scenarios examined, untapped.
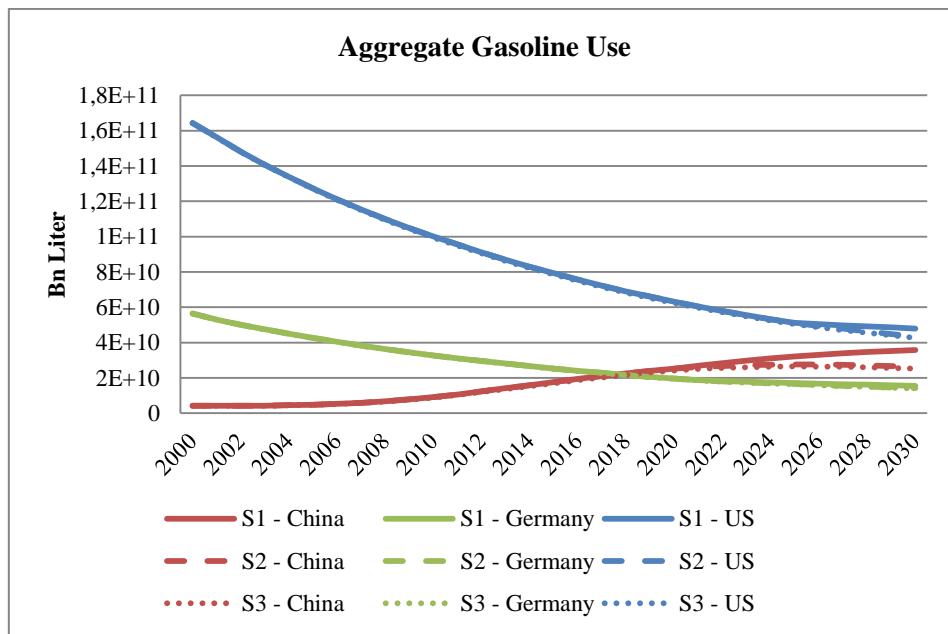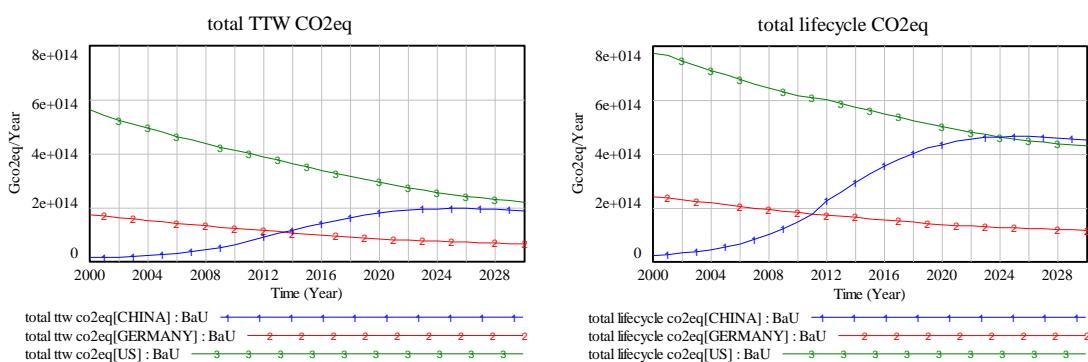

Figure 12 – Energy impacts: "aggregate gasoline use"
Source: own work using Vensim® and Excel®

*Note the different scale of the Y-axis.

Figure 13 – GHG impacts: "TTW" and "lifecycle" emissions (S1)
Source: own work using Vensim®

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Sensitivity Analysis and Discussion

In order to investigate the critical assumption reflected by the variable "share of technology switching", a simple sensitivity analysis was undertaken. For this purpose, a Monte-Carlo simulation using Vensim® sensitivity setup was conducted. The critical parameter was represented using a random uniform distribution [0,1] and, as an example, the chosen output variable was the stock of gasoline cars in China. The resulting confidence bounds are shown in Figure 14.
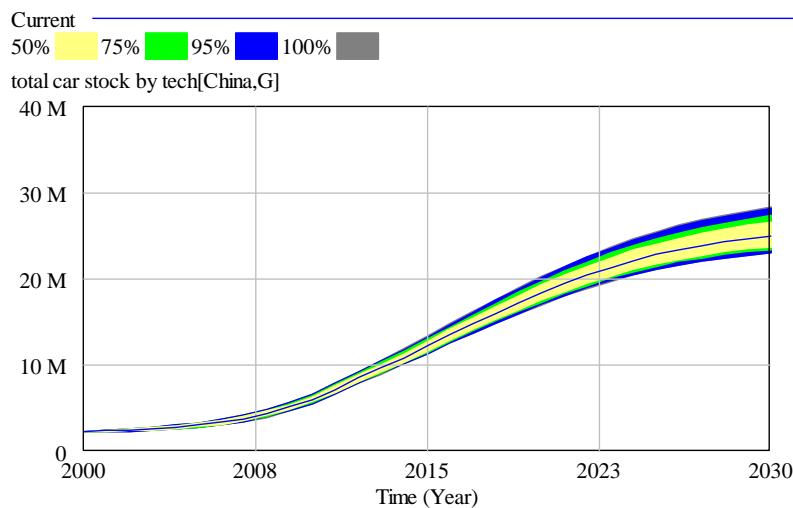

Figure 14 – Sensitivity of "car stock (G)" to "share of technology switching"
Source: own work using Vensim®

Only three scenarios out of a potentially long list of plausible scenarios have been constructed as part of the modeling exercise presented here. Much work remains to be done concerning the construction of alternative scenarios, policy analysis and sensitivity analysis. Nevertheless, the benefits of designing and conducting experiments on such a simulation model can be, at this point, highlighted.

5. CONCLUSIONS AND FURTHER RESEARCH
Summary and Conclusions

For this study, a simulation model based on the SD approach has been developed. The SD model is capable of generating scenarios for the market penetration of different car powertrain technologies at the national level until 2030. Furthermore, the model enables the user to explore a set of 11 policy options. In this paper, the application of the model to three key car markets (China, Germany and the US) has been illustrated by means of scenario building.

Based on the modeling exercise and SD simulation results, the authors conclude that the market scenarios outcomes are highly sensitive to the different assumed input policies. The simulation output also confirms a reasonable initial hypothesis: given the larger

distance from car saturation in the Chinese market, the prospects of a more rapid penetration of non-conventional cars is more promising than in the mature German and US markets. This, however, depends greatly on the assumption concerning the lock-in of mature technologies, represented by the proxy variable "share of technology switching".

Perhaps the most insightful result is the one arising from comparing total gasoline use and lifecycle GHG emissions, in particular for China and the US which have a similar level of car stock around 2030. This, at first counterintuitive, result can be explained upon a second thought by three key aspects: (i) emissions are higher for manufacturing than for scrappage and China's projected number of sales is unmatched by the other two mature markets; (ii) manufacturing emissions (but not scrappage) are higher for BEV than for conventional cars and the former penetrate the Chinese market more rapidly than in Germany and the US; (iii) the larger number of cars operating in China and the assumed slow de-carbonization of the electricity grid. This example highlights the need to strive for the expansion of model boundaries. By "trespassing" the narrow frontier of on-road transport emissions on those commonly located in the energy system (i.e. moving from TTW to WTT and overall WTW emissions analysis), we gained valuable insights into the far-reaching environmental impacts of a specific market scenario.

Finally, the modeling exercise illustrates the suitability of the SD approach to investigate the dynamic problems inherent in this area of research. With minor adaptations, the same model structure could be used to represent systems from different countries, from which a variety of behavior patterns can arise.

Limitations and Further Research

In our view, this study contains four main limitations. The first one is related to the arbitrary definition of the system (model) boundary. Secondly, the critical issue of modeling replacement sales by technology. The third one is the need to refine key model assumptions and to collect the most recently available data, particularly for China. Lastly, the hypothesis that EV deployment worldwide is expected to lead to beneficial economies of scale and battery cost reductions is not explicitly covered in the current version of the model.

Given the aforementioned limitations, we expect to devote additional research effort on four main areas: (i) expansion of model boundaries to take into account potential feedback processes (e.g. rebound effects); (ii) rethinking the causal structure for the demand for car replacement, probably adding a Bass sub-model; (iii) update of the model assumptions related to technology choices in view of new available knowledge (e.g. data from revealed preference surveys and new discrete choice models); (iv) model extension to include other relevant markets (in particular, France, India and Japan) leading to the explicit consideration of technological leaps in the global automotive market.

REFERENCES

Achtnicht, M., 2011. German car buyers' willingness to pay to reduce CO2 emissions. Clim. Change 113, 679–697. doi:10.1007/s10584-011-0362-8

Al-Alawi, B.M., Bradley, T.H., 2013. Review of hybrid, plug-in hybrid, and electric vehicle market modeling Studies. Renew. Sustain. Energy Rev. 21, 190–203. doi:10.1016/j.rser.2012.12.048

Armenia, S., Baldoni, F., Falsini, D., Taibi, E., 2010. A System Dynamics energy model for a sustainable transport system. Presented at the System Dynamics Society Conference, Seoul.

Barlas, Y., 1996. Formal aspects of model validity and validation in system dynamics. Syst. Dyn. Rev. 12, 183–210. doi:10.1002/(SICI)1099-1727(199623)12:3<183::AID-SDR103>3.0.CO;2-4

Ben-Akiva, M., Lerman, S., Ben-Akiva, 1985. Discrete Choice Analysis: Theory and Application to Travel Demand. Mit Pr, Cambridge, Mass.

BenDor, T., Ford, A., 2006. Simulating a combination of feebates and scrappage incentives to reduce automobile emissions. Energy 31, 1197–1214. doi:10.1016/j.energy.2005.05.024

Bossel, H., 2007. Systems and models: complexity, dynamics, evolution, sustainability. Books on Demand, Norderstedt.

Brownstone, D., Bunch, D.S., Train, K., 2000. Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transp. Res. Part B Methodol. 34, 315–338. doi:10.1016/S0191-2615(99)00031-4

Brownstone, D., Train, K., 1998. Forecasting new product penetration with flexible substitution patterns. J. Econom. 89, 109–129. doi:10.1016/S0304-4076(98)00057-8

Bunch, D.S., Bradley, M., Golob, T.F., Kitamura, R., Occhiuzzo, G.P., 1993. Demand for clean-fuel vehicles in California: A discrete-choice stated preference pilot project. Transp. Res. Part Policy Pract., Special Issue Energy and Global Climate Change 27, 237–253. doi:10.1016/0965-8564(93)90062-P

Dahl, C.A., 2004. International Energy Markets: Understanding Pricing, Policies & Profits. Pennwell Pub, Tulsa, Okla.

Dargay, J., Gately, D., Sommer, M., 2007. Vehicle Ownership and Income Growth, Worldwide: 1960-2030. Energy J. 28, 143–170. doi:10.2307/41323125

Dieckhoff, C., Appelrath, H.-J., Fischedick, M., Grunwald, A., Höffler, F., Mayer, C., Weimer-Jehle, W., 2014. Zur Interpretation von Energieszenarien. Deutsche Akademie der Technikwissenschaften, München.

Dieckhoff, C., Fichtner, W., Grunwald, A., Meyer, S., Nast, M., Nierling, L., Renn, O., Voß, A., Wietschel, M., 2011. Energieszenarien : Konstruktion, Bewertung und Wirkung - "Anbieter" und "Nachfrager" im Dialog. KIT Scientific Publishing.

EVI, 2015. Global EV Outlook. 2015 Update. Electric Vehicles Initiative.

EVI, 2013. Global EV Outlook - Understanding the Electric Vehicle Landscape to 2020. Electric Vehicles Initiative.

Ford, A., 1995. Simulating the controllability of feebates. Syst. Dyn. Rev. 11, 3–29. doi:10.1002/sdr.4260110103

Forrester, J.W., 1968. Principles of Systems. Pegasus Communications, Waltham, MA.

Forrester, J.W., 1961. Industrial Dynamics. MIT Press, Cambridge, Mass.

Forrester, J.W., 1958. Industrial Dynamics. Harv. Bus. Rev. 36, 37–66.

Gomez, J., Jochem, P., Fichtner, W., 2014. Car Technology Scenarios using System Dynamics: Exploring Market Penetration and Energy Consumption in China, Germany and US. In 2014 Proceedings of the Student Chapter, System Dynamics Society.

Gomez, J., Jochem, P., Fichtner, W., 2013. The impact of electric vehicles on the global oil demand and CO2 emissions. Presented at the World Conference on Transport Research Society (WCTRS) Rio de Janeiro.

Hackbarth, A., Madlener, R., 2013. Consumer preferences for alternative fuel vehicles: A discrete choice analysis. Transp. Res. Part Transp. Environ. 25, 5–17. doi:10.1016/j.trd.2013.07.002

ICCT, 2012. Global Transportation Energy and Climate ROADMAP: The impact of transportation policies and their potential to reduce oil consumption and greenhouse gas emissions.

IEA, 2009. Transport, Energy and CO2: Moving Toward Sustainability.

IPCC, 2015. Climate Change 2014: Mitigation of Climate Change: Working Group III Contribution to the IPCC Fifth Assessment Report. Cambridge University Press.

IPCC, 2006. IPCC Guidelines for National Greenhouse Gas Inventories.

Keith, D.R., 2012. Essays on the dynamics of alternative fuel vehicle adoption : insights from the market for hybrid-electric vehicles in the United States (Thesis). Massachusetts Institute of Technology.

Keles, D., Wietschel, M., Möst, D., Rentz, O., 2008. Market penetration of fuel cell vehicles – Analysis based on agent behaviour. Int. J. Hydrog. Energy 33, 4444–4455. doi:10.1016/j.ijhydene.2008.04.061

Kieckhäfer, K., 2013. Marktsimulation zur strategischen Planung von Produktportfolios: Dargestellt am Beispiel innovativer Antriebe in der Automobilindustrie, Auflage: 2013. ed. Springer Gabler, Wiesbaden.

Krail, M., 2009. System-Based Analysis of Income Distribution Impacts on Mobility Behaviour. Nomos, Baden-Baden.

Kühn, A., Glöser, S., 2012. System-based feedback analysis of e-mobility diffusion in China. Presented at the System Dynamics Society Conference, St. Gallen.

Martinez-Moyano, I.J., 2012. Documentation for model transparency. Syst. Dyn. Rev. 28, 199–208. doi:10.1002/sdr.1471

McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. J. Appl. Econom. 15, 447–470. doi:10.1002/1099-1255(200009/10)15:5<447::AID-JAE570>3.0.CO;2-1

Meadows, D.H., Wright, D., 2008. Thinking in systems: a primer. Chelsea Green Pub., White River Junction, Vt.

Meyer, G., 2009. Analyse und technisch-ökonomische Bewertung von Gesetzesfolgen im Individualverkehr: dargestellt am Beispiel der Automobilindustrie Japans und Deutschlands.

Möst, D., Fichtner, W., Grunwald, A., 2009. Energiesystemanalyse : Tagungsband des Workshops "Energiesystemanalyse" vom 27. November 2008 am KIT Zentrum Energie, Karlsruhe. Universität Karlsruhe Universitätsbibliothek, Karlsruhe.

Oil-price.net, 2015. Crude oil price [WWW Document]. URL http://www.oil-price.net

Park, S.Y., Kim, J.W., Lee, D.H., 2011. Development of a market penetration forecasting model for Hydrogen Fuel Cell Vehicles considering infrastructure and cost reduction effects. Energy Policy 39, 3307–3315. doi:10.1016/j.enpol.2011.03.021

Rahmandad, H., Sterman, J.D., 2012. Reporting guidelines for simulation-based research in social sciences. Syst. Dyn. Rev. 28, 396–411. doi:10.1002/sdr.1481

Randers, J., 1980. Elements of the System Dynamics Method. Pegasus Communications.

Richardson, G.P., 2011. Reflections on the foundations of system dynamics. Syst. Dyn. Rev. 27, 219–243. doi:10.1002/sdr.462

Richardson, G.P., 1991. Feedback Thought in Social Science and Systems Theory. University of Pennsylvania Press, Philadelphia.

Schade, W., 2005. Strategic Sustainability Analysis: Concept and application for the assessment of European Transport Policy, Auflage: 1. ed. Nomos, Baden-Baden.

Schipper, L., Marie-Lilliu, C., Gorham, R., 2000. Flexing the Link Between Transport and Greenhouse Gas Emissions: A Path for the World Bank. International Energy Agency.

Schühle, F., 2014. Die Marktdurchdringung der Elektromobilität in Deutschland: Eine Akzeptanz-und Absatzprognose, Auflage: 1. ed. Hampp, R, München; Mering.

SDS, 2014. System Dynamis Society. Introduction to System Dynamics [WWW Document]. URL http://www.systemdynamics.org/what-is-s/

Senge, P.M., 2006. The Fifth Discipline. Crown Business, New York.

Shepherd, S., Bonsall, P., Harrison, G., 2012. Factors affecting future demand for electric vehicles: A model based study. Transp. Policy, URBAN TRANSPORT INITIATIVES 20, 62–74. doi:10.1016/j.tranpol.2011.12.006

Shepherd, S., Emberger, G., 2010. Introduction to the special issue: system dynamics and transportation. Syst. Dyn. Rev. 26, 193–194. doi:10.1002/sdr.454

Shepherd, S.P., 2014. A review of system dynamics models applied in transportation. Transp. B Transp. Dyn. 2, 83–105. doi:10.1080/21680566.2014.916236

Sterman, J.D., 2002. All models are wrong: reflections on becoming a systems scientist. Syst. Dyn. Rev. 18, 501–531. doi:10.1002/sdr.261

Sterman, J.D., 2000. Business Dynamics: Systems Thinking and Modeling for a Complex World. McGraw-Hill/Irwin.

Struben, J., Sterman, J.D., 2008. Transition challenges for alternative fuel vehicle and transportation systems. Environ. Plan. B Plan. Des.

Toyota, 2015. Toyota Mirai – The Turning Point [WWW Document]. URL http://www.toyota.com/fuelcell/ (accessed 3.18.15).

UN, 2012. World Population Prospects: The 2012 Revision. United Nations, Department of Economic and Social Affairs. Population Division, Population Estimates and Projections Section [WWW Document]. URL http://esa.un.org/wpp/ (accessed 3.18.15).

UNECE, 2015. UNDA Project on CO2 emissions and ForFITS. United Nations Economic Commission for Europe [WWW Document]. URL http://www.unece.org/trans/theme_forfits.html

Walther, G., Wansart, J., Kieckhäfer, K., Schnieder, E., Spengler, T.S., 2010. Impact assessment in the automotive industry: mandatory market introduction of

alternative powertrain technologies. Syst. Dyn. Rev. 26, 239–261. doi:10.1002/sdr.453

Wansart, J., 2012. Analyse von Strategien der Automobilindustrie zur Reduktion von CO2-Flottenemissionen und zur Markteinführung Alternativer Antriebe: Ein . . ., Auflage: 2012. ed. Springer Gabler, Wiesbaden.

WB, 2014. The World Bank Data. World Bank [WWW Document]. URL http://data.worldbank.org/ (accessed 3.18.15).

Weikl, R., 2010. Simulation zur Abschätzung der Marktanteilsentwicklung unterschiedlicher Antriebsvarianten am deutschen Fahrzeugmarkt : ein systemdynamisches Modell zur Entscheidungsunterstützung in der strategischen Marktanalyse / Robert Weikl. GUC, Verl. der Ges. für Unternehmensrechnung und Controlling, Chemnitz.

Wolff, P. de, 1938. The Demand for Passenger Cars in the United States. Econometrica 6, 113–129. doi:10.2307/1907143

Ziegler, A., 2012. Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for Germany. Transp. Res. Part Policy Pract. 46, 1372–1385. doi:10.1016/j.tra.2012.05.016

APPENDIX

In line with suggestions by (Rahmandad and Sterman, 2012) (Martinez-Moyano, 2012) on model transparency and reproducibility, this appendix contains the model documentation using SDM-Doc. The version of the model used in this paper is available (Vensim® Reader format) from the main author upon request.

Model Summary

Model Assessment Results

Model Information	Number
Total Number of Variables	312
Total Number of State Variables (Level+Smooth+Delay Variables)	17 (5.4%)
Total Number of Stocks (Stocks in Level+Smooth+Delay Variables) †	165 (52.9%)
Total Number of Macros	0
Variables with Source Information	73 (23.4%)
Variables with Dimensionless Units	24 (7.7%)
Variables without Predefined Min or Max Values	277 (88.8%)
Function Sensitivity Parameters	0
Data Lookup Tables	0
Time Unit	Year
Initial Time	2000
Final Time	2030
Reported Time Interval	TIME STEP
Time Step	1
Model Is Fully Formulated	Yes
Modeler-Defined Groups	- No -
VPM File Available	- No -

Warnings	Number
Undocumented Equations	91 (29.2%)
Equations with Embedded Data (0 and 1 constants ignored)	10 (3.2%)
Equations With Unit Errors or Warnings	Unavailable
Variables Not in Any View	0
Incompletely Defined Subscripted Variables	0
Nonmonotonic Lookup Functions	0
Cascading (Chained) Lookup Functions	0
Non-Zero End Sloped Lookup Functions	0
Equations with "IF THEN ELSE" Functions	2 (0.6%)
Equations with "MIN" or "MAX" Functions	0
Equations with "STEP", "PULSE", or Related Functions	0

Potential Omissions	Number
Unused Variables	26
Supplementary Variables	0
Supplementary Variables Being Used	0
Complex Variable Formulations (Richardson's Rule = 3)	10
Complex Stock Formulations	0

List of 10 Views and Their 312 Variables

View	Variables
Policy-maker's Lab	11 vars (3.5%)
Country-specific Indicators	2 vars (0.6%)
Population-GDP	17 vars (5.4%)
Travel Demand by Car	7 vars (2.2%)
Car Stock	38 vars (12.2%)
Car Attributes & Infrastructure	51 vars (16.3%)
Ownership & Driving Costs	33 vars (10.6%)
Technology Choice	27 vars (8.7%)
Energy	63 vars (20.2%)
Emissions	183 vars (58.7%)

Model Code

Note that, due to space constraints, only selected equations are shown below. The list contains the code for the following subscripts: Germany and Gasoline (G). The full model documentation (including the complete list of equations) can be obtained by running the model using the SDM-Doc tool.

birth rate[Germany] = FRACTIONAL BIRTH RATE[]*Population[]

death rate[Germany] = Population[]/LIFETIME EXPECTANCY[]

FRACTIONAL BIRTH RATE[Germany] = 0.0131196

FRACTIONAL GDP GROWTH RATE[Germany] = 0.0105939

GDP[Germany] = ∫GDP growth rate[] dt + [INITIAL GDP[]]

GDP growth rate[Germany] = FRACTIONAL GDP GROWTH RATE[]*GDP[]

GDP per capita[Germany] = GDP[]/Population[]

INITIAL GDP[Germany] = 2.94843e+012

INITIAL POPULATION[Germany] = 8.35125e+007

LIFETIME EXPECTANCY[Germany] = 70

Population[Germany] = ∫birth rate[]-death rate[] dt + [INITIAL POPULATION[]]

annual VKT by car[Germany] = daily VKT by car[]*365

AVERAGE TRIP DISTANCE[Germany] = 18.06

car occupancy rate[Germany] = 1.2

daily VKT by car[Germany] = TRIPS PER DAY BY CAR[]*AVERAGE TRIP DISTANCE[]

PKM by car[Germany] = car occupancy rate[]*annual VKT by car[]

TRIPS PER DAY BY CAR[Germany] = 1.82

ADJUSTMENT TIME (Year) = 1

ageing[Germany,G] = New Car Stock[]/AVERAGE AGEING TIME[]

AVERAGE AGEING TIME[Germany,G] = 1

AVERAGE LIFETIME[Germany,G] = 14

BETA COEF[Germany] = -25

car ownership ratio[Germany] = CAR SATURATION LEVEL[]*EXP(BETA COEF[]*EXP(GAMMA COEF[]*coef GDP per cap[]))

CAR SATURATION LEVEL[Germany] = 557

coef GDP per cap[Germany] = GDP per capita[]/in thousand[]

divergence between projected and simulated car stock[Germany] = (projected car stock[]-total car stock[])/ADJUSTMENT TIME

FIRST SALES RATE[Germany] = 0

GAMMA COEF[Germany] = -0.169167

INITIAL CAR[Germany,G] = 3.3e+007

INITIAL NEW CAR[Germany,G] = 1e+006

market share first sales[Germany,G] = exp U[]/denominator[Germany]

New Car Stock[Germany,G] = ∫sales rate[]-ageing[] dt + [INITIAL NEW CAR[]]

Older Car Stock[Germany,G] = ∫ageing[]-scrappage rate[] dt + [INITIAL CAR[]]

Population[Germany] = ∫birth rate[]-death rate[] dt + [INITIAL POPULATION[]]

projected car stock[Germany] = car ownership ratio[]/1000*Population[]

replacement sales[Germany,G] = scrappage rate[]*SHARE OF TECHNOLOGY SWITCHING[Germany]

sales rate[Germany,G] = (market share first sales[]*FIRST SALES RATE[Germany])+(market share first sales[]*divergence between projected and simulated car stock[Germany])+replacement sales[]

scrappage rate[Germany,G] = Older Car Stock[]/AVERAGE LIFETIME[]

SHARE OF TECHNOLOGY SWITCHING[Germany] = 0.5

total car stock[Germany] = total new car stock[]+total older car stock[]

total car stock by tech[Germany,G] = New Car Stock[]+Older Car Stock[]

total new car stock[Germany] = ∑(New Car Stock[])

total older car stock[Germany] = ∑(Older Car Stock[])

total sales[Germany] = ∑(sales rate[])

total scrappage[Germany] = ∑(scrappage rate[])