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Analysis and testing of electric car incentive scenarios in the Netherlands and Norway

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ABSTRACT

Past and future electric vehicle sales shares in the Netherlands and Norway are analysed with the Powertrain Technology Transition Market Agent Model. This system dynamics model was expanded to include the leading Norwegian car market and updated with recent data on policy incentives. Three model validation tests are discussed: the reproduction of past behaviour from 2010 till 2017, policy sensitivity, and feedback loop knock-out analysis. Findings point in the direction that regulation on emission targets for manufacturers are necessary for a transition away from new sales of fossil fuel-based vehicles. Only strong incentives resulted in large sales shares of zero emission vehicles in the Netherlands and Norway.

1. Introduction

Car use causes a series of negative externalities (Parry et al., 2007). At the local level, air pollutant emissions have an adverse impact on human health (Hoek et al., 2013; Künzli et al., 2000). At the global level, greenhouse gas (GHG) emissions contribute to climate change (Lorenzoni and Pidgeon, 2006; Woodcock et al., 2009). Petrol and diesel cars generate both types of emissions. Compared to petrol cars, diesel cars have lower GHG emissions but higher air pollutant emissions such as nitrogen oxides (NO_x). The importance and urgency for a transition to lower emissions of the global car fleet is widely accepted (UNFCCC, 2015), and a transition to electric vehicles (EVs) is often reasoned to be best.

The International Energy Agency (IEA) anticipates a global vehicle stock of 130 million EVs by 2030, accounting for current and announced policies (these include battery electric vehicles, BEVs; fuel cell vehicles, FCVs; and plug-in hybrid electric vehicles, PHEVs; and excluding two- and three-wheelers (IEA, 2018)). In an IEA 'accelerated EV deployment' scenario in which the 2030 sales share of new vehicles would consist of 30% EVs, the EV stock of light duty vehicles, trucks and buses is expected to reach 228 million by 2030. In terms of EV market share, the Netherlands and Norway can be considered at the forefront of the EV revolution with passenger vehicle sales shares of 2.6% in the Netherlands and near 40% in Norway in 2017 (excluding light duty vehicles, trucks and buses; EAFO, 2018a; RVO, 2018). Both countries counted passenger EV stocks of near 110,000 and 190,000 for Netherlands and Norway respectively at the end of 2017 (EAFO, 2018a).

Interestingly, the Netherlands and Norway have achieved records in EV sales shares while putting in place very different combinations of incentives (Figenbaum, 2016; Netherlands Enterprise Agency, 2017; RVO, 2018). The Dutch government in its coalition agreement of 2017 states to strive in its policy for having all new cars sold to be zero-emission vehicles (ZEVs) by 2030 latest (Rutte et al., 2017). Based on analyses of these targets for passenger vehicles, the Dutch Environmental Assessment Agency concludes this would require strong political will at different levels (Koelemeijer et al., 2017). At the European Union (EU) level, by the means of emission penalties for manufacturers; and at the national level, by means of financial incentives for users (Koelemeijer et al., 2017).

The Norwegian parliament has stated a similar goal of having only ZEVs sold by 2030, and to achieve this goal not through command-and-control regulation (e.g. sales bans for conventional technologies) but via implementation of the polluter-pays principle (Norsk elbilforening, 2018). Next to that, the Norwegian transport agencies suggest to have all new passenger cars and buses sold in 2025 to be ZEVs (Fridstrøm and Østli, 2016).

Figenbaum and Kolbenstvedt (2013) concluded that the use of EVs is a possible roadmap to reducing emissions to such an extent that the Norwegian and the EU climate policy goals can be reached. Later research on EVs and energy policies in the EU reached similar conclusions (Thiel et al., 2016).

This research analyses the sales shares of new passenger vehicles for the Netherlands and Norway, and builds on previous modelling work with the

Abbreviations: BEV, Battery Electric Vehicle; EV, Electric Vehicle; FCV, Fuel Cell Vehicle; GHG, greenhouse gas; ICEV, Internal Combustion Engine Vehicle; PHEV, Plug-in Hybrid Electric Vehicle; PTTMAM, Powertrain Technology Transition Market Agent Model; ZEV, Zero Emissions Vehicle – BEV and FCV

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Powertrain Technology Transition Market Agent Model (PTTMAM) (Harrison et al., 2016; Harrison and Thiel, 2017a, 2017b; Pasaoglu et al., 2016). This work particularly builds forward on Harrison and Thiel (2017a), in which BEVs and PHEVs sales shares in the Netherlands and the United Kingdom (UK) were investigated. First it extends the considered historical time frame from 2015 till 2017, and reflects on the appropriateness of PTTMAM to explain past sales of EVs over this period, with comparing the 2010-2015 period with previous research (Harrison and Thiel, 2017a). Secondly, it explores possible future scenarios with combinations of three incentive stimulus: continuing subsidizing EVs, taxing cars based on tail-pipe emissions, and penalizing manufacturers based on the average tail-pipe emissions of sold cars. It then shortly compares these future scenarios with another previous publication with PTTMAM (Harrison and Thiel, 2017b). Third, by means of loop knock-out analysis dominant structure of the model is explored to see to what extent it causes sales of EVs in 2030 and 2050 in the Netherlands and Norway. The reason for focusing here on Norway instead of the UK is that Norway was recently implemented in the PTTMAM, and the Netherlands and Norway have achieved the highest levels of EVs in sales shares in Europe. We mainly distinguish between BEVs, PHEVs and FCVs. With EVs we refer to all three, and with ZEVs we refer only to BEVs and FCVs (hybrid electric vehicles, HEVs, are not plug-in vehicles, and are not referred to when EVs are mentioned).

The remainder of this paper is organized as follows: the next section continues with a literature review, providing more detailed background of the problem and data that is used in the method. Section 3 shortly introduces system dynamics, PTTMAM, and the procedures of the three validity tests.

Table 1
Historic EV incentives in Norway and the Netherlands.

Country	Starting year	Powertrain	Policy type	Details
Norway	1990	BEV	Exemption on import taxes	
			Exemption from registration costs	Can reach levels of up to 100% on the sales price for conventional cars. (Figenbaum, 2016)
	1996		Reduced circulation taxes	50 € in 2016, whereas owners of conventional cars paid fees of 350-410 € annually (Figenbaum, 2016)
	1997		Alternative incentives**	None or reduced charges on toll roads, ferries, and municipal parking, and allowance on bus lanes (assumed parameter: 'subsidies to parking/congestion charges' set to 50% in 1997, starting with free toll roads; and to 100% from 1999 onwards, due to free parking; included in the 'current incentives stay' and the 'all incentives end' scenario from section 3.3.2 onwards)
	2000		Reduced private use tax*	15% till 2017, 18% in 2018 (instead of 30%)
	2001		Exemption from VAT	
	2007	PHEV/BEV	Charging infrastructure subsidies**	Governmental incentives for the deployment of home- and public charging infrastructure (Figenbaum, 2016)
Netherlands	2010	HEV	Reduced registration costs	Also ending 2010
		PHEV/BEV	Subsidies for charging infrastructure**	Local application procedures for free public charging infrastructure (assumed parameter: 'electric fuel costs', set to 50% till 2020; not part of the continuation of incentives tests from section 3.3.2 and onwards)
		PHEV	Reduced registration costs	Also ending 2010
	2011		Exemption from registration costs	Ending 2014
		ZEV	Exemption from registration costs	
			Exemption from circulation taxes	Circulation taxes are high in the Netherlands compared to other European countries
		PHEV	Exemption from circulation taxes	Ending 2016
		HEV	Exemption from circulation taxes	Ending 2013
		ZEV	No addition to taxable income*	Ending 2013
	2012	PHEV	No addition to taxable income*	Ending 2013
		HEV	Reduced addition to taxable income*	14%, 21% in 2016, and 22% in 2017
Norway	2013	PHEV	Reduced registration costs	
Netherlands	2013	PHEV/ZEV	Local purchase subsidies**	ZEV purchase- and charging infrastructure subsidies ranging from 2,500 € to 9,000 € in several municipalities (congruent with Harrison and Thiel (2017a), assumed parameter set to 5,000 € till 2016)
	2014	ZEV	Reduced addition to taxable income*	4%
		PHEV	Reduced addition to taxable income*	7%, 15% in 2016, and 22% in 2017
	2015		Reduced registration costs	

*for company owned cars only

**containing large geographical and temporal detail, input parameters are assumed values and often simplified

Section 4 reports and discusses the results of the validation tests. Finally, Section 5 summarizes the main conclusions from this paper, reflects on the limitations of this research and discusses potential future research directions.

2. Literature review

2.1. EV incentives in the Netherlands and Norway

The Netherlands and Norway have known various incentives for stimulating sales of EVs. The incentives reported here are used as updated input to PTTMAM, discussed in Section 3.2.

Table 1 provides an overview of the incentives discussed here. The details column provides context, ending years and technical notes on the implementation to the input of the model. Starting from circulation taxes in the Netherlands, from 2011 Dutch ZEV owners were exempted from circulation taxes, which are high in the Netherlands compared to other European countries (ACEA, 2017, 2016, 2015, 2014, 2013, 2011, 2010). The PHEV circulation taxes were also exempt between 2011 and 2016, and between 2011 and 2013 this was also the case for HEVs.

Since 2011 buyers of ZEVs are also exempt from registration costs. Only in 2010, HEV purchasers could profit from reduced registration costs. Next to that, PHEV buyers received a small reduction in registration costs in 2010, and a full exemption between 2011 and 2014, after which it became a large reduction since 2015. There was no addition to taxable income for company ZEVs till 2013, whereas for PHEVs this was only the case for 2012 and 2013. For company cars including HEVs with emissions below set standards reductions were in place in the percentage addition to taxable income of 14% at least from 2012 till 2015 (Weekers, 2011). Since 2014 owners of company ZEV pay 4% addition to taxable income, where company PHEV owners pay 7%. Company PHEV owners pay 15% since 2016. In the same year the percentage for HEV sales reached 21%, and 22% in 2017 (ACEA, 2017, 2016, 2015, 2014, 2013, 2011, 2010). Since the end of 2013 several municipalities have been offering subsidies ranging between 2500 € and 9000 € on the purchase of ZEVs or personal charging infrastructure (Netherlands Enterprise Agency, 2017, 2016, 2015).

Since the technology of PHEVs and BEVs is still not as mature as that of ICEVs, and sales shares are very small, EV buyers can be categorized as innovators (Rogers, 1962). The historic sales share of PHEVs in the Netherlands, shown in Fig. 3, provides a good example of unexpected developments in sales due to sensitivity to pricing. In the case of PHEVs in the Netherlands it was suggested that large proportions of potential buyers made their purchases in 2013 and 2015 instead of 2014 and 2016, since a possible end of the incentives was publicly debated (Lévay et al., 2017; Thiel et al., 2015). In 2017 the financial incentives for PHEVs in the Netherlands became minimal and consequently the sales shares dropped even further.

As Table 1 shows, Norway has an extensive history of different incentives for BEVs, and later also for PHEVs of which the cost effectiveness and fairness have been debated (Aasness and Odeck, 2015; Holtsmark and Skonhoft, 2014). The incentives started with an exemption on import tax for BEVs in 1990 (Figenbaum, 2016). From 1996 till 2016 BEVs had a reduced circulation tax, which was for example 50 € in 2016, whereas owners of conventional cars paid fees of 350-410 € annually (Figenbaum, 2016). Since 1990, BEVs were exempt of registration costs, which can reach levels of up to 100% on the sales price for conventional cars. Since 2013 also PHEVs had reduced registration costs (Figenbaum and Kolbenstvedt, 2013). Since 2003 BEVs were allowed on bus lanes. Company car tax was halved since 2000, where the effect for the vehicle owner is dependant on income (Figenbaum, 2016; Norsk elbilforening, 2018). Since 1997 BEV owners had various incentives related to charges on toll roads, ferries, and municipal parking. Moreover, since 2001 BEVs were exempt from VAT, and there have been governmental incentives for the deployment of home- and public charging infrastructure. We have not sought for a complete representation of all incentives that could have influenced a Norwegian vehicle owner at each year from 1995 till 2017; it was assumed that this information covered the needed external input for the tests that are performed.

Unintended consequences from toll exemptions and access to bus lanes were found in reductions in toll revenues and increased travel times for public transport users (Aasness and Odeck, 2015). It was found that Norwegian EV policy has reduced overall GHG emissions, but it is argued that this is not easily transferrable to other countries since electricity in Norway originates largely from renewable energy in the form of hydropower (Aasness and Odeck, 2015).

Hardman et al. (2017) discussed the effectiveness of purchase incentives for BEVs and PHEVs. They found that sales tax exemptions, VAT exemptions, and purchase subsidies are most effective, and that this effect is greater when the sales tax and VAT are high for ICEVs, which is the case in Norway and the Netherlands.

Their findings are that (i) distinctions in incentives should be made between PHEVs with high- and low electric range, where those with high electric range should receive proportionally higher incentives, as well as between high- and low-end BEVs, where incentives were found to be more important for low-end BEVs (Hardman and Tal, 2016; Tal and Nicholas, 2016); (ii) consumers are not aware enough of the incentives, and more education and awareness campaigns are recommended; and (iii) withdrawing incentives too early is hypothesized to have a negative effect on BEV and PHEV adoption, and as such incentives should be designed for the long-term. Hardman et al. (2017) also stated that incentives should be applied at the point of sale, for example by reduction in VAT or registration costs, or subsidies. Their review is limited to incentives that target the moment of buying a car and exclude reoccurring or indirect incentives like the effects of circulation tax, access to infrastructure or free parking. Thus, no comparison between these types of incentives and incentives at the point of sale was made in their review.

The incentives in the Netherlands and Norway discussed here do not reflect policies related to the first four incentives mentioned. Although policy in the Netherlands does include emission criteria for the different sets of incentives, for example the purchase tax depending on the CO_2 emissions (Hardman et al., 2017), such detail on incentives is not implemented in the current analysis. Assumed is that the current model's classification on powertrains provides enough detail for the analysis.

2.2. Previous modelling work of EV markets in Norway and the Netherlands

Al-Alawi and Bradley, 2013 and Jochem et al., 2017 reviewed studies on EV adoption modelling and forecasting. Jochem et al. (2017) concluded that a current trend is visible towards data driven and hybrid-modelling approaches and suggested that effective modelling exercises need to include

Table 2
Overview of the eight scenarios S1 to S8 and their assumptions.

Scenario	Description
S1 Base 'incentives end 2020'	No incentives are present after 2020
S2 (c) 'current incentives stay'	Incentives as they were in place in 2017 remain in place
S3 (p) 'polluter pays'	Step increase in circulation tax based on vehicle emissions at 2020
S4 (e) 'emission targets'	Manufacturers penalty based on average emissions of yearly sold cars will gradually decrease to reach zero in 2030, starting 2020
S5 'c + p'	Current incentives stay and increased circulation tax from 2020
S6 'c + e'	Current incentives stay and emission penalties to manufacturers reach zero in 2030 starting 2020
S7 'c + p + e'	Current incentives stay, and increased circulation tax together with emission penalties for manufacturers target to zero in 2030 starting in 2020
S8 'p + e'	The current incentives end in 2020, but at the same time circulation taxes will be imposed and the target for emission penalties will gradually decrease to zero in 2030

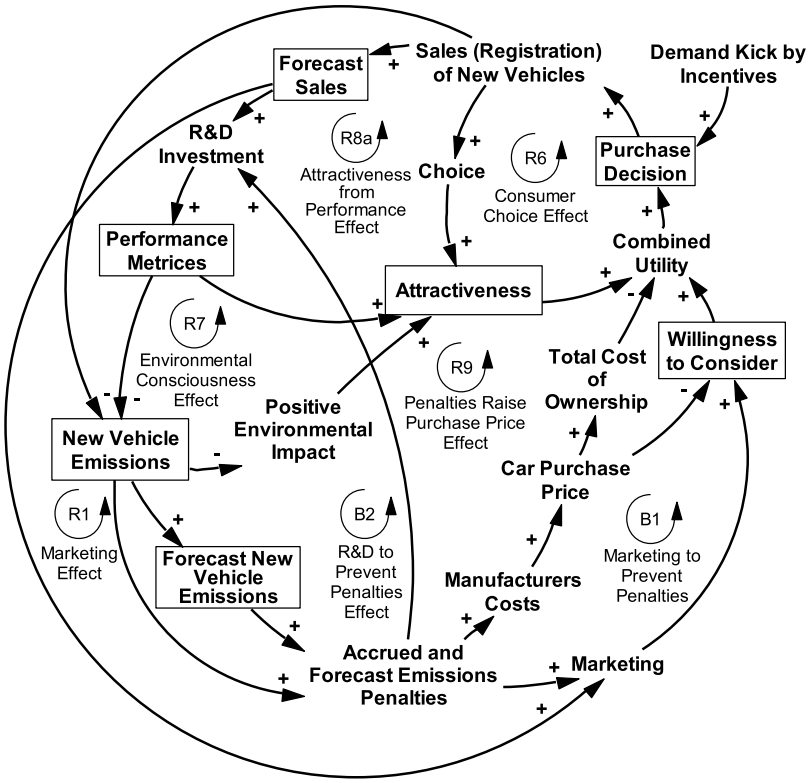

Fig. 1. PTTMAM causal loop diagram (part 1 of 2).
Note: Stocks are indicated by boxes. Variables appearing in both CLDs represent the same equation; all incoming arrows to one variable together make up the equation of that variable (e.g. Attractiveness is a function of five variables: Choice, Performance Metrices, Environmental Impact, displayed in Fig. 1, and of Popularity and Convenience, shown in Fig. 2).

both the macro- and micro-level of decision factors, and distinction between different types of user groups. Al-Alawi and Bradley (2013) argued that modelling of HEV, PHEV and EV sales shares "should include improved interfaces with consumer surveys, modelling of automakers' actions, federal and state policy and its effect on automotive markets, competition amongst technologies, market volume, vehicle classifications, and model parameters sensitivity analysis" (Al-Alawi and Bradley, 2013, p. 1). In this section we will further focus on specific stock and flow modelling work in relation to PTTMAM and Norway and the Netherlands.

Harrison and Thiel (2017a) compared the sales shares of powertrains in PTTMAM scenarios with data from other studies taken from an earlier modelling study (Pasaoglu et al., 2012), concluding that PTTMAM is generally conservative in scenarios on sales shares for all powertrains except for HEVs, and that the relative shares between alternative powertrains is congruent with previous studies.

Another system dynamics model sharing many similarities with PTTMAM is reported by Keith, Naumov, and Sterman (2017). Sensitivity analysis with this model shows relatively high HEV and low BEV market shares compared to PTTMAM. However, since this model captures only the United States (US) market, it can be argued that making a thorough comparison between the outcomes of the two models is not useful, given the differences between the US and the EU passenger markets.

Fortunately, modelling work for the Netherlands and Norway is also available. Fridstrøm and Østli from the Norwegian Institute of Transport Economics make projections based on the 'BIG' stock and flow model (BIG being a Norwegian acronym for vehicle cohort model). Two reported BIG scenarios for new registrations of passenger vehicles are the 'trend path' (trendbanen) and 'ultra-low emission policy' scenarios (Fridstrøm and Østli, 2016). Both scenarios show an increase in sales shares of BEVs, but only the 'ultra-low emissions policy' scenario from 2030 onwards includes FCVs. FCVs do not appear in the 'trend path' scenario, where BEVs are complemented with PHEVs and HEVs. What is not explicitly stated is whether BIG includes feedback processes, such as is the case for PTTMAM between consumers, manufacturers and infrastructure.

A model that contains both the Netherlands and Norway is the ASTRA (ASsessment of TRAnsport Strategies) model (Fiorello et al., 2010). In an application of the model, ZEVs are simulated to account for over half of the EU27 car stock in 2050 under two of the four reported scenarios (Krail and Schade, 2016). However, to the best of our knowledge, no recent results on EV market development in these two countries derived from ASTRA are available in the literature.

More recently, Testa and Bakken (2018) compared scenarios of EV adoption in Norway and Sweden, concluding that a coexistence of BEVs and ICEVs is unlikely. Further analysis found that even when all incentives end in 2020 a transition to BEVs will take place, although the scenario for reaching zero emission goals by 2050 required at least current policies to be prolonged. Under an 'accelerated policies' scenario a complete transition in sales to BEVs was established within two decades (Testa and Bakken, 2018).

This paper contributes to the existing future scenarios literature by constructing eight different scenarios till 2050, which are partially based on the goals of the Dutch and Norwegian governments and their stated means for reaching these (see Sections 3.3.2 and 4.2; Norsk elbilforening, 2018; Rutte et al., 2017). The scenarios focus on policy measures and differ by the level of ambition of financial incentives and emission targets, and three of these scenarios are used in policy sensitivity tests. As discussed earlier, the Norwegian approach is stated to focus on a 'polluter pays' principle, instead of a ban on conventional vehicles (Norsk elbilforening, 2018). The scenario analysis includes several policies, such as taxes to conventional vehicles (referred to as Polluter Pays), and emission targets for manufacturers (which is a step removed from banning conventional vehicles), and tests these in both countries, by single policies and combinations of policies within the scenarios (see Table 2).

3. Model-based analysis of the Dutch and Norwegian car markets using system dynamics

3.1. System dynamics

Pioneered by Jay W. Forrester, system dynamics emphasizes insight to nonlinear behaviour as result of feedback structure (Forrester, 1961; Sterman, 2000), and is often applied for comprehensive public policy analysis or learning through management flight simulators (Forrester et al., 1976; Keith et al., 2017). A system dynamics model consists of a set of integral equations, in which so called 'stock' variables represent the state of

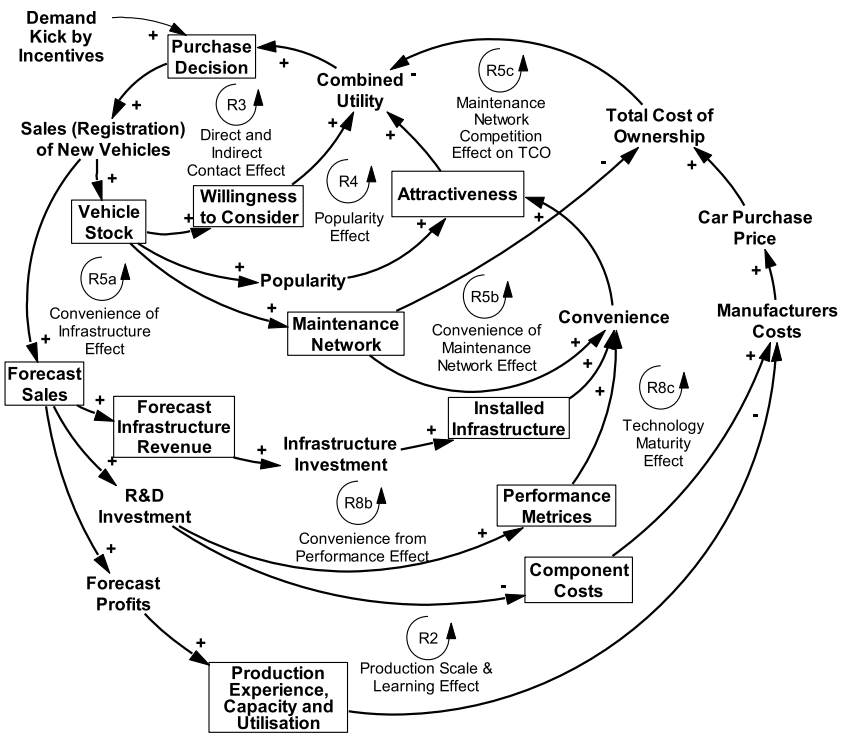

Fig. 2. PTTMAM causal loop diagram (part 2 of 2).

the modelled system by "accumulating or draining over time". Simulated behaviour is due to -and described from the perspective of- feedback loops, communicated through causal loop diagrams (CLDs) (cf. Section 3.3.3). A CLD often consists of three elements: 1) the causal connections, shown as arrows between variables, 2) causal polarity, and 3) singled out representations of feedback loops (indicated by either a positive/reinforcing loop denoted *R* or a negative/balancing loop denoted *B*). In part of this work a previous model diagram, published by Harrison and Thiel (2017a), is used for constructing two CLDs that provide a high level overview of the full model structure, representing 15 reinforcing and two balancing loops, later used for feedback loop knock-out analysis.

3.2. Model description and extension

We used PTTMAM, a system dynamics model of the EU vehicle market implemented in Vensim (Ventana Systems Inc, 2018). In PTTMAM, the interactions of four market agents (Users, Manufacturers, Infrastructure Providers and Authorities) are captured via decision rules and feedback loops, of which the latter two are depicted at high-level overview in Figs. 1 and 2 (appendix A.2 provides more detailed diagrams and indication of the four market agents). The model includes various subsets such as 29 countries, two vehicles classes (passenger and light commercial, of which only the first is considered in this research), three vehicle sizes, three types of users: (i) private, (ii) fleet (company owned cars) and (iii) public (national and local government owned cars), four classes of vehicle age, eight types of fuel, and amongst others, 16 types of powertrains: Petrol ICEV, Diesel ICEV, LPG ICEV, CNG ICEV, Biodiesel ICEV, Bioethanol ICEV, Petrol HEV, Diesel HEV, Biodiesel HEV, Bioethanol HEV, Petrol PHEV, Diesel PHEV, Biodiesel PHEV, Bioethanol PHEV, BEV and FCV. For an exhaustive description of PTTMAM, we refer to Harrison et al. (2016). Previous applications of the model can be found in Pasaoglu et al. (2016) and Harrison and Thiel (2017a). An earlier version of the model (excluding Norway) is available at: https://ec.europa.eu/jrc/en/pttmam.

For the purpose of this analysis, we extended PTTMAM by modelling for the first time Norway. As a result, the current version of the model contains 29 European countries. Though the Norwegian experience with EVs predates 2007, the model assumption that BEVs do not become commercially viable before 2007 was, for simplicity, retained. Besides this, also the EU regulation for manufacturers emission targets remained active in its effect on marketing efforts. Here it is also for simplicity assumed that manufacturers act similarly in Norway as they do in EU countries. As a first step, a database for Norway was created. The sources of Norwegian data were (EAFO, 2018b; Figenbaum, 2016; Norsk elbilforening, 2018; Ntziachristos et al., 2008; Papadimitriou et al., 2013; SSB, 2018; United Nations, 2015).

Thanks to a greater availability of reports on incentives, the input for the model was improved compared to previous publications for the Netherlands (Harrison and Thiel, 2017b, 2017a). The incentives as described in Section 2.1 have all been implemented and different formulations of modelling consumer choice have been tested by means of a 'demand kick'. Harrison and Thiel introduced the demand kick as follows: "the market share determined by the user group could be influenced by 'demand kicks' from subsidies and exemptions. This demand kick is a calibrated multiplier of market share over the period that the incentive is in place, the value of which is determined by a sensitivity of a base demand kick to the magnitude of the subsidy/exemption. This characteristic did not originally include the circulation or registration tax exemption" (Harrison and Thiel, 2017a, p. 5). The same authors summarize the demand kick elsewhere as "[subsidies in place] can lead to increased marketing of the powertrain by manufacturers and a demand kick over and above the standard utility as users are aware of the offer being in place, and possibly short-lived" (2017b, p. 168; referring to the 'combined utility' as depicted in Figs. 1 and 2).

The results from testing different formulations of consumer choice by means of a demand kick are described in Section 4.1, and the final model structure including the demand kick is shown in Figs. 1 and 2. After iterative testing as described in Section 4.1 an extended demand kick formulation was arrived at. This formulation is partially deployed in the second test for the policy sensitivity plots in Section 4.2, here both an active and a completely deactivated demand kick are used in sampling for constructing the scenarios in Figs. 4 and 5 where it becomes more evident that the effect of the demand kick is negligible when comparing future scenarios to 2030 and beyond. The extended formulation is fully used in the third test with loop knock-out analysis (where each of the loops in Figs. 1 and 2 are once deactivated).

Although the purpose of the PTTMAM is understanding the general and long-term dynamic of a transition towards new powertrains, and not for explaining early adopters behaviour, Harrison and Thiel (2017a) provide

scenarios that came close to reproducing the actual shares of new sales of BEVs in the period of 2010 to 2015 in the UK and the Netherlands, when financial incentives in these countries were implemented in the model. The actual shares of new sales were in the region of 0.02%-0.7% of sales for the Netherlands and 0.06%-0.4% for the UK, such that the adopters can be considered as innovators (Rogers, 1962). In Norway the share of new sales for BEVs until 2008 has not been greater than 0.1%, hence this research has not attempted to explain the sales of BEVs in Norway before this time and retains the PTTMAM's original assumption that BEVs have not become commercially viable before 2007.

The current version of PTTMAM computes the user purchase decisions based on a standard multinomial logit choice framework, which is well described in the exploratory policy analysis paper by Harrison and Thiel (2017b). The resulting market share is assumed to be influenced by 'demand kicks' from subsidies and exemptions (Harrison and Thiel, 2017a, p. 5), which was already partially described in Harrison and Thiel and the technical report (Harrison et al., 2016). An optimization procedure was used to provide the demand kick parameters for non-ZEVs and ZEVs in the Netherlands and Norway with historically most accurate market shares during the years that the incentives have been in place (see the procedure followed in the behaviour reproduction test described in Sections 3.2.1 and 4.1). Eqs. 1 and 2 in Section 4.1, together with the equations in the before mentioned publications (Harrison et al., 2016; Harrison and Thiel, 2017b), provide an exhaustive description for the formulation that is used in this paper. In effect, the users purchase decision for the Netherlands differs from Harrison and Thiel (Harrison and Thiel, 2017a) by a more detailed external input on incentives, and a single demand kick structure that distinguishes amongst both PHEVs and BEVs for the different temporary strengths of the effects of incentives.

3.3. Validation tests

The system dynamics literature highlights several aspects of model validity and proposes a series of validation tests. Distinctions are made between several types of validity such as structural, behavioural, empirical and application validity (Barlas, 1996; Barlas and Carpenter, 1990; Bossel, 2007). A comprehensive list of validation tests can be found in Table 21-4 in Sterman (2000). In this paper, we focus on empirical validity and assess model behaviour by carrying out three types of tests: behaviour reproduction, sensitivity analysis and behaviour anomaly tests in the form of loop knock-out analysis. The results of these tests are summarized in Section 4.

The outcome measure of the tests will be the sales shares of ZEVs in Norway and the Netherlands in 2030 and 2050. This outcome measure was decided based on the willingness of both governments to have this sales share increased to 100% by 2030. Besides that, for validation tests and completeness of the outcomes both 2030 and 2050 values are reported, since some feedback effects are shown to be amplified or diminished between 2030 and 2050 in the different scenarios. Moreover, the scenarios show that greater sales shares are unlikely to be apparent by 2030 and could rise faster till 2050.

Table 3
Theil's inequality statistics indicating fit to historic behaviour.

Statistics over 2010-2017, with deactivated demand kick; for future model improvement	R^2	Bias	Variation	Covariation
Norway PHEVs	0.93	0.31	0.68	0.01
Norway BEVs	0.94	0.48	0.47	0.05
Netherlands PHEVs	0.07	0.20	0.25	0.55
Netherlands BEVs	0.93	0.07	0.17	0.75
Statistics over 2010-2015, with active demand kick, for output comparison with improved input for incentives and updated demand kick formulation	**R^2**	**Bias**	**Variation**	**Covariation**
Netherlands BEVs	0.89	0.23	0.42	0.35
Netherlands BEVs (Harrison and Thiel, 2017a)*	0.98	0.57	0.01	0.42
Netherlands PHEVs	0.60	0.19	0.22	0.59
Netherlands PHEVs (Harrison and Thiel, 2017a)**	0.55	0.02	0.00	0.98

compared to the scenarios *NL_14 and **NL_15

3.3.1. Test 1: behaviour reproduction test

The purpose of the behaviour reproduction test is to determine the correspondence of model output with the observed behaviour of the relevant system variables. In practice, this is done by computing descriptive statistics and iterative testing (Oliva, 2003; Sterman, 2000).

The fit to historical data has been visually judged in previous work by Harrison and Thiel (2017a). Their policy analysis on PHEVs and BEVs in the Netherlands and the UK starts out with a base scenario without any incentives as external input (Harrison and Thiel, 2017a). Tests with many different scenarios based on simple external inputs of incentives led to improved model settings for reproducing historical behaviour (we refer to scenarios NL_14 and NL_15 for BEVs and PHEVs in the Netherlands in Harrison and Thiel, 2017a). Where these authors performed their analysis over 2010 and 2015, we found in early tests that replicating their scenario settings did not provide a similar fit for 2016 and 2017 for the Netherlands. Moreover, availability of information on the diversity in incentives that had been present for both PHEVs and BEVs is currently more detailed than it was when Harrison and Thiel (2017a, 2017b) conducted their analysis. Aiming for a near point by point prediction, the external inputs have been improved and are currently set as described in Section 2.1.

The original model settings did not provide a satisfactory fit with historical data after improvement of the external inputs, so an iterative process of testing different model formulations, together with automated calibration for the parameters was conducted. The goal of automated calibration was to test whether the derived parameter settings are congruent with what we know about the system (Oliva, 2003). Different formulations have been rejected based on fit to historical behaviour and feasibility of the parameters. The feasibility was judged according to whether the calibrated parameter was at one of the limits of the range or not. The pre-set ranges for the parameters were set between 0.1 and 7, as to stay consistent with earlier practice (Harrison et al., 2016).

Norway and the Netherlands had good information availability on purchase incentives and sales shares of BEVs and PHEVs. This availability was a requirement for the calibration procedure, similar to earlier practice for Sweden (Harrison et al., 2016). During the iterative process the 'demand kick' was calibrated to account for the rapid and short-lived effects of incentives (Harrison et al., 2016, see also Sections 3.2 and 4.1).

To compare the model fit to historical behaviour and identify potential improvement, Theil's inequality statistics are reported. Theil's inequality statistics decompose the mean square error (MSE) amongst three components: (UM), error due to bias; (US), unequal variation between the simulation and the data; and (UC), unequal covariation (Bliemel, 1973; Sterman, 1984; Theil, 1966, 1965).

Oliva (2003) mentions that Theil's inequality statistics do reveal systematic errors in model formulation but are ineffective in diagnosing the output of automated calibration procedures, since these hide the error in the calibrated parameters. Since the demand kick externally controls for innovators behaviour (Rogers, 1962), and potential model improvements would likely focus on endogenously explaining this type of behaviour, the Theil's inequality statistics are here applied to the scenarios in which the demand kick is not active. In contrast to model improvement, to compare the final scenario of the Dutch BEV and PHEV sales shares over 2010-2015 with those in the previous publication of Harrison and Thiel (2017a), the calibrated values for the demand kick were used to compare the best fitting scenario's by means of the Theil's inequality statistics (see also the two sections within Table 3).

3.3.2. Test 2: policy sensitivity

Three main types of sensitivity analysis tests are found in the system

dynamics literature: numerical, behavioural and policy. Policy sensitivity tests are performed by keeping the policy parameters which make up the scenarios constant and adjusting those parameters that are most sensitive and uncertain (Sterman, 2000). Compared to extensive exploratory policy analysis for the EU, including 24 scenarios with different infrastructure subsidy policies, also by Harrison and Thiel (2017b), this test reports on only eight scenarios, with simpler assumptions (an overview of the eight scenarios is provided in Table 2). We add to the previous work of Harrison and Thiel (2017b) by policy sensitivity plots that include dynamic confidence bounds accounting for part of uncertainty in various parameters: for example by varying the assumptions on costs reduction through learning effects, and the year FCVs become available (see Table A.2 in the appendix; variables where the policy scenarios influence the model are portrayed in appendix A.2).

Besides a base scenario (S1), three types of policies are tested for their effects on sales shares (the single policies and combination of policies that are tested in the Dutch and Norwegian contexts are here referred to as incentive scenarios): S2 'current incentives stay' (shortly indicated with the letter 'c'), S3 'polluter pays' by circulation tax starting in 2020 (indicated with the letter 'p'), and S4 'emission targets' reach zero in 2030 for manufacturers (indicated with the letter 'e'). The S2 (c) 'current incentives stay' scenario assumes that all incentives as used in the base scenario at time 2017 stay present and unchanged till 2050 (see Section 2.1 for the incentives that have been present in 2017). The S3 (p) 'polluter pays' scenario is derived by an average percentage increase of circulation taxes for users with vehicles whose emissions are greater than the average. The assumption in the S3 (p) 'polluter pays' scenario is a policy that will penalize higher-emission vehicles and adapt as the average emissions fall. To create one 'polluter pays' scenario the average percentage increase of circulation taxes for Norway and the Netherlands was derived by a simplistic but clear rule of thumb: testing which round percentage of circulation tax increase would result in around 4% increase in ZEVs sales share in 2030, provided this is the only policy incentive in place. To reach this in the model, the external input for average percentage increase of circulation taxes had to be set on 250% in the Netherlands, and 500% in Norway starting 2020. Norway's circulation tax is several times lower than in the Netherlands, so encouraging potential buyers and owners for a switch to a vehicle with less tailpipe emissions needs a higher percentage increase. These average percentage increases imply an even greater increase for the most polluting vehicles, but a smaller or no increase for little and non-polluting vehicles in the model.

The S4 (e) 'emission targets' scenario is parametrized such that the compliance target of 95 g CO_2/km (European Parliament and Council of the European Union, 2014), is lowered gradually to zero in 2030, starting with a target value of 50 g CO_2/km in 2023, and decreasing yearly with 10 between 2026 and 2030. This encourages R&D spending for reducing tail-pipe emissions and marketing spending for sales of low emission vehicles.

A list of PTTMAM's most sensitive parameters can be seen in Annex II of Harrison et al. (2016). For uncertainty around FCVs and battery packs for EVs (Schmidt et al., 2017), four other parameter values are included which are recognized to include a high degree of uncertainty: "Cost Reduction Fraction From Learning", for the parameters BEV battery, Hydrogen Storage Tank, and Fuel Cell System, between 0.1 and 0.5; and the "Year Powertrain Becomes Available", for the parameter FCV between 2020 and 2030. Finally, uncertainty around the effects of the demand kick are accounted for by structural variance; sampling the parameter value of the variable "Active Demand Kick" with either on (1) or off (0). The dynamic confidence bounds for policy sensitivity are generated based on 1000 simulation runs with Latin hypercube sampling over the parameter space specified in Table A.2. As such, this test is to some extent congruent with the practices of Exploratory Modelling and Analysis, where there is an emphasis on dealing with uncertainty through exploring parametric variations, structural variations, and different non-linear lookup functions (Kwakkel and Pruyt, 2013). Table A.2 shows mostly parametric variations, whereas sampling from both an active and inactivate demand kick represents a structural variation.

Inspired by the Norwegian and Dutch governments' goals of reaching high ZEVs sales shares by 2030 (Norsk elbilforening, 2018; Rutte et al., 2017), the incentive scenarios 'polluter pays' and 'emission targets' have rather extreme model input settings. Such extreme parameter settings are mentioned to be useful in assessing dominant structures during loop knock-out analysis (Sterman, 2000).

3.3.3. Test 3: loop knock-out analysis

Loop Knock-out, or Loop Deactivation Methods have been used for exploring dominant structure in models (Duggan and Oliva, 2013). According to Groesser and Schwaninger (2012), a model of which the microstructures are already validated can be validated on the meso level, to grasp the effect of 'multiple dynamics'. One of the ways of doing this is through loop knock-out tests. The tests employed here originated in the works by Richardson and Ford (Ford, 1999; Richardson, 1986). Keijser et al. (2012) concluded that Ford's loop deactivation method is unsuitable for large models, mainly when exhaustively targeting all loops. Although nowadays formal assessment methods are available in automated toolsets (Naumov and Oliva, 2018) these do currently not yet support models with arrays, which PTTMAM adopts plentifully. In this paper, a pragmatic approach is taken by only knocking out the 17 loops telling by the two CLDs, one at a time, and reporting the effects on ZEVs sales shares in 2030 and 2050. Groesser and Schwaninger (2012) suggest invoking control variables to deactivate feedback relationships by which the impact of the still active structure on the behaviour can "easily be traced and evaluated" (p. 165). The CLDs in Figs. 1 and 2, based on the high-level overview published by Harrison and Thiel (2017a, p. 3), were the bases for selecting loops and locations for where to invoke control variables (Table A.3 provides an overview of the equations that are used for loop deactivation, and the red rectangles in appendix A.2 give a visual overview). The results of this analysis are scenarios in which a loop is inactive, and these are reported by showing the relative change in sales share compared to the base scenario, answering the question: "What if this feedback effect would not be in place?". Due to the size of PTTMAM, this is merely an attempt to explore the relative effects of parts of the model structure in two specific points in time, and does not intent to reveal the actual dominant structure in certain time frames which is usually aimed for in these types of tests (Oliva, 2016).

4. Results and discussion

4.1. Test 1: behaviour reproduction test

The automated calibration procedure together with testing different model formulations went through an iterative process (see A1). The final formulation calibrated 24 parameters (see Table A.1) for the demand kick, where the original formulation would have calibrated 12 for two countries. A further distinction from the original demand kick was arrived at by invoking different parameters for ZEVs and PHEVs and for the effect of access to bus lanes for BEVs in Norway, resulting in Eqs. 1 and 2 (together with the previous publications of Harrison et al., 2016 and Harrison and Thiel, 2017b, these provide a complete overview of the current formulation for the sales shares).

$$\text{Market Share Adjusted for Incentives}_{P,\,C} = \text{active demand kick} * \left(\frac{\text{EU Vehicle Market Share}_{P,\,C} * \text{smoothed total demand kick for subsidies effect}_{P,\,C}}{\sum_P (\text{EU Vehicle Market Share}_{P,\,C} * \text{smoothed total demand kick for subsidies effect}_{P,\,C})} \right) + (1 - \text{active demand kick}) * \left(\frac{\text{EU Vehicle Market Share}_{P,\,C}}{\sum_P (\text{EU Vehicle Market Share}_{P,\,C})} \right) \quad (1)$$

Eq. (1): Market share adjusted for incentives for powertrain P in country C. The variable 'active demand kick' only assumes the values 0 or 1, for comparing runs with and without demand kick, and sampling over both in Section 4.2.

$$\begin{aligned} &\text{total demand kick for subsidies effect}_{P,\,C} \\ &= \text{demand kick from running costs subsidies}_{P,\,C} \\ &\quad + \text{demand kick from subsidies}_{P,\,C} \\ &\quad + \text{demand kick from access to bus lane}_{P,\,C} \end{aligned} \quad (2)$$

Eq. (2): The unsmoothed effect of incentives affecting the running costs, the purchase costs, and the effect from access to bus lanes (only in Norway)

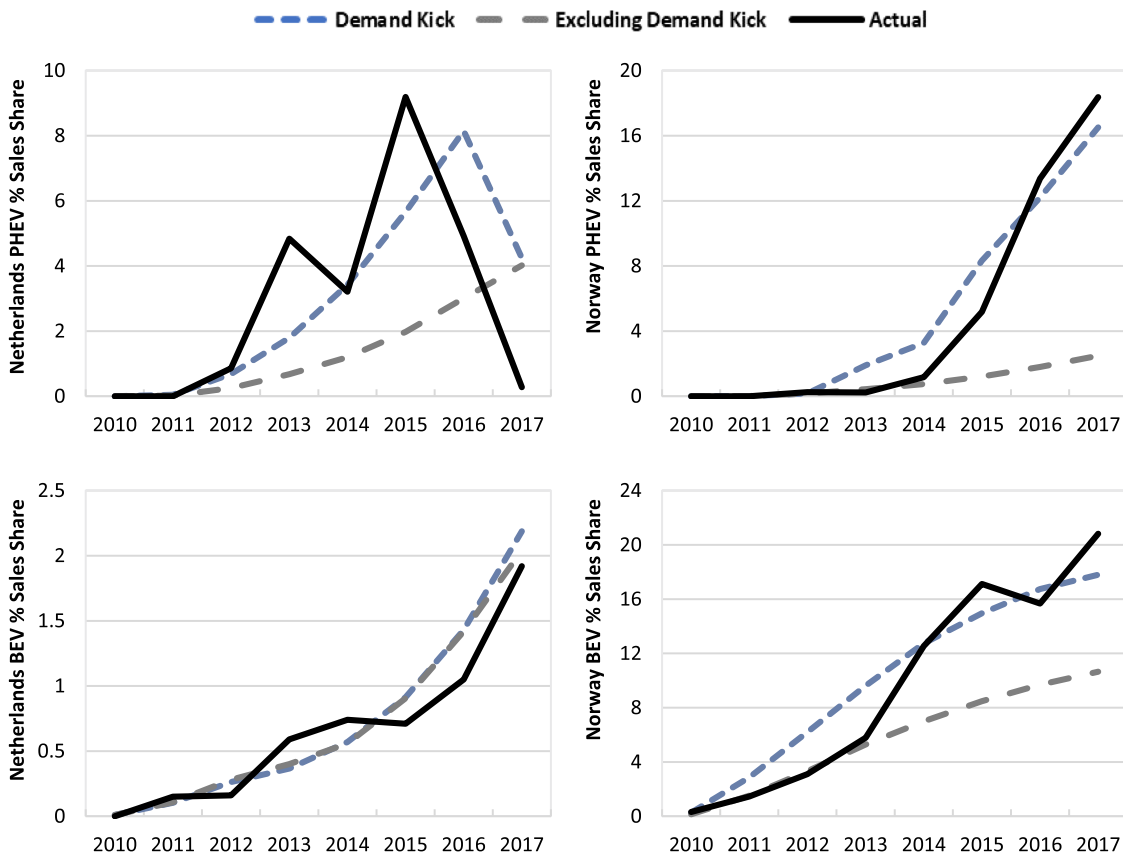

Fig. 3. Model fit to historical data, with and without calibration.

for powertrain P in country C.

The calibration was found to have little effect on the PHEVs and BEVs sales shares behaviour towards 2030 and 2050 compared to an inactive demand kick. More than half of the parameters ended at the limits of the range (0.1 or 7), and for several parameters a similar fit at multiple values was reported (see Table A.1 for the calibrated parameters). Although this was not in line with feasibility of the parameters, a last calibration was performed with wider intervals. This barely improved the historic fit over 2010-2017, neither did it have a visual effect on the scenarios till 2030 and 2050.

Fig. 3 shows the historical development of PHEVs and BEVs in Norway and the Netherlands over 2010 till 2017, compared to simulations with the final demand kick formulation and a simulation with the demand kick inactive. These results are strong evidence that the current endogenous model structure does not provide a fully satisfactory explanation of early adopters behaviour, neither does the current formulation of the external structure in the form of the demand kick.

The output of the final automated calibration procedure points at a high level of model uncertainty with regards to the effects of incentives. This model uncertainty is accounted for in the policy sensitivity tests, by showing dynamic confidence bounds in Figs. 4 and 5 including both runs with the calibrated parameters (an active demand kick), and runs without the calibrated parameters (not active demand kick). Although, as mentioned before, the calibrated parameters in the final formulation were found to have little effect on the sales shares of ZEVs in the Netherlands and Norway between 2030 and 2050.

The Theil's inequality statistics from comparing the simulation of a deactivated demand kick with the actual historic data are reported in the upper part of Table 3. The statistics point out that the simulated EV market share, which excludes the short lived 'kicks' from financial incentives, has a bad fit with historic data of Norway since 2014 for BEVs and from 2015 onward for PHEVs. The statistics show that the error for Norway is concentrated in bias and variation. The error in bias indicates that parameter adjustments could correct for this, which is visible in the calibrated demand kick simulation. However, the error in variation can be due to abstractions from reality in the model assumptions.

In contrast, the bias and variation error in PHEVs in the Netherlands is smaller, but visual inspection and the low R^2 indicates that the model behaviour does not explain the oscillatory behaviour which can be due to factors not captured in the model. The simulated behaviour of BEVs in the Netherlands without demand kick barely differs from the calibrated active demand kick; and the statistics indicate that only a small portion of the error is concentrated in bias or variation, which could indicate that error is mainly due to unsystematic noise.

The lower part of Table 3 reports the statistics with an active demand kick to compare with the best scenarios in the previous publication of Harrison and Thiel (2017a). It shows that with respect to PHEVs it does slightly better, which was expected since a large part of the improvements of the input on incentives were related to PHEVs. Moreover, the new demand kick formulation differentiates between ZEVs and PHEVs, whereas the previous formulation did not. In contrast, for BEVs the current scenario performs worse. The demand kick was calibrated to reflect the best possible fit between 2010 and 2017, and since the sales share of BEVs in 2016 and 2017 deviates substantially from the 2010-2015 period, the worse fit is reasoned to be caused by the automated calibration procedure in which the payoff for a better fit on 2016-2017 compensates for the slightly worse fit on 2010-2015. Two differences between the NL_14 scenario for BEVs in Harrison and Thiel (2017a) and the standard model assumptions in this paper have been in place, and were considered out of the scope of this research. First, the registration costs are accounted as fixed costs in NL_14, which spreads them out over the expected years that the first owner keeps the vehicle, instead of being part of the purchase price. The second difference is that the registration and circulation tax are not part of the demand kick for BEVs in NL_14, such that the temporary kicks from these taxes do not appear. These differences in assumptions could explain the differences in the model fit with actual historic behaviour, and perhaps put a different light on how future

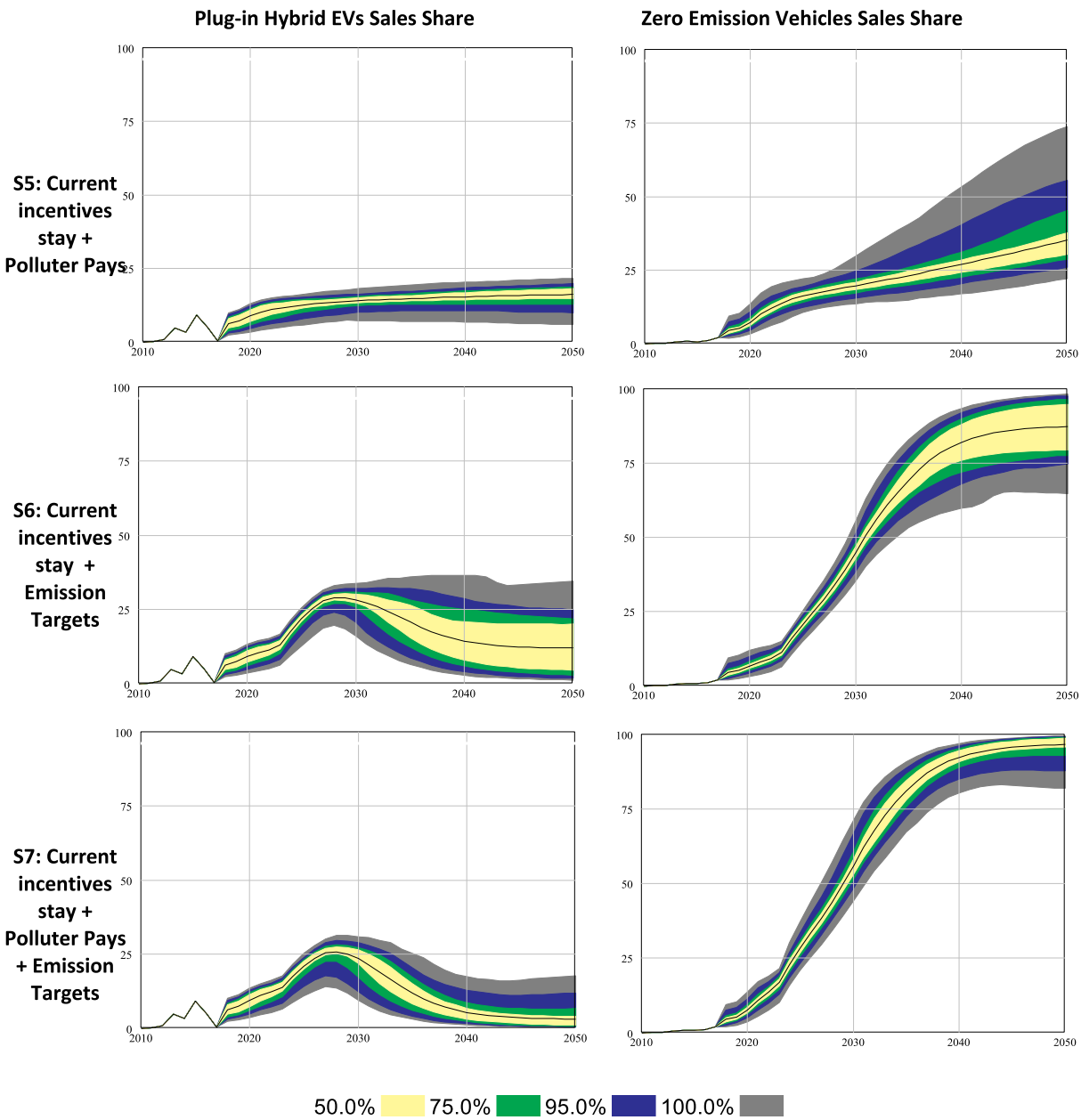

Fig. 4. Netherlands policy sensitivity plots for PHEVs and ZEVs under scenarios S5, S6 and S7.
Note: S5, S6 and S7 assume more drastic policies to get effect after 2020 (polluter pays starts 2020, and the effects of emission targets become visible around 2023), hence there are relatively lower adoption rates during 2018-2020 than could perhaps be expected by the reader. The black line indicates the mean value of the 1000 simulation runs. Note that the outer grey area (100%) is limited to the uncertainty space explored within this analysis.

model formulations could be tested. In any case, these results indicate that part of the innovators behaviour in Norway and the Netherlands is unsatisfactorily predictable with the current model formulation. Although, as can be seen in the second test, this is of little consequence for most of the sales shares scenarios till 2050 (where PHEVs in Norway is the greatest exception).

4.2. Test 2: policy sensitivity

The results of the policy sensitivity tests are reported in Table 4, which provides the numerical results for all eight scenarios. Figs. 4 and 5 show dynamic confidence bounds in behaviour over time plots for PHEVs and ZEVs in the Netherlands and Norway for three of the eight scenarios.

The results of the scenarios for ZEVs sales shares (and the proportion of which is FCVs) in 2030 and 2050 are provided in Table 4. Table 4 also shows the scenarios S5 to S8, which are combinations of incentive scenarios S2 to S4.

The results in Table 4 show that none of the tested scenarios reaches a 2030 ZEVs sales share that satisfies the targets of the Netherlands or Norway. Only the combination of all three incentive scenarios reaches a ZEVs sales share over 50% for 2030. Moreover, only the scenarios in which manufacturers emission targets reach zero in 2030 make it to a significant transition towards ZEVs by 2050. That regulatory CO_2 emission targets weigh heavy in sales shares for EVs, and in particular for FCVs, was also concluded from the previous work by Harrison and Thiel for the EU (2017b).

The findings for Norway differ from those in the scenarios by Testa and Bakken (2018), since a transition which fulfils zero emission goals is not reached by 2050 when current incentives stay. This could be due to the difference in incentives, such as the option in PTTMAM to impose emission targets on manufacturers.

In the 'polluter pays' scenario it is contradicting to expectations that the large increases in circulation tax would result in a meagre effect on ZEVs

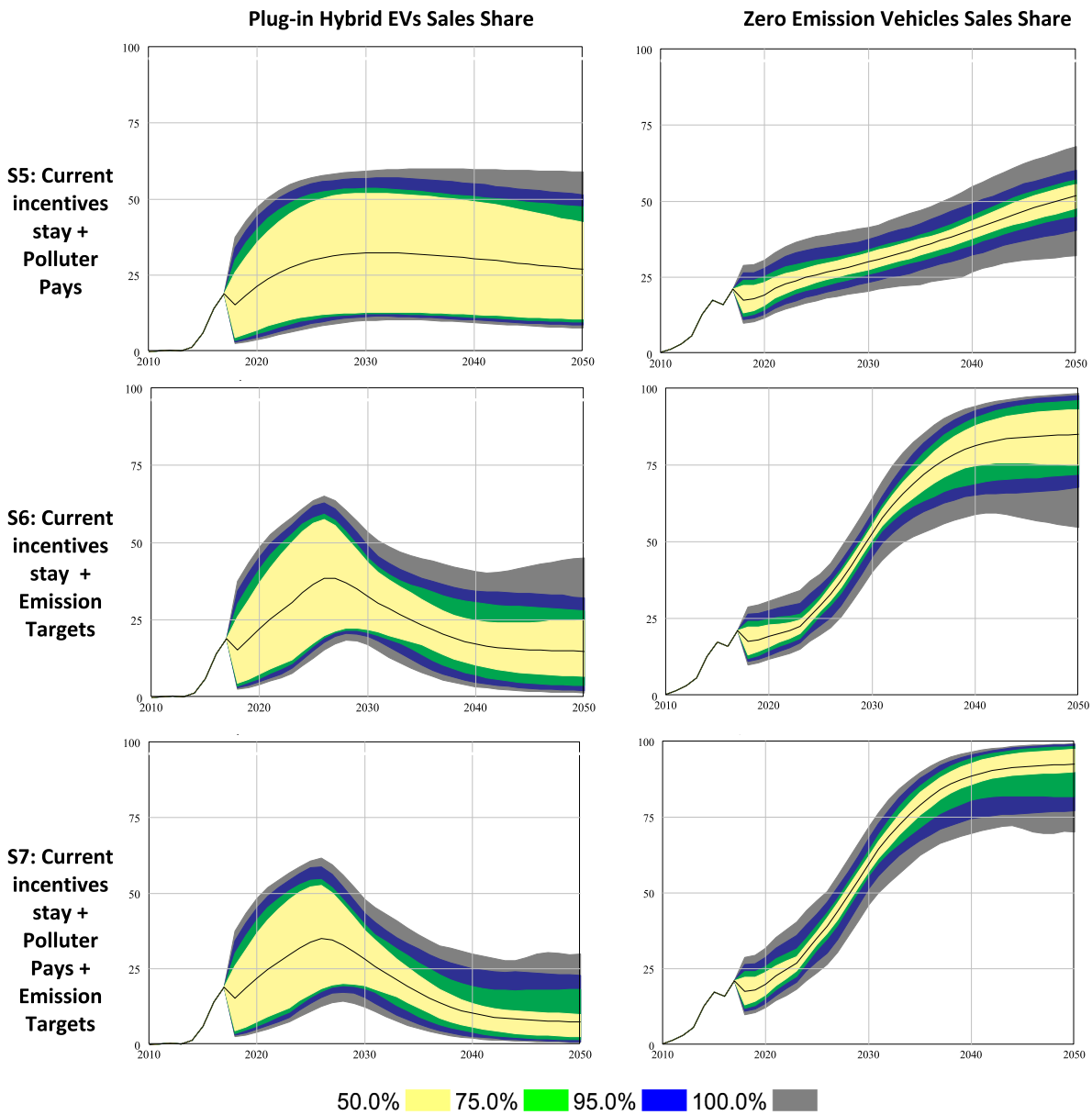

Fig. 5. Norway policy sensitivity plots for PHEVs and ZEVs under scenarios S5, S6 and S7 (note of Fig. 4 equally applies).

sales share (portrayed by the total cost of ownership in Figs. 1 and 2, but circulation costs are not part of a feedback loop, and thus not represented in these diagrams). This could point at an insensitivity to the financial attractiveness of vehicles in the model, which was also suspected in the first test related to the effects of subsidies. Nevertheless, it is reasonable that an increase in circulation tax for polluters can increase the sales share of ZEVs, therefore this scenario is kept as part of the further analysis.

Figs. 4 and 5 show policy sensitivity plots for the S5, S6, and S7 combinations of policy scenarios. Although the policy scenarios c, p and e only take effect after 2020, the sampling space as provided in Table A.2 is active already from 2018. These dynamic confidence bounds show that there is greater confidence in reaching a ZEVs sales share of over 50% by 2030 when a combination of all these three policies is in place. The S5 scenario shows that a full transition to ZEVs has not taken place till 2050 when only relying on current incentives and emission taxes to vehicle owners. The S6 scenario comes very close to the S7 scenario, but the ZEVs sales share is much more likely to stay below half of the total sales at 2030, whereas in the S7 scenario it is in more than 75% of the simulations over half of the total sales.

When a rapid transition to zero emission vehicles is the aim, the S7 policy set shows the most promising results for 2030 and 2050. The tested difference between the S8 and S7 scenario (see Table 3) shows that keeping the current incentives provides a major difference for the 2030 targets. Moreover, Figs. 4 and 5 show that in the S7, 'current incentives stay'- scenario a greater number of simulation-runs reaches a zero emission vehicles sales share above 50%, compared to the S5 and S6 scenarios in which most of the simulations stay below 50% in 2030.

The sales shares for PHEVs show a much greater uncertainty in Norway than in the Netherlands. In the Netherlands each scenario of PHEVs sales share is at any time below 40%, whereas in Norway this could be between 0 and 70%. Driving with two motors, as is the case with plug-in hybrid vehicles, is unnecessary, but the uncertainty of the speed at which batteries improve together with the not-well understood effects of current incentives (including recent PHEV subsidies in Norway), amongst others, evolved here in the widened confidence intervals pictured in Fig. 5.

4.3. Test 3: loop knock-out analysis

For exploring relative effects of feedback loops, each indicated loop portrayed in Figs. 1 and 2 was deactivated. The impact on ZEVs sales shares are reported in Table 5. This section discusses the differences in the effects of

Table 4
Sales shares in 2030 and 2050 for ZEVs and which part is FCVs for the eight scenarios S1 to S8.*.

Scenario	Netherlands				Norway			
	2030		2050		2030		2050	
	ZEVs	FCVs	ZEVs	FCVs	ZEVs	FCVs	ZEVs	FCVs
S1 Base 'incentives end 2020'	8,4	1,8	10,6	3,7	9,1	1,5	11,2	3,8
S2 (c) 'current incentives stay'	12	2,7	26,5	17,2	22,7	4,9	43,7	28
S3 (p) 'polluter pays'	12,5	2	19,1	4,8	12,9	1,5	15,8	3,9
S4 (e) 'emission targets'	36,6	10,8	94,8	51,8	34,6	8,8	93,5	52,3
S5 c+p	21	4,3	48,1	30,1	29,7	5,9	52	32
S6 c+e	45,9	12,6	94,4	50,9	49,9	12,2	88,8	52,3
S7 c+p+e	59,5	15,1	98,5	52,1	58,8	13,2	95,5	52,7
S8 p+e	44,8	11,4	97,9	45	41,3	8,3	96,3	44,8

* darker green reflects a greater share of ZEVs

Table 5
Results of loop knock-out analysis*.

Loop deactivated		S1: Base scenario 'incentives end 2020'				S7: Combination incentive scenarios c+p+e			
		Change in ZEVs Sales Share Norway		Change in ZEVs Sales Share Netherlands		Change in ZEVs Sales Share Norway		Change in ZEVs Sales Share Netherlands	
		2030	2050	2030	2050	2030	2050	2030	2050
R1	Marketing Effect	3%	3%	1%	0%	2%	0%	1%	0%
R2a	Learning Effect	0%	6%	-1%	6%	10%	3%	1%	1%
R2b	Scale Effect	0%	1%	0%	1%	1%	1%	0%	0%
R3a	Direct Word-of-Mouth Effect	4%	3%	1%	0%	6%	1%	3%	0%
R3b	Indirect Word-of-Mouth Effect	14%	50%	4%	11%	1%	2%	-2%	0%
R4	Popularity Effect	0%	0%	0%	0%	0%	0%	0%	0%
R5a	Infrastructure Convenience Effect	2%	1%	1%	0%	1%	0%	1%	0%
R5b	Maintenance Network Convenience Effect	0%	0%	0%	0%	0%	0%	0%	0%
R5c	Maintenance Network Competition Effect	0%	0%	0%	0%	1%	0%	1%	0%
R6	Consumer Choice Effect	1%	0%	1%	0%	0%	-1%	1%	0%
R7	Environmental Consciousness Effect	-1%	0%	0%	0%	-2%	0%	-2%	0%
R8a	Attractiveness from Performance Effect	1%	0%	1%	2%	-2%	-2%	0%	0%
R8b	Convenience from Performance Effect	2%	1%	1%	0%	1%	0%	1%	0%
R8c	Technology Maturity Effect	-2%	-5%	-4%	-5%	-4%	1%	-9%	0%
R9	Penalties Raise Purchase Price Effect	1%	3%	1%	3%	1%	-3%	-3%	-1%
B1	Marketing to Prevent Penalties Effect	2%	-1%	-5%	-7%	17%	3%	3%	1%
B2	R&D to Prevent Penalties Effect	-1%	-4%	-2%	-3%	-3%	-1%	-4%	0%

* darker green reflects a greater share of ZEVs in the corresponding year, scenario and country (the loop had a stimulating effect on the adoption of ZEVs, showing negative values when knocked-out), whereas darker red reflects a lesser share of ZEVs (the loop had an inhibiting effect on the adoption of ZEVs, and showing positive values when knocked-out).

the feedback loops, and the change in these effects between the S1, 'incentives end 2020′ base scenario and the combined incentive scenario of S7, 'current incentives stay', 'polluter starts paying in 2020′, and 'manufacturers emission targets reach zero by 2030′.

The results in Table 5 show that deactivating loop R3b, the Indirect Word-of-Mouth Effect, results in an increased ZEV sales shares under the base scenario 'incentives end 2020′. This indicates that, when no incentives are in place, the indirect word-of-mouth effect is comparatively a large inhibitor of a transition away from current powertrains. This is in line with expectations, since potential buyers have the propensity to make the same decisions as whom they know, and new innovations are not easily adopted by the majority, especially when their face value -the value without calculating for all the possible subsidies- is less financially attractive, and the performance metrics (like range) are below what is used to. What was unexpected was the fact that the indirect word-of-mouth effect turned out to be comparatively stronger than the direct word-of-mouth effect. Conceptually this could suggest that the effect of two persons discussing a vehicle type they both do not own is stronger than the effect of one of them owning such a vehicle type (Struben and Sterman, 2008).

Eight feedback loops are found not to affect the ZEV sales share with more than 2%: R2b, Scale Effect; R4, Popularity Effect; R5b, Maintenance Network Convenience Effect; R5c, Maintenance Network Competition Effect; R6, Consumer Choice Effect; R7, Environmental Consciousness Effect; R8a, Attractiveness from Performance Effect; and R8b, Convenience from Performance Effect. Except for loop R2b, Scale Effect, the other seven feedback loops mentioned are all direct or indirect inputs to the Attractiveness variable. It could be that in reality these feedback loops do have stronger effects on the consumers choice, but that the loop knock-out analysis shows that these are comparatively underrepresented in the current model formulation. However, when the current formulation does satisfactorily represent reality, these Attractiveness indicators could be of less influence than was formerly assumed in recent work (Hoen and Koetse, 2014; Jensen et al., 2014; Struben and Sterman, 2008). It must be noted that the scenario analysis excludes any incentives related to infrastructure and maintenance networks, which could put the effects of these loops in a different light. Also unexpected is the comparatively small effect of the loop R2b, Scale Effect, since the benefits of scale are reasoned to bring a substantive decrease of the unit production costs, and subsequently should decrease car prices such that sales shares can rise.

In contrast, deactivating feedback loop R8c, Technology Maturity Effect, results in the biggest decrease in ZEV sales shares. The results in Table 5 show that the composition of the strongest feedback loops changes from the base scenario to the combination of incentive scenarios. The strongest inhibitor of transition to ZEVs without any incentives, the indirect word-of-mouth effect, becomes far less important in the combined incentives scenario. Moreover, the Technology Maturity Effect (R8c) plays a stronger role till 2030, but less on the longer term till 2050. The Penalties Raise Purchase Price Effect (R9) has a comparatively small inhibiting effect when incentives are absent but becomes strong and positive in its effect on ZEV sales shares till 2050 in the case of combined incentives.

The feedback loops R2a, Learning Effect, and B1, Marketing to Prevent Penalties Effect, show a significant inhibition of the transition to sales of ZEVs in 2030, and this effect in 2050 is still comparatively the largest (although small in absolute change in sales share). The 17% difference by 2030 in Norway was unexpected. This could have been caused by the contradictory stimuli present in scenario S7, in which both PHEVs remain incentivized (PHEV incentives were recently put in place in Norway), but manufacturers are starting to be more penalized based on average emissions from sold cars. This pushes manufacturers in the model to market PHEVs in early stages, which undermines the uptake of ZEVs in later years. Also, this is in line with the broad uncertainty envelop pictured in Fig. 5. However, since penalties for manufacturers only apply in EU member states, and not in Norway, it is uncertain how this effect plays out.

Most of the feedback loops have less effect in the combined incentive scenario in 2050 compared to the base scenario. This shows that in the combined incentives scenario the dynamics of the transition are less influenced by feedback loop effects within the market, compared to when the market is not subjected to regulatory interventions. Generally, these results can be interpreted such that tax and subsidy incentives, together with penalties remain necessary for a transition to occur in both Norway and the Netherlands.

5. Conclusions and future research

The Netherlands and Norway both have a unique history with the use of EVs and the incentives that have been in place (Figenbaum, 2016; Netherlands Enterprise Agency, 2017; Norsk elbilforening, 2018; RVO, 2018). The governments of both countries have pledged targets for 2030 of only zero emission vehicle sales (Norsk elbilforening, 2018; Rutte et al., 2017). Given their history and the available data, combined with current high sales shares of EVs and the future targets, these countries are of special interest to analysis, and the insights and pitfalls are potentially transferrable to other contexts.

In this research the system dynamics model known as PTTMAM was extended to include Norway - the global leader in the electric car market when measured in sales market share - and updated to include recent information on incentives in the Netherlands and Norway. The model was subjected to further validation tests: behaviour reproduction, policy sensitivity and loop knock-out analysis, including an outlook on future scenarios.

The main findings from the behaviour reproduction test are: (i) when comparing the results for the Netherlands to Harrison and Thiel (2017a), the historic fit in terms of R^2 worsens for BEVs but improves for PHEVs; and (ii) the current model structure does not explain adequately early adopters behaviour.

For the purpose of the policy sensitivity test, eight scenarios were constructed and analysed, complementing those reported by Harrison and Thiel (2017b). By accounting for parametric variance in fourteen highly uncertain variables and using structural variance by the means of sampling both with the demand kick activated and deactivated, we find: (i) confirmatory evidence that stringent CO_2 emission targets have a crucial impact on ZEV uptake; and (ii) that the small impact the large emission taxes have in the 'polluter pays' scenario casts doubts on the formulation of the effect of financial attractiveness.

The main findings from the loop knock-out analysis are: (i) the reduction in the costs of components is comparatively the strongest feedback effect when no incentives are in place; and (ii) it is confirmed that the variables combined in attractiveness do not currently have a large impact on the uptake of ZEVs in the model. The latter touches upon a point previously highlighted by Pasaoglu et al. (2016), namely the need to improve the way users' choice is modelled.

We conclude from our simulations that, given the current speed of the transition, it is unlikely that all new passenger cars sold in 2030 will be ZEVs in the Netherlands and Norway. However, there is the potential to reach near 100% in 2050, with over 50% sales shares of ZEVs by 2030, under the conditions that strong incentives in the forms of penalties for manufacturers that do not meet emission targets (or self-directed transition to ZEVs) and emission taxes for consumers come in place, likely to be accompanied with continued financial incentives to make a transition financially possible for consumers and manufacturers over the coming 30 years.

Drawing on the policy sensitivity analysis, the best-case scenarios for the Norwegian and Dutch governments' 2030 targets are the policy simulations that include at least (i) a manufacturers emission target of zero emissions by 2030, and either (ii) the continuation of current incentives, or (iii) emission taxes to car owners. Still then the targets are only potentially met by 50% ZEVs sales share and are likely to be lower according to the analysis. Reaching beyond 50% becomes much more likely when all three policies are included, whilst keeping the manufacturer's emission targets and stopping current incentives, or not imposing any emission taxes on car owners, makes it more likely that 50% will not be reached by 2030.

Future research could explore the proportions and sensitivity of incentives that stimulate the market to transfer earlier and more rapidly by 2030 further, which could show what is needed to draw nearer to the Norwegian and Dutch governments' 2030 targets before 2030 has passed. However, the current set of tested incentives contains (i) a 2030 target for

zero emissions of manufacturers vehicle sales (which implies that manufacturers must pay penalties on vehicles that do have emissions, but can still be sold), and (ii) already proportionally large financial incentives. Nonetheless, contradicting the current analysis, the 2030 targets might still be approximated more closely or reached in the future due to factors that must be addressed in further research. In the meantime, the targets provide guidance for reducing vehicle emissions, for less severe effects on human health and climate change (Hoek et al., 2013; Künzli et al., 2000; Lorenzoni and Pidgeon, 2006; Parry et al., 2007; Woodcock et al., 2009).

Doing further tests in comparing these countries can identify more of the structure that is responsible for the different effects. Differences in outcomes from the loop knock-out analysis could form the input for recommended exercises like parameter sensitivity analysis or consumer surveys (Al-Alawi and Bradley, 2013). Notably, the unexpected outcome on the indirect word-of-mouth effect (recall Section 3.3.3) and the fact that this differs for Norway and the Netherlands can be subjected to further testing in future research for model improvement and insight in the real-life processes.

Next to that, similar to the different future policy scenarios in this paper, the differences between the two countries with respect to their historical developments can be explored by 'altering history' tests in future research. Furthermore, insights from these differences can then be subjected to analysis on what extent these keep hold in scenarios differing from the Netherlands and Norway, testing the potentially transferability to other countries in future research, similar to Harrison and Thiel (2017a), who implement policies tested in the Dutch and UK settings in other European countries in PTTMAM.

Implementing Norway made several gaps of the model come to light. Norway has a relatively long history of BEVs with the first experiments of industrial development in 1989, and the first financial incentive being an exemption from registration tax starting as early as 1990 (Figenbaum, 2016). Also, the context of BEVs in Norway differs from EU countries with respect to the allowance of driving on bus lanes and the reduced or exempt fees for toll lanes and the use of ferries. For the allowance of driving on bus lanes a new external variable that stimulates direct market uptake was implemented as part of the demand kick. Although this variable has been part of the automated calibration procedure there is still a large uncertainty to the change in numerical settings for this effect. Moreover, the early years of BEVs in Norway were characterized by the actions of consumer groups influencing policy makers for introducing incentives and keeping them in place (Figenbaum, 2016). Furthermore, it has been suggested that part of the people who purchased an EV, did not purchase the EV to replace an existing vehicle, but as an extra car for short distance trips (Holtsmark and Skonhoft, 2014). At its current state, PTTMAM does not model explicitly purchases of an extra car.

Future research on vehicle market modelling, adaptations on PTTMAM, and policy design should also take note of the recommendations by Hardman et al. (2017), Hardman and Tal (2016), and Tal and Nicholas (2016): (i) distinguishing between PHEVs with high- and low electric range, analysing the effects when high electric range receives proportionally higher incentives; (ii) distinguishing between high- and low-end BEVs, with incentives that are focused on the low-end BEVs; (iii) considering consumers awareness, which is congruent with our suggestion that improving replication of the 2010 to 2017 historic period potentially benefits from more accurate modelling of different groups of consumers and their awareness of incentives; and, finally, (iv) that withdrawing incentives too early can have a negative effect on BEV and PHEV adoption, and policy design should take a long-term perspective.

As a result of the validation tests, two main specific areas where the behavioural assumptions of the model may be improved are identified: (i) incorporating additional variables representing factors that might influence choice (e.g. public policy discussions that lead to hastened purchase decisions (Lévay et al., 2017)); and (ii) replacing the current users' choice formulation with one supported by empirical evidence (the implementation of a statistical model based on a survey amongst European car owners (Gómez Vilchez et al., 2017) is currently underway). In addition, further research is needed to understand the effectiveness of incentives for EV purchase and translate this into the model.

In line with previous research (Harrison and Thiel, 2017b), we found that certain powertrain technologies can lock-in, in which high levels of PHEVs adoption in earlier stages results in lower sales shares of ZEVs later. A similar phenomenon could be present between FCVs and BEVs. PHEVs are reasoned to be a stepping stone for the transition towards ZEVs, useful in consumer acceptance of electric charging and for cost reductions in the production of batteries, but less attractive once BEV range substantially increases, for example when lithium-ion battery energy density continues to improve (Turcheniuk et al., 2018; Zubi et al., 2018). Finally, and since the Netherlands and Norway also have ambitious FCV plans (European Commission, 2017; Norsk elbilforening, 2018), further research on the market prospects of this powertrain technology is needed.

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Appendix

A.1. Iterative process of formulation and automated calibration for alternative demand kick structures to externally approach the effects of (financial) EV incentives in the Netherlands and Norway

For the first formulation we started with a mostly complete external input for the several incentives that had been in place for Norway and the Netherlands. Next to that we rejected the notion of the demand kick, based on the reasoning that the effects of incentives could have their impact through the variables that make up the function of the combined utility. A non-linear analytical function as used in the demand kick was inserted to the variables that are part of the combined utility function. Then automated calibration was used to find optimal values for these parameters, with the sales shares of PHEVs and BEVS in Norway and the Netherlands between 2010 and 2017 being the payoff variables. Automated calibration to the external input was also performed in the original model with the demand kick, given that good information on alternative powertrain subsidies and resulting demand should be available (Harrison et al., 2016), which is the case for Norway and the Netherlands. The results did not yield a better visual fit with historical values for any of the four payoff variables.

Based on the reasoning that the combined utility for PHEVs and BEVs could have different parameter values, since range anxiety applied to BEVs but not to PHEVs, we proceeded with a second formulation in which the parameters are separately calibrated for BEVs (ZEVs) and PHEVs. This second formulation did also not result in a near fit with historical values, and it was reasoned that the markets in Norway and the Netherlands both react different. The third formulation calibrated the parameters for both countries separately, this time a good fit with historical values was the result, however the calibrated values were on the limits of the pre-set ranges. Whilst expanding the ranges the parameters reached levels beyond what could be consistent with common sense,

Table A.1
Current values of the automated calibrated parameters (pre-set range of 0.1 to 7).

Variable name	Current value
base subsidies for demand kick[Netherlands]	7.00
base subsidies for demand kick[Norway]	0.61
sensitivity of demand kick to subsidies[Netherlands]	0.10
sensitivity of demand kick to subsidies[Norway]	1.05
base demand kick for subsidies[Netherlands]	0.10
base demand kick for subsidies[Norway]	0.73
base subsidies for running cost demand kick[Netherlands]	3.73
sensitivity of demand kick to running costs subsidies [Netherlands]	0.95
base demand kick for running costs subsidies[Netherlands]	0.80
base effect of access to bus lane demand kick[Norway]	7.00
sensitivity of demand kick to effect of access to bus lane [Norway]	0.10
base demand kick for effect of access to bus lane[Norway]	0.10
ZEV base demand kick for running costs subsidies[Netherlands]	0.10
ZEV base demand kick for running costs subsidies[Norway]	0.10
ZEV base demand kick for subsidies[Netherlands]	0.10
ZEV base demand kick for subsidies[Norway]	0.26
ZEV base subsidies for demand kick[Netherlands]	7.00
ZEV base subsidies for demand kick[Norway]	5.88
ZEV base subsidies for running cost demand kick[Netherlands]	7.00
ZEV base subsidies for running cost demand kick[Norway]	5.83
ZEV sensitivity of demand kick to running costs subsidies [Netherlands]	0.10
ZEV sensitivity of demand kick to running costs subsidies [Norway]	0.64
ZEV sensitivity of demand kick to subsidies[Netherlands]	0.10
ZEV sensitivity of demand kick to subsidies[Norway]	0.99

Table A.2
Sample space for the Latin hypercube sampling used in multivariate Monte Carlo analysis for policy sensitivity.

Variable name, subscript, distribution and range
initial base unit production cost[Petrol ICEV,Small] = RANDOM_UNIFORM(6000,10,000)
annual change in passenger importance of criterion[Environment,Fleet,Urban] = RANDOM_UNIFORM(-0.05,0.5)
annual change in passenger importance of criterion[Environment,Private,Urban] = RANDOM_UNIFORM(-0.05,0.5)
reference minimum price differential for wtc = RANDOM_UNIFORM(0,0.25)
initial powertrain utility[Diesel ICEV,Medium,Environment] = RANDOM_UNIFORM(0.5,0.8)
annual change in passenger importance of criterion[Choice,Fleet,Urban] = RANDOM_UNIFORM(-0.05,0.5)
annual change in passenger importance of criterion[Popularity,Fleet,Urban] = RANDOM_UNIFORM(-0.05,0.5)
annual change in passenger importance of criterion[Popularity,Private,Urban] = RANDOM_UNIFORM(-0.05,0.5)
initial base unit production cost[Petrol HEV,Small] = RANDOM_UNIFORM(6000,10,000)
annual change in passenger importance of criterion[Choice,Private,Urban] = RANDOM_UNIFORM(-0.05,0.5)
active demand kick = VECTOR(0,1,1)
cost reduction fraction from learning[BEV battery] = RANDOM_UNIFORM(0.1,0.5)
cost reduction fraction from learning[Hydrogen storage tank] = RANDOM_UNIFORM(0.1,0.5)
cost reduction fraction from learning[Fuel cell system] = RANDOM_UNIFORM(0.1,0.5)
year powertrain becomes available[FCV] = RANDOM_UNIFORM(2020,2030)

Table A.3
Equations used for loop deactivation (when 'sw [loop name]' set to 1: loop active, 0: loop knocked-out).

Loop		Equation for Deactivation
R1	Marketing Effect	marketing effort from sales forecast = min(1, ZIDZ((("country long-term forecast sales share"[Country,Powertrain]*sw R1)),base sales for marketing[Country])^sensitivity of marketing to forecast sales share)
R2a	Learning Effect	strength of learning curve = LOG(1-cost reduction fraction from learning[Component]*sw R2a, 2)
R2b	Scale Effect	effect of economies of scale on costs = min(max economies of scale effect on costs,"production / economies of scale"(EU powertrain production capacity[Powertrain]/base powertrain production capacity for economies of scale)* max economies of scale effect on costs*sw R2b)
R3a	Direct Word-of-Mouth Effect	EU Direct Exposure to Powertrain = (EU frequency and effectiveness of direct contacts between drivers and powertrains [Country]*sw R3a)*EU Willingness to Consider Powertrain[Country,Current Powertrain,Powertrain]*EU Powertrain Proportion of Vehicle Stock[Country,Powertrain]*average cost impact on wtc in country[Country,Powertrain]
R3b	Indirect Word-of-Mouth Effect	EU Indirect Exposure to Powertrain = sum((EU frequency and effectiveness of non direct contacts between drivers and powertrains [Country]*sw R3b)*EU Willingness to Consider Powertrain[Country,Current Powertrain!,Powertrain]*EU Powertrain Proportion of Vehicle Stock[Country,Current Powertrain!]*average cost impact on wtc in country[Country,Powertrain])
R4	Popularity Effect	EU powertrain popularity = min(1,((ZIDZ(EU Powertrain and Size Proportion of Vehicle Stock[Country,Powertrain,Vehicle Size],base prevalence for popularity)^sensitivity of popularity to prevalence[Country])*sw R4))
R5a	Infrastructure Convenience Effect	effective infrastructure modifier for EU powertrain convenience = min(1,(ZIDZ((actual EU power train effective infrastructure [Country,Powertrain]/Percent),reference effective infrastructure)^ sensitivity of convenience to effective infrastructure [Country])*sw R5a)
R5b	Maintenance Network Convenience Effect	effective maintenance network = "base maintenance convenience, OEM only" + (min(1,sw R5b*"% Non-OEM maintenance network serving powertrain"[Country,Powertrain]/("reference maintenance/repair network"*Percent))) * (1-"base maintenance convenience, OEM only")

(*continued on next page*)

Table A.3 (*continued*)

Loop		Equation for Deactivation
R5c	Maintenance Network Competition Effect	"Maintenance/Repair Costs" = "Base Maintenance/Repair Costs"[Powertrain,Vehicle Size]* ((1 - "Maintenance/Repair Costs Reduction from competition"[Country,Powertrain,Vehicle Size])*sw R5c)
R6	Consumer Choice Effect	EU attribute value[Choice] = min(1,powertrain technology availability[Powertrain,Vehicle Size]*sw R6)
R7	Environmental Consciousness Effect	marketing influence on importance of environmental impact = min(1,(SMOOTH(reference multiplier of importance of environmental impact*("low-emission marketing"[Country]/"reference low-emission marketing")^"sensitivity of importance of environmental impact to low-emission marketing",marketing effect on environmental importance smoothing period))*sw R7)
R8a	Attractiveness from Performance Effect	EU attribute value [component criteria] = (if then else(component criteria = Convenience,EU convenience criterion [Country,Powertrain,Vehicle Size],if then else(component criteria = Environment,EU emissions performance[Powertrain,Vehicle Size],(min(1,powertrain utility value[Powertrain,Vehicle Size,component criteria]*sw R8a))))*powertrain commercially available [Powertrain])
R8b	Convenience from Performance Effect	EU convenience criterion = min(1, (min(1,powertrain utility value[Powertrain,Vehicle Size,Convenience]*sw R8b))*effective infrastructure modifier for EU powertrain convenience[Country,Powertrain,Vehicle Size]*effective maintenance network [Country,Powertrain])
R8c	Technology Maturity Effect	base component cost = sw R8c*initial component cost[Component,Vehicle Size]*component maturity cost modifier[Component] + (1-sw R8c)*initial component cost[Component,Vehicle Size]
R9	Penalties Raise Purchase Price Effect	emissions penalty as fraction of revenue = ZIDZ(Max(sum(sw R9*Forecast EU Excess Emission Premium[Vehicle Class!]),EU Excess Emission Premium),total EU revenue); Additional costs from emissions premiums = ZIDZ((sw R9*EU Excess Emission Premium*epbe*relative excess emissions[Powertrain]),EU powertrain Manufacturer Sales[Powertrain])
B1	Marketing to Prevent Penalties Effect	forecast emissions penalty influence on additional marketing = ((emissions penalty as fraction of revenue*sw B1)/base emissions penalties for marketing) ^sensitivity of marketing to emissions penalties
B2	R&D to Prevent Penalties Effect	"powertrain R&D stimulus for manufacturers to reduce CO2 emissions" = sum(sw B2*Forecast EU Excess Emission Premium[Vehicle Class!]) * ZIDZ(powertrain potential environmental improvement[Powertrain], sum(powertrain potential environmental improvement[Powertrain!]))

besides that it yielded unexplainable scenarios for the PHEVs and BEVs sales shares behaviour towards 2050.

A fourth attempt returned to the use of the original demand kick formulation, siding with the argumentation as provided in the technical report that the model offers a difference between the underlying market share and "temporary "kicks" as a result of incentives offered by authorities and/or manufacturers. The available data suggests this influence is rapid (very little delay between incentive and resulting increase in demand) and short-lived (ending soon after the incentives are removed)" (Harrison et al., 2016, p. 33). This formulation did also not yield a good fit for neither PHEVs nor BEVs in both Norway and the Netherlands. Finally, a closer fit was found in a sixth formulation that calibrated these parameters also independently for PHEVs and ZEVs, described and discussed in the main text.

A.2. PTTMAM CLDs with market agent-related variable classification and knock-out edge

Figs. 6 and 7.

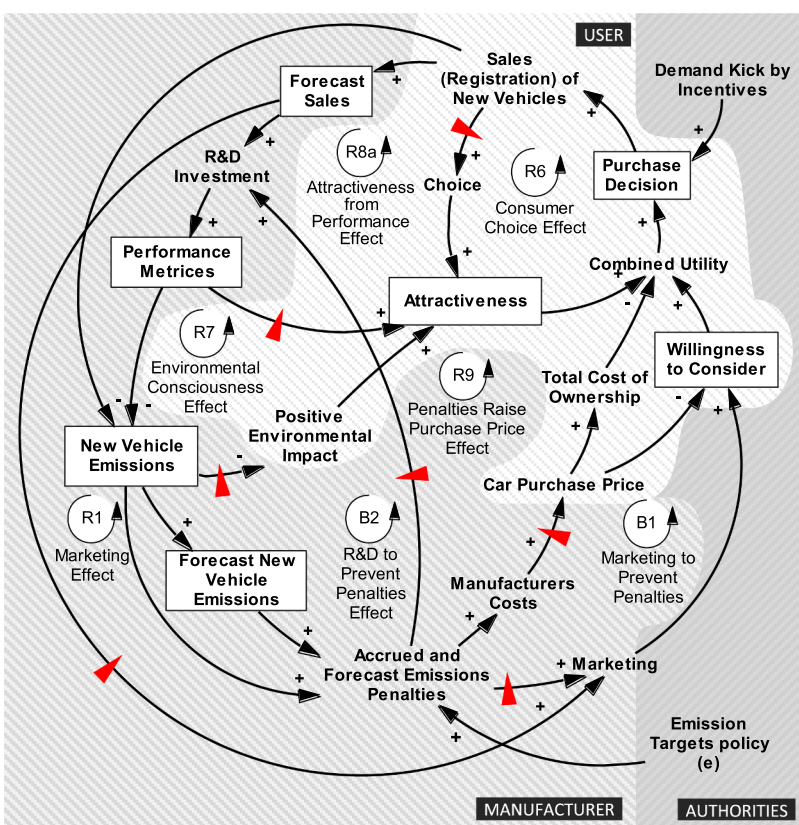

Fig. 6. PTTMAM CLD part 1 of 2 with loop knock-out places (red) and market agent (background).

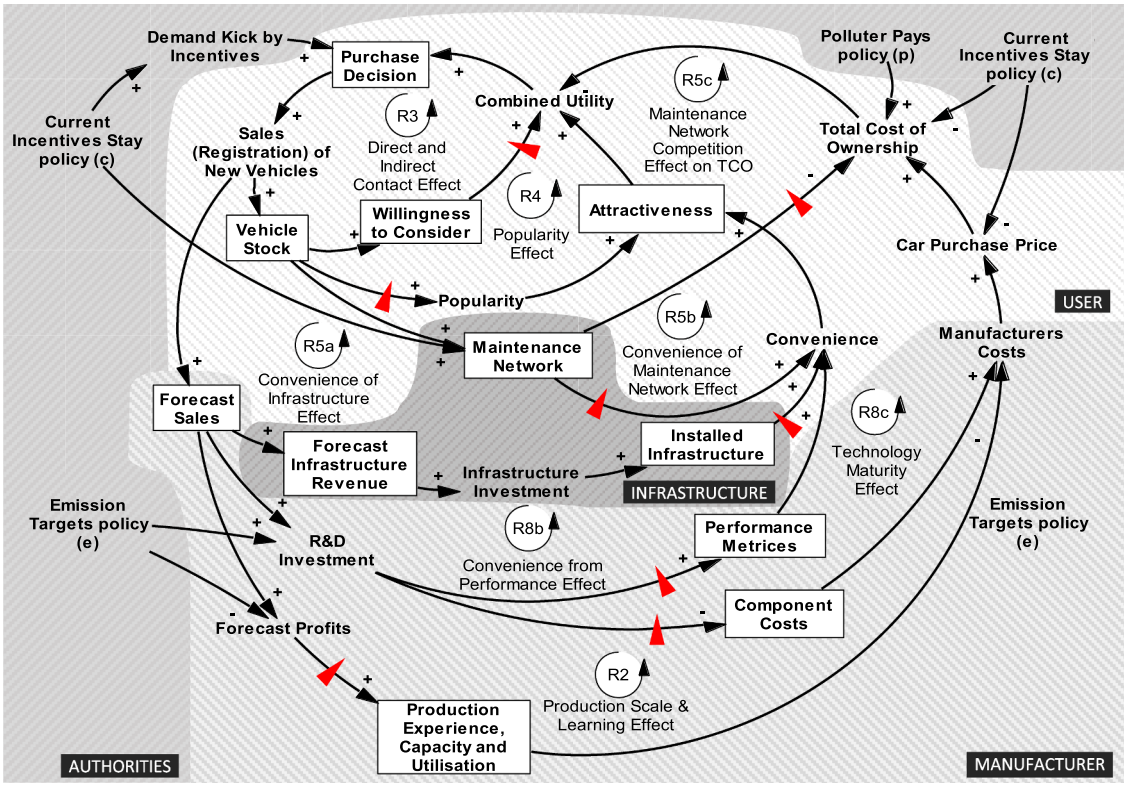

Fig. 7. PTTMAM CLD part 2 of 2 with loop knock-out places (red) and market agent (background).

References

Aasness, M.A., Odeck, J., 2015. The increase of electric vehicle usage in Norway—incentives and adverse effects. Eur. Transp. Res. Rev. 7. https://doi.org/10.1007/s12544-015-0182-4.

ACEA, 2017. Overview of Tax Incentives For Electric Vehicles in the EU. ACEA - European Automobile Manufacturers' Association.

ACEA, 2016. Overview of Tax Incentives For Electric Vehicles in the EU in 2016. ACEA - European Automobile Manufacturers' Association.

ACEA, 2015. Overview of Purchase and Tax Incentives For Electric Vehicles in the EU in 2015. ACEA - European Automobile Manufacturers' Association.

ACEA, 2014. Overview of Purchase and Tax Incentives For Electric Vehicles in the EU. ACEA - European Automobile Manufacturers' Association.

ACEA, 2013. Overview of Purchase and Tax Incentives For Electric Vehicles in the EU. ACEA - European Automobile Manufacturers' Association.

ACEA, 2011. Overview of Tax Incentives For Electric Vehicles in the EU, 2011. ACEA - European Automobile Manufacturers' Association.

ACEA, 2010. Overview of Tax Incentives For Electric Vehicles in the EU. ACEA - European Automobile Manufacturers' Association.

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. https://doi.org/10.1016/j.rser.2012.12.048.

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

Barlas, Y., Carpenter, S., 1990. Philosophical roots of model validation: two paradigms. Syst. Dyn. Rev. 6, 148–166.

Bliemel, F., 1973. Theil's forecast accuracy coefficient: A clarification. J. Mark. Res. 10, 444–446.

Bossel, H., 2007. Systems and Models: Complexity, Dynamics, Evolution, Sustainability. BoD.

Duggan, J., Oliva, R., 2013. Methods for identifying structural dominance. Syst. Dyn. Rev. 29.

EAFO, 2018a. European Alternative Fuels Observatory [WWW Document]. URLhttp://www.eafo.eu/countries (accessed 4.17.18).

EAFO, 2018b. EAFO Norway Summary Statistics [WWW Document]. URLhttp://www.eafo.eu/content/norway#country_ng_market_share_graph_anchor (accessed 1.23.18).

European Commission, 2017. Summary on national plans for alternative fuel infrastructure.

European Parliament, Council of the European Union, 2014. Regulation (EU) No 333/2014. Off. J. Eur. Union 15–21.

Figenbaum, E., 2016. Perspectives on Norway's supercharged electric vehicle policy. Environ. Innov. Soc. Transitions 25, 14–34. https://doi.org/10.1016/j.eist.2016.11.002.

Figenbaum, E., Kolbenstvedt, M., 2013. Electromobility in Norway - Experiences and Opportunities With Electric Vehicles. Institute of Transport Economics (TØI) Oslo, Norway.

Fiorello, D., Fermi, F., Bielanska, D., 2010. The ASTRA model for strategic assessment of transport policies. Syst. Dyn. Rev. 26, 283–290.

Ford, D.N., 1999. A Behavioral Approach to Feedback Loop Dominance. Syst. Dyn. Rev. 15, 3–36.

Forrester, J.W., 1961. Industrial Dynamics. MIT Press, Cambridge, Massachusetts, USA.

Forrester, J.W., Mass, N.J., Ryan, C.J., 1976. The system dynamics national model : understanding socio-economic behavior and policy alternatives. Technol. Forecast. Soc. Chang. 9, 51–68.

Fridstrøm, L., Østli, V., 2016. Vehicle fleet forecasts based on stock-flow modeling. Oslo.

Gómez Vilchez, J., Harrison, G., Kelleher, L., Smyth, A., Thiel, C., Lu, H., Rohr, C., 2017. Quantifying the factors influencing people's car type choices in Europe: Results of a stated preference survey. Luxembourg.

Groesser, S.N., Schwaninger, M., 2012. Contributions to model validation: hierarchy, process, and cessation. Syst. Dyn. Rev. 28, 157–181.

Hardman, S., Chandan, A., Tal, G., Turrentine, T., 2017. The effectiveness of financial purchase incentives for battery electric vehicles – A review of the evidence. Renew. Sustain. Energy Rev. 80, 1100–1111. https://doi.org/10.1016/j.rser.2017.05.255.

Hardman, S., Tal, G., 2016. Exploring the decision to adopt a high-end battery electric vehicle: role of financial and nonfinancial motivations. Transp. Res. Rec. 2572, 20–27.

Harrison, G., Thiel, C., 2017a. Policy insights and modelling challenges: The case of passenger car powertrain technology transition in the European Union. Eur. Transp. Res. Rev. 9, 1–14. https://doi.org/10.1007/s12544-017-0252-x.

Harrison, G., Thiel, C., 2017b. An exploratory policy analysis of electric vehicle sales competition and sensitivity to infrastructure in Europe. Technol. Forecast. Soc. Change 114, 165–178. https://doi.org/10.1016/j.techfore.2016.08.007.

Harrison, G., Thiel, C., Jones, L., 2016. JRC Technical Reports: Powertrain Technology Transition Market Agent Model (PTTMAM). 10.2790/719385.

Hoek, G., Krishnan, R.M., Beelen, R., Peters, A., Ostro, B., Brunekreef, B., Kaufman, J.D., 2013. Long-term air pollution exposure and cardio- respiratory mortality: a review. Environ. Heal. 12, 43. https://doi.org/10.1186/1476-069X-12-43.

Hoen, A., Koetse, M.J., 2014. A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. Transp. Res. Part A Policy Pract. 61, 199–215.

Holtsmark, B., Skonhoft, A., 2014. The Norwegian support and subsidy policy of electric cars. Should it be adopted by other countries? Environ. Sci. Policy 42, 160–168. https://doi.org/10.1016/j.envsci.2014.06.006.

IEA, 2018. Global EV Outlook 2018. 10.1787/9789264302365-en.

Jensen, A.F., Cherchi, E., de Dios Ortúzar, J., 2014. A long panel survey to elicit variation in preferences and attitudes in the choice of electric vehicles. Transportation (Amst)

41, 973–993.
Jochem, P., Gómez Vilchez, J.J., Ensslen, A., Schäuble, J., Fichtner, W., 2017. Methods for forecasting the market penetration of electric drivetrains in the passenger car market drivetrains in the passenger car market. Transp. Rev. https://doi.org/10.1080/01441647.2017.1326538.
Keijser, B.M.J., Kwakkel, J.H., Pruyt, E., 2012. How to explore and manage the future? Formal model analysis for complex issues under deep uncertainty. In: Proceedings of the 30th International Conference of the System Dynamics Society. St. Gallen, Switzerland.
Keith, D.R., Naumov, S., Sterman, J., 2017. Driving the future: a management flight simulator of the US automobile market. Simul. Gaming 48, 735–769. https://doi.org/10.1177/1046878117737807.
Koelemeijer, R., Daniëls, B., Boot, P., Koutstaal, P., Kruitwagen, S., Geilenkirchen, G., Menkveld, M., Ros, J., van den Born, G.J., Lensink, S., van Hout, M., 2017. Analyse Regeerakkoord Rutte-III. Effecten op Klimaat en Energie, Den Haag.
Krail, M., Schade, W., 2016. Measures to promote the diffusion of alternative fuel vehicles in EU27. In: André, M., Samaras, Z. (Eds.), Energy and Environment. John Wiley & Sons, Ltd, pp. 155–171. https://doi.org/10.1002/9781119307761.ch11.
Künzli, N., Kaiser, R., Medina, S., Studnicka, M., Chanel, O., Filliger, P., Herry, M., Horak, F.J., Puybonnieux-Texier, V., Quénel, P.J., Schneider, R, Seethaler, J-C, Vergnaud, H.S., 2000. Public-health impact of outdoor and traffic-related air pollution: a European assessment. Lancet 356, 795–801. https://doi.org/10.1016/S0140-6736(00)02653-2.
Kwakkel, J.H., Pruyt, E., 2013. Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty. Technol. Forecast. Soc. Chang. 80, 419–431.
Lévay, P.Z., Drossinos, Y., Thiel, C., 2017. The effect of fiscal incentives on market penetration of electric vehicles: A pairwise comparison of total cost of ownership. Energy Policy 105, 524–533. https://doi.org/10.1016/j.enpol.2017.02.054.
Lorenzoni, I., Pidgeon, N.F., 2006. Public views on climate change: European and USA perspectives. Clim. Change 77, 73–95. https://doi.org/10.1007/s10584-006-9072-z.
Naumov, S., Oliva., R., 2018. Structural Dominance Analysis Toolset [WWW Document]. URLhttp://iops.tamu.edu/faculty/roliva/research/sd/sda/ (accessed 11.24.18).
Netherlands Enterprise Agency, 2017. Electric transport in the Netherlands 2016 highlights. Utrecht.
Netherlands Enterprise Agency, 2016. Electromobility in the Netherlands Highlights 2015. Utrecht.
Netherlands Enterprise Agency, 2015. Electromobility in the Netherlands Highlights 2014. Utrecht.
Norsk elbilforening, 2018. Norwegian EV Policy [WWW Document]. URLhttps://elbil.no/english/norwegian-ev-policy/ (accessed 3.23.18).
Ntziachristos, L., Mellios, G., Kouridis, C., Papageorgiou, T., Theodosopoulou, M., Samaras, Z., Zierock, K.H., Kouvaritakis, N., Panos, E., Karkatsoulis, P., 2008. European database of vehicle stock for the calculation and forecast of pollutant and greenhouse gases emissions with TREMOVE and COPERT. Lab Appl. Thermodyn. 8, 260.
Oliva, R., 2016. Structural dominance analysis of large and stochastic models. Syst. Dyn. Rev. 32, 26–51. https://doi.org/10.1002/sdr.
Oliva, R., 2003. Model calibration as a testing strategy for system dynamics models. Eur. J. Oper. Res. 151, 552–568. https://doi.org/10.1016/S0377-2217(02)00622-7.
Papadimitriou, G., Ntziachristos, L., Wüthrich, P., Notter, B., Keller, M., Fridell, E., Winnes, H., Styhre, L., Sjödin, A., 2013. Transport data collection supporting the quantitative analysis of measures relating to transport and climate change (TRACCS) final report prepared for the Directorate-General for Climate Action. Eur. Comm.
Parry, I.W.H., Walls, M., Harrington, W., 2007. Automobile externalities and policies. J. Econ. Lit. 45, 373–399.
Pasaoglu, G., Harrison, G., Jones, L., Hill, A., Beaudet, A., Thiel, C., 2016. A system dynamics based market agent model simulating future powertrain technology transition: Scenarios in the EU light duty vehicle road transport sector. Technol. Forecast. Soc. Change 104, 133–146. https://doi.org/10.1016/j.techfore.2015.11.028.
Pasaoglu, G., Honselaar, M., Thiel, C., 2012. Potential vehicle fleet CO2 reductions and cost implications for various vehicle technology deployment scenarios in Europe. Energy Policy 40, 404–421. https://doi.org/10.1016/j.enpol.2011.10.025.
Richardson, G.P., 1986. Dominant structure. Syst. Dyn. Rev. 2, 68–75. https://doi.org/10.1002/sdr.4260020107.
Rogers, E.M., 1962. Diffusion of Innovations, 1st ed. Free Press of Glencoe, New York.
Rutte, M., van Haersma Buma, S., Pechtold, A., Segers, G., 2017. Vertrouwen in de toekomst: Regeerakkoord 2017-202. Den Haag.
RVO, 2018. Elektrisch Rijden – Personenauto's en laadpunten Analyse over 2017.
Schmidt, O., Hawkes, A., Gambhir, A., Staffell, I., 2017. The future cost of electrical energy storage based on experience rates. Nat. Energy 2, 17110.
SSB, 2018. Statistisk sentralbyrå [WWW Document]. Stat. Norw. URLhttps://www.ssb.no/statbank/ (accessed 4.17.18).
Sterman, J.D., 2000. Business dynamics: Systems Thinking and Modeling For a Complex World. Irwin/McGraw-Hill, Boston.
Sterman, J.D., 1984. Appropriate summary statistics for evaluating the historical fit of system dynamics models. Dynamica 10 (2), 51–66.
Struben, J., Sterman, J.D., 2008. Transition challenges for alternative fuel vehicle and transportation systems. Environ. Plan. B Plan. Des. 35, 1070–1097. https://doi.org/10.1068/b33022t.
Tal, G., Nicholas, M., 2016. Exploring the impact of the federal tax credit on the plug-in vehicle market. Transp. Res. Rec. 2572, 95–102.
Testa, G., Bakken, B.E., 2018. A comparative, simulation supported study on the diffusion of battery electric vehicles in Norway and Sweden. In: Proceedings of the 36th International Conference of the System Dynamics Society. Reykjavik, Iceland. pp. 1–5.
Theil, H., 1966. Applied Economic Forecasting. In: Studies in mathematical and managerial economics. North-Holland, Amsterdam.
Theil, H., 1965. The information approach to demand analysis. Econom. J. Econom. Soc. 67–87.
Thiel, C., Krause, J., Dilara, P., 2015. Electric vehicles in the EU from 2010 to 2014 - is full scale commercialisation near? 10.2790/921495.
Thiel, C., Nijs, W., Simoes, S., Schmidt, J., van Zyl, A., Schmid, E., 2016. The impact of the EU car CO2 regulation on the energy system and the role of electro-mobility to achieve transport decarbonisation. Energy Policy 96, 153–166. https://doi.org/10.1016/j.enpol.2016.05.043.
Turcheniuk, K., Bondarev, D., Singhal, V., Yushin, G., 2018. Ten years left to redesign lithium-ion batteries. Nature 559, 467–470. https://doi.org/10.1038/d41586-018-05752-3.
UNFCCC, 2015. Paris Declaration on Electro-Mobility and Climate Change & Call to Action [WWW Document]. URLhttps://unfccc.int/news/the-paris-declaration-on-electro-mobility-and-climate-change-and-call-to-action (accessed 10.8.18).
United Nations, D. of E. and S.A., 2015. World Urbanization Prospects: The 2014 Revision. 10.4054/DemRes.2005.12.9.
Ventana Systems Inc, 2018. Vensim User Guide [WWW Document]. URLhttps://www.vensim.com/documentation/index.html?users_guide.htm.
Weekers, F.H.H., 2011. Autobrief over de fiscale stimulering van (zeer) zuinige auto's en enkele andere onderwerpen op het gebied van de autobelastingen. Tweede Kamer der Staten-Generaal [WWW Document]. URL https://www.tweedekamer.nl/kamerstukken/brieven_regering/detail?id=2011Z11680&did=2011D28978.
Woodcock, J.W., Edwards, P., Tonne, C., Armstrong, B.G., Ashiru, O., Banister, D., Beevers, S., Chalabi, Z., Chowdhury, Z., Cohen, A., Franco, O.H., Haines, A., Hickman, R., Lindsay, G., Mittal, I., Mohan, D., Tiwari, G., Woodward, A., Roberts, I., 2009. Public health benefits of strategies to reduce greenhouse-gas emissions: urban land transport. Lancet 374, 1930–1943. https://doi.org/10.1016/S0140-6736(09)61714-1.
Zubi, G., Dufo-lópez, R., Carvalho, M., Pasaoglu, G., 2018. The lithium-ion battery: State of the art and future perspectives The lithium-ion battery : State of the art and future perspectives. Renew. Sustain. Energy Rev. 89, 292–308. https://doi.org/10.1016/j.rser.2018.03.002.

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