Preference elicitation for a dynamic simulation: powertrain choices in the European Union car market

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ABSTRACT

A nested logit model was estimated from a survey carried out among European car owners. For the purpose of improving choice assumptions, this model was embedded within the Powertrain Technology Transition Market Agent Model. This system dynamics model focuses on vehicle powertrain uptake in the European Union. This paper describes the modeling process and shows its application to German car sales market shares until 2025. In conclusion, the integration of discrete choice frameworks based on stated preference surveys into system dynamics models remains a useful approach to explore empirically-grounded factors of technology adoption and feedback processes.

Keywords: *electric vehicles, stated preference survey, discrete choice model, system dynamics, automotive*

1. INTRODUCTION

In 2015, the transport sector emitted 1,048 megatonnes of CO_2 equivalent ($MtCO_{2eq}$) in the European Union (EU). By 2050, EU transport emissions should not exceed 333 $MtCO_{2eq}$ (EEA, 2019). The EU vehicle market plays a crucial role in achieving that goal. The uptake of low- and zero-emission vehicle (in particular electric vehicles (EVs)) technologies is being facilitated mainly by CO_2 emissions performance standards (EU, 2009, 2017b), deployment of alternative fuels infrastructure (EU, 2014) and financial incentives (ACEA, 2018) (EEA, 2018b).

To simulate the impact of these policy measures on the EU passenger car and light commercial vehicle markets over time, the Powertrain Technology Transition Market Agent Model (PTTMAM) was developed[1]. This is a system dynamics (SD) model representing feedback structures and capturing the interactions of four agent groups: users, manufacturers, infrastructure providers and authorities (Harrison, Thiel, & Jones, 2016). At the core of the model lies a key assumption, namely users' powertrain choice.

Harrison and Thiel (2017) used PTTMAM to construct policy scenarios for the Netherlands and the United Kingdom (UK). The authors acknowledged that "*in future development the choice model will be further refined to obtain more specific preference parameters*" (p. 37). Hence PTTMAM developers settled for integrating the utility coefficients of a discrete choice (DC) model into the SD model. The needs of PTTMAM could, to a certain extent, be accommodated from the outset in the survey that underpins the DC model. To our knowledge, this is the first attempt to date at designing and conducting a survey tailored to the requirements of an SD model focusing on EV market uptake. The objective of this paper is to describe this modeling process and the corresponding results. The focus of this study is on the car market.

The structure of the paper is as follows: section 2 provides a concise overview of the literature, the survey and the resulting DC model are briefly described in section 3, in section 4 the process through which the DC model was integrated into the SD model is described, section 5 shows the results, and in section 6 conclusions are drawn.

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[1] PTTMAM is available at: https://ec.europa.eu/jrc/en/pttmam. The model used for this paper is a simplified version with updated data.

2. LITERATURE REVIEW

Consumer choice can be modeled using different methods with the most common ones being, in the context of electric car deployment, diffusion of innovation theory, agent-based modeling and discrete choice (DC) analysis. An overview of the former can be found in Al-Alawi and Bradley (2013). Applied examples of the last two methods are Gnann (2015) and Hackbarth and Madlener (2013), respectively. A multi-method approach can also be identified in the literature: for example, whereas Kieckhäfer *et al.* (2014) used German data to link agent-based modeling with SD, Jensen *et al.* (2016) used Norwegian data to combine the diffusion and DC methods.

Embedding a DC model into an SD model is not entirely new (for the pioneering work and a more recent example, see respectively Ford (1995) and Shepherd *et al.* (2012)). From a review of this body of literature (see Gómez Vilchez and Jochem [*under review*]), it can be concluded that in previous studies the development of the logit model preceded the conceptualisation of the SD model, with the latter sometimes requiring adaptations to accommodate the set of alternatives and/or attributes included in the choice set of the former. In some cases, operations to reconcile both models (for an example related to the units of measurement, see section 5.4.5 in Meyer (2009)) had to be carried out. In contrast, in this work PTTMAM preceded the DC analysis.

3. STATED PREFERENCE SURVEY AND LOGIT MODEL

The survey sought to answer the following research question: which powertrain technologies are EU consumers willing to adopt and how do they trade-off between important attributes of electric and other cars? To this end, a stated preference (SP) survey was designed and conducted in mid-2017 using an existing online panel by computer-assisted web interviewing. The sample comprised a total of 1,248 car owners from six EU countries: France, Germany, Italy, Poland, Spain and the United Kingdom. The questionnaire and a description of the survey respondents can be found in Gómez Vilchez *et al*. (2017). The survey built upon another survey that had been carried out in 2012 (Thiel *et al.* 2012). In contrast to the latter, the 2017 survey included two choice experiments, from which a statistical model was estimated after pooling the data (further details on the design and analysis can be found in Rohr *et al.* (2019)). The five powertrain options offered in the second choice experiment (see Figure A1 in the Appendix) were: petrol, diesel, hybrid (with conventional or plug-in hybrid electric vehicle (PHEV) as a variable), battery electric vehicles (BEVs) and fuel cell electric vehicles (FCEVs).

Relying on random utility theory (refer to e.g. Ben-Akiva & Lerman (1985)), the model that was estimated using the survey data was a special case of the Generalized Extreme Value (GEV) model, namely the Nested Multinomial Logit (NMNL) model. The formulation of the Multinomial Logit (MNL) model is improved by introducing a nesting structure, thereby mitigating the undesirable impact of the Independence of Irrelevant Alternatives (IIA) property. Whereas the error terms of the alternatives are independent and identically distributed (IID) within a nest, they are not across nests. The nesting structure was empirically tested, finding higher elasticities between hybrids and zero emission vehicles (ZEVs: BEVs and FCEVs) ('low emissions' nest) compared to internal combustion engine vehicles (ICEVs: petrol and diesel). In other words, respondents perceive low emissions (hybrids) and ZEVs to be more "similar" to each other and thus they are more likely to switch between these alternatives compared to the petrol and diesel cars. The preferred nesting structure of the model can be seen in Fig. 1. A statistically significant (at the 90% confidence level) θ value of 0.613 was estimated for the low emissions nest (see Fig. 1). By lying between zero and one, this value is consistent with the assumption of utility maximization. A value of one would mean that the NMNL collapses into the MNL model. As it approaches zero the degree of independence within a nest reduces, leading to increasing substitution within each nest.

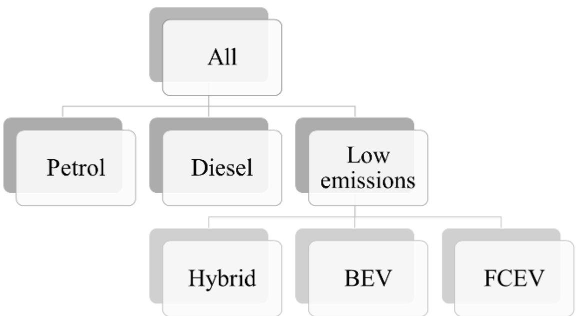

Figure 1. Preferred nesting structure of the logit model
Source: own work

The model was specified with nine car attributes (see Table A1 in the Appendix): purchase price, hire purchase (HP) option, personal contract purchase (PCP) option, operating cost, retained value (i.e. depreciation), range, re-fuelling/-charging time, level of emissions and low emission car incentive. The estimated utility coefficients for each of these attributes can be found in Table 2 in Rohr *et al.* (2019).

4. MODELING APPROACH

4.1 Reduction of subscript range

PTTMAM is a comprehensive model that disaggregates car technology demand by country (28 Member States), vehicle category (passenger cars, light commercial vehicles), user (private, public, fleet), geography (urban, non-urban), size (small, medium, large) and powertrain (16 technologies). In addition, several vehicle attributes are taken into account (see Harrison *et al.* (2016)). This leads to a complex formulation of powertrain choice, which entered into conflict with the need to reduce the cognitive burden to survey respondents.

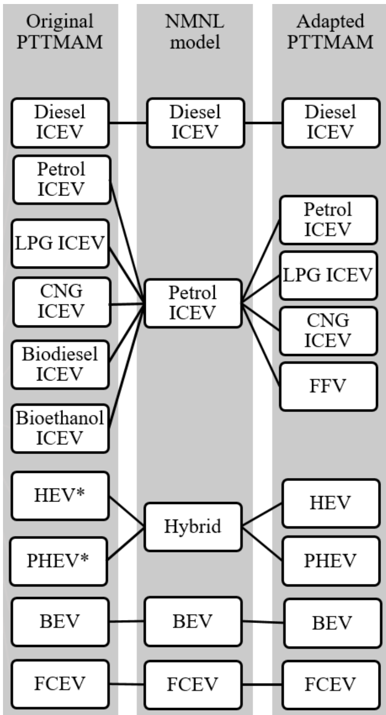

Figure 2. Powertrain options, by model

*This powertrain is further disaggregated into gasoline, diesel, biodiesel and ethanol. Source: own work

Figure 2 shows how the 'powertrain' subscript array was simplified. The most important changes in PTTMAM are the deletion of cars powered by biodiesel and the substitution of bioethanol cars by flexible fuel vehicles (FFV: ethanol 85).

4.2 Extension of feedback loops related to battery attributes

One of the attributes included in the NMNL model is re-charging time for electric cars (re-fuelling for the rest). This variable, however, was not explicitly considered in the original version of PTTMAM. The possibility of simply creating an exogenous variable was considered less satisfactory than the inclusion of an endogenous variable, as the potential for representing additional feedback processes would in this way be exploited. Specifically, three new variables were created (*battery capacity* [kWh/component], *electric range* [km] and *recharging time* [minute]) and three new feedback loops represented (see Fig. 3). This approach had been previously implemented in the model by Gómez Vilchez (2019). For the component cost, the unit of measurement of the battery component was modified from [euro/component] to [euro/kWh].

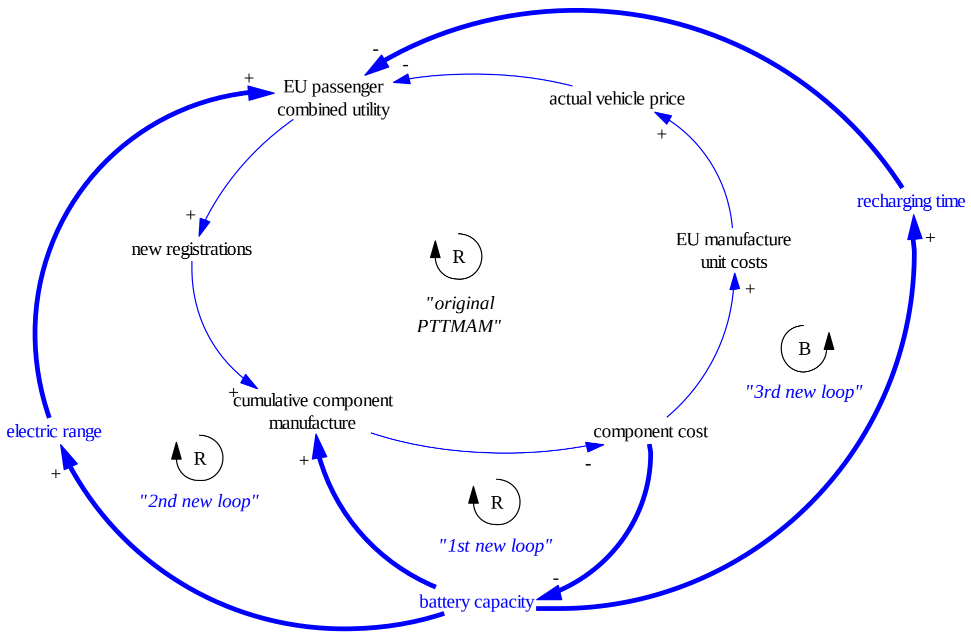

Figure 3. New feedback loops in PTTMAM
Note that this is a highly simplified CLD: various variables are usually present along the causal links displayed here. Source: own work using Vensim®

4.3 Embedment of the discrete choice model within the system dynamics model

Next, the results of NMNL model were embedded within PTTMAM following Equations 1-5 (see also Figure A2 in the Appendix).

For the NMNL model, the probability function can be written as two parts (logits):

$$P_i = P_{i|B} P_B \qquad \text{(Eq. 1)}$$

Among them, the conditional probability of choosing alternative i given that an alternative in nest B_k is chosen is defined as below:

$$P_{i|B} = \frac{e^{V_i}}{\sum_{j \in B} e^{V_j}} \qquad \text{(Eq. 2)}$$

The marginal probability of choosing an alternative in nest B_k is determined by:

$$P_B = \frac{e^{\theta k.Ik}}{\sum_{l \in K} e^{\theta l.Il}} \qquad \text{(Eq. 3)}$$

Then the "logsum" term, which brings information from the lower nest model to the upper model is:

$$I_k = \ln(\textstyle\sum_{j \in B} e^{Y_j}) \qquad \text{(Eq. 4)}$$

The observable part of the utility function V_i for each powertrain/fuel type alternative is written as:

$$V_{SPi} = \textstyle\sum_k \beta\_SP_{iks} X_{ik} + \beta_{ASC} \quad \text{(Eq. 5)}$$

There are two components of the systematic utility coefficient: the coefficients from the SP models, β_SP_{ik}, that multiply the observed 'k' attribute values, i.e. X_{ik}. It is noted that some of the coefficients vary across different segments. Specifically, purchase price and operating cost coefficients vary by vehicle size. Range varies by vehicle type (one term for ICEVs and diesel cars, one for low emission vehicles). Information on both is required to run the model. We dropped the coefficient for left-choice bias, which is not required for implementation of the model (it is included in the estimation of the model to ensure that the resulting coefficients are not biased by such behaviour).

The concept of willingness-to-consider (WtC) a platform (i.e. powertrain), which was present in PTTMAM as a model variable, was also dropped. The reason for this being that the WtC term, which represents "*the formation of a driver's consideration set*" (Struben & Sterman, 2008: 1077), is incorporated implicitly in the DC approach though the attribute weights and alternative-specific constants (ASCs). The advantage of this is that the policy analyst does not need to predict that variable, but rather can focus on car attributes.

The utility equation for each vehicle type also requires an ASC, which reflects the additional utility required for the utility for each car type to ensure that the model incorporates attributes not measured in the choice experiment and replicates observed market shares. We estimated ASCs from the SC data and these were found to vary by age, education level and country. However, it is not appropriate to use constants from SP exercises in forecasting for a number of reasons, including:

- These reflect the choices that were presented in the choice experiments, which may not reflect real-world conditions (e.g. costs varied substantially in the experiments);
- The SP approach assumes that each respondent has perfect knowledge of all alternatives and captures stated (not observed) choices;
- Not all alternatives were able to be included in the choice experiments, e.g. FFVs.

It was therefore necessary to calculate these constants from real-world data.

4.4 Calibration to historical data

The calibration of the model presupposes the availability of an up-to-date dataset with the country-specific historical market shares. Given the aggregate nature of the available real-world data, we adopted the following sequential approach:

- Step 1: PTTMAM's database was updated with time series on car sales. For this purpose, data from EAFO (2018), EEA (2018a), Eurostat (2017) and OICA (2017) was collected. However, historical car sales market shares disaggregated by country, size and powertrain were available for all the countries only until 2015. The categorisation of car size was primarily made based on engine size and, for electric cars, on segment (e.g. B for small cars or C for medium; see CEC (1999));
- Step 2: The values of the car attributes were simulated in PTTMAM to derive the '*utility sum of attributes*' by country, size and powertrain (see Fig. A2), which represents the systematic utility coefficient in Eq. 5;

- Step 3: The term β_{ASC} (‘*ASC SP*’ in Fig. A2) was set equal to -50 if a particular powertrain was not available in the market for a given size, otherwise equal to -zero;
- Step 4: The term β_{ASCRPi} (‘*INITIAL ASC RP*’ in Fig. A2) was calibrated from the collected market information;
- Step 5: In addition to the ASCs, the lambda scale term (λ) would ideally be calibrated to ensure that the models reflect real-world car type choices. For simplicity, we assumed that this value is by default 1, i.e. that the scale of choices in the real world derived from revealed preference (RP) data are equal to the scale of the SC choices. Although it may also be possible to incorporate other attributes into the RP utility equations (e.g. number of brands), which could provide an indication of the supply side of the market and may improve the quality of the choice models, high-quality market information on this was not available at the time this analysis was conducted.
- Step 6: For the calculation of the car type probabilities, adjustments in the ASCs as per Eq. 6 to ensure that the model replicates observed market shares;

$$\varepsilon = ln(\frac{observed\ share}{predicted\ share}) \qquad \text{(Eq. 6)}$$

- Step 7: The calibrated utility (‘*V from RP*’ in Fig. A2) is determined following Eq. 7:

$$V_{RPi} = \sum_k \lambda(V_{SPi}) + \beta_{ASCRPi} \qquad \text{(Eq. 7)}$$

- Step 8: Finally, the nesting structure and θ parameter (recall section 3 and Eq. 2-4) are used to simulate the market shares by country, powertrain and size (see Fig. A2).

To render information exchange between methods feasible, an Excel template was created thereby reconciling the PTTMAM assumptions for each attribute and the DC model output. Those assumptions are considered in section 4.6.

Finally, simulation errors were found for these three subscripted elements in the variable ‘*exp V from RP low emission nest’*: in 2009 for [France,BEV,Large] and in 2011 for [Bulgaria, FFV,Medium] and [Bulgaria,HEV,Medium]. This was caused by very low registration values and solved by setting them to zero.

4.5 Transferability to the remaining powertrains and countries

As can be suspected from Fig. 1 and 2, the five powertrain options considered in the discrete choice analysis needed to be re-mapped into the adapted version of PTTMAM. We assumed that HEVs, PHEVs, BEVs, and FCEVs belong to the low emissions nest. Conversely, the remaining powertrains were assumed to be outside of this nest (i.e. are part of the ICEV nest).

Concerning the transferability of results to the remaining EU countries, the generic operating cost coefficient was used for all the countries, except for France or Italy. Since we had estimated lower price sensitivity to operating cost for these two countries, we used their specific coefficients.

4.6 Numerical assumptions of powertrain attributes

Once the choice structure was updated, the future values of the attributes of each powertrain (and size, as relevant) were required to run PTTMAM. From Fig. 3, electric range and recharging time are expected to play an important role in BEV choice. Though not shown in Fig. 3, average recharging time is also affected by the proportion of normal power and high power (i.e. fast) recharging infrastructure availability. The assumed dynamic behaviour of these variables is shown in the next three figures. In this paper, the model time horizon considered extends until 2025.

Fig. 4 shows the simulated (*sim*) growth in BEV electric range, from ca. 160 km in 2012 to over 600 in 2025. As a reference, data based on the New European Driving Cycle (NEDC) from three specific BEVs is shown: Renault Zoe (small), Nissan Leaf (medium) and Tesla S (large). The assumed increase in range is due to higher battery energy density over time and, especially, to a step increase in battery capacity in 2019.

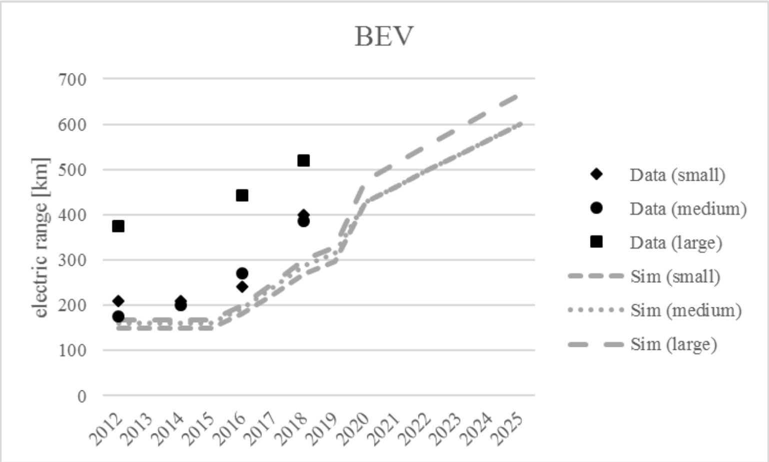

Figure 4. Dynamic behaviour of BEV range, by size: data vs. simulation
Source: own work based on data from Wikipedia (2019) own simulations

Fig. 5 shows the evolution of recharging points in the EU, distinguishing between normal and high power (or fast, with >22 kW following EU (2014)). The 2020 target corresponds to the value determined in EU (2017a). For simplicity, no growth in recharging infrastructure is assumed between 2020 and 2025 in this paper. At the country level, the proportion of normal versus (vs.) rapid recharging infrastructure varies, which influences country-specific average recharging times. For fast recharging, a value of 100 kW is assumed.

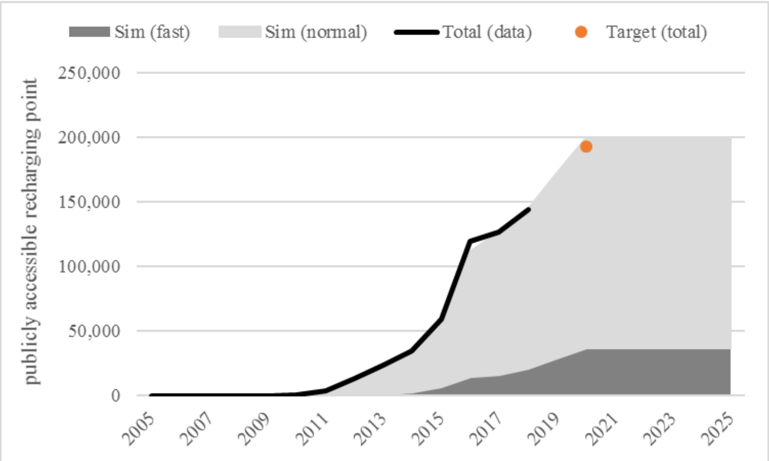

Figure 5. Deployment of normal vs. high power recharging points in the EU
Source: own work based on data from EU (2017a) and EAFO (2018) and own simulations

Fig. 6 shows the average simulated recharging time for medium-sized BEVs in five major European car markets that were covered in the aforementioned survey. By increasing the proportion of fast recharging, Italy achieves a noticeable reduction in recharging time between 2013 and 2019. The assumed increase in battery capacity in 2019 adversely impacts average recharging times. As the proportion of normal vs. fast recharging remains constant post-2020, no changes in recharging times are simulated in the last five years of the model time horizon.

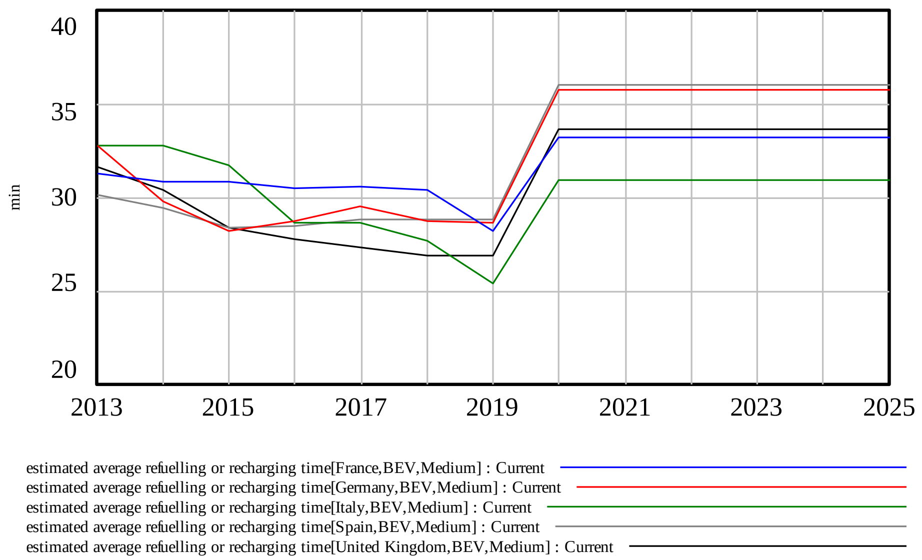

Figure 6. Dynamic behaviour of medium BEV recharging time in five countries
Source: own simulations using Vensim®

5. RESULTS

The results of executing the approach described in section 4 are reported for the largest car market in the EU: Germany. Fig. 7 shows the historical observations vis-à-vis simulated values of petrol and diesel car sales market shares. These powertrain options clearly dominated the German market for new cars over the period. As can be seen, the data could be replicated, via year-by-year adjustments of the ASCs, with the NMNL framework embedded in PTTMAM.

Figure 7. ICEV car sales market share [%] in Germany (2005-2016): data vs. simulation
Source: data from EAFO (2018) own simulations

In this market, alternative powertrain options exhibited very low sales market shares during the calibration period considered. Because of the potential of electric cars to replace ICEVs, annual sales of PHEVs and BEVs were calculated. The results for Germany are shown in Fig. 8. As can be seen, the fit to data worsens, particularly in 2015 (the last year for which disaggregated historical data was considered in the calibration). Although the simulation matches the data in 2017, it exhibits a more sluggish behaviour than the 2018 value and current real-world policy developments suggest.

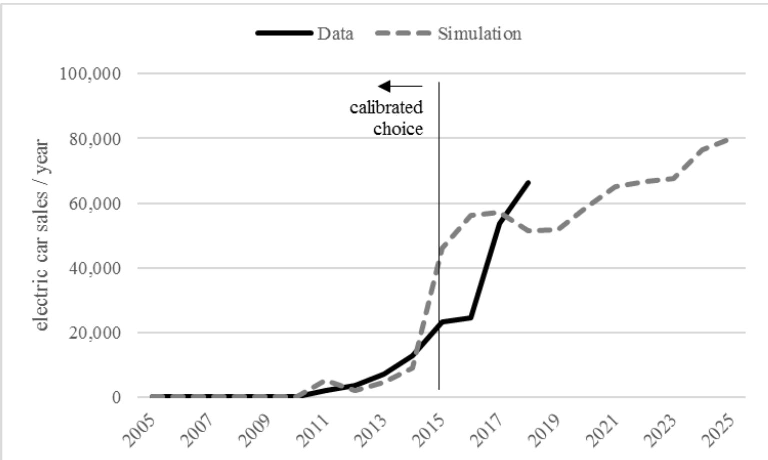

Figure 8. Electric car annual sales in Germany (2005-2025): data vs. simulation
Source: data from EAFO (2018) own simulations

6. CONCLUSIONS AND OUTLOOK

We conclude that the linkage between DC and SD remains useful in this field of application because the results of the former can be tested in the presence of feedback loops while the latter benefits from an empirically grounded representation of choice. The main contribution of this paper is the presentation of how the responses of an SP survey designed with an SD model in mind may be incorporated into simulated aggregate market shares in the EU car powertrain system.

A series of limitations related to this work can be pointed out. First, since PTTMAM does not disaggregate the users market agent by demographic and socio-economic characteristics, the presence of this information in the DC model could not be exploited in the simulation part. Second, the modeling assumptions concerning the transferability of the estimated utility coefficients into other powertrain alternatives and countries can be challenged as e.g. the attributes of FFVs were not considered in the choice experiments. This points to a third limitation, namely the need to devote greater resources to ensure that: (i) a larger sample and more representative by including respondents from other EU countries can be secured; (ii) the scope of the survey widens by extending the duration of the survey, so that additional powertrain alternatives can be inserted in the choice experiments; (iii) more sophisticated DC models such as cross-nested (Hess *et al*., 2012), mixed logit and latent-class (Shen, 2009) are estimated and their relative superiority tested; and (iv) the survey can be replicated in the future, so that preference stability can be gauged, and be complemented with RP data.

The survey undertaken in 2017 was, by nature, static. Placing the resulting DC model in a dynamic context raises intriguing questions: how can the aggregation problem be in practice successfully addressed? Do ASCs become by necessity dynamic when framed in a time-varying context? These need to be addressed in future research.

Further work along the following lines is required: (i) updating the database to a more recent year and re-calibrating the model for that period; (ii) assessing the accuracy of the new formulation by performing e.g. Theil's inequality tests; (iii) analysing different policy measures and constructing scenarios at the EU level with an extended model time horizon; and (iv) scaling these choice assumptions into other users and vehicle types.

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Appendix

Figure A1 shows one of the choice scenarios respondents were presented.

	Internal combustion engine		Hybrid vehicles	Zero emission	
Fuel Type	Petrol	Diesel	Plug - in	Electric battery	Hydrogen fuel cell
Purchase price (outright price)	£15,000	£15,000	£40,000	£25,000	£15,000
Personal Contract Plan (monthly price for 36 month)*	£290 per month with a final payment of £5,000	£290 per month with a final payment of £5,000	£830 per month with a final payment of £13,200	£510 per month with a final payment of £8,250	£290 per month with a final payment of £5,000
Operating cost (pence/ mile)	24p/ mile	22p/ mile	18p/ mile	6p/ mile	12p/ mile
Low Emission Vehicle Incentive (daily charge £/ day)	Working or living in an urban area: £12.00	Working or living in an urban area: £12.00	Working or living in an urban area: £9.00	Working or living in an urban area: £2.40	Working or living in an urban area: £0.00
	Other areas: £2.00	Other areas: £2.00	Other areas: £1.50	Other areas: £0.40	Other areas: £0.00
Vehicle value (after 3 years)	£3,750	£5,250	£10,000	£6,250	£5,250
Range on a full tank/ charge (miles)	400 miles	520 miles	400 miles	300 miles	400 miles
Refuel / Recharge time at a service station (for electric vehicles, time to recharge the battery to at least half its capacity)	5 mins	5 mins	5 mins, if Electric: 4 hours	4 hours	5 mins

* with a £1000 deposit

Figure A1. Scenario in the second choice experiment

Source: Rohr *et al.* (2019)

Figure A2 shows an excerpt of the module where powertrain choice takes place in the updated version of PTTMAM.

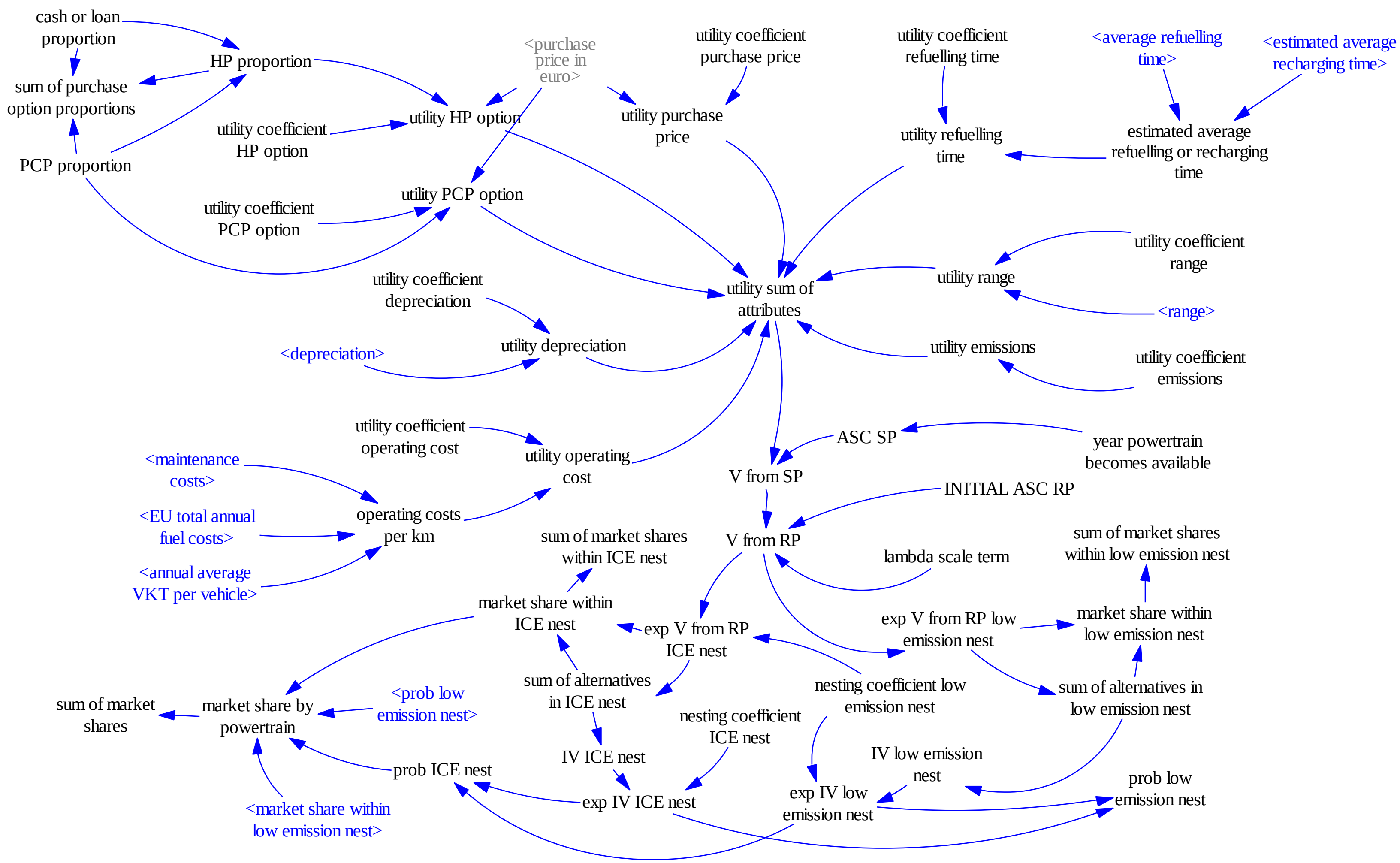

Figure A2. NMNL model embedded within PTTMAM

Source: own work using Vensim®

Table A1 shows a description of the eight attributes and their associated coefficient terms used in the NMNL model.

Table A1. Attributes and coefficients in the systematic utility equation for implementation of the model

	Attribute values in the utility equation (X_{ik})		Coefficients in utility (β)	
Attribute	**Attribute description (inputs to the model)**	**Units**	**Coefficient terms**	**Description**
Purchase price	Purchase price in euros, it is expected that these will vary by vehicle type, vehicle size and across EU countries	1,000s of euros	*purpr_sm, purpr_md, purpr_lg*	Coefficient is generic (the same) across all vehicle-type alternatives, but varies by size of vehicle
HP	Proportion of vehicles purchased by HP multiplied by the price of vehicle (assumed HP proportion likely to vary by country, price varies as above)	HP proportion x purchase price (1,000s of euros)	*HP_ct*	Coefficient is generic across all vehicle-type alternatives, size of vehicle and country
PCP	Proportion of vehicles purchased by PCP multiplied by the price of vehicle (assumed PCP proportion likely to vary by country, price varies as above).	PCP x purchase price	*PCP_ct*	Coefficient is generic across all vehicle-type alternatives, size of vehicle and country
Operating cost	Operating cost, in euros per km, assume that these will vary by vehicle type, vehicle size and country	Cents/km	*oper_ct (all vehicles), oper_FR (France, additive), oper_IT (Italy, additive)*	Coefficient is generic across all vehicle-type alternatives, but varies across countries for France and Italy
Retained vehicle value (i.e. depreciation)	Retained value of vehicle, in euros, assumed that these will vary by vehicle type, vehicle size(?) and country	1,000s of euros	*depr_ct*	Coefficient is generic across all vehicle-type alternatives, size of vehicle and country
Range	Range vehicle can travel, in km, assumed that these will vary by vehicle type and vehicle size (?)	km	*eff_range, eff_rLo*	Separate values for low emission and other vehicles, but the same across countries and size of vehicle
Re-fueling / re-charging time	Time to refuel, these will vary by vehicle type (and perhaps vehicle size)	Mins	*refuel*	Coefficient is generic across all vehicle-type alternatives, size of vehicle and country
Emissions	Emission level for vehicle, will vary by vehicle type (and perhaps vehicle size)	Categorical variables	*ZeroEmiss, LowEmiss, MedEmiss, HighEmiss (set as reference = 0)*	Coefficients are generic across all vehicle-type alternatives, size of vehicle and country

Note: a ninth attribute (low emission car incentive) was included in the second experiment only.
Source: own work